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SPATIAL PANEL REGRESSION AND GEOGRAPHICALLY WEIGHTED PANEL REGRESSION MODELING OF DENGUE HEMORRHAGIC FEVER CASES IN WEST JAVA PROVINCE

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Abstract. Dengue Hemorrhagic Fever (DHF) is an infectious disease caused by the dengue virus, transmitted through the bites of Aedes aegypti and Aedes albopictus mosquitoes. DHF case data containing spatial and temporal information is a form of spatial panel data that can be analyzed using spatial panel modeling. Spatial panel regression is a regression approach used to assess spatial autocorrelation in the data. Geographically Weighted Panel Regression (GWPR) is a local regression method capable of capturing spatial heterogeneity effects. This study aims to develop spatial panel regression and GWPR models to estimate the number of DHF cases and their associated factors at the regency/city level in West Java Province from 2021 to 2023. The results of the spatial panel lag regression model show that the number of hospitals and the percentage of households using safely managed sanitation services are statistically significant in explaining DHF cases. In contrast, the GWPR model with an adaptive bisquare kernel reveals variations in the local influence of variables. Significant variables in several regions include population density, number of hospitals, number of health centers, percentage of households with safely managed sanitation services, access to improved sanitation, poverty rate, and average number of elementary school students. Both models complement each other in the spatio-temporal analysis of DHF cases distribution.
Keywords: Dengue Hemorrhagic Fever, Geographically Weighted Panel Regression, Spatial Autocorrelation, Spatial Heterogeneity, Spatial Panel Regression

I. INTRODUCTION

Dengue Hemorrhagic Fever (DHF) is an infectious disease caused by the dengue virus from the Flavivirus genus, transmitted primarily through the bites of Aedes aegypti and Aedes albopictus mosquitoes [1]. DHF is commonly found in tropical and subtropical regions. The transmission of the dengue virus is influenced by various factors such as climate, environmental conditions, population density, and rapid urbanization without adequate planning [2]. Over the last decade, the number of DHF cases has increased significantly on a global scale. Reported DHF cases rose from approximately 505,000 in the year 2000 to 5.2 million in 2019. The highest peak occurred in 2023, with more than 80 countries reporting cases. Since the beginning of that year, ongoing transmission and unpredictable surges led to over 6.5 million reported cases [3]. The number of DHF cases in Indonesia has fluctuated from year to year. In 2023, there were 114,720 reported cases nationwide, resulting in 894 deaths. In West Java Province, DHF remains a serious public health concern, with 19,328 cases and 134 deaths recorded in the same year [4].

DHF control requires long-term healthcare governance and intersectoral coordination [3]. Low awareness of clean and healthy living habits remains a major obstacle, while socioeconomic factors also influence control effectiveness. This highlights the importance of studying the relationship between sociodemographic factors and DHF incidence [5]. The correlation between sociodemographic conditions and DHF cases suggests that disease distribution is not only determined by health-related factors but also by environmental and socioeconomic conditions. DHF case data, along with related influencing variables and geographic information, represent spatial data that can be further analyzed using spatial modeling to identify disease patterns and risk factors across regions. When such measurements are taken over multiple time periods, the data are referred to as panel data, which consist of observations on the same entities over time [6]. The integration of spatial and temporal dimensions in one dataset is known as spatial panel data [7].

The issue of DHF cases in Indonesia, particularly in West Java Province, has persisted for years. Therefore, a study that spans multiple time periods using spatial panel data is needed. One commonly used model for analyzing spatial panel data is the spatial panel regression model. This model captures location dependencies over several time periods [8], taking into account not only spatial relationships between adjacent regions but also temporal changes in the data. Several studies have applied spatial panel regression models to investigate the spread of DHF. Nabila and Yotenka examined factors influencing DHF cases in Java and Bali from 2015 to 2019 using a spatial panel lag model [9]. Their findings showed that healthy settlement policies, poverty levels, and healthcare facilities significantly affected DHF incidence in the studied regions. Additionally, Shragai et al. investigated the spatial distribution of dengue cases in Medellín, Colombia, using a spatial panel lag regression model [10]. The study found that access to public transportation was positively associated with dengue incidence, especially in low socioeconomic areas.

Spatial panel regression models have limitations because they assume that the influence of independent variables is spatially homogeneous across all regions. In reality, the effects of independent variables may vary across regions due to spatial heterogeneity [11]. This limitation requires a model that is capable of capturing local variations in the effects of variables. One such model is the Geographically Weighted Panel Regression (GWPR), which allows regression coefficients to vary both spatially and temporally, making it more responsive to local patterns [12]. Several studies have implemented the GWPR model to examine the spread of DHF. Putri dan Rakhmawati used the adaptive bisquare kernel GWPR model to analyze DHF cases in North Sumatra Province from 2022 to 2023 [13]. Their findings revealed that the model was capable of identifying spatial and temporal variations in the effects of environmental variables on DHF cases. Furthermore, Salim et al. investigated DHF cases in Yogyakarta City from 2017 to 2022 using a GWPR model with a fixed exponential kernel function, which successfully captured spatial variability in the effects of independent variables across subdistricts [14].

This study focuses on the simultaneous application of two modeling approaches, namely spatial panel regression and GWPR, on the same dataset. Additionally, the study introduces comparative analysis between the spatial panel lag and error models, as well as comparisons among various GWPR kernel functions, including fixed exponential, adaptive exponential, fixed bisquare, and adaptive bisquare. This approach enables both global and local analyses, providing a comprehensive understanding of the variables potentially influencing DHF cases in West Java Province. This study aims to construct two models, namely spatial panel regression and GWPR, to model DHF cases and their influencing variables at the district/city level in West Java Province from 2021 to 2023. The performance of both models will be evaluated using the coefficient of determination and Root Mean Square Error (RMSE). The combined analysis is expected to offer a more comprehensive global and local perspective on the spatio-temporal distribution patterns of DHF cases in West Java Province during the 2021–2023 period.

II. METHODOLOGY

3.1 Data

The research data consist of 27 regencies or cities in West Java Province from 2021 to 2023. The data used in this study are secondary data obtained from official sources. The dependent variable is the number of DHF cases (Y). The independent variables are population density (KP), number of hospitals (JRS), number of public health centers (JPUS), percentage of households using safely managed sanitation services (LSA), percentage of households with access to improved drinking water sources (AML), percentage of the population living below the poverty line (PPM), average number of students per kindergarten (RTK), and average number of students per elementary school (RSD). The data analysis workflow in this study are presented in the following flowchart.

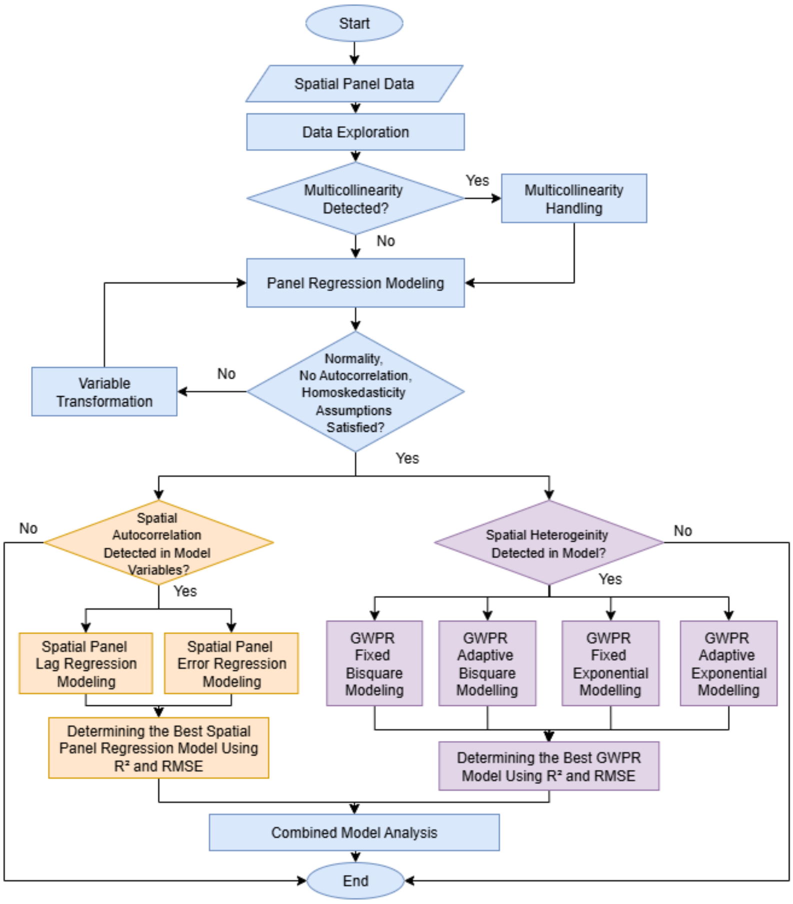

Figure 1. Data Analysis Workflow

3.2 Spatial Panel Regression

Spatial panel regression is a regression model that captures spatial dependence observed over multiple time periods. This model employs a spatial weight matrix based on contiguity [15]. In this study, the spatial weight matrix is constructed using queen contiguity, which assigns $w_{ij} = 1$ if location i and location j share a common edge or vertex, and $w_{ij} = 0$ otherwise [16].

The spatial panel data model can be extended into two models, the spatial panel model with a spatial lag and the spatial panel model with a spatial error. The spatial lag panel regression model includes the spatial dependence in the dependent variable in the panel regression equation [17]. The general form of the spatial lag panel regression model with fixed effects is expressed as follows [17]:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \boldsymbol{X_{it}\beta} + \mu_i + \varepsilon_{it} \qquad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T \tag{1}$$

where y_{it} is the dependent variable at location i and time t, w_{ij} is an element of the spatial weight matrix, $\boldsymbol{X_{it}}$ is a $1 \times K$ row vector of independent variables at location *i* and time *t* with a total of NT rows, $\boldsymbol{\beta}$ is a $K \times 1$ vector of regression coefficients, μ_i is the fixed effect for location i, ε_{it} is the error term at location *i* and time *t*, and δ is the spatial lag coefficient.

The spatial error panel regression model is a model that includes spatial dependence in the error term in the panel regression equation. Specifically, this model assumes that the error in a given spatial unit and time period is influenced by the average error of neighboring spatial units at the same point in time [17]. The general form of this model is written as follows [17]:

$$y_{it} = \boldsymbol{X_{it}\beta} + \mu_i + \phi_{it} \tag{2}$$

$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij}\, \phi_{jt} + \varepsilon_{it}$$

$$i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T$$

where y_{it} is the dependent variable at location i and time *t,* w_{ij} is an element of the spatial weight matrix, $\boldsymbol{X_{it}}$ is a $1 \times K$ row vector of independent variables at location *i* and time *t* with a total of NT rows, $\boldsymbol{\beta}$ is a $K \times 1$ vector of regression coefficients, μ_i is the fixed effect for location i, ϕ_{it} is the error term that exhibits spatial autocorrelation, ε_{it} is the error term at location *i* and time *t*, and ρ is the spatial error coefficient.

3.3 Geographically Weighted Panel Regression

Spatial heterogeneity refers to the condition in which spatial units within an area of observation have non-uniform or heterogeneous characteristics [12]. One of the models that can be used to address spatial heterogeneity is the Geographically Weighted Panel Regression (GWPR). GWPR is a hybrid model that combines the Geographically Weighted Regression (GWR) model with the panel regression model by introducing a temporal component into the GWR model [12]. The GWPR model used in this study is a fixed effect panel regression model combined with GWR. The model equation is defined as follows [12]:

$$\ddot{y}_{it} = \sum_{k=1}^{K} \beta_k(u_i, v_i)\ddot{x}_{itk} + \ddot{\epsilon}_{it}$$
$$\ddot{y}_{it} = y_{it} - \overline{y_i};\ \ddot{x}_{itk} = x_{itk} - \bar{x}_{ik};\ \ddot{\epsilon}_{it} = \epsilon_{it} - \overline{\epsilon_i} \tag{3}$$
$$i = 1, 2, \dots, N;\ t = 1, 2, \dots, T;\ k = 1, 2, \dots, K$$

where $\ddot{y}_{it}$ is the corrected average value of the dependent variable at location i and time t, $\ddot{x}_{itk}$ is the corrected average value of the k-th independent variable at location i and time t, $\beta_k(u_i, v_i)$ is the regression coefficient of the corrected average value of the k-th independent variable at location i, and $\ddot{\epsilon}_{it}$ is the corrected average error at location i and time t.

Spatial weights in the GWPR model can be calculated using a kernel function [18]. A kernel function requires the distance between observations i and j, as well as a bandwidth value. Bandwidth refers to the distance measured from the center of location i to a threshold radius that defines the boundary between locations considered influential and those that are not in estimating the value at location i. There are two types of bandwidth, namely fixed bandwidth and adaptive bandwidth. Fixed bandwidth means that the same bandwidth value is applied to all locations within the study area, whereas adaptive bandwidth allows each location to have a different bandwidth value [11]. The kernel functions used in this study are fixed bisquare, adaptive bisquare, fixed exponential, and adaptive exponential [19].

III. RESULT AND DISCUSSION

3.1 Panel Regression Modeling

Before model construction, a multicollinearity test was conducted to examine potential correlations among the independent variables. Since all independent variables had Variance Inflation Factor (VIF) values below 10, it can be concluded that there was no multicollinearity in the dataset, and all independent variables could be included in the model development.

Next, panel regression modeling was estimated. In panel regression analysis, three common models are typically considered: the common effect model, fixed effect model, and random effect model. This study employed the individual fixed effect model, which accounts for differences in characteristics across observational units. To determine the most appropriate model for the data, model selection tests were conducted, namely the Chow test and the Hausman test. The Chow test was used to compare the common effect and fixed effect models, while the Hausman test was used to compare the fixed effect and random effect models. Since both of p-value are less than $0{,}05$, then H_0 is rejected. Therefore, based on both tests, the fixed effect model is more appropriate for the data. Therefore, the panel regression model was estimated using the fixed effect approach. The estimated regression coefficients and other statistical values for the fixed effect panel regression model are presented in Table 1.

Partial significance test was then conducted to assess whether each independent variable is statistically significant in explaining the dependent variable within the panel regression model. Based on Table 2, it can be concluded that the number of hospitals (JRS) and the percentage of households with access to safely managed sanitation services (LSA) are statistically significant in explaining the number of DHF cases (Y) in the panel regression model. Next, the assumptions of the panel regression model were tested. Based on the Jarque-Bera test, *p-value* $= 0{,}4524 > 0{,}05$ indicates that the residuals of the panel regression model follow a normal distribution. Based on the Durbin Watson test, $p\text{-}value = 1 > 0{,}05$ indicates no autocorrelation in the residuals. However, the plot of the estimated y values against the residuals shows an indication of heteroskedasticity in the model. Therefore, further testing using the Breusch-Pagan test can be conducted to statistically confirm the presence of spatial heterogeneity in the model.

Table 1. Estimation Values of the Individual Fixed Effect Panel Regression Model

Variable	Estimate	Standard Error	t-value	p-value
KP	−0,2624	0,447	−0,5872	0,56
JRS	−489,749	91,4567	−5,355	$2{,}79 \times 10^{-6}$*
JPUS	109,3864	120,0984	0,9108	0,3672
LSA	84,2395	28,9071	2,9141	0,0055*
AML	−17,2491	36,9422	−0,4669	0,6428
PPM	−31,5766	181,9149	−0,1736	0,863
PHBS	−9,3512	12,0095	−0,7787	0,4402
RTK	−0,0998	12,1469	−0,0082	0,9935
RSD	−2,0895	3,28079	−0,6369	0,5274
F-statistic	4,3149			0,0004*
R^2	0,4632			
RMSE	485,1346			
Jarque-Bera	1,5875			0,4524*
Durbin-Watson	2,882			1*
Breusch-Pagan	21,739			0,0097*

Table 2. Moran's Index Values and p-values of Each Variables

Variable	2021		2022		2023	
	Moran's I	*p-value*	*Moran's I*	*p-value*	*Moran's I*	*p-value*
Y	**0,2056**	**0,033**	0,1128	0,1201	**0,3677**	0,0018
KP	**0,259**	**0,0155**	**0,2573**	**0,0163**	**0,2584**	**0,0159**
JRS	**0,6245**	**$1{,}48 \times 10^{-7}$**	**0,6421**	**$9{,}12 \times 10^{-8}$**	**0,6306**	**$1{,}89 \times 10^{-7}$**
JPUS	−0,1481	0,7887	−0,1462	0,7847	−0,1332	0,7554
LSA	**0,3035**	**0,0055**	**0,226**	**0,0304**	**0,2491**	**0,0198**
AML	**0,1981**	**0,0418**	**0,1981**	**0,0418**	**0,2064**	**0,0394**
PPM	**0,4616**	**0,0002**	**0,4795**	**0,0001**	**0,4774**	**0,0001**
PHBS	0,0943	0,166	−0,0202	0,449	−0,0649	0,575
RTK	0,097	0,1276	0,0786	0,1677	0,0304	0,2843
RSD	**0,277**	**0,0126**	**0,2864**	**0,0106**	**0,2141**	**0,0351**

3.2 Spatial Panel Regression Modeling

A spatial autocorrelation test was conducted to identify whether there are spatial patterns in the distribution of each research variable. The test was performed using Moran's Index. A statistically significant Moran's Index value indicates the presence of spatial autocorrelation, suggesting the existence of geographically clustered similar values. The calculated Moran's Index values and corresponding p-values for each variable from 2021 to 2023 are presented in Table 2.

The Moran's Index values indicate that most variables in this study exhibit spatial autocorrelation. Although not all variables show statistically significant spatial autocorrelation, the use of spatial modeling approaches remains relevant, as the majority display significant spatial patterns [20]. The next stage involves constructing the spatial panel lag regression model and the spatial panel error regression model, followed by a comparison based on the coefficient of determination $\left(R^2\right)$ and Root Mean Square Error (RMSE). A summary of the R^2 and RMSE values for both models is presented in Table 3.

Table 3. Performance Measures of Spatial Panel Regression Models

Model	R^2	RMSE
Spatial Panel Lag Regression	0,8707	340,7406
Spatial Panel Error Regression	0,8364	383,3655

Based on Table 3, the spatial panel lag regression model shows a higher R^2 value and a lower RMSE compared to the spatial panel error regression model. Therefore, it can be concluded that the spatial panel lag regression model is the most suitable model for analyzing the number of DHF cases in regencies and cities in West Java Province during the 2021–2023 period.

Table 4. Estimation Values of the Spatial Panel Lag Regression Model

Variable	Estimate	*Standard Error*	t-value	p-value
KP	−0,0116	0,3155	−0,0367	0,9707
JRS	−488,1453	64,4877	−7,5696	$3{,}744 \times 10^{-14}$*
JPUS	117,1418	84,3566	1,3887	0,1649
LSA	69,1016	20,5461	3,3632	0,0007*
AML	−27,8979	25,9613	−1,0746	0,2825
PPM	−204,6319	137,3684	−1,4897	0,1363
PHBS	−6,8422	8,4349	−0,81	0,4179
RTK	1,8949	8,5683	0,2212	0,825
RSD	−1,6063	2,3065	−0,6964	0,4861
δ	0,2569	0,0966	2,658	0,0079*
R^2	0,8707			
RMSE	340,7406			
Jarque-Bera	3,0725			0,2152*

The spatial panel lag regression model used in this study uses individual fixed effects approach. This choice is based on the consideration that each regency or city in West Java possesses unique characteristics that cannot be directly observed. The parameter estimation results of the spatial panel lag regression model are presented in Table 4 below.

Partial significance test was then conducted to assess whether each independent variable is statistically significant in explaining the dependent variable within the spatial panel lag regression model. Based on Table 5, the number of hospitals (JRS) and the percentage of households using safely managed sanitation services (LSA) are statistically significant in explaining the number of DHF cases (Y) in the spatial panel lag regression model. The estimated lag coefficient (δ) is also statistically significant in explaining the dependent variable in the model. This result suggests the presence of spatial interaction in the dependent variable among regencies/cities in West Java. The R^2 value indicates that 87.07% of the variation in the number of DHF cases (Y) can be explained by the independent variables in the model, while the remaining 12.93% is attributed to other factors outside the model.

Next, the assumptions of the spatial panel lag regression model were tested. Based on the Jarque-Bera test, p-value $= 0{,}2152 > 0{,}05$ indicates that the residuals of the spatial panel regression model follow a normal distribution. The estimated spatial panel lag regression model for the number of DHF cases during the 2021–2023 period is as follows:

$$\begin{aligned}\hat{Y}_{it} = \mathbf{0{,}2569} \sum_{j=1}^{27} w_{ij}\hat{Y}_{jt} - 0{,}0116KP_{it} - \mathbf{488{,}1453}JRS_{it} + 117{,}1418JPUS_{it} \\ + \mathbf{69{,}1016}LSA_{it} - 27{,}8979AML_{it} - 204{,}6319PPM_{it} \\ - 6{,}8422PHBS_{it} + 1{,}8949RTK_{it} - 1{,}6063RSD_{it} + \hat{\mu}_i\end{aligned} \tag{4}$$

3.3 Geographically Weighted Panel Regression Modeling

Before constructing the GWPR model, a spatial heterogeneity test was conducted to examine the presence of spatial heterogeneity in the panel regression model. If spatial heterogeneity is found, it provides a basis for proceeding to continue the analysis using the GWPR model, which accounts for spatial heterogeneity. Based on the Breusch-Pagan test, spatial heterogeneity exists in the panel regression model. Therefore, constructing the GWPR model is appropriate as the next step in the analysis. The next stage involves estimating the parameters for four GWPR models, each based on a different kernel function. This estimation yields regression coefficients that vary across spatial units and time periods.

Based on Table 5, the best-fitting GWPR model for explaining the variation in the research data is the GWPR model with the adaptive bisquare kernel function, as it has the highest R^2 value and the lowest RMSE compared to the other three models. The R^2 value of 0,7007 indicates that approximately 70.07% of the data variation can be explained by the model. Although this value reflects a reasonably good model fit, it is not particularly high. Therefore, the model may still have limitations in fully explaining the overall variation in the data.

The next step is to determine the most suitable GWPR model for explaining the spatial variation of DHF cases in West Java Province by evaluating four combinations of GWPR models. The selection of the best model is based on the values of R^2 and Root Mean Square Error (RMSE), as shown in Table 5 below.

Table 5. Performance Measures of GWPR Models

GWPR Model	R^2	RMSE
Adaptive Bisquare	**0,7007**	**518,4952**
Adaptive Exponential	0,646	563,9217
Fixed Exponential	0,4924	675,2696
Fixed Bisquare	0,4873	678,6418

The next step is to perform partial significance tests to determine whether each independent variable has a statistically significant influence on the dependent variable in the GWPR model for each observation location. The spatial variation of the estimated parameters was then assessed to understand how each independent variable contributes to the number of DHF cases at the local level. To provide a clearer picture, the regencies/cities were grouped based on the independent variables that were statistically significant in the GWPR model. Table 7 presents the list of regencies/cities based on each significant independent variable, while Figure 2 displays the classification of all 27 regencies/cities in West Java Province according to which independent variables were significant in explaining the number of DHF cases locally.

Table 7. Groups of Regencies/Cities in West Java Based on Significant Independent Variable

Significant Variable	Regencies/Cities
KP	Bogor Regency, Sukabumi Regency, Cianjur Regency, Garut Regency, Bogor City, Sukabumi City, Bekasi City, and Depok City.
JRS	Bogor Regency, Sukabumi Regency, Cianjur Regency, Purwakarta Regency, West Bandung Regency, Bogor City, Sukabumi City, Depok City, and Cimahi City
JPUS	Bogor Regency, Sukabumi Regency, Cianjur Regency, Bandung Regency, Garut Regency, Tasikmalaya Regency, Ciamis Regency, Kuningan Regency, Cirebon Regency, Majalengka Regency, Sumedang Regency, Indramayu Regency, Subang Regency, Purwakarta Regency, Karawang Regency, Bekasi Regency, West Bandung Regency, Bogor City, Sukabumi City, Bandung City, Cirebon City, Bekasi City, Depok City, Cimahi City, and Tasikmalaya City.
LSA	Sukabumi Regency, Cianjur Regency, West Bandung Regency, and Sukabumi City.
AML	Bogor Regency, Sukabumi Regency, Cianjur Regency, Bandung Regency, Garut Regency, West Bandung Regency, Bogor City, Sukabumi City, Bandung City, Depok City, and Cimahi City
RSD	Sukabumi Regency, Cianjur Regency, and Garut Regency
PPM	Subang Regency

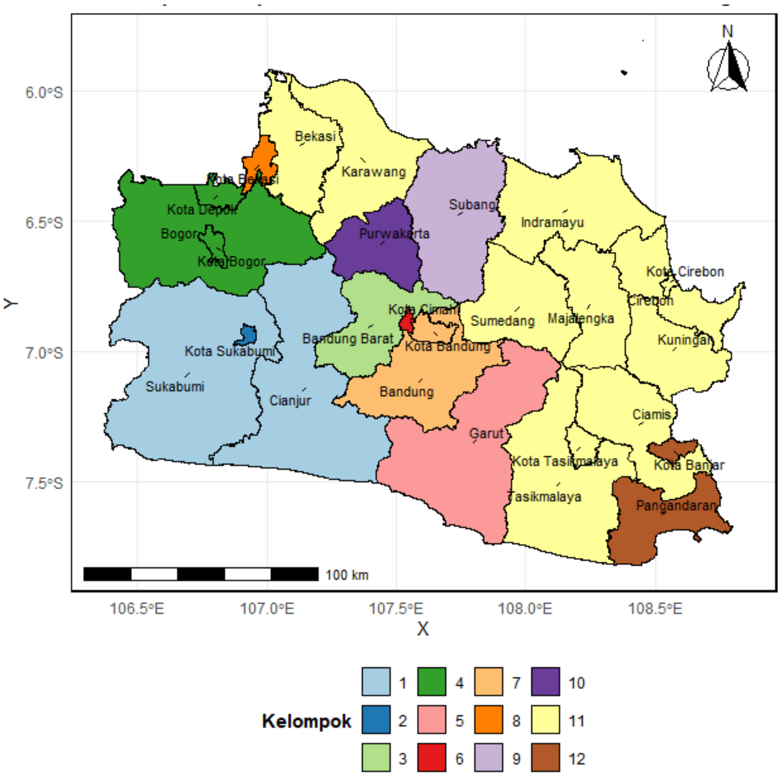

Figure 2. Map of Regencies/Cities Based on Significant Independent Variables

Based on the grouping results of regencies/cities according to the locally significant independent variables associated with dengue cases, twelve distinct groups were identified across West Java Province. Although the composition of each group varies, all of them share one common variable, the number of community health centers (JPUS) as a locally significant factor. This finding highlights that the distribution of community health centers is a dominant factor in explaining local variations in dengue cases in most regencies/cities of West Java Province.

3.4 Model Performance Evaluation

The model performance was evaluated based on the coefficient of determination (R^2) and Root Mean Square Error (RMSE), as presented in Table 9.

Table 9. Performance Measures of All Models

Model	R^2	RMSE
Spatial Panel Lag Regression	0,8707*	340,7406*
Spatial Panel Error Regression	0,8364	383,3655
GWPR *(Adaptive Bisquare)*	0,7007	518,4952
GWPR *(Adaptive Exponential)*	0,646	563,9217
GWPR *(Fixed Exponential)*	0,4924	675,2696
GWPR *(Fixed Bisquare)*	0,4873	678,6418

Based on Table 9, it can be observed that the spatial panel regression model explains the variation in the data more effectively than the other models based on R^2 values. This model also has a lower RMSE value compared to the GWPR model, indicating better predictive performance. Although the two models cannot be directly compared due to their different approaches and analytical objectives, both offer complementary insights. The spatial panel regression model provides a global overview of the relationships between variables across the entire study area, while the GWPR model produces locally varying parameter estimates, enabling spatial variation analysis at the regency/city level.

IV. CONCLUSION

The spatial panel regression lag model is identified as the best-performing spatial panel model for analyzing the number of dengue hemorrhagic fever (DHF) cases and its influencing variables in West Java Province during the 2021–2023 period. The estimation results of the spatial panel regression lag model indicate that the number of hospitals (JRS) and the percentage of households using safely managed sanitation services (LSA) are statistically significant in explaining the number of DHF cases in the West Java Province. These findings suggest that health infrastructure and sanitation factors play an important role in influencing the spread of DHF cases in the region. Furthermore, the GWPR model with the adaptive bisquare kernel function is identified as the best-performing GWPR model for modeling the number of DHF cases and its associated variables in West Java Province during the same period. The estimation results of the GWPR model reveal that the relationship between independent variables and DHF cases varies across regions. Seven independent variables were found to be locally significant: population density (KP), number of hospitals (JRS), number of public health centers (JPUS), percentage of households using safely managed sanitation services (LSA), percentage of households with access to improved sanitation sources (AML), percentage of people living in poverty (PPM), and average number of students per elementary school (RSD). Performance evaluation shows that the spatial panel regression model performs better in explaining the variation in the data and provides more accurate global predictions. However, the GWPR model offers a key advantage by capturing local variations between regions that cannot be detected by a global model.

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