

Geographically Weighted Regression with Adaptive Gaussian and Bisquare Kernels for Dengue Cases in South Sulawesi

Nurul Amelia, Hardianti Hafid*, Rahmat. H S

Department of Statistics, Universitas Negeri Makassar, Indonesia

Keywords: Adaptive Bisquare Kernel, Adaptive Gaussian Kernel, AIC, DHF, GWR

Abstract:

This study aims to model the factors influencing the number of Dengue Hemorrhagic Fever (DHF) cases in South Sulawesi Province and to compare the performance of Adaptive Gaussian Kernel and Adaptive Bisquare Kernel weighting functions in the Geographically Weighted Regression (GWR) model. GWR is used because it can accommodate spatial heterogeneity, where the relationships between variables differ across locations due to variations in geographic conditions, population density, and environment. Model evaluation was conducted using the Akaike Information Criterion (AIC) and the coefficient of determination (R^2). The results show that the GWR model with Adaptive Bisquare Kernel weighting performs better ($AIC = 307.3784$; $R^2 = 0.9263$) compared to the Adaptive Gaussian Kernel ($AIC = 340.7891$; $R^2 = 0.6106$). Thus, the Adaptive Bisquare Kernel is more suitable for modeling DHF cases in South Sulawesi Province as it better captures local spatial variation.

1. Introduction

Dengue hemorrhagic fever (DHF) is an infectious disease caused by the dengue virus and transmitted to humans through the bite of the *Aedes aegypti* mosquito. DHF remains a public health problem in Indonesia because it can affect all age groups and can cause death within a relatively short time, especially in children (Li et al., 2020). In South Sulawesi Province, 4,975 DHF cases with 20 deaths were recorded in 2024, according to the Early Warning and Response System (SKDR) report. Of these, the highest numbers of cases were reported in Sidrap, Maros, and Bulukumba regencies, each of which recorded more than 300 DHF cases.

DHF is closely related to spatial aspects because its spread is influenced by environmental, geographic, and social factors in a region. Therefore, a statistical approach that considers spatial variation is important for analyzing and modeling the spread pattern of DHF (Giofandi et al., 2023; Lin & Wen, 2011; Muna et al., 2025). One method commonly used to analyze the relationship between the number of DHF cases and the factors that influence it is regression modeling. However, for DHF cases whose spread is geographically uneven, conventional regression models are considered inadequate because they cannot capture spatial dependence or spatial variation between regions (Ikbal et al., 2024). In South Sulawesi, DHF cases have previously been modeled using geographically weighted Poisson regression (Musdar et al., 2024). To overcome these limitations, this study uses a spatial regression approach.

Spatial regression is a statistical method used to model relationships between variables while accounting for the effect of location or geographic position. In spatial regression analysis, two types of spatial effects need to be considered, namely spatial dependence and spatial heterogeneity (Fatati et al., 2017). According to Fotheringham et al. (2002), one method that can be used to model the relationship between a response variable and explanatory variables in data with spatial heterogeneity is Geographically Weighted Regression (GWR). GWR is an extension of the regression model that allows parameter estimates to differ at each observation location. Parameters in GWR are estimated by weighting observations according to their proximity to the location, so that nearer areas have a greater influence than

* Corresponding author.

E-mail address: hardiantihf@unm.ac.id



farther areas. In constructing the weighting matrix, a weighting function governed by a specific measure called the bandwidth is used (Amaliasari, 2015).

In GWR, there are two types of kernel weighting functions, namely fixed kernels and adaptive kernels. Adaptive kernels take two forms, namely the adaptive Gaussian kernel and the adaptive bisquare kernel. The difference between the Gaussian and bisquare kernel functions lies in how weights are assigned with respect to the distance between areas. The Gaussian kernel function gives weights that decrease progressively as the distance between locations increases, whereas the bisquare kernel function gives zero weight when a location lies outside a specified radius or bandwidth (Agustin, 2017). Several previous studies have shown that the GWR model is effective for modeling data with spatial variation using various weighting functions. Lutfiani et al. (2019) and Carolina (2022) found that the Gaussian kernel function gave the best performance in modeling poverty. Meanwhile, Sartika and Murniati (2021) showed that the GWR model performs better than global regression. On the other hand, the results of Ulhaq (2020) and Nisa (2022) show that the choice of the best weighting function, such as the adaptive Gaussian kernel or the fixed bisquare kernel, depends heavily on the characteristics of the case and the study location. Comparisons between adaptive and fixed kernels (Ulfie & Amaliana, 2021) and between adaptive Gaussian and adaptive bisquare kernels (Wahyudi et al., 2023) have also been reported.

Based on this description, this study focuses on Geographically Weighted Regression (GWR) modeling with adaptive Gaussian kernel and adaptive bisquare kernel weighting functions for DHF cases in South Sulawesi Province. This study is important because the spread of DHF cases has spatial characteristics that differ between regions, so a method capable of capturing local variation in the relationship between the number of DHF cases and the factors that influence it is required. The objectives of this study are: (1) to model the number of DHF cases in South Sulawesi Province using the GWR method with adaptive Gaussian kernel and adaptive bisquare kernel weighting functions; and (2) to determine the better weighting function for modeling the number of DHF cases in South Sulawesi Province.

2. Literature Review

2.1 Multiple Linear Regression Analysis

Regression analysis is a general method for predicting the response variable Y using the predictor variable $(x_1, \dots, x_k)$. Regression helps identify linear relationships and significant effects among factors. Multiple linear regression is used to examine the interaction of two or more variables with the dependent variable, with the general form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p + \varepsilon \quad (1)$$

In matrix notation, the equation can be written as:

$$Y = X\beta + \varepsilon \quad (2)$$

where Y is the response vector of size $n \times 1$, X is the predictor matrix of size $n \times (p + 1)$, β is the coefficient vector of size $(p + 1) \times 1$, and ε is the error vector of size $n \times 1$.

2.2 Parameter Estimation of the GWR Model

Parameter estimation in the Geographically Weighted Regression (GWR) model is carried out using the Weighted Least Squares (WLS) method. Unlike global linear regression, WLS assigns different weights to each study location based on its spatial proximity. Parameter estimates are obtained by minimizing the weighted sum of squared errors ε :

$$L = \sum_{i=1}^n w_i (u_i, v_i) \varepsilon_i^2 \quad (3)$$

By differentiating with respect to the parameter vector and setting the result equal to zero, the GWR parameter estimator vector at each location i is obtained as follows:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y \quad (4)$$

where:

$\hat{\beta}(u_i, v_i)$: parameter estimator vector at location i with coordinates (u_i, v_i)
 X : predictor variable matrix with dimension $n \times (p + 1)$
 $W(u_i, v_i)$: diagonal weighting matrix of size $n \times n$, specific to each location i.
 y : response variable vector with dimension $n \times 1$.

2.3 Normality Test

The normality test in the GWR model aims to ensure that the model residuals as a whole are normally distributed. This check is performed on the global residuals with the following hypotheses:

H_0 : The residuals are normally distributed.
 H_1 : The residuals are not normally distributed.

This study uses the Kolmogorov-Smirnov test with the test statistic:

$$D = \max |F_n(x) - F(x)| \quad (5)$$

Notes:

$F_n(x)$: empirical distribution function of the sample
 $F(x)$: theoretical normal distribution function
 D : Kolmogorov-Smirnov test statistic

Decision Criteria:

The decision is based on the p -value. If the p -value > 0.05 , then H_0 is accepted (the residuals are normally distributed). Conversely, if the p -value < 0.05 , then H_1 is rejected (the residuals are not normally distributed).

2.4 Spatial Weighting Matrix

The weighting matrix plays a crucial role in the GWR model because it represents the location of the observations and the relationships among locations. Spatial weighting is generally carried out using kernel functions; this study focuses on two types of adaptive kernel functions:

1. Adaptive Gaussian Kernel

This function gives weights that decrease as the distance between observation locations (d_{ij}) increases. The weighting matrix is expressed as follows:

$$W_{ij} = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}}{h_i} \right)^2 \right] \quad (6)$$

2. Adaptive Bisquare Kernel

The adaptive bisquare kernel weighting function is calculated as follows (Chasco et al., 2007):

$$W_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i} \right)^2 \right]^2, & d_{ij} \leq h_i \\ 0, & d_{ij} \text{ otherwise} \end{cases} \quad (7)$$

Where:

$i, j : 1, 2, \dots, n; i \neq j$

d_{ij} : Euclidean distance between observation location i and location j

h_i : bandwidth at observation location i

d_{ij} is the Euclidean distance function, defined as follows:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \quad (8)$$

The selection of the bandwidth (h) is a crucial step in GWR modeling because it determines the accuracy of the kernel weight estimates. A bandwidth that is too large makes the weights nearly uniform across locations (oversmoothing), whereas a bandwidth that is too small makes the weights decay very quickly, so that only a few observations contribute to each local estimate. Both situations affect model accuracy.

The optimum bandwidth in this study is determined using the Cross Validation (CV) method as follows:

$$CV(h) = \sum_{i=1}^n [y_i - \hat{y}_{\neq i}(h)]^2 \quad (9)$$

where $\hat{y}_{\neq i}(h)$ is the fitted value of y_i , obtained by omitting the observation at location i in the prediction process. The optimum bandwidth is then obtained through an iterative process until the minimum CV is reached (Fotheringham et al., 2002).

2.5 GWR Model

A method for analyzing spatial data that takes geographic aspects into account was formulated and later became known as Geographically Weighted Regression (GWR). In GWR, the estimated parameters are local, so each observation location has a different regression coefficient value. The GWR model is as follows (Caraka & Yasin, 2017):

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)X_{ik} + \varepsilon_i \quad (10)$$

Where:

Y_i	: value of the response variable at observation location i
$\beta_0(u_i, v_i)$	: GWR constant (intercept)
$\beta_k(u_i, v_i)$	: k -th regression coefficient at observation location i
u_i, v_i	: latitude and longitude coordinates of observation location i
X_{ik}	: value of the k -th predictor variable at observation location i
ε_i	: error at location i

2.6 Parameter Testing of the GWR Model

Testing of the GWR model is carried out in two main stages:

1. Simultaneous Test (Goodness of Fit)

This test aims to determine whether the GWR model explains the data better than the linear regression model. The test statistic used for the goodness-of-fit test of the GWR model is as follows:

$$F^* = \frac{MS_{Improvement}}{MS_{GWR_Residuals}} \quad (11)$$

2. Partial Test of the GWR Model

The parameters of the GWR model are tested partially. This test aims to determine which parameters significantly affect the response variable.

The hypotheses used are:

$$\begin{aligned} H_0 &: \beta_k(u_i, v_i) = 0 \\ H_1 &: \beta_k(u_i, v_i) \neq 0 \end{aligned}$$

The test statistic used is the t statistic:

$$T = \frac{\hat{\beta}_k(u_i, v_i)}{se[\hat{\beta}_k(u_i, v_i)]} \quad (12)$$

where $se[\hat{\beta}_k(u_i, v_i)]$ is the standard error obtained from the positive square root of $var[\hat{\beta}_k(u_i, v_i)]$. The decision criterion is that, if $|T| > t_{\alpha/2, v}$ then H_0 is rejected. Here, α is the significance level and v is the degrees of freedom, with a value of $(n-p-1)$.

2.7 Spatial Heterogeneity Test

The Breusch-Pagan test is used to test spatial heterogeneity. The hypotheses of the Breusch-Pagan test are as follows (Rahmawati & Bimanto, 2021):

$H_0 = \sigma_1^2 = \sigma_2^2 = \dots = \sigma_N^2 = \sigma^2$ (there is no spatial heterogeneity)

$H_1 = \text{At least one } \sigma_i^2 \neq \sigma^2 ; i = 1, 2, \dots, N$ (there is spatial heterogeneity).

The test statistic used is as follows:

$$BP = \left(\frac{1}{2}\right) f^t (Z^T Z)^{-1} Z^T \sim \chi^2_{(p)} \quad (13)$$

The decision criterion is to reject H_0 if $BP > \chi^2_{(p)}$ or $p\text{-value} < \alpha$, which means that there is variation among regions.

2.8 Multicollinearity

Multicollinearity is a condition in which an independent variable is correlated with another independent variable in the regression model. In GWR modeling, the VIF value is calculated for each predictor variable. The VIF is expressed as follows (Abdullah et al., 2017; Arthayanti et al., 2017):

$$VIF_k(u_i, v_i) = \frac{1}{1 - R_k^2(u_i, v_i)} \quad (14)$$

where $R_k^2 = \frac{\sum_{i=1}^n w_{ij} (X_i - \bar{X})^2}{\sum_{i=1}^n w_{ij} (X_i - \bar{X})^2}$ is the coefficient of determination at each location.

2.9 Best Model Selection

According to Fotheringham et al. (2002), model goodness of fit is assessed using the Akaike Information Criterion (AIC). A model is considered good when its AIC value is small and its R^2 is high. The selection criteria used are as follows (Agustin, 2017). The AIC is expressed as:

$$AIC = 2n \log(\hat{\sigma}) + n \log(2\pi) + n \left(\frac{n + \text{tr}(S)}{n - 2 - \text{tr}(S)} \right) \quad (15)$$

where:

$$\hat{\sigma} = \sqrt{MSE}$$

n : the number of locations.

The coefficient of determination (R^2) is denoted by:

$$R^2 = \frac{SSR}{SST} \quad (16)$$

Where:

SSR is the total regression sum of squares and SST is the total sum of squares.

3. Research Method

3.1 Research Type

Based on the available data, this study uses a quantitative approach. The quantitative research method is carried out by collecting the necessary data and then analyzing it using Geographically Weighted Regression (GWR) with the Adaptive Gaussian Kernel and Adaptive Bisquare Kernel weighting functions.

3.2 Data Source

The data used in this study were obtained from the South Sulawesi Provincial Health Office. The data are secondary data, that is, data that already exist and were not collected directly by the researcher.

3.3 Variable Definitions

The variables used in this study consist of two types, namely the response variable (Y) and the predictor variables (X). Information on the variables used is presented in Table 1:

Table 1. Research Variables for DHF Cases

	Variable	Scale
Y	Number of DHF Cases	Ratio
X ₁	Number of Households with Access to Adequate Sanitation	Ratio
X ₂	Larva-Free Index (ABJ)	Ratio
X ₃	Number of Community Health Centers (Puskesmas)	Ratio
X ₄	Percentage of Households with Clean and Healthy Living Behavior (PHBS)	Ratio
X ₅	Population Density	Ratio
X ₆	Access to Clean Water	Ratio
X ₇	Percentage of Poor Population	Ratio
X ₈	Severe Malnutrition	Ratio

3.4 Analysis Steps

The analysis steps used in modeling the number of DHF cases with the GWR model are as follows:

1. Perform descriptive statistical analysis
2. Test the normality of the residuals using the K-S test.
3. Detect multicollinearity among variables using the Variance Inflation Factor (VIF) test
4. Test the spatial heterogeneity assumption
5. Build the GWR model
 - a. Determine the optimum bandwidth based on the CV criterion.
 - b. Calculate the weighting matrix using the Adaptive Gaussian Kernel and Adaptive Bisquare Kernel weighting functions
 - c. Calculate Euclidean distances based on geographic location
 - d. Test the GWR model parameters partially
 - e. Test the GWR model parameters simultaneously
6. Select the best model based on the AIC and R² values of each weighting function
7. Interpret the GWR model.

4. Results and Discussion

4.1 Descriptive Analysis

The descriptive analysis shows that, among the regencies/cities of South Sulawesi Province, the lowest number of DHF cases was in Palopo City, with 42 cases, and the highest was in Makassar City, with 1,977 cases.

4.2 Normality Test

The normality test in this study uses the Kolmogorov-Smirnov test. The hypotheses used in the Kolmogorov-Smirnov test are:

H_0 : the residuals are normally distributed

H_1 : the residuals are not normally distributed

The results of the Kolmogorov-Smirnov test are shown in Table 2:

Table 2. Normality Test Results

Test Statistic	Value
D (Test Statistic)	0.11148
<i>p-value</i>	0.2785

Based on the normality test using the Kolmogorov-Smirnov criterion, the test statistic D is 0.1148 with a p -value of 0.2785. Because the p -value > 0.05 , H_0 is accepted, indicating that the residuals are normally distributed. Therefore, the normality assumption is satisfied, and the data are suitable for further analysis.

4.3 Multicollinearity Test

The multicollinearity assumption can be tested by examining the Variance Inflation Factor (VIF) values.

Table 3. VIF Values in the Regression Model

Variable	VIF
X_1	2.498
X_2	1.524
X_3	2.351
X_4	1.381
X_5	1.887
X_6	1.637
X_7	1.471
X_8	1.884

Based on the VIF values in Table 3, all VIF values are < 10 ; therefore, it can be concluded that there is no multicollinearity, so all variables are suitable for use in the GWR analysis.

4.4 Spatial Heterogeneity Test

The spatial heterogeneity test aims to determine whether there is variation among the regions of the province, using the Breusch-Pagan test. The Breusch-Pagan test results are shown in Table 4.

Table 4. Breusch-Pagan Test Results

Test Statistic	Value
BP (<i>Breusch-Pagan</i>)	22.603
Df (Degrees of Freedom)	8
<i>p-value</i>	0.003914

Based on the Breusch-Pagan test in Table 4, the p -value is 0.003914. At the 5% significance level, H_0 is rejected. Therefore, it can be concluded that spatial heterogeneity exists in DHF cases in South Sulawesi Province.

4.5 GWR Modeling

The first step in GWR modeling is to calculate the Euclidean distance between one observation location and another. The following is an example of the distance calculation between Selayar Islands Regency and Bantaeng Regency.

$$\begin{aligned}
 d_{ij} &= \sqrt{(-5.4833 + 2.55770)^2 + (119.9833 - 121.3142)^2} \\
 &= \sqrt{(-2.92563)^2 + (-1.3309)^2} \\
 &= \sqrt{10.332} \\
 &= 3.214
 \end{aligned}$$

After the distances between observation locations (d_{ij}) are obtained, the next step is to determine the optimum bandwidth using the adaptive Gaussian kernel and adaptive bisquare kernel weighting functions. The optimum bandwidth is selected using the Cross Validation (CV) method. The optimum bandwidth for each weighting function is shown in Table 5:

Table 5. Optimum Bandwidths of the Adaptive Gaussian and Adaptive Bisquare Kernels

Regency/City	h_{ij}	
	<i>gaussian</i>	<i>bisquare</i>
Bantaeng	1.633	1.915
Barro	1.126	1.230
Bone	1.207	1.291
Bulukumba	1.589	1.913
Enrekang	1.701	1.731
Gowa	1.706	1.821
Jeneponto	1.798	2.035
Selayar	2.861	3.042
Makassar	2.670	2.722
Palopo	2.541	2.623
Pare-pare	1.540	1.757
Luwu	1.433	1.638
East Luwu	2.140	2.246
Maros	1.167	1.381
Pangkep	1.328	1.402
Pinrang	1.540	1.709
Sidrap	3.081	3.421
Sinjai	1.398	1.417
Soppeng	1.690	1.732
Takalar	1.103	1.274
Toraja	1.801	1.905
North Toraja	2.059	2.186
Wajo	2.133	2.259
North Luwu	1.381	1.404

Based on Table 5, the optimum bandwidth values produced by the adaptive Gaussian kernel and adaptive bisquare kernel weighting functions differ across observation locations. This means that each observation location has a different radius of influence that is considered optimal in forming the model parameters of that location. Once the optimum bandwidths are obtained, the next step is to form the weighting matrix for each observation location based on the adaptive Gaussian kernel and adaptive bisquare kernel weighting functions to estimate the GWR models, so that the model for each regency/city in South Sulawesi Province is different. The parameter estimation results of the GWR models are shown in the following table.

Table 6. Parameter Estimation Results

Variable	Gaussian			Bisquare		
	Minimum	Maximum	Range	Minimum	Maximum	Range
Intercept	-1.413x10 ³	2.114x10 ³	3.528x10 ³	-7.739x10 ³	-1.755x 10 ³	5.983x 10 ³
β_1	-1.398x10 ⁻²	1.423x10 ²	2.822x10 ⁻²	-3.701x 10 ⁻²	4.284x 10 ⁻¹	3.914x 10 ⁻¹
β_2	-6.030x10 ⁻¹	4.850x10	4.247x10	-3.747x 10	1.177x 10 ²	1.214x 10 ²
β_3	-1.140 x 10 ⁻¹	-1.006x10	1.039x10 ¹	-3.250x 10 ¹	-8.599x 10 ⁻¹	3.164x 10 ¹
β_4	3.198 x 10	1.790x10 ¹	1.470x10 ¹	-1.536x 10 ¹	2.294x 10 ¹	3.831x 10 ¹
β_5	-2.620 x 10 ¹	8.693x10	3.489x10 ¹	-1.084x 10 ¹	3.135x 10 ¹	4.219x 10 ¹
β_6	-1.222x10	7.320x10	1.954x10 ¹	-4.739x 10 ¹	2.320x 10 ¹	7.059x 10 ¹
β_7	1.732x10	9.721x10	7.989x10	-3.997x 10	3.330x 10 ¹	3.730x 10 ¹
β_8	-9.225 x10 ¹	1.217x10 ¹	1.044x10 ²	-2.592x 10 ²	5.595x 10 ¹	3.151x 10 ²

4.6 Model Goodness-of-Fit Test

The results of the model goodness-of-fit test are as follows:

Table 7. F Test

Model	F_{calc}	F_{table}
Adaptive Gaussian Kernel	2.942	2.660
Adaptive Bisquare Kernel	3.961	3.321

Based on Table 7, $F_{calc} > F_{table}$, so H_0 is rejected, which means that there is a significant difference between the OLS and GWR regression models; in other words, the GWR model is better than the OLS model.

4.7 Partial Test

The partial significance test of the GWR parameters is carried out to determine which parameters significantly affect DHF incidence in each regency/city of South Sulawesi Province. The decision rule used in the partial test of the GWR model is to reject H_0 if $|T_{calc}| \geq |T_{table}| = 2.131$. The results of the parameter significance test of the GWR model in Selayar Islands Regency are shown in the following table:

Table 8. Partial Test Results of the GWR Model Parameters in Selayar Islands Regency

Parameter	Adaptive Gaussian Kernel				Adaptive Bisquare Kernel			
	Estimate	t-value	p-value	Remarks	Estimate	t-value	p-value	Remarks
β_0	2114.741	0.826	0.980	Not Significant	6.571	-2.001	0.063	Not Significant
β_1	-0.011	-0.177	0.862	Not Significant	-7739.495	1.929	0.115	Not Significant
β_2	4.056	0.349	0.733	Not Significant	0.428	3.855	0.014	Significant
β_3	-11.406	-0.966	0.353	Not Significant	117.743	-2.415	0.034	Significant
β_4	17.053	2.994	0.010	Significant	-25.856	3.430	0.021	Significant
β_5	-26.206	-1.436	0.177	Not Significant	22.947	-0.090	0.932	Not Significant
β_6	-10.733	-1.118	0.286	Not Significant	-1.693	-5.267	0.004	Significant
β_7	8.311	1.025	0.325	Not Significant	-45.398	4.377	0.008	Significant
β_8	87.606	2.153	0.040	Significant	33.303	-5.508	0.003	Significant

Based on the parameter test results of the GWR model in Selayar Islands Regency, the adaptive Gaussian kernel model shows that the variables significant for DHF cases are Clean and Healthy Living Behavior (PHBS) (X_4) and the Percentage of Severe Malnutrition (X_8). Variable X_4 has a positive effect, whereas X_8 has a negative effect on the number of DHF cases.

In the adaptive bisquare kernel model, the significant variables are X_2 , X_3 , X_4 , X_6 , X_7 , and X_8 . Variables X_2 , X_3 , and X_8 have positive effects, whereas X_4 , X_6 , and X_7 have negative effects on the number of DHF cases. These results show spatial differences in the influence of DHF factors in South Sulawesi Province.

Table 9. Variables with Significant Effects in Each Regency/City by Weighting Function

Weighting Function	Regency/City	Significant Variables
Adaptive Gaussian Kernel	Selayar Islands Regency, Makassar City, Pinrang Regency, Sinjai Regency, Enrekang Regency, North Luwu Regency	X_4
	Palopo City, East Luwu Regency, Wajo Regency, North Toraja Regency	X_4 , X_8

Weighting Function	Regency/City	Significant Variables
Adaptive Bisquare Kernel	Makassar City, Palopo City, East Luwu Regency, Wajo Regency,	$X_2, X_3, X_4, X_6, X_7, X_8$
	North Toraja Regency	
	Selayar Islands Regency	X_2, X_4, X_6, X_7, X_8
	Enrekang Regency	X_2, X_6, X_7, X_8

4.8 Formation of the GWR Models

GWR modeling with the adaptive Gaussian kernel and adaptive bisquare kernel weighting functions produces local model parameters for each observation point or location. The following are examples of the general GWR models formed using the adaptive Gaussian kernel and adaptive bisquare kernel weighting functions for Selayar Islands Regency:

1. GWR Model with the Adaptive Gaussian Kernel Weighting Function for Selayar Islands Regency

$$\hat{Y}_{Selayar} = 2114.741 - 0.011X_1 + 4.056X_2 - 11.406X_3 + 17.053X_4 - 26.206X_5 - 10.733X_6 + 8.311X_7 - 87.606X_8$$

2. GWR Model with the Adaptive Bisquare Kernel Weighting Function for Selayar Islands Regency:

$$\hat{Y}_{Selayar} = 6.571 - 7739.495X_1 + 0.428X_2 + 117.743X_3 - 25.856X_4 + 22.947X_5 - 1.693X_6 - 45.398X_7 + 33.3032X_8$$

4.9 Best Model Selection

Model goodness can be measured by comparing the AIC value and the coefficient of determination R^2 . The best model results are shown in Table 10.

Table 10. Best Model

Model	AIC Value	R^2
GWR with Adaptive Gaussian Kernel Weighting Function	340.789	0.610
GWR with Adaptive Bisquare Kernel Weighting Function	307.378	0.926

Based on Table 10, the best model for modeling the number of DHF cases in South Sulawesi Province is the GWR model with the Adaptive Bisquare Kernel weighting function. This is shown by its smallest AIC value of 307.378 and R^2 of 0.926, whereas the Adaptive Gaussian Kernel weighting function has an AIC of 340.789 and R^2 of 0.610. Therefore, it can be concluded that the model with the Adaptive Bisquare Kernel weighting function is better for modeling the number of DHF cases in South Sulawesi Province.

4.10 Discussion

The results show that the number of DHF cases differs among regencies/cities in South Sulawesi Province. The spatial heterogeneity test indicates a spatial effect, so the Geographically Weighted Regression (GWR) method is more suitable than global regression. Based on the model evaluation, GWR with the Adaptive Bisquare Kernel weighting function is the best model, with an AIC of 307.378 and R^2 of 0.926, compared with the Adaptive Gaussian Kernel, with an AIC of 340.789 and R^2 of 0.610. This shows that the Adaptive Bisquare Kernel model is better at explaining the variation in DHF cases in South Sulawesi Province.

5. Conclusion

This study modeled the number of dengue hemorrhagic fever (DHF) cases in South Sulawesi Province using Geographically Weighted Regression (GWR) with adaptive Gaussian kernel and adaptive bisquare kernel weighting functions. The spatial heterogeneity test indicated that the relationship between DHF cases and the predictor variables varies across locations, and the F test showed that GWR fits the data significantly better than global regression. The modeling produced a local model for each of the 24 regencies/cities, and the significant predictor variables differed

between locations and between the two kernels. The adaptive bisquare kernel gave the better fit ($AIC = 307.378$; $R^2 = 0.926$) compared with the adaptive Gaussian kernel ($AIC = 340.789$; $R^2 = 0.610$), so it is the more suitable weighting function for modeling DHF cases in South Sulawesi Province in 2024.

References

- Abdullah, N. A., Amran, & Saleh. (2017). Pemodelan geographically weighted regression multikolinearitas menggunakan regresi ridge [Geographically weighted regression modeling of multicollinearity using ridge regression]. *Jurnal FMIPA Universitas Hasanuddin*. <https://core.ac.uk/download/pdf/89562167.pdf>
- Agustin, G. K. (2017). *Pemodelan geographically weighted regression (GWR) dengan fungsi pembobot adaptive Gaussian kernel dan adaptive bisquare kernel* [Geographically weighted regression (GWR) modeling with adaptive Gaussian kernel and adaptive bisquare kernel weighting functions] [Undergraduate thesis, Universitas Brawijaya]. <http://repository.ub.ac.id/id/eprint/155340/>
- Amaliasari, C. (2015). *Penggunaan pembobot adaptive Gaussian kernel dan adaptive bisquare kernel pada model geographically weighted negative binomial regression (GWNBR)* [The use of adaptive Gaussian kernel and adaptive bisquare kernel weights in the geographically weighted negative binomial regression (GWNBR) model] [Undergraduate thesis, Universitas Brawijaya].
- Arthayanti, Y., Srinadi, I. G. A. M., & Gandhiadi, G. K. (2017). Geographically weighted ridge regression dalam kasus multikolinearitas pada Indeks Pembangunan Manusia di kabupaten/kota Provinsi Jawa Timur [Geographically weighted ridge regression in the case of multicollinearity on the Human Development Index in the regencies/cities of East Java Province]. *Jurnal Matematika*, 7(2), 124. <https://doi.org/10.24843/jmat.2017.v07.i02.p89>
- Caraka, R. E., & Yasin, H. (2017). *Geographically weighted regression (GWR): Sebuah pendekatan regresi geografis* [Geographically weighted regression (GWR): A geographic regression approach]. *Mobius*. <https://doi.org/10.5281/zenodo.1168741>
- Carolina, M. (2022). *Perbandingan model geographically weighted regression (GWR) dengan fungsi pembobot fixed Gaussian kernel dan adaptive Gaussian kernel* [Comparison of geographically weighted regression (GWR) models with fixed Gaussian kernel and adaptive Gaussian kernel weighting functions] [Undergraduate thesis, UIN Sunan Kalijaga Yogyakarta].
- Chasco, C., Garcia, I., & Vicens, J. (2007). *Modeling spatial variations in household disposable income with geographically weighted regression* (MPRA Paper No. 9581). Munich Personal RePEc Archive.
- Fatati, I. F., Wijayanto, H., & Sholeh, A. M. (2017). Analisis regresi spasial dan pola penyebaran pada kasus demam berdarah dengue (DBD) di Provinsi Jawa Tengah [Spatial regression analysis and distribution pattern of dengue hemorrhagic fever (DHF) cases in Central Java Province]. *Media Statistika*, 10(2), 95–105. <https://doi.org/10.14710/medstat.10.2.95-105>
- Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons.
- Giofandi, E. A., Purwantiningrum, P., Madino, F., & Lumbantobing, A. (2023). Analisis faktor spasial terhadap kejadian demam berdarah dengue menggunakan pendekatan geographically weighted regression di Kota Pekanbaru, Provinsi Riau [Analysis of spatial factors of dengue hemorrhagic fever incidence using a geographically weighted regression approach in Pekanbaru City, Riau Province]. *Jurnal Ilmu Lingkungan*, 22(1), 50–59. <https://doi.org/10.14710/jil.22.1.50-59>
- Ikbal, A., Purnamasari, A. I., & Ali, I. (2024). Analisis klasterisasi untuk prediksi jumlah kasus DBD berdasarkan jenis kelamin dan kabupaten/kota di Jawa Barat [Cluster analysis for predicting the number of DHF cases by sex and regency/city in West Java]. *JATI (Jurnal Mahasiswa Teknik Informatika)*, 7(6), 3789–3796. <https://doi.org/10.36040/jati.v7i6.8296>

- Li, Z., Fotheringham, A. S., Oshan, T. M., & Wolf, L. J. (2020). Measuring bandwidth uncertainty in multiscale geographically weighted regression using Akaike weights. *Annals of the American Association of Geographers*, 110(5), 1500–1520. <https://doi.org/10.1080/24694452.2019.1704680>
- Lin, C., & Wen, T. (2011). Using geographically weighted regression (GWR) to explore spatial varying relationships of immature mosquitoes and human densities with the incidence of dengue. *International Journal of Environmental Research and Public Health*, 8(7), 2798–2815. <https://doi.org/10.3390/ijerph8072798>
- Lutfiani, N., Sugiman, S., & Mariani, S. (2019). Pemodelan geographically weighted regression (GWR) dengan fungsi pembobot kernel Gaussian dan bi-square [Geographically weighted regression (GWR) modeling with Gaussian and bi-square kernel weighting functions]. *Unnes Journal of Mathematics*, 8(1), 82–91. <https://doi.org/10.15294/ujm.v8i1.17103>
- Muna, M. L. L., Sutningsih, D., Martini, M., Fauzi, M., & Dharmawan, Y. (2025). Geographically weighted regression (GWR) analysis of factors related to dengue hemorrhagic fever in Central Java Province, Indonesia. *International Journal of Mosquito Research*, 12(2), 19–24. <https://doi.org/10.22271/23487941.2025.v12.i2a.830>
- Musdar, Y., Aswi, & Mar'ah, Z. (2024). Pemodelan geographically weighted Poisson regression untuk kasus DBD di Provinsi Sulawesi Selatan tahun 2022 [Geographically weighted Poisson regression modeling of DHF cases in South Sulawesi Province in 2022]. *Jurnal MSA (Matematika dan Statistika serta Aplikasinya)*, 12(2), 16–21. <https://doi.org/10.24252/msa.v12i2.51242>
- Nisa, K. (2022). Penerapan model geographically weighted Poisson regression untuk demam berdarah dengue di Kabupaten Bojonegoro [Application of the geographically weighted Poisson regression model to dengue hemorrhagic fever in Bojonegoro Regency]. *Jurnal Statistika dan Komputasi*, 1(1), 12–22. <https://doi.org/10.32665/statkom.v1i1.444>
- Rahmawati, D., & Bimanto, H. (2021). Perbandingan spatial autoregressive model dan spatial error model dalam pemodelan indeks pembangunan manusia di Provinsi Jawa Timur [Comparison of the spatial autoregressive model and the spatial error model in modeling the human development index in East Java Province]. *Jurnal Statistika dan Aplikasinya*, 5(1), 41–50. <https://doi.org/10.21009/JSA.05104>
- Sartika, E., & Murniati, S. (2021). Application of the geographically weighted regression (GWR) with the bi-square weighting function on the poverty model in the city/regency of West Java. In *Proceedings of the 2nd International Seminar of Science and Applied Technology (ISSAT 2021)* (Advances in Engineering Research, Vol. 207, pp. 201–207). Atlantis Press. <https://doi.org/10.2991/aer.k.211106.031>
- Ulfie, S., & Amaliana, L. (2021). Model geographically weighted regression dengan fungsi pembobot adaptive dan fixed kernel pada kasus kematian ibu di Jawa Timur [Geographically weighted regression model with adaptive and fixed kernel weighting functions for maternal mortality cases in East Java]. *Jurnal Statistika dan Aplikasinya*, 5(2), 208–220. <https://doi.org/10.21009/jsa.05209>
- Ulhaq, H. (2020). Geographically weighted logistic regression (GWLR) with Gaussian adaptive kernel weighting function, bisquare, and tricube in case of malnutrition of toddlers in Indonesia. *Jurnal Litbang Edusaintech*, 1(1), 5–13. <https://doi.org/10.51402/jle.v1i1.2>
- Wahyudi, R., Fauzi, Y., & Rizal, J. (2023). Analisis kemiskinan ekstrem Provinsi Bengkulu menggunakan metode geographically weighted regression (GWR) dengan pembobot adaptive Gaussian kernel dan adaptive bi-square [Analysis of extreme poverty in Bengkulu Province using the geographically weighted regression (GWR) method with adaptive Gaussian kernel and adaptive bi-square weights]. *Journal of Mathematics UNP*, 8(2), 134. <https://doi.org/10.24036/unpjomath.v8i2.14914>