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Identification of Dengue Hotspots in Aceh, Indonesia: a SARMA Analysis of Population Density, Climate, and Sanitation Factors

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ABSTRACT

Incidence of Dengue Hemorrhagic Fever (DHF) is rising in Aceh, reflecting an increase in population density and human mobility. There has been a significant surge in DHF cases, with numbers rising from 366 in 2021 to 1,988 in 2022. This alarming trend highlights the urgent need to understand the spatial and temporal distribution of dengue cases, and to identify the key factors driving its transmission. Spatial regression analysis is use to examine the relationship between the incidence of dengue fever and independent socio-demographic and environmental variables, while accounting for spatial autocorrelation. This study used secondary data from the Aceh Health Profile and the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). Climate is consider a significant factor influencing the incidence of dengue fever. This study investigated the impact of three climatic variables: rainfall, air temperature, and air humidity. As climate data are primarily available at BMKG weather stations, kriging is use to interpolate these data spatially and generate complete datasets for each district/city within the study area. The Spatial Autoregressive Moving Average (SARMA) was selected as the most suitable model based on its significant performance in the Lagrange Multiplier (LM) test, with an AIC value of 58.483 and an R^2 of 65.5%. The analysis identified several key factors influencing dengue fever incidence in Aceh, including population density, the percentage of households with access to adequate sanitation, the ratio of health workers, the average air temperature, and the average air humidity.

1.Introduction

Dengue Hemorrhagic Fever (DHF) is a prevalent disease endemic to tropical and subtropical regions worldwide. Its rapid transmission within affected areas poses a significant public health concern. In Indonesia, DHF constitutes a major public health challenge. The number of cases and the geographic extent of outbreaks are escalating, driven by factors such as increased human mobility and population density. In 2022, the Ministry of Health of the Republic of Indonesia reported a cumulative 143,000 DHF cases, nationally, the number of dengue cases is much lower than the estimated incidence of dengue in Indonesia. This wide gap caused by the fact that among those who have dengue symptoms, only 30% seek health care and most of them experience misdiagnosis (Ministry of Health of the Republic of Indonesia, 2023). Aceh Province experienced a substantial increase in DHF cases, with the Aceh Health Office recording 366 cases in 2021 and a surge to 1,988 cases in 2022 (Aceh Health Office, 2023). Addressing this issue necessitates a comprehensive approach, including analyzing the spatial distribution of DHF cases and identifying the underlying contributing factors. These factors encompass a diverse range of influences, including geographic, climatic, environmental, socio-economic, and community-level factors.

This aligns with findings from several studies conducted by various researchers. For example, spatial estimation of relative risk for dengue fever in Aceh province using Conditional Autoregressive method, the findings of the study indicate that the estimates of the relative risk of dengue hemorrhagic fever (DHF) cases, as determined by the Bayesian Conditional Autoregressive (CAR) approach of the Besag-York-Mollie (BYM) Model, in Aceh Province are consistent with all categories and their respective relative risk values (Rahayu et al., 2023a). A number of districts and cities have been observed to exhibit both elevated relative risk values and diminished relative risk values with respect to dengue hemorrhagic fever (DHF) cases. Previous research has also explored the application of spatial modeling in various contexts, such as (Kesuma et al., 2022), which examined factors influencing stunting in children under five years of age in Indonesia, (Rahayu et al., 2023b) which investigated geospatial determinants of maternal mortality, and (Kamal et al., 2023) which utilized satellite imagery to analyze the spatial relationship betw een urban environmental factors and dengue incidence in Dhaka in 2019, and evaluated land surface temperature, urban heat islands, land use–land cover, population census data, and dengue case records.

In term of spatial interpolation, kriging can be used to predict the value of a random variable at unobserved locations based on values at nearby observed locations. Kriging is more flexible and suitable than other spatial interpolation techniques such as inverse distance weighted, spline, and polynomial methods when spatial autocorrelation is present, meaning that values at a given location tend to correlate with values in the surrounding area (Montero et al., 2015). The kriging interpolation technique uses variograms as a basic tool for measuring the spatial correlation between each observation. These variograms indicate the extent to which measurement points are dependent on each other.

Statistical analysis that can describe the influence of independent variables on the dependent variable is regression analysis. Traditional linear regression models do not explicitly account for spatial elements or the location of the data. The inclusion of spatial elements in the model can lead to spatial effects, such as spatial autocorrelation. This occurs when the value of the dependent variable at one location is influenced by its neighboring locations, as observed in phenomena like disease spread, housing prices, and crime rates. In such cases, spatial regression analysis is necessary.

Spatial regression was first introduced by (Cliff and Ord, 1972). The aim of this research was to present a statistic, I, that could be used to test for correlation between geographically located error terms arising from least squares regression.

The existence of spatial dependence is one of the assumptions that must be met in spatial regression analysis. There are several models in spatial regression, namely Spatial Autoregressive model (SAR), Spatial Error Model (SEM), and Spatial Autoregressive Moving Average (SARMA).

Given the high incidence of dengue fever in Aceh, this research aims to analyze the spatial distribution of dengue cases. This involves identifying the most suitable spatial regression model and determining the key factors influencing dengue transmission. The findings of this research will be valuable for relevant stakeholders, particularly the Aceh Health Office, in developing more effective dengue prevention and control programs.

2. Overview of Dengue Hemorrhagic Fever (DHF) and Spatial Regression

Dengue virus is transmitted mostly by the Aedes aegypti mosquito. These mosquitoes typically thrive in tropical and subtropical climates, generally between latitudes 35° North and 35° South at altitudes below 1000 m. Mosquitoes contract the dengue virus only by biting an infected human. In comparison with the nine reporting countries in the 1950s, the current geographic distribution encompasses more than 100 countries worldwide. A significant proportion of these subjects had not reported dengue for at least 20 years, and several lacked a documented medical history of the disease. According to estimates by the World Health Organization (WHO), a global public health authority, more than 2.5 billion individuals worldwide are at risk of contracting dengue fever (Guha-Sapir and Schimmer, 2005). One factor that is thought to influence the spread of dengue fever is the spatial relationship between areas. The spatial relationship between areas is thought to influence the spread of dengue fever. When certain variables are unavailable for all spatial units, spatial interpolation techniques can be used to estimate missing data points and ensure the completeness of the spatial analysis.

Kriging is a statistical interpolation method that is optimal in the sense that it makes best use of what can be inferred about the spatial structure in the surface to be interpolated from an analysis of the control point data. (O'Sullivan and Unwin, 2010) Kriging methods are the centerpiece of geostatistics, initially developed in the early 1900s for use in mining. Kriging estimators were developed to incorporate trends, autocorrelation. and stochastic variation and also provide some estimate of the local variance in the predictable variable (Bolstad, 2019).

All approaches to kriging aim to find the optimal weights, λ, to assign to the n available data, $z(\mathbf{s}_i)$ to predict the unknown value at the location $\mathbf{s}_0$. The kriging prediction $\hat{z}(\mathbf{s}_0)$, is expressed as:

$$\hat{z}(\mathbf{s}_0) = \sum_{i=1}^{n} \lambda_i z(\mathbf{s}_i) \quad (1)$$

It is usually the case that only the n observations nearest to $\mathbf{s}_0$ are used for kriging.

Simple kriging (SK) is, as its name suggests, the most simple variant of kriging, OK is used if the mean varies across the region of interest. With OK, the mean is considered constant within a moving window. Where a secondary variable is available that is cross-correlated with the primary variable, both variables may be used simultaneously in prediction using cokriging (CK). As well as being a means to characterise spatial structure, the variogram is used in kriging to assign weights to observations to predict the value of some property at locations for which data are not available, or where there is a desire to predict to a different support or grid spacing. To use the variogram in kriging, a mathematical model must be fitted to it, such that the coefficients may then be used in the system of kriging equations (Christopher D.Lloyd, 2011).

The variogram cloud is a plot that also helps us understand the autocorrelation pattern in a spatial data set. Similarly, the semivariogram, which is fundamental to more advanced methods of interpolation, is another approach to characterizing autocorrelation in a continuous field.

There are two principal classes of variogram model. Transitive models have a sill (finite variance) and are indicative of second-order stationarity. With transitive models, the lag at which the sill is reached, the limit of spatial dependence in the variogram, is called the range *a*, and where. *h* indicates the lag (distance and direction). Only pairs of values closer together than the range are spatially dependent.

Theoretically, the semivariance at zero lag is zero. In practice, the value at which the model fitted to the variogram crosses the intercept is usually some positive value, known as the nugget variance (c_0). The nugget effect in most contexts arises from variation that has not been resolved spatially dependent variation at lags that are shorter than the smallest sampling interval used, any measurement errors, and random variation. The structured component of the variogram (excluding the nugget variance) is signified by c. The total sill, or combined sill, is given by c_0+c .

Three of the most frequently used models are the spherical model, the exponential model and the Gaussian model, each of which is defined in turn. The exponential model is given by:

$$\gamma(h) = C\left[1 - exp\left(-\frac{h}{a}\right)\right] \tag{2}$$

The spherical model

$$\gamma(h) = \begin{cases} C\left[\left(\frac{3h}{2a}\right) - \left(\frac{h}{2a}\right)^2\right] & 0 \le \mathrm{h} \le a \\ C & h > a \end{cases} \tag{3}$$

The Gaussian model is given by

$$\gamma(h) = C\left[1 - exp\left(-\frac{h^2}{a^2}\right)\right] \tag{4}$$

A spatial weighting matrix (***W***) is used in spatial analysis to assign weights to each location based on neighborhood relationships. It is also used to calculate the Moran index and other spatial indices (Farkas, 2017). It is an n×n matrix containing values of 0 and 1, where n is the number of areas studied. A weight of 1 indicates that area i is adjacent to another area. The weight is 0 if area i is not adjacent to another area. The general form of the matrix is as follows:

$$\boldsymbol{W}_{n\times n} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & \cdots & w_{1n} \\ w_{21} & w_{22} & w_{23} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & w_{n3} & \cdots & w_{nn} \end{bmatrix} \tag{5}$$

According to (Kosfeld, 2006), contiguity can be defined in several ways:

1. *Rook contiguity*, the neighborhood area is determined by the intersecting sides.
2. *Bishop Contiguity*, the neighborhood area is determined by the intersection of the corners.
3. *Queen Contiguity*, the neighborhood area is determined by the intersection of sides and corners.

The stages in carrying out spatial regression analysis are as follows:

1. Perform a spatial autocorrelation test

The first step was to determine the nearest neighbors for each district/city using Queen contiguity. Queen contiguity is determining neighbors based on the intersecting sides and angles. After obtaining the spatial weighting matrix, the global Moran index value is used to see whether there is global spatial autocorrelation among districts/cities regarding dengue cases. The local Moran index value is used to see whether there is spatial autocorrelation in each district/city and influenced by neighboring regions. The test statistics used for the Global Moran Index and the local Moran Index are as follows

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i}^{n}(y_i-\bar{y})(y_j-\bar{y})}{(\sum_{i=1}^{n}(y_i-\bar{y})^2)(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})} \tag{6}$$

$$Z_{score} = \frac{I-E(I)}{\sigma(I)} \tag{7}$$

$$E\,(I) = \frac{-1}{(n-1)} \tag{8}$$

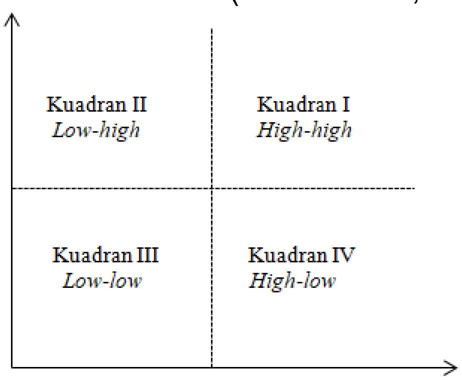
where I is the Moran index, n is the number of observations (region), y_i = value in the i-th region (i=1, 2, .., n), y_i = value in the j-th region (j=1, 2, .., n), $\bar{y}$ is average value y_i of n regions and w_{ij} is spatial weighting elements (Christopher D.Lloyd, 2011).

The hypothesis for testing the significance of the local Moran index is as follows:

H_0 : I_i = 0 (there is no local spatial autocorrelation in region-i)

H_1 : I_i ≠ 0 (there is local spatial autocorrelation in region-i)

The results of the local Moran index test is visualized in the form of a Moran scatter plot. A Moran scatterplot consists of four quadrants that illustrate the relationship between values on the map and the sum of neighboring values. If observations on a Moran scatterplot are located in quadrants 1 and 3, this indicates positive autocorrelation, whereas if observations are located in quadrants 2 and 4, this indicates negative autocorrelation (Griffith et al., 2019).



Moran scatterplot

2. Spatial heterogeneity is a condition in which the same independent variable produces different responses in different locations within a study area (Caraka and Ysin, 2017). The spatial heterogeneity test was conducted using the Breusch-Pagan test (BP test). The test statistics used are based on equations:

$$BP_j = \left(\frac{1}{2}\right).\mathbf{f}_j^T\mathbf{Z}_j\left(\mathbf{Z}_j^T\mathbf{Z}_j\right)\mathbf{Z}_j^T\mathbf{f}_j \quad (9)$$

Where $\mathbf{f}_j = \left(f_{1j}, f_{2j}, \ldots, f_{nj}\right)^T$ and **Z** is the *N* by (*P*+1) matrix containing the **z** vectors for each observation (Luc Anselin, 1988).

The spatial heterogeneity test was conducted using the Breusch-Pagan (BP) test. This test aims to identify the presence or absence of heteroscedasticity in the residual variance. Hypotheses used are as follows:

H0 : $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = 0$ (there is no spatial heterogeneity between regions)

H1 : at least one $\sigma_i^2 \neq \sigma^2$ (there is spatial heterogeneity between regions)

Decision making based on statistical test results where H_0 reject if $BP > X^2{}_{(p)}$ or *p-value* < *α*.

3. For estimation of the parameter of the spatial regression, the ordinary least squares (OLS) estimator has limitations for this model, therefore, the parameters are estimated using the maximum likelihood estimation (MLE) method. Estimation of the parameters of the spatial regression model (*β, ρ, λ*) is performed using the Maximum Likelihood Estimation (MLE). The general form of the three spatial regression models by (Luc Anselin, 1988) is as follows :

a. SAR model : $\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \boldsymbol{\varepsilon},$

$$\boldsymbol{\varepsilon} \sim N\,(\mathbf{0}, \sigma^2\mathbf{I}) \quad (10)$$

with y and ε as vectors of variable and error terms, and W as the corresponding spatial weighted matrix.

Parameter estimation in the SAR model is carried out using the Maximum Likelihood Estimation (MLE) method, in which the unknown parameters are obtained by maximizing a log-likelihood function (Yasin et al., 2020).

b. SEM model : $\mathbf{y} = \mathbf{X}\beta + \mathbf{u}$ (11)

where $\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}, \boldsymbol{\varepsilon} \sim N\,(\mathbf{0}, \sigma^2\mathbf{I})$ (12)

$$\mathbf{y} = \mathbf{X}\beta + \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad (13)$$

The parameter (λ) indicates the magnitude of the spatial influence of errors in one region on other regions around it. The parameter is estimated using the maximum likelihood method with the estimated parameters being *β, λ, σ*².

c. SARMA model : $\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ (14)

Where $\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}\,,\ \boldsymbol{\varepsilon} \sim N\,(\mathbf{0}, \sigma^2\mathbf{I})$ (15)

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad (16)$$

The parameter *ρ* expresses the degree of autocorrelation of the spatial component of a region with other regions around it, and *λ* expresses the degree of correlation of the spatial component of the error of a region with other regions around it.

The selection of the best spatial regression model is performed when there is more than one significant model, and the selection of the best model is based on the smallest AIC value and the largest R^2 value of the significant spatial regression model. In this study, we did not report the Bayesian Information Criterion (BIC) because the spatial econometric models employed (e.g., SAR, SEM, SARMA) and the software used do not provide BIC outputs. Therefore, model selection was based primarily on AIC as the information criterion, complemented by R^2 as a measure of goodness-of-fit.

The Lagrange Multiplier (LM) test is a basic test for selecting an appropriate spatial model. There are two tests in the LM test, namely the LM lag test and the LM error test. The LM lag test is used to identify the presence of spatial lag autocorrelation in the dependent variable. The LM error test is used to identify spatial autocorrelation in the error. The SAR model is used if the LM lag is significant. The SEM model is used if the LM error is significant. Meanwhile, the SARMA model is used if the LM lag and LM error tests are significant. This is because the SARMA model is a combination of the SAR and SEM models. The hypothesis used in the LM lag test is as follows:

H_0 : $\rho = 0$ (there is no spatial lag dependence on the dependent variable)

H_1 : $\rho \neq 0$ (there is spatial lag dependence on the dependent variable)

The test statistics used are as follows :

$$LM_{lag} = \frac{\left[\varepsilon'\mathbf{W}\boldsymbol{y}/(\frac{\varepsilon\varepsilon'}{n})\right]^2}{D} \quad (17)$$

where

$$D = \left[\frac{(\mathbf{WX\beta})'\,(\mathbf{I}-\mathbf{X}(\mathbf{X'X})^{-1}\mathbf{X}'(\mathbf{WX}\widehat{\boldsymbol{\beta}})}{\widehat{\sigma}^2}\right] + tr(\mathbf{W'W}+\mathbf{WW}) \quad (18)$$

Decision making is based on the results of statistical tests where H_0 reject if $LM_{lag} > X^2{}_{\alpha(p)}$ or *p-value* < *α*, with is the number of spatial parameters. Therefore, the appropriate model is the SAR model. The hypothesis used in the LM error test is as follows :

H_0 : $\lambda = 0$ (there is no dependence spatial error on the dependent variable)

H_1 : $\lambda \neq 0$ (there is dependence spatial error on the dependent variable)

The test statistics used are as follows :

$$LM_{error} = \frac{\left[\boldsymbol{\varepsilon}'\mathrm{W}\boldsymbol{\varepsilon}/(\frac{\boldsymbol{\varepsilon\varepsilon}'}{\boldsymbol{n}})\right]^2}{tr\,(\mathbf{W'W+WW})} \quad (19)$$

Decision making is based on the results of statistical tests where H_0 is rejected if $LM_{error} > X^2{}_{\alpha(p)}$ or *p-value* < *α*, so that the appropriate model is the SEM.

The following hypotheses are used for the SARMA model:

H_0 : $\rho.\lambda = 0$ (there is no dependence spatial lag and spatial error on the model)

H_1 : $\rho.\lambda \neq 0$ (there is dependence spatial lag and spatial error on the model)

The test statistics used are as follows :

$$LM_{(lag.error)} = E^{-1}\{(R_y)^2T - 2R_yR_\varepsilon T + (R_\varepsilon)^2(D+T)\} \quad (20)$$

With

$$R_y = \frac{\varepsilon' W y}{\sigma^2},\ R_\varepsilon = \frac{\varepsilon' W \varepsilon}{\sigma^2}, T = tr\{(\mathbf{W}'+\mathbf{W})\mathbf{W}\}, \quad (21)$$

$$\mathrm{D} = \sigma^2(\mathbf{W'X\beta})'\mathbf{M}(\mathbf{WX\beta}), \quad (22)$$

$$\boldsymbol{M} = I - \mathbf{X}(\mathbf{X'X})^{-1}\mathbf{X}', E = (D+T)T - (T)^2 \quad (23)$$

Decision making is based on the results of statistical tests where H_0 is rejected if $LM_{lag.error} > X^2{}_{\alpha(p)}$ or *p-value* < *α*, so that the appropriate model is the SARMA.

Spatial regression model parameter test was conducted to determine the factors that influence the number of dengue fever cases in Aceh. This test is performed on all parameters of the selected model.

The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given dataset. It considers both the model's goodness and its complexity. To calculate an AIC value, the likelihood function and number of parameters of each model must be obtained. These values are then entered into the AIC formula. The AIC values of the different models are then compared, and the model with the lowest AIC value is selected. The AIC equation is as follows (Akaike, 1987):

$$AIC = -2ln(L) + 2k \quad (24)$$

Where k is the number of parameters estimated in the model and L is the maximum value of the likelihood function.

The coefficient of determination R^2 is a value that determines the accuracy or suitability of a regression line representing a set of observed data and how well the resulting model explains actual conditions. It is a measure of the significant contribution of independent variables to dependent variables. The following equation is used to calculate the R^2 value (Draper and Smith, 1998):

$$R^2 = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} \quad (25)$$

where $\hat{y}_i$ is estimated value in region i, y_i is the observed value in region i, and $\bar{y}$ is the average value of n regions. The coefficient of determination value is between $0 \leq R^2 \leq 1$.

3. Research Methodology

Aceh Province has 23 regencies/cities, but this research only included 21 regencies/cities which are located in Sumatra Island. Two other regencies, Simeulue and Sabang, were excluded from the analysis because they are located in separated islands.

Figure 1. shows the distribution of the number of dengue fever cases in Aceh which are classified into 4 classes which are colored differently. Areas marked with darker colors indicate a higher number of dengue cases, while lighter colors indicate a lower number of dengue cases.

The variables used in this research consist of the dependent variable (number of dengue fever cases) and independent variables (population density, percentage of poor people, percentage of households with access to adequate drinking water, percentage of households with access to adequate sanitation facilities, ratio of health workers, amount of rainfall, average air temperature, and average air humidity). For climate data variables (rainfall, air temperature and air humidity), not all districts/cities have measured climate data, this is because not all areas have climate measuring devices so that climate data is only measured in areas where there are Meteorological, Climatological, and Geophysical Agency (BMKG) stations.

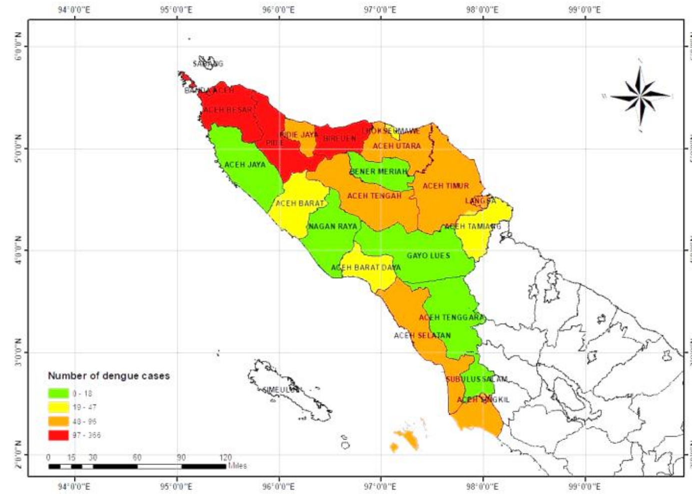


Figure 1: Map of the distribution of the number of the DHF cases in Aceh 2022

Aceh has five stations that collect climate data, so kriging interpolation is used to estimate climate around areas without stations with data sourced from five BMKG stations in Aceh and eight BMKG stations in North Sumatra. Data from North Sumatra BMKG station were included in the research for the estimation of climate data in the region of Aceh Province, which is adjacent to the province of North Sumatra.

For this research, we chose ordinary kriging, as it is the most commonly used approach when the mean of the spatial process is assumed to be unknown but constant across the study area.

Because it is the one most often used, we will illustrate the technique by examining ordinary kriging. In order to interpolate in this way, three steps are involved: 1. The spatial variation in the sample control point data is described; 2. Summarizing this spatial variation by a regular mathematical function; 3. Using this model to determine interpolation weights.

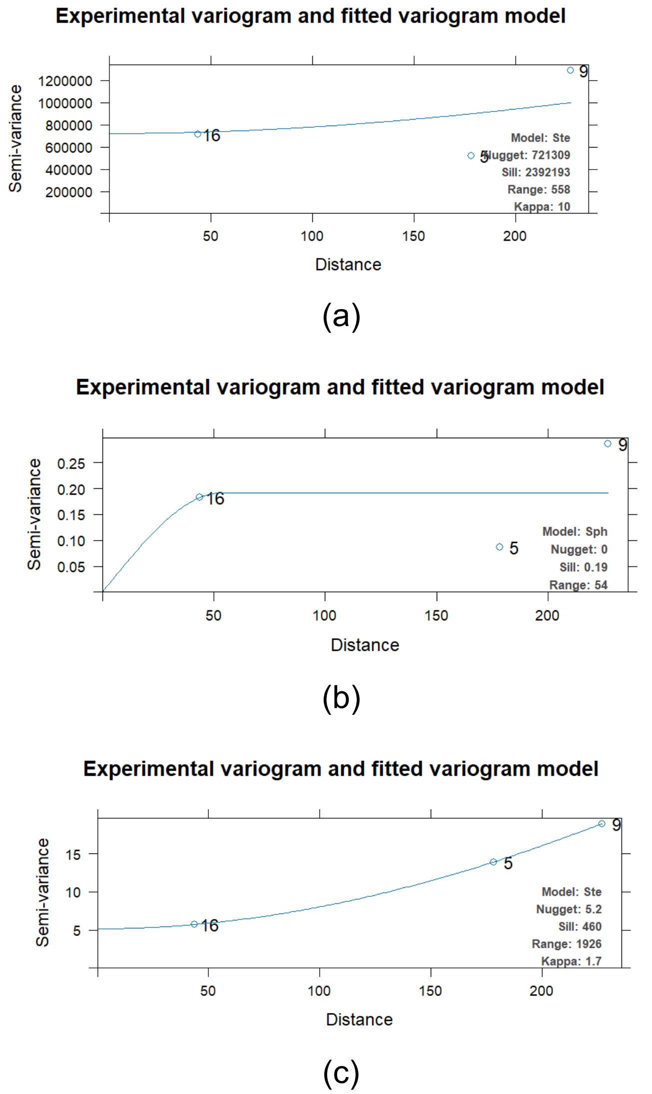
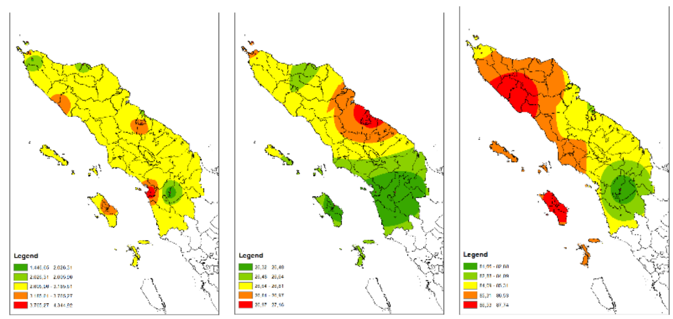


Figure 2: Variogram for (a) rainfall, (b) temperature, and (c) humidity.

Based on Figure 2, the model selected for the variogram of rainfall is stable and approximates the Gaussian model. For the temperature variable, the spherical model is selected. The model selected for humidity is also stable and approximates the Gaussian model. This can be seen from the distance and direction of the data points. For each of these models, spatial interpolation was performed for the three variables.



(a) (b) (c)

Figure 3: Map of Interpolation Results Using Ordinary Kriging in Aceh area for Climate Data: a) Rainfall, b) Air Temperature, c) Air Humidity

Figure 3. shows the results of interpolated of climate data, namely rainfall, air temperature and air humidity in Aceh, and the results are classified into five different color group. The results of this interpolation are in the form of raster data, presented in the form of interpolated maps that illustrate the resulting spatial pattern, and average of each pixel were used for climate data for each district/ city in Aceh. Raster data is a representation of spatial data arranged in the form of grids or pixel, where each pixel shows one value.

4. Result

Summary statistics are used to provide an overview of the data used. Table 1. is a statistical summary of the data.

Table 1. Summary statistics for each variable used

Variable	Variable Description	Min	Average	Max
Y	Number of dengue cases	0	91.33	366
X_1	Population density (People/km²)	18	369.1	4,199
X_2	Percentage of poor people	7.13	14.83	19.18
X_3	Percentage of households with access to adequate drinking water	56.02	88.43	98.69
X_4	Percentage of households with access to adequate sanitation	46.33	77.23	96.88
X_5	Health worker ratio (%)	0.53	0.93	1.53

Variable	Variable Description	Min	Average	Max
X_6	Amount of rainfall (mm/year)	2,485	2,917	3,206
X_7	Average air temperature (°C)	26.60	26.71	26.88
X_8	Average air humidity (%)	84.27	85.89	87.26

Table 1. shows that the average number of dengue fever cases in districts/cities in Aceh is about 91 cases, with the highest number of dengue fever cases is 366 cases, namely in Banda Aceh and the lowest being 0 cases, namely in Gayo Lues. Furthermore, the average population density in districts/cities in Aceh is about 369 people/km2, with the most densely populated area being Banda Aceh (4,199 people/km^2) and the least densely populated area being Gayo Lues (18 people/km^2). The average percentage of poor people in districts/cities in Aceh is 14.83%, with the highest percentage of poor people being Aceh Singkil (19.18%) and the lowest being Banda Aceh (7.13%).

The average percentage of households with access to adequate drinking water in districts/cities in Aceh is 88.43%, with the highest percentage in Lhokseumawe (98.69%) and the lowest in Subulussalam (56.02%). The average percentage of households with access to adequate sanitation facilities in districts/cities in Aceh is 77.23%, with the highest percentage in Banda Aceh (96.88%) and the lowest in Gayo Lues (46.33%). The average ratio of health workers in districts/cities in Aceh is 0.93%, with the highest ratio of health workers in Banda Aceh (1.53%) and the lowest in Aceh Besar (0.53%).

The average amount of rainfall in districts/cities in Aceh is 2,917 mm/year, with the highest rainfall in Nagan Raya (3,206 mm/year) and the lowest in Lhokseumawe (2,485 mm/year). The average air temperature in districts/cities in Aceh Province is 26.71℃, with the highest air temperature in Aceh Tamiang (26.88℃) and the lowest in Aceh Singkil (26.60℃). The average air humidity in districts/cities in Aceh Province is 85.89% with the highest air humidity in Nagan Raya (87.26%) and the lowest in Langsa (84.27%).

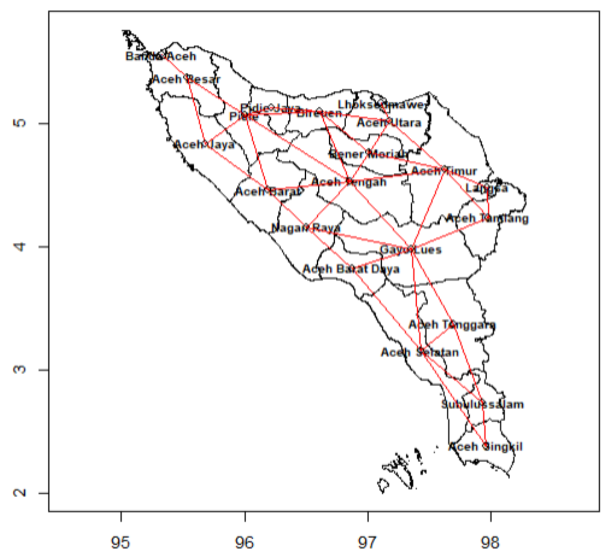


Figure 4: Nearest neighbors using Queen contiguity

The results of the the nearest neighboring analysis for each district/city in Aceh are shown in Fig 4. Next, a spatial weighting matrix can be formed by giving a weight of 1 if the region is a neighbor and 0 for regions that are not neighbors The global Moran Index value obtained from the analysis results for the number of DHF cases in Aceh is 0.432 with p-value 0.01. This indicates that there is positive spatial autocorrelation in the number of dengue fever cases in districts/cities in Aceh Province in 2022 with neighboring areas of 0.432.

After the global spatial autocorrelation test is satisfied, it is necessary to perform a local spatial autocorrelation test to find out which districts/cities have significant spatial autocorrelation or which districs/cities are really influenced by neighboring regions. Based on the calculation of the local Moran index value, the resulting Z-value and p-value with α = 0.05 shows that there are four regencies/cities that have significant spatial autocorrelation, namely Banda Aceh, Aceh Besar , Aceh Jaya, and Pidie Jaya (Shown in Table 2).

Tabel 2: Local Moran's index value of the number of dengue fever cases in each district/city in Aceh.

No.	District/ City	Ii	*Z-hitung*	*P-value*
1	Aceh Barat	−0.040	−0.129	0.897
2	Aceh Barat Daya	0.347	1.134	0.257
3	Aceh Besar	2.535	2.793	0.005*

No.	District/ City	Ii	*Z-hitung*	*P-value*
4	Aceh Jaya	−0.941	−2.102	0.036*
5	Aceh Selatan	0.145	1.526	0.127
6	Aceh Singkil	0.099	0.682	0.495
7	Aceh Tamiang	0.170	0.635	0.525
8	Aceh Tengah	−0.018	−0.135	0.893
9	Aceh Tenggara	0.415	1.148	0.251
10	Aceh Timur	−0.021	−1.320	0.187
11	Aceh Utara	0.004	0.074	0.941
12	Banda Aceh	4.997	2.465	0.014*
13	Bener Meriah	−0.139	−0.270	0.787
14	Bireuen	0.150	0.485	0.628
15	Gayo Lues	0.369	1.501	0.133
16	Langsa	0.039	0.350	0.726
17	Lhokseumawe	0.068	0.181	0.857
18	Nagan Raya	0.390	1.275	0.202
19	Pidie	0.467	1.031	0.302
20	Pidie Jaya	−0.234	−2.286	0.022*
21	Subulussalam	0.266	0.751	0.452

The results of the local Moran index analysis can be presented in a thematic map as shown in Figure 5.

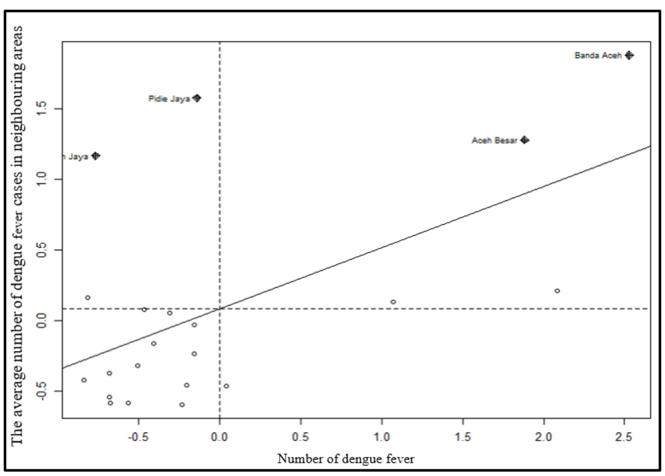


Figure 5: Moran's *scatterplot*

Figure 5 shows the distribution of *Z*-scores from the local Moran's index in each district/city in Aceh.

The x-axis is the standardized number of dengue cases in the *i*-th district/city in Aceh, and the *y*-axis is the average value of the standardized number of dengue cases in neighboring areas in the i-th district/city in Aceh. On the thematic map, the High-High, Low-High, High-Low and Low-Low classifications are determined based on the Z-score value.

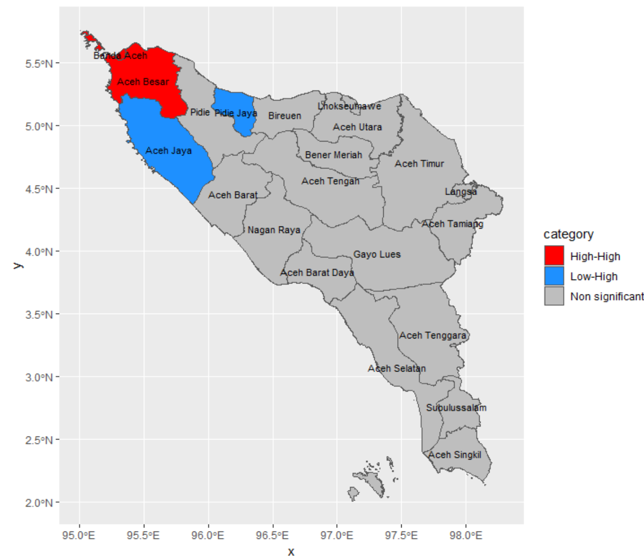


Figure 6: Thematic map based on local Moran's test

In Figure 6, for the local Moran thematic map, two districts/cities have high dengue cases and are surrounded by neighboring areas that also have high dengue cases. Districts/cities colored blue are included in the Low-High quadrant. The districts/cities included in this quadrant are Aceh Jaya and Pidie Jaya. This shows that these two districts have low numbers of dengue cases and are surrounded by neighboring areas with high numbers of dengue cases. The gray areas indicate districts/cities that were not significant in the local spatial autocorrelation test.

Spatial heterogeneity is a condition where the same independent variable gives different responses at different locations. The Breusch-Pagan test (BP) test was used to test the spatial heterogeneity, and the result value is 10.971 (*p*-value = 0.203). It can be conclude that the dengue data in Aceh does not show significant spatial heterogeneity, indicating homogeneous residual variance across districts/cities. Therefore the applied model is statistically appropriate and stable for assessing spatial patterns of dengue cases in Aceh.

There are three spatial regression models, SAR, SEM, and SARMA. The spatial regression parameters for the three models are estimated using the maximum likelihood. The results of parameter estimation for the three spatial regression models can be seen in Table 3. The best model is selected based on the model that is significant in the LM test. The LM test is a test of the spatial dependence of lag and error to select an appropriate spatial regression model for modeling. The LM test there is more than one significant model, the model that has the smallest AIC value and the largest R^2 selected. The results of the LM test, AIC and R^2 values for each model are as follows.

Table 3: Results of estimating spatial regression model parameters

Variable	Variable Description	Parameter Estimation		
		SAR	SEM	SARMA
Intercept	-	−0.050	−0.281	−0.380
Rho (ρ)	-	0.587	-	−0.359
Lamda (λ)	-	-	0.837	0.906
X_1	Population density (People/km²)	0.812	0.964	0.875
X_2	Percentage of poor people	0.039	−0.129	−0.086
X_3	Percentage of households with access to adequate drinking water	0.206	0.036	0.015
X_4	Percentage of households with access to adequate sanitation	−0.381	−0.555	−0.470
X_5	Health worker ratio (%)	−0.515	−0.894	−0.783
X_6	Amount of rainfall (mm/year)	0.073	0.286	0.280
X_7	Average air temperature (°C)	−0.455	−0.952	−0.899
X_8	Average air humidity (%)	−0.288	−0.780	−0.873

Table 4: Choosing the best model

Spatial Regression Model	Test statistics	*P-value*	AIC	R^2
SAR	4.293	0.038	64.456	0.310
SEM	2.576	0.108	57.526	0.587
SARMA	6.887	0.032	58.483	0.655

Based on the results in Table 3, we can seen that with a real level (α) of 0.05, there are two significant models, the SAR and SARMA models, because they have a p-value < α. A model is said to be better if it has the smallest AIC value and the largest R^2 when compared to other models. Based on Table 4, it can be seen from the two significant spatial regression models, namely the SAR and SARMA models, that the SARMA model has the smallest AIC value, namely 58.483 and the largest R^2 value, namely 0.655 (65.5%). Based on these results, it can be concluded that the best model to be used in analyzing spatial dependence of the number of dengue fever cases in Aceh Province is the SARMA model. Therefore, the SARMA model is the model used in this research.

Based on Table 4, the SARMA model equation for the number of dengue fever cases in Aceh Province is written in the following equation:

$$\hat{y}_i = -0.359\sum_{j=1,i\neq j}^{n} w_{ij}y_j - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906\sum_{j=1,i\neq j}^{n} w_{ij}u_j \quad (26)$$

The significance test of model parameters was conducted to determine the parameters that have a significant impact on the number of dengue fever cases in Aceh Province. The significance test of spatial regression parameters in SARMA model is as follows

Table 5: Results of the SARMA model parameter significance tests

Variable	Variable Description	Parameter Estimation		
		SAR	SEM	SARMA
Intercept	-	−0.050	−0.281	−0.380
Rho (ρ)	-	0.587	-	−0.359
Lamda (λ)	-	-	0.837	0.906
X_1	Population density (People/km²)	0.812	0.964	0.875
X_2	Percentage of poor people	0.039	−0.129	−0.086
X_3	Percentage of households with access to adequate drinking water	0.206	0.036	0.015

Variable	Variable Description	Parameter Estimation		
		SAR	SEM	SARMA
X_4	Percentage of households with access to adequate sanitation	−0.381	−0.555	−0.470
X_5	Health worker ratio (%)	−0.515	−0.894	−0.783
X_6	Amount of rainfall (mm/year)	0.073	0.286	0.280
X_7	Average air temperature (°C)	−0.455	−0.952	−0.899
X_8	Average air humidity (%)	−0.288	−0.780	−0.873

Based on Table 5. It can be seen that with a real level (α) of 0.05 there are five independent variables with p-value smaller than α, namely population density (X_1), percentage of households with access to adequate sanitation (X_4), ratio of health workers (X_5), average air temperature (X_7), and average air humidity (X_8). It can be concluded that five variables are significant in the number of dengue fever cases in Aceh.

The SARMA model equation can be interpreted to mean that the value of population density coefficient (X_1) of 0.875 means that if the population density in a district/city increases by 10 people/km^2, then the number of dengue fever cases in that district/city in Aceh will increase by 8.75 ≈ 9 cases. The results of this research are consistent with the research conducted by (Schmidt et al., 2011), It is noteworthy that rural areas may contribute to the dissemination of dengue fever to a comparable extent as urban areas. The enhancement of water supply and vector control measures in regions exhibiting high population density, which is a critical factor in dengue transmission, holds considerable potential in augmenting the efficacy of control interventions.

The coefficient of the percentage of households with access to adequate sanitation (X_4) of -0.470 means that for every 10% increase in the percentage of households with access to adequate sanitation in a district/city in Aceh, the number of dengue fever cases in that district/city will decrease by 4.70 ≈ 5 cases. Based on the research conducted by (Yulianti and Hidayani, 2022) in Indonesia, there were a relationship between when the variable and the occurrence of dengue hemorrhagic fever (DHF). There were a relationship between environmental sanitation (water storage, garbage disposal, and 3M Plus measures) with the incidence of dengue hemorrhagic fever (DHF). The other research are also consistent with this result conducted by (Kusumawati et al., 2016), which shows that education ≥ senior high school, family income ≥ regional minimum wage, adequate home sanitation, and sense of belonging are associated with healthier behavior, in patients with DHF.

The coefficient for the health worker ratio (X_5) of -0.783 means that for every 10% increase in the health worker ratio in a district/city in Aceh, the number of dengue cases in that district/city will decrease by 7.83 ≈ 8 cases. According to the research conducted by (Rosita et al., 2020) there is a significant relationship between population, regional characteristics, health service capabilities, financial management patterns and accreditation of PHC's (Public Health Center), and planning of health human resources needs with the availability of five types of promotion and prevention health workers in PHC's. Need strategies effort for fulfilling health workers starting from the utilization planning stage, including in terms of supervision and evaluation. So that health workers are distributed evenly throughout all PHC's in Indonesia. This is consistent with the research finding of (Mohammed Yusuf and Abdurashid Ibrahim, 2019) which concluded that with Multinomial logistic regression indicated that the type of health profession, type of health facility, and participation in dengue prevention training were significantly linked to the knowledge, attitudes, and practices of healthcare professionals.

The average air temperature coefficient (X_7) of -0.899 means that for every 10℃ increase in average air temperature, the number of dengue fever cases in each district/city in Aceh will decrease by 8.99 ≈ 9 cases. The results of this research are consistent with the research conducted by (Arcari et al., 2007), which states that rainfall is the primary climatic factor influencing the geographic distribution and timing of incidence, whereas temperature plays a crucial role in determining the severity of outbreaks. (Bhatia et al., 2013) in their research, the Aedes mosquito, A potent and adaptive vector has evolved in longevity and survival, exhibiting sensitivity to seasonality and climate variability, as well as to socio-cultural and economic factors associated with human habitation and development. This review offers insights into the evolving epidemiology and its contributing factors in Southeast Asia, a region that has emerged as a significant epicenter for dengue cases worldwide. It emphasizes the major factors that are influencing these rapid changes.

The coefficient of average humidity (X_8) of -0.873 means that for every 10% increase in average humidity, the number of dengue fever cases in each district/city in Aceh will decrease by 8.73 ≈ 9 cases. The results of this research are consistent with the research conducted by (Xu et al., 2014), which concluded that Absolute Humidity (AH) appeared to be the most consistent factor in modeling dengue incidence in Singapore, AH had a more stable impact on dengue incidence than temperature when virological factors were taken into consideration.

The $w_{ij}y_j$ matrix can be interpreted as the effect of changes in the number of dengue fever cases in neighboring areas of a district/city on the number of dengue cases in that district/city. That is, if the number of dengue cases in a neighboring district/city increases or decreases, then the number of dengue cases in that district/city will also increase or decrease. Meanwhile, the $w_{ij}u_j$ matrix can be interpreted as the influence of changes in spatial residuals in neighboring areas of a district/city on the spatial residuals in that district/city. That is, if the spatial residual in a neighboring district/city increases or decreases, then the spatial residual in that district/city will also increase or decrease.

The coefficient ρ in the SARMA model is -0.359, which means that if a district/city is surrounded by several neighboring regions, then the influence of these neighboring regions is -0.359 multiplied by the weight of the neighboring regions.

Furthermore, the coefficient λ in the SARMA model is 0.906, which means that if a district/city is surrounded by several neighboring regions, then the residual spatial influence of the neighboring regions is 0.906 times the weight of the neighboring regions.

There are twenty-one spatial regression models for each district/city in Aceh using SARMA (Table. 6)

Table 6. SARMA models for each district/city

No.	SARMA Model
1	$\hat{y}_{Aceh\ Barat} = -0.359[0.25(y_{Aceh\ Jaya} + y_{Nagan\ Raya} + y_{Pidie} + y_{Aceh\ Tengah}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0,25(u_{Aceh\ Jaya} + u_{Nagan\ Raya} + u_{Pidie} + u_{Aceh\ Tengah})]$
2	$\hat{y}_{Aceh\ Barat\ Daya} = -0.359[0.33(y_{Nagan\ Raya} + y_{Aceh\ Selatan} + y_{Gayo\ Lues}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Nagan\ Raya} + u_{Aceh\ Selatan} + u_{Gayo\ Lues})]$
3	$\hat{y}_{Aceh\ Besar} = -0.359[0.33(y_{Banda\ Aceh} + y_{Aceh\ Jaya} + y_{Pidie}) - 0.380 + 0.875X_1 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Banda\ Aceh} + u_{Aceh\ Jaya} + u_{Pidie})]$
4	$\hat{y}_{Aceh\ Jaya} = -0.359[0.33(y_{Aceh\ Besar} + y_{Aceh\ Barat} + y_{Pidie}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Aceh\ Besar} + u_{Aceh\ Barat} + u_{Pidie})]$
5	$\hat{y}_{Aceh\ Selatan} = -0.359[0.2(y_{Aceh\ Barat\ Daya} + y_{Aceh\ Tenggara} + y_{Gayo\ Lues} + y_{Aceh\ Singkil} + y_{Subulussalam}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.2(u_{Aceh\ Barat\ Daya} + u_{Aceh\ Tenggara} + u_{Gayo\ Lues} + u_{Aceh\ Singkil} + u_{Subulussalam})]$
6	$\hat{y}_{Aceh\ Singkil} = -0.359[0.5(y_{Aceh\ Selatan} + y_{Subulussalam}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.5(u_{Aceh\ Selatan} + u_{Subulussalam})]$
7	$\hat{y}_{Aceh\ Tamiang} = -0.359[0.33(y_{Aceh\ Timur} + y_{Gayo\ Lues} + y_{Langsa}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Aceh\ Timur} + u_{Gayo\ Lues} + u_{Langsa})]$
8	$\hat{y}_{Aceh\ Tengah} = -0.359[0.143(y_{Aceh\ Timur} + y_{Bener\ Meriah} + y_{Bireuen} + y_{Pidie} + y_{Aceh\ Barat} + y_{Nagan\ Raya} + y_{Gayo\ Lues}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.143(u_{Aceh\ Timur} + u_{Bener\ Meriah} + u_{Bireuen} + u_{Pidie} + u_{Aceh\ Barat} + u_{Nagan\ Raya} + u_{Gayo\ Lues})]$
9	$\hat{y}_{Aceh\ Tenggara} = -0.359[0.33(y_{Subulussalam} +$

	$y_{Gayo\ Lues} + y_{Aceh\ Selatan}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Subulussalam} + u_{Gayo\ Lues} + u_{Aceh\ Selatan})]$
10	$\hat{y}_{Aceh\ Timur} = -0.359[0.167(y_{Langsa} + y_{Aceh\ Tamiang} + y_{Gayo\ Lues} + y_{Aceh\ Tengah} + y_{Bener\ Meriah} + y_{Aceh\ Utara}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.167(u_{Langsa} + u_{Aceh\ Tamiang} + u_{Gayo\ Lues} + u_{Aceh\ Tengah} + u_{Bener\ Meriah} + u_{Aceh\ Utara})]$
11	$\hat{y}_{Aceh\ Utara} = -0.359[0.25(y_{Lhokseumawe} + y_{Bireuen} + y_{Aceh\ Timur} + y_{Bener\ Meriah}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.25(u_{Lhokseumawe} + u_{Bireuen} + u_{Aceh\ Timur} + u_{Bener\ Meriah})]$
12	$\hat{y}_{Banda\ Aceh} = -0.359(y_{Aceh\ Besar}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906(u_{Aceh\ Besar})$
13	$\hat{y}_{Bener\ Meriah} = -0.359[0.25(y_{Aceh\ Utara} + y_{Aceh\ Timur} + y_{Aceh\ Tengah} + y_{Bireuen}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.25(u_{Aceh\ Utara} + u_{Aceh\ Timur} + u_{Aceh\ Tengah} + u_{Bireuen})]$
14	$\hat{y}_{Aceh\ Selatan} = -0.359[0.2(y_{Aceh\ Barat\ Daya} + y_{Aceh\ Tenggara} + y_{Gayo\ Lues} + y_{Aceh\ Singkil} + y_{Subulussalam}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.2(u_{Aceh\ Barat\ Daya} + u_{Aceh\ Tenggara} + u_{Gayo\ Lues} + u_{Aceh\ Singkil} + u_{Subulussalam})]$
15	$\hat{y}_{Gayo\ Lues} = -0.359[0.143(y_{Aceh\ Tenggara} + y_{Aceh\ Selatan} + y_{Aceh\ Barat\ Daya} + y_{Nagan\ Raya} + y_{Aceh\ Tengah} + y_{Aceh\ Timur} + y_{Aceh\ Tamiang})] - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.143(u_{Aceh\ Tenggara} + u_{Aceh\ Selatan} + u_{Aceh\ Barat\ Daya} + u_{Nagan\ Raya} + u_{Aceh\ Tengah} + u_{Aceh\ Timur} + u_{Aceh\ Tamiang})]$
16	$\hat{y}_{Langsa} = -0.359[0.5(y_{Aceh\ Tamiang} + y_{Aceh\ Timur}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.5(u_{Aceh\ Tamiang} + u_{Aceh\ Timur})]$
17	$\hat{y}_{Banda\ Aceh} = -0.359(y_{Aceh\ Utara}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906(u_{Aceh\ Utara})$
18	$\hat{y}_{Nagan\ Raya} = -0.359[0.25(y_{Aceh\ Barat} + y_{Aceh\ Barat\ Daya} + y_{Gayo\ Lues} + y_{Aceh\ Tengah}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.25(u_{Aceh\ Barat} + u_{Aceh\ Barat\ Daya} + u_{Gayo\ Lues} + u_{Aceh\ Tengah})]$
19	$\hat{y}_{Pidie} = -0.359[0.167(y_{Aceh\ Besar} + y_{Aceh\ Jaya} + y_{Aceh\ Barat} + y_{Bireuen} + y_{Aceh\ Tengah} + y_{Pidie\ Jaya})] - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.167(u_{Aceh\ Besar} + u_{Aceh\ Jaya} + u_{Aceh\ Barat} + u_{Bireuen} + u_{Aceh\ Tengah} + u_{Pidie\ Jaya})]$
20	$\hat{y}_{Pidie\ Jaya} = -0.359[0.5(y_{Pidie} + y_{Bireuen}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.5(u_{Pidie} + u_{Bireuen})]$
21	$\hat{y}_{Subulussalam} = -0.359[0.33(y_{Aceh\ Selatan} + y_{Aceh\ Singkil} + y_{Aceh\ Tenggara}) - 0.380 + 0.875X_1 - 0.086X_2 + 0.015X_3 - 0.470X_4 - 0.783X_5 + 0.280X_6 - 0.899X_7 - 0.873X_8 + 0.906[0.33(u_{Aceh\ Selatan} + u_{Aceh\ Singkil} + u_{Aceh\ Tenggara})]$

For example, the interpretation for the SARMA model in Aceh Besar is that if the number of dengue fever cases in Banda Aceh ($y_{Banda\ Aceh}$) increases by 10 cases, then the number of dengue fever cases in Aceh Besar Regency will decrease by 1.18 ≈ 1 case, assuming other variables are constant. Similarly, the influence of Aceh Jaya ($y_{Aceh\ Jaya}$) and Pidie (y_{Pidie}) on Aceh Besar is interpreted in the same way. Then, if the spatial residual in Banda Aceh ($u_{Banda\ Aceh}$) increases by 1 unit, then the spatial residual in Aceh Besar will increase by 0.299 assuming the other variables are constant. Similarly, the influence of Aceh Jaya ($u_{Aceh\ Jaya}$) and Pidie ($u_{Aceh\ Jaya}$) on Aceh Besar is interpreted in the same way. Meanwhile, the interpretation of the factors that influence the number of dengue cases as the previous explanation.

4. Conclusion

The conclusion of this study shows that globally, the Moran index value indicates that there is a positive spatial autocorrelation in the number of DHF cases in districts/cities in Aceh in 2022 with its neighboring areas. Locally, there are four districts/cities that have significant spatial autocorrelation, namely Banda Aceh, Aceh Besar, Aceh Jaya and Pidie Jaya. This means that these regions have spatial autocorrelation influenced by their neighboring regions. The best spatial regression model for the number of dengue cases in Aceh is the SARMA model, which was selected based on the LM test results with an AIC value of 58.483 and R^2 of 65.5%. Factors that influence the number of DHF cases in Aceh are population density (X_1), percentage of households with access to proper sanitation (X_4), ratio of health workers (X_5), average air temperature (X_7) and average air humidity (X_8). Based on the SARMA model obtained, we can interpret that if the population density increases by 10 people/km2 in a district/city, the number of dengue fever cases in districts/cities in Aceh will increase by 9 cases. for every 10% increase in the percentage of households with access to proper sanitation in a district/city in Aceh Province, the number of dengue fever cases in that district/city will decrease by 5 cases. for every 10% increase in the ratio of health workers in a district/city in Aceh Province, the number of dengue fever cases in that district/city will decrease by 8 cases, for every 10℃ increase in average air temperature, the number of dengue fever cases in each district/city in Aceh Province will decrease by 9 cases, and for every 10% increase in average air humidity, the number of dengue fever cases in each district/city in Aceh Province will decrease by 9 cases.

By knowing the factors that can effect with dengue cases in Aceh, it is expected that local governments and related agencies will focus more on factors that affect dengue cases, especially population density, access to proper sanitation, and health workers in area with high dengue cases.

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