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Spatial Model of Geographic Distribution of Leprosy Cases in East Java Province, Indonesia

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Abstract

Leprosy is an infectious disease and serious health problem that causes disability. According to the World Report on Disability from the World Health Organization (WHO), leprosy is one of the main causes of disability. It can be transmitted through inhalation or contact with patients, which allows it to spread easily and generally occurs in developing countries, including Indonesia. The number of leprosy cases in Indonesia also fluctuates every year, particularly in East Java Province. This study aimed to apply leprosy spatial modeling by evaluating the heterogeneity of data distribution in East Java Province. Using data from the health profile of the East Java Province, the study analyzed socioeconomic variables, access to health services, and the condition of the home environment. Spatial analysis using Moran's Index and the Spatial Error Model was employed to obtain spatial distribution and modeling patterns. Variables such as Human Development Index, poverty, access to health centers, and the physical condition of the home environment spatially affect leprosy cases. Cross-sectoral collaboration is needed to address leprosy cases.

INTRODUCTION

Leprosy is an infectious disease caused by Mycobacterium leprae. This disease can cause complex problems, not only from a medical perspective, such as physical disability, but also from social, economic, cultural, security, and national security perspectives (J. G. Barreto et al., 2014; Nsagha et al., 2011; Penna et al., 2009). Leprosy can cause disabilities, creating barriers for patients to live socially and meet their socioeconomic needs. In several regions in Indonesia, the prevalence rate of leprosy remains high, and the problems it causes are very complex. Leprosy is prevalent in developing countries, with most cases arising from economically disadvantaged groups. This is due to the limited capacity of the state to provide adequate services in health, education, and socioeconomic welfare (Feenstra et al., 2011; Oktaria et al., 2018).

The economic factors are important in the incidence of leprosy, as evidenced in European countries. Improved socioeconomic conditions have led to a reduction in leprosy cases. Sanitation factors in the residential environment play a significant role in the transmission of infectious diseases. Poor housing can trigger infectious dise-

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ases, including leprosy. Sanitation can encompass the condition of floors, walls, roofs, and sources of clean water (de Andrade et al., 2019).

A study in Lamongan district, East Java, found relationships between economic status, contact history of cases, the habit of bathing with soap, use of footwear, occupancy density, the condition of the house floor, and sources of clean water, and the incidence of leprosy (Aprizal et al., 2017). Geographical conditions may contribute to the high number of leprosy cases in East Java. Although much research on the incidence of leprosy has been conducted in Indonesia, it is limited in terms of considering geographical aspects between regions. This study hypothesized that there are differences in the factors affecting the prevalence rate of leprosy between regions due to spatial influences (J. G. Barreto et al., 2014; R. S. Freitas et al., 2014).

Spatial analysis is used to examine the relationship between the human environment and health aspects such as nutrition, disease, and the health care system, to explain spatial linkages. Spatial analysis is considered more accurate than non-spatial analysis because non-spatial analysis cannot address several questions, such as understanding the distribution of health problems (Cromley & McLafferty, 2012).

It is necessary to analyze the characteristics of areas that differentiate between regions and then consider spatial relationship analysis (Lepper et al., 1995). Spatial techniques commonly used in health research include disease mapping, clustering techniques, diffusion studies, and identification of risk factors through map comparisons and regression analysis. Spatial autocorrelation analysis measures the similarity of objects in space (distance, time, and area) and the correlation between variables based on space. Spatially, it can refer to the correlation between values at location-i and values at location-j (Anselin & Getis, 1992).

This study aimed to create a geographic distribution model of leprosy cases in East Java Province. It focused on utilizing spatial modeling techniques to analyze health data, specifically leprosy epidemiology, to assess the variability in data distribution across the province. The researchers hypothesized that spatial modeling could serve as a valuable tool for comprehending the dynamics of leprosy and illustrating the spatial heterogeneity of various factors influencing the occurrence of this disease.

METHODS

Study Area

The research area, East Java Province, is located between 7012' S - 8048' S Latitude and 11100' E - 11404' E Longitude. The northern part of East Java Province is bordered by the Java Sea, the eastern part by the Bali Strait, the southern part by the Indian Ocean, and the western part by Central Java Province. The area of East Java is 47,799.75 km2. The population density in East Java in 2018 reached 826.39 people/km2. The highest population density is in Surabaya City with 8,233.01 people/km2 and the lowest density in Banyuwangi Regency with 78.43 people/km2. Based on health data for 2020, the morbidity rate of leprosy in East Java was 0.54 per 10,000 population (target morbidity rate of <1 per 10,000 population), but there are still 5 districts that have not eliminated leprosy: 4 districts in Madura and Situbondo District. In 2020, 4 districts achieved leprosy elimination: Jember, Probolinggo, Lumajang, and Tuban.

Sampling Design and Methods

This study used an ecological study design with a spatial approach, utilizing models in ecology to achieve various objectives. Models in ecology can illustrate ideas, construct parameters in complex real-world situations, make general predictions, and perform statistical and spatial analyses. The development of these models involved a statistical approach specifically designed to test spatial autocorrelation, aiming to identify spatial patterns present in research data (Achmadi, 2008; Koenig, 1999; Legendre & Fortin, 1989)

This study used city and district administrative-level data to obtain risk distribution maps and identify the spatial dependency of leprosy in East Java Province. The research data came from several reliable sources, including the provincial report from the 2018 Basic Health Research published by the Health Research and Development Agency, the East Java Province Health Profile published by the Indonesian Ministry of Health, and socio-demographic data from the district level reported by the National Health Agency and the Center for Statistics of East Java Province.

The data used in this study can be accessed freely through the official website of each agency. This study involved data from all regencies in East Java Province, which consists of 9 cities and 29 regencies. The use of data at the district administration level allows researchers to analyze the risk distribution and spatial dependence of leprosy at the local level, providing a deeper understanding of conditions in each region and assist in planning and making appropriate decisions regarding leprosy prevention efforts. It is important to note that the data sources used in this research may change over time; therefore, it is recommended that readers access the most recent official data sources related to this topic.

Data Management and Analysis

Since this study utilized secondary data from publicly available sources, specifically the profiles of Basic Health Research (https://dinkes.jatimprov.go.id/) and the Central Bureau of Statistics for East Java Province (https://jatim.bps.go.id/publication/2022/), the researchers determined that ethical approval was not necessary. Ethical approval is typically required for studies involving primary data collection from human participants, as it ensures that the research is conducted ethically, protects participants' rights and well-being, and maintains confidentiality (Newson & Lipworth, 2015).

In this study, the dependent or response variable was the percentage of leprosy, measured by dividing the number of leprosy patients by the total number of leprosy cases in the province. Data on leprosy cases were obtained from surveillance reports conducted at the district level. This study also used several district-level indicators that may be related to leprosy cases. There were 11 indicators covering the characteristics of access to health services, the physical condition of houses and sanitation, and the region's socioeconomic conditions. These indicators were selected based on previous findings and are considered to have a potential relationship with leprosy cases at the district level. The selection of these indicators was based on previous findings regarding factors contributing to leprosy cases. Several factors identified in this study include:

a) Access to Health Services: This factor involves the ease with which the population can access health service facilities. Previous research has shown that a lack of accessibility to health services can contribute to the spread of leprosy cases (Kabir & Hossain, 2019, p. 20; Zhang et al., 2009).

b) The Physical Condition of the House and Sanitation: This factor includes aspects such as environmental cleanliness, sanitation, and the physical condition of the house. Previous studies have shown that poor environmental conditions and inadequate sanitation can increase the risk of leprosy cases (Prakoeswa et al., 2020; R. S. Freitas et al., 2014).

c) Socioeconomic Area: This factor involves social and economic indicators related to the regional level, such as education, income, and poverty. Previous studies have shown that these socioeconomic factors can play a role in the spread and prevalence of leprosy cases (de Andrade et al., 2019, p. 201; Oktaria et al., 2018; R. S. Freitas et al., 2014).

Descriptive statistical analysis was used to present the mean, standard deviation (SD), minimum, and maximum values of each variable. The correlation between each independent and the prevalence of leprosy was tested using Pearson or Spearman's Rank correlation (J. G. Barreto et al., 2014). Statistically significant variables correlated with leprosy cases were then classified into quantiles, and scores from one to five were calculated for these variables, indicating quantiles from lowest to highest. The total score was then calculated by summing the scores of all variables and was also reclassified into quantiles, representing the risk distribution from very low to very high risk of leprosy. Overlay analysis of the Geographic Information System (GIS) with QGIS 2.8.1 software was used to map the distribution of leprosy risk by the district in East Java Province.

Local Moran's Index was used to identify the spatial autocorrelation and local autocorrelation of the leprosy risk score. Global Moran's Index informs the spatial dependence or independence of the data (Anselin & Getis, 1992; Taher Buyong, 2007). Global Moran's Index values (ranging from -1 to 1) higher than expected values of the observed Moran's Index – E(I) – indicate positive spatial autocorrelation (i.e., greater similarity between neighboring locations or high and/or clustered values). If the Moran Index value $I > E(I)$, it suggests a clustered spatial pattern, while if $I < E(I)$, it indicates a scatter pattern. Conversely, a lower Global Moran's I value compared to E(I) indicates negative spatial autocorrelation (i.e., the dispersion of high and/or low values). The presence of spatial autocorrelation was also evaluated with a significant Global Moran's I p-value ($p < 0.05$) using the 99-permutation criterion.

Local Indicator Spatial Autocorrelation (LISA) can be used to test Moran's Index values for each district. LISA results indicate whether the observed variable values in a given area have statistically significant spatial autocorrelation with values in other locations (i.e., are related to, influenced by, or have an influence on values in other locations). In this study, LISA was applied to identify high-high-risk for leprosy clusters. The high-high-risk cluster identifies districts with high leprosy risk surrounded by high-risk neighboring districts. This study used GeoDa 1.8.10 software to perform statistical spatial analysis. The Moran's Index Map and the LISA Map considered only areas with a significant Moran index (p-value <0.05).

Following the identification of variables related to leprosy cases, the next analysis involved Spatial Autoregressive Models, which follow an autoregressive process indicated by a dependency relationship between a set of observations or locations. This relationship is shown by the lag in the dependent and independent variables. Types of Spatial Autoregressive Models include Spatial Error Model (SEM) (Anselin & Getis, 1992).

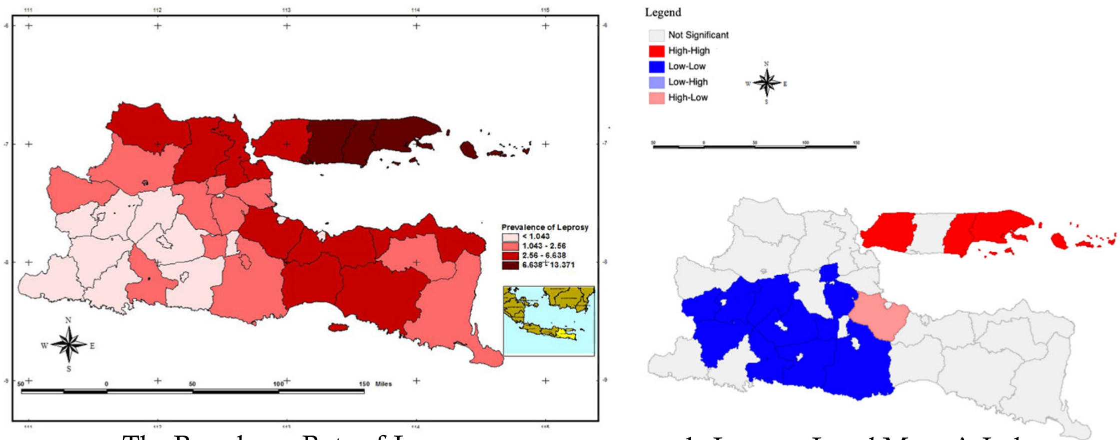
RESULTS AND DISCUSSION

Prevalence of Leprosy

Leprosy, despite its decreased prevalence in many countries, remains a public health problem due to active transmission and new case findings. This is particularly true in the developing world, which has characteristics that facilitate the reproduction and spread of the disease, with complex transmission patterns linked to environmental, social, and economic factors (J. G. Barreto et al., 2014; M. L. Barreto et al., 2011; Leano et al., 2019; Nery et al., 2019).

In 2019, the prevalence rate of leprosy in East Java Province was 1.829%. Figure 1 shows that the highest leprosy prevalence is concentrated in the coastal areas of East Java Province, particularly in the Madura islands, Sampang district (13.37%), Sumenep district (11.85%), and Pamekasan district (8.20%). In contrast, the prevalence rate in the southwest region of the province is less than 1.043%.

The highest prevalence of leprosy is observed in the coastal areas of East Java Province, especially in the Madura islands (Sampang, Sumenep, and Pamekasan districts), while mainland areas show a low prevalence. The geographic conditions of the region are among the variables that influence the spread of leprosy (de Andrade et al., 2019).



a. The Prevalence Rate of Leprosy

b. Leprosy Local Moran's Index

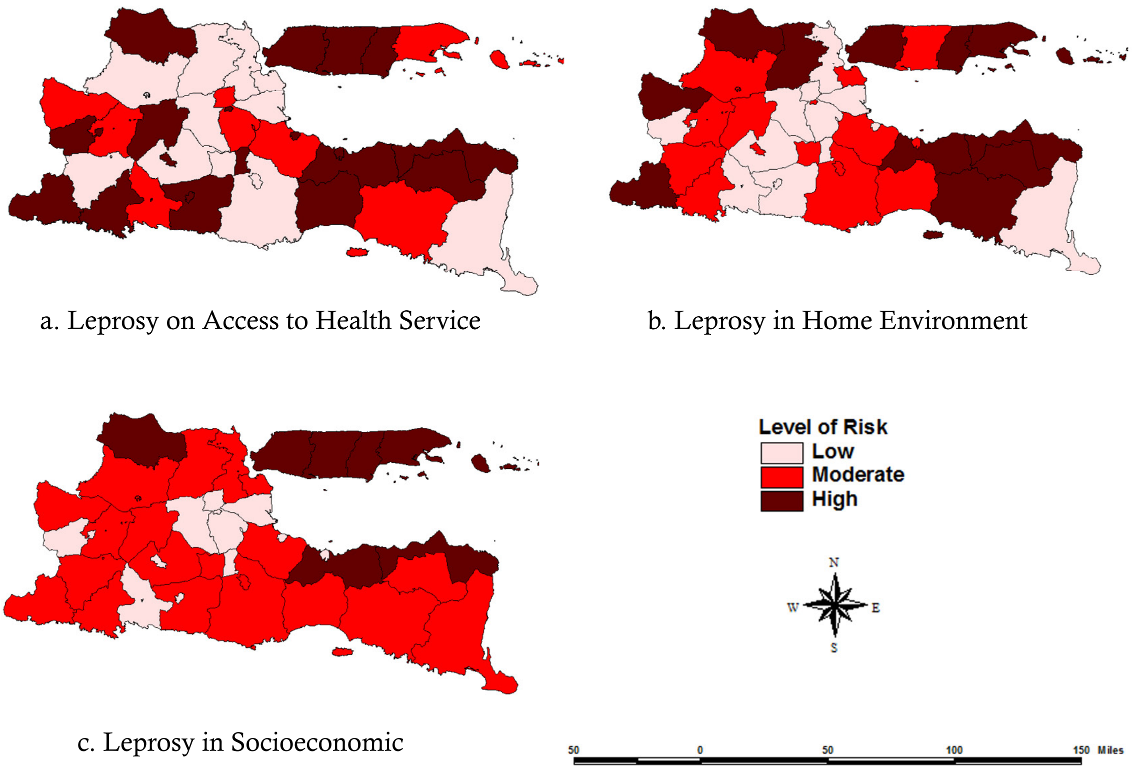
Figure 1. Leprosy Prevalence and Distribution Pattern of the Local Moran's Index

The results of the correlation analysis between the dependent variable (leprosy cases) and the independent variables (access to health services, the physical environment of the house, and the socioeconomic area) indicate that the risk levels of leprosy cases fall into three categories: high, medium and low. The high-risk category includes areas with leprosy cases, low access to health services, poor physical housing environments, and low socioeconomic areas. The low-risk category includes areas with low leprosy cases, high access to health services, good physical housing environments, and high socioeconomic areas. The risk category is considered moderate if one of the variables has a high or low value in relation to leprosy cases and independent variables such as access to health services, physical housing environments, and the socioeconomic areas.

The correlation between leprosy cases and access to health services shows that districts in the Madura archipelago fall into the high to moderate risk categories, while most districts in the eastern region of East Java Province, particularly those on the south coast, are predominantly in the high-risk category. There are 26 districts/cities with high leprosy risk and low access to health services.

The correlation between leprosy cases and the socioeconomic areas shows that most districts in East Java Province fall into the medium-risk category, while all district in the Madura Islands are classified as high-risk areas, characterized by high leprosy cases, low HDI scores, and high numbers of poor individuals.

The results of the correlation analysis of leprosy cases with the variables of access to health



a. Leprosy on Access to Health Service

b. Leprosy in Home Environment

c. Leprosy in Socioeconomic

Figure 2. Risk of Leprosy Cases in East Java Province

services, the physical housing environments, and the socioeconomic areas show that most of the coastal areas are classified in the high-risk category. The high-risk level associated with access to services indicates that these areas have high leprosy cases and low access to health services. Various studies have demonstrated a significant relationship between the incidence of leprosy and socioeconomic factors, poverty, and poor housing conditions. This suggests that improved socioeconomic conditions could help reduce the incidence of leprosy (de Andrade et al., 2019; R. S. Freitas et al., 2014). Socioeconomic development has been shown to impact leprosy epidemiological behavior (Leano et al., 2019; Nery et al., 2019).

Four factors contribute to a person's health status: genetic factors, health services, behavior, and the environment. Environmental and behavioral factors are the most dominant influences on health status; therefore, maintaining a healthy environment and adopting healthy behaviors are crucial. The environment is one of the most important factors and has a positive influence on the realization of public health status. The environment is a key determinant in the transmission and causation of both communicable and non-communicable diseases. Previous research has indicated that environmental factors, particularly related to housing conditions, affected the incidence of leprosy (Matos et al., 2018; Prakoeswa et al., 2020; R. S. Freitas et al., 2014).

Spatial Pattern of Distribution of Leprosy Cases

Based on the results of univariate statistical analysis, Local Moran index (Table 1) shows that the distribution pattern of leprosy in East Java Province is clustered, with an I value of 0.8970, which is greater than the E(I) value.

The analysis of the relationship between leprosy cases and variable such as access to health centers, the number of health centers, the number of nurses in health centers, the availability of windows, the availability of house ventilation,

Table 1. Leprosy Distribution Pattern

Variable	I	E [I]	Mean	P-value	Pattern
Leprosy	0.8970	-0.0156	-0.0153	0.001*	Clustered

*Significant at 0.05

sunlight to houses, proper sanitation, HDI, and poverty reveals a p-value <α (0.05). This indicates spatial autocorrelation among leprosy case locations in East Java.

The LISA bivariate analysis show various distribution patterns (Table 2). LISA bivariate analysis examines the spatial relationship between the dependent variable, leprosy cases, and

Table 2. Bivariate LISA

Variable	I	E [I]	Mean	P-value	Pattern
Access to the health center	-0.409	-0.0278	-0.0107	0.001*	Scattered
The number of health centers	0.208		-0.0069	0.003*	
The number of doctors in a health center	0.043	-0.0278	-0.0289	0.279	Clustered
The number of nurses in a health center	0.240		-0.0135	0.014*	
The availability of windows	-0.376	-0.0278	0.0201	0.001*	Scattered
The availability of house ventilation	-0.219		0.0182	0.02*	
Sunlight to houses	-0.269	-0.0278	0.0135	0.01*	Clustered
Ground floor house	0.125		-0.012	0.093	
Proper sanitation	-0.303	-0.0278	0.0137	0.006*	Scattered
HD	0.188	-0.0278	0.0144	0.038*	Clustered
Poverty	0.211		-0.0179	0.026*	

*Significant at 0.05

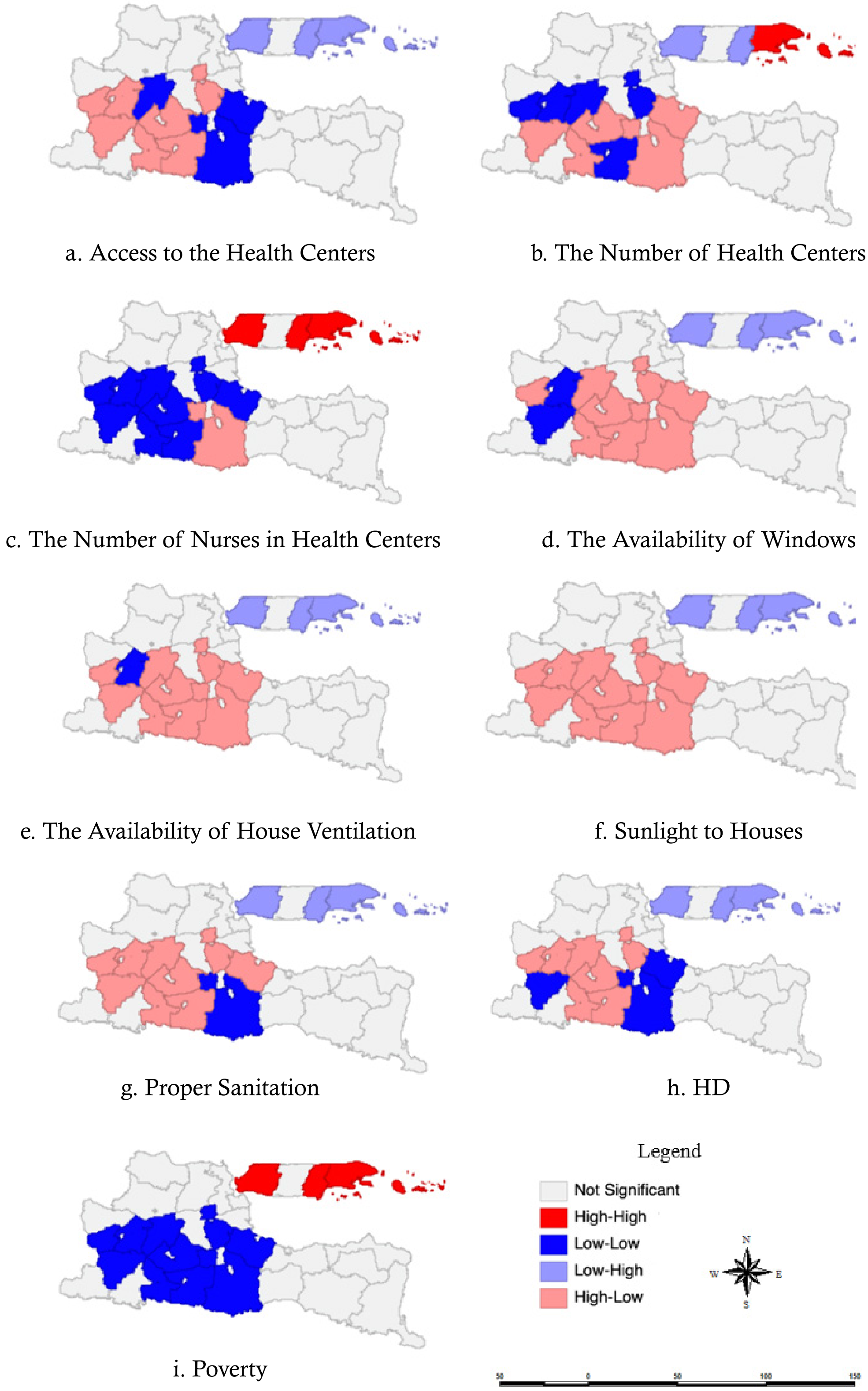
the independent variables (access to the health centers, health workers at health centers, the physical condition of houses, sanitation, and socioeconomic factors). The distribution patterns observed are both scattered and clustered patterns. Scattered patterns are seen in variables such as access to the health centers, windows, house ventilation, and proper sanitation. Conversely, clustered patterns are observed in variables such as the number of health centers, doctors in health centers, nurses at health centers, sunlight, ground floor houses, and socioeconomic factors (HDI and poverty).

The distribution of leprosy cases is observed in districts with altitudes ranging from 47 to 800 meters above sea level. There are seven districts (e.g., Trenggalek, Blitar, Malang, Malang City) with altitudes above 100 meters where leprosy cases are low. Several studies suggest that leprosy is transmitted mainly through direct contact between cases and other individuals, with environmental conditions facilitating its reproduction. Factors affecting leprosy incidence include altitude, air temperature, humidity, lighting, residential density, and personal hygiene (de Andrade et al., 2019; Prakoeswa et al., 2020). Regional altitude and type also influence the growth of M. leprae bacteria (Matos et al., 2018; R. S. Freitas et al., 2014; Sterne et al., 1995). The LISA bivariate analysis results indicate that the spatial patterns are both scattered and clustered. The scattered pattern is associated with variables such as access to health centers, availability of windows and good house ventilation, and proper sanitation. Clustered patterns are seen in variables such as number of health centers, doctors and nurses in health centers, sunlight, ground floor houses, and socioeconomic factors (HDI and poverty).

The LISA bivariate analysis mapping results (figure 3) show that the red variables are in the High–High category, indicating that areas with a high number of leprosy cases are adjacent to other high-case areas. The High-High spatial relationship shows that high-case areas are surrounded other high-case areas. The Low–Low spatial relationship indicates that areas with low leprosy cases are adjacent to other low-case areas. Areas colored in light blue fall into the Low–High category, meaning they have low leprosy cases but are adjacent to high-case areas as indicated by the red color (High – High). Regions with a high-low spatial relationship have high numbers of cases but are adjacent to low-case areas.

In LISA bivariate mapping results, most independent variables are shown in blue (Low-Low) and pink (High-Low) colors. The different colors represent various types of spatial autocorrelation between regions. Red areas indicate statistically significant positive high-high correlations, meaning districts with high incidence rates are adjacent to other districts with high incidence rates. Areas with High-Low or Low-High values are considered spatial outliers. These outliers are found in districts in the central and southern parts of East Java Province (Figure 3).

The distribution pattern of leprosy cases in East Java Province forms a clustered pattern. Leprosy is classified as a Low-Low or cold-spot



a. Access to the Health Centers

b. The Number of Health Centers

c. The Number of Nurses in Health Centers

d. The Availability of Windows

e. The Availability of House Ventilation

f. Sunlight to Houses

g. Proper Sanitation

h. HD

i. Poverty

Figure 3. LISA Bivariate Analysis

category in several districts in the center of East Java Province. This clustered distribution pattern is significant (∝ < 0.05) and in the Low-low category, indicating that districts with low leprosy cases are surrounded by districts with similarly low cases, reflecting spatial interaction between districts.

Access to primary health care is a fundamental human right in any region. Geographical accessibility to health services refers to residents' ability to reach these services and facilities (Haynes et al., 2003; Kuupiel et al., 2020; Wang et al., 2018). The spatial distribution pattern of leprosy in relation to access to health centers shows that health facilities are evenly distributed throughout East Java. The even distribution of health facilities suggests no significant geographical barriers for accessing health services (Haynes et al., 2003).

The analysis of the relationship between leprosy cases and the availability of health workers and health centers reveals differences in distribution patterns compared to access to health services. The spatial distribution pattern of health centers indicates a clustered pattern, whereas access to health services appears scattered. Health centers (Puskesmas) serves as centers for promotional and preventive health services targeting communities and individuals, and they act as primary health service centers where their locations typically aligns with population density and settlements (Anita et al., 2016).

The spatial distribution of leprosy in relation to socioeconomic variables also forms a clustered pattern. In mainland East Java Province (Figure 3), bivariate LISA results for socioeconomic variables (HDI and poverty) categorize these areas as cold-spot areas (Low-Low), indicating low leprosy cases and low poverty. Conversely, in the Madura Archipelago, areas are categorized as hotspot areas (High-High) with high leprosy cases and high socioeconomic factors. This suggests that while leprosy is associated with poverty, there is limited evidence of socioeconomic factors directly influencing leprosy cases (Nery et al., 2019; R. S. Freitas et al., 2014). Thus, it should be noted that poverty itself does not necessarily lead to disease transmission but is associated with conditions such as high population density, poor housing conditions (lack of ventilation and sunlight), inadequate nutrition (Feenstra et al., 2011; Prakoeswa et al., 2020) and limited access to health services (Zhang et al., 2009).

Spatial Model of Leprosy

The results of the LISA bivariate analysis show that not all independent variables exhibit spatial autocorrelation (i.e., they are insignificant), so the variables of the number of doctors in health centers and the ground floor houses were excluded from the spatial regression analysis.

Diagnostic results for spatial dependence are used to determine the presence of spatial dependence. The conclusion on the value of P(α)

Table 3. Spatial Modeling of Leprosy Cases

Variable	OLS			SEM		
	Coefficient	**t-Statistic**	**P-value**	**Coefficient**	**z-value**	**P-value**
Constant	4.7914	0.532	0.562	21.977	3.143	0.00167
Access to health centers	-0.0875	-1.9297	0.057*	-0.091	-2.854	0.00432*
Number of health centers	-0.271	-0.874	0.384	-0.058	-0.2804	0.779
Number of nurses in health centers	0.4348	1.165	0.247	0.068	0.253	0.80024
Availability of windows	-0.0143	-0.4154	0.679	-0.0674	-2.175	0.0295*
Availability of house ventilation	0.126	2.976	0.0039*	0.176	5.191	0.00001*
Sunlight to houses	-0.1068	-1.694	0.0944	-0.1395	-3.134	0.0017*
Ground floor houses	-0.0069	-0.2602	0.7954	0.0498	2.289	0.022*
Proper sanitation	0.00503	0.0417	0.966	-0.205	-2.213	0.0268*
HDI	0.3678	3.094	0.0028*	0.1976	2.222	0.0262*

Variable	OLS			SEM		
	Coefficient	**t-Statistic**	**P-value**	**Coefficient**	**z-value**	**P-value**
Diagnostics for Spatial Dependence						
Lagrange Multiplier (lag)		0.0074				
Lagrange Multiplier (error)		0.0052				
LAMBDA				0.778	12.729	0.00001
AICC	353.242			326.017		
R^2	0.838			0.899		

**Significant at 0.05*

= 0.05 is the Lagrange Multiplier value (lag) = 0.0074, indicating spatial dependency on the dependent variable. The Lagrange Multiplier error value is 0.0052. Both values are less than P(α)=0.05, indicating spatial dependency on the error or residual. Based on these two outputs, it can be concluded that there is a spatial effect on the model of the influence of the independent variables on leprosy cases in East Java (Table 4).

The Lambda coefficient results are positive and significant at the 0.05 confidence level (Table 4), in the independent variables (access to the Health Center, availability of windows and good house ventilation, good sunlight entering the house, proper sanitation, HDI, and poverty), meaning that there is the relationship between leprosy cases in an area with other adjacent areas. The Lambda value suggests that leprosy cases in an area are influenced by factors such as access to health centers, availability of windows, good house ventilation, sunlight, proper sanitation, HDI, and poverty, as well as spatial residual values from neighboring areas with similar characteristics.

Table 4 shows that several variables are significant in both the OLS model and SEM models. These variables include access to health centers, availability of good house ventilation, and poverty. The β value for access to health centers is 0.778, indicating that higher access to the health centers correlates with higher leprosy cases. This variable significantly affects leprosy cases. The β value for house ventilation is -0.08, indicating that higher ventilation correlates with lower leprosy cases, and this variable has a significant spatial effect on leprosy cases. Based on the R-squared and AIC values, the R-squared of the Spatial Error Model is 0.74, higher than the classical regression (0.62) and the AIC value of the Spatial Error model is 168.28 less than the classical regression (177.47). This suggests that the SEM model is more appropriate for analyzing leprosy risk in East Java Province.

Using the Spatial Error Model (SEM) analysis, several independent variables were found to be significant (P-value < 0.05), including access to health centers, availability of house windows, availability of house ventilation, sunlight, proper sanitation, HDI, and poverty. Spatial modeling is an important tool for statistically studying the geographical relationship between independent variables and disease outbreaks (Mollalo & Tatar, 2021). This study examined various regressive and autoregressive spatial models to assess the variation in leprosy cases in East Java Province based on factors as health service access, home environmental conditions, and socioeconomic conditions.

The significant independent variables identified in the spatial models can be used for spatial planning in East Java Province to address leprosy cases. Socioeconomic factors and home environmental conditions continue to influence leprosy incidence in Indonesia (Aprizal et al., 2017; Luhung Mustika Budiharti & Sunendiari, 2021). Improving sanitation hygiene and maintaining nutritional status are essential to preventing leprosy cases. Maintenance of sanitary hygiene can be achieved by ensuring proper environmental conditions, clean water facilities, latrines, waste disposal facilities, and personal hygiene (Prakoeswa et al., 2020).

Leprosy is classified by the World Health Organization (WHO) as one of the 14 Neglected Tropical Diseases (NTDs). It is caused by the bacterium Mycobacterium leprae, and its transmission is closely related to overcrowding, low family income, poor home sanitation, malnutrition, low knowledge, and genetic factors (Moreira et al., 2014). East Java is the province with the highest number of new leprosy cases in Indonesia. Sampang district has the highest leprosy rate in East Java based on average prevalence per 10,000 population. Characteristics of individuals with leprosy, such as gender, age, education level, knowledge level, personal hygiene, and nutritional status, are believed to be associated with the incidence of leprosy (N et al., 2018).

Research has shown that socioeconomic variables influence leprosy cases and treatment, with education and income levels affecting how individuals with leprosy understand their symptoms and treatment (de Andrade et al., 2019; Sterne et al., 1995). Social vulnerability is strongly associated with leprosy transmission and disease maintenance. Leprosy control programs should target populations with high social vulnerability (Souza et al., 2019).

CONCLUSION

The distribution pattern of leprosy cases in East Java Province is clustered, with access to health services, home environmental conditions, and socioeconomic factors being spatially significant variables that exhibit regional interactions within East Java Province.

It is recommended that cross-sectoral cooperation be implemented to address leprosy cases, as the factors influencing the spatial distribution are not limited to the leprosy cases themselves but also include socioeconomic influences and access to health services.

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