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A Comparison of the Adaptive Gaussian Kernel and Bisquare Weighting Functions in the Geographically Weighted Regression (GWR) Model for Rice Production Modeling in West Sumatra in 2025

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Abstract

When a global regression model exhibits spatial effects, conventional regression may produce biased or inefficient estimates because it ignores spatial heterogeneity. Geographically Weighted Regression (GWR) addresses this issue by allowing regression coefficients to vary across locations through a spatial weighting matrix. Since kernel selection substantially influences local parameter estimation, this study compares the Adaptive Gaussian and Adaptive Bisquare kernel functions to identify the most appropriate weighting scheme for modeling rice production in West Sumatra in 2025. Unlike previous studies that commonly employ a single kernel function, this study provides a direct comparison of two adaptive kernel weighting schemes within the same GWR framework, offering evidence on their relative performance for agricultural spatial modeling. Secondary data obtained from the Central Statistics Agency (BPS) were analyzed using GWR with both kernel functions. Model performance was evaluated using the Akaike Information Criterion (AIC) and the coefficient of determination (R^2). The results indicate that rice prices, land area, and the poverty line significantly influence rice production, although their effects vary spatially across districts. The Adaptive Bisquare kernel outperformed the Adaptive Gaussian kernel, producing a lower AIC (39.93) and a higher R^2 (63.3%). These findings demonstrate that the Adaptive Bisquare kernel provides a more effective spatial weighting scheme for modeling regional variation in rice production in West Sumatra.

Keywords: Spatial Regression; GWR; Adaptive Gaussian Kernel; Adaptive Bisquare Kernel.

1. Introduction

Rice production is a key factor in maintaining national food security in Indonesia. As the primary staple food for the majority of the population, the availability of rice must be ensured on an ongoing basis. Rice production in a region is influenced by various factors such as harvested area, land productivity, rainfall, and the socioeconomic conditions of the community. Differences in geographical conditions between regions

result in uneven rice production, necessitating an analysis capable of incorporating spatial aspects into its modeling [1].

One method that can be used to analyze spatial data is Geographically Weighted Regression (GWR). This method is capable of describing relationships between variables at the local level because the model parameters can vary at each observation location. In the GWR model, the weighting process plays a crucial role because it determines the extent of the influence of the surrounding area on a given location. Weighting functions commonly used in GWR models include the adaptive Gaussian kernel and the adaptive Bisquare kernel. These two functions have distinct characteristics in determining weights based on the distance between areas, thereby enabling the generation of different models [2].

Previous studies have employed the Geographically Weighted Regression (GWR) method in spatial data modeling, including within the agricultural sector. However, most studies have used only one type of weighting function without comparing kernel functions. Furthermore, research specifically comparing the use of the adaptive Gaussian kernel and the adaptive Bisquare kernel in rice production modeling, particularly in West Sumatra, remains limited. In fact, the different regional characteristics in West Sumatra allow for quite large spatial variations in rice production.

The novelty of this study lies in the comparison of two weighting functions the adaptive Gaussian kernel and the adaptive Bisquare kernel in the Geographically Weighted Regression (GWR) model for modeling rice production in West Sumatra in 2025. Additionally, this study provides an overview of the spatial variation in rice production at the district/city level in West Sumatra.

This study aims to compare the performance of the adaptive Gaussian kernel and adaptive Bisquare kernel weighting functions in the Geographically Weighted Regression (GWR) model for modeling rice production in West Sumatra in 2025. Furthermore, this study aims to determine which weighting function yields the best model for explaining variations in rice production across regions.

This study is expected to contribute to the development of spatial analysis methods, particularly the use of Geographically Weighted Regression (GWR) with adaptive Gaussian kernel and adaptive Bisquare kernel weighting functions. In addition, this study is expected to provide useful information for local governments in understanding the factors that influence rice production in West Sumatra, so that it can be used as a basis for decision-making regarding policies to increase rice production. This study is also expected to serve as a reference for future research utilizing the GWR method in the agricultural sector and other fields.

Despite the growing application of Geographically Weighted Regression (GWR) in agricultural and regional studies, most previous research has focused on applying a single kernel weighting function without evaluating whether different adaptive kernels produce substantially different local estimation results. Consequently, there is limited empirical evidence regarding the most appropriate adaptive kernel for modeling spatial heterogeneity in rice production. This study addresses this research gap by conducting a systematic comparison between the Adaptive Gaussian and Adaptive Bisquare kernel functions within the same GWR framework using identical datasets, bandwidth selection procedures, and evaluation criteria. This comparison provides a more rigorous assessment of how kernel choice influences model performance and spatial interpretation.

This study contributes to the literature in three important ways. First, it offers an empirical evaluation of two widely used adaptive kernel functions under consistent modeling conditions, thereby extending previous GWR studies that relied on only a single kernel. Second, it identifies the kernel function that provides superior model performance for explaining spatial variation in rice production across districts in West Sumatra. Third, the findings provide practical guidance for researchers and policymakers in selecting appropriate spatial weighting functions for agricultural planning and regional development, particularly in areas characterized by spatial heterogeneity.

2. Materials and Methods

2.1. Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is a model derived from the development of regression models, in which each parameter depends on each location, such that each geographic location has different regression parameter values [3]. This means that in the GWR model, the response variable y is estimated using predictor variables, each of which has a regression coefficient that depends on the location where the data was observed. The GWR model can be formulated as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \, ; i = 1,2,3, \dots, n \qquad (1)$$

where:

y_i = dependent variable at the i −th location point ($i = 1,2,3, \dots, n$)

x_{ik} = the k −th independent variable at the i −th observation point ($i = 1,2,3, \dots, n$)

$\beta_0(u_i, v_i)$ = constant at the i −th observation

$\beta_k(u_i, v_i)$ = the k −th regression coefficient at the i −th observation location

(u_i, v_i) = longitude and latitude coordinates of the i − th location in a geographical area

ε_i = error term assumed to be identical, independent, and normally distributed with zero mean and variance σ^2

2.2. Bandwidht GWR

In the kernel weighting function, there is a key coefficient known as bandwidth. Bandwidth controls the size of the kernel. The choice of kernel depends largely on the spatial form. Bandwidth can be analogized to the radius (h) of a circle, such that an observation point located within the circle's radius is still considered influential in determining the parameter at the i-th observation point. Selecting the optimal bandwidth is crucial because it affects the results obtained by GWR [4]. According to [3], there are several methods for determining the optimal bandwidth, one of which is the Cross Validation (CV) method. The mathematical equation for CV is as follows:

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

where:

$\hat{y}_{\neq i}$ = The predicted value y_i corresponding to the observation at location (u_i, v_i) is excluded from the prediction process.

2.3. Weighting GWR

The role of weighting in GWR is a crucial aspect, as the weights depend on the distances between observation points. The weighting is represented by a diagonal matrix, where the diagonal elements constitute a weighting function for each observation point. The purpose of the weighting matrix is to determine or estimate different parameters at each observation point. The proximity relationship between locations is expressed in a spatial weighting matrix W with elements W_{ij}. The type of weighting used for point data is distance weighting, obtained from the latitude and longitude coordinates of a point. The magnitude of the weighting for each different location can be determined using a kernel function. The kernel function provides weights according to the optimal bandwidth, the value of which depends on the data conditions. The kernel function is used to estimate parameters in the GWR model if the distance function (W_{ij}) is a continuous function [2]. There are two types of kernel functions: fixed kernel and adaptive kernel. If the observation points are densely distributed around the i −th observation location, the resulting bandwidth is relatively narrow. Conversely, if the observation points are relatively far from the $i-$ th observation location, the resulting bandwidth becomes wider. The two adaptive kernel functions used in GWR are the adaptive Gaussian kernel and the adaptive Bisquare kernel.

2.3.1. Pembobot Adaptive Kernel Gaussian

According to [5], in spatial analysis, an observation located closer to location i is assumed to have a greater influence on parameter estimation than an observation located farther away. The adaptive Gaussian kernel weighting equation is:

$$W_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_{i_{(q)}}}\right)^2\right) \quad (3)$$

with:

$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$ = is the Euclidean distance between location (u_i, v_i) and location (u_j, v_j)

h_i = optimum bandwidth value at each location

Where:

d_{ij} = the Euclidean distance between location i −th and observation j −th.

h_i = Bandwidth width at the i −th observation location.

u = Longitude

v = Latitude

2.3.2. Adaptive Bisquare Kernel Weighting

Bandwidth is the maximum distance from a point within a radius b of the central location, which is used as the basis for determining the weight of each observation in the regression model for that location. The equation for adaptive Bisquare kernel weighting is:

$$W_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_{i_{(q)}}}\right)^2\right)^2, & if\ d_{ij} \le h \\ 0, & if\ d_{ij} > h \end{cases} \quad (4)$$

with:

$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}$ = is the Euclidean distance between the location (u_i, v_i) and the location (u_j, v_j)

h_i = optimal bandwidth values for each location

2.4. Estimation of GWR Model Parameters

The method used to estimate the parameters in each GWR model is the Weighted Least Squares (WLS) method, in which each location is assigned a different weight based on the observation point from which the data was collected. The weighting notation used for each location is $w_j(u_i, v_i)$ where $j = 1, 2, 3, \ldots, n$ locations. The GWR parameter estimate $\beta_k(u_i, v_i)$ for the k −th variable at the i −th observation location is as follows:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y \quad (5)$$

Where:

$\hat{\beta}(u_i, v_i)$ = estimated parameter at the i −th location

X = independent variable matrix of size $n \times (p + 1)$

$W(u_i, v_i)$ = weight matrix at the i-th location of size $n \times n$

Y = dependent variable vector of size $n \times 1$

2.5. Selection of the Best Model

2.5.1. Coefficient of Determination

An R^2 value close to zero indicates that the independent variables have a very limited ability to explain the dependent variable, whereas an R^2 value close to one indicates that the independent variables have a very strong ability to explain the dependent variable. In the GWR model, the coefficient of determination can be calculated using the following equation [6]:

$$R_i^2 = \frac{JKT_{GWR} - JKS_{GWR}}{JKT_{GWR}} \quad (6)$$

2.5.2. Akaike Information Criterion (AIC)

The best model is determined based on the smallest AIC value [3], and the calculation is as follows:

$$AIC = 2n \ln(\hat{\sigma}) + n \ln(2\pi) + n + tr(L) \quad (7)$$

Where:

$\hat{\sigma}$ = standard deviation estimator value with error obtained from maximum likelihood estimation

$\hat{\sigma} = al\hat{\sigma}^2 = \frac{JKS}{n} = \frac{Y^T(I-L)^T(I-L)Y}{n}$

L = Projection matrix with $\hat{y} = Ly$

2.6. Research Methodology

The data used in this study are secondary data obtained from the Central Statistics Agency (BPS) of West Sumatra Province in 2025. The data for this study can be accessed or obtained at the website https://sumbar.bps.go.id/id. In the study "Comparison of the Adaptive Kernel Gaussian and Bisquare Weighting Functions in the Geographically Weighted Regression (GWR) in Rice Production Modeling in West Sumatra in 2025," four variables were used, consisting of one dependent variable, namely Rice Production(Y), and three independent variables, namely Rice Price (X_1), Area (X_2), and Poverty Line (X_3). The research steps are as follows.

1. Describing the data using descriptive statistics.
2. Detecting multicollinearity among independent variables using the Variance Inflation Factor (VIF).
3. Testing for spatial effects using the Breusch-Pagan test.
4. Determining the optimal bandwidth for each observation location using Cross Validation (CV).
5. Calculating the spatial weighting matrix using the Adaptive Kernel Gaussian and Adaptive Kernel Bisquare weighting functions.
6. Estimating the GWR model coefficients.
7. Identifying the best model by comparing the Adaptive Kernel Gaussian and Adaptive Kernel Bisquare weighting functions based on the largest R^2 value (or one closest to 1) and the smallest AIC value.
8. Interpretation

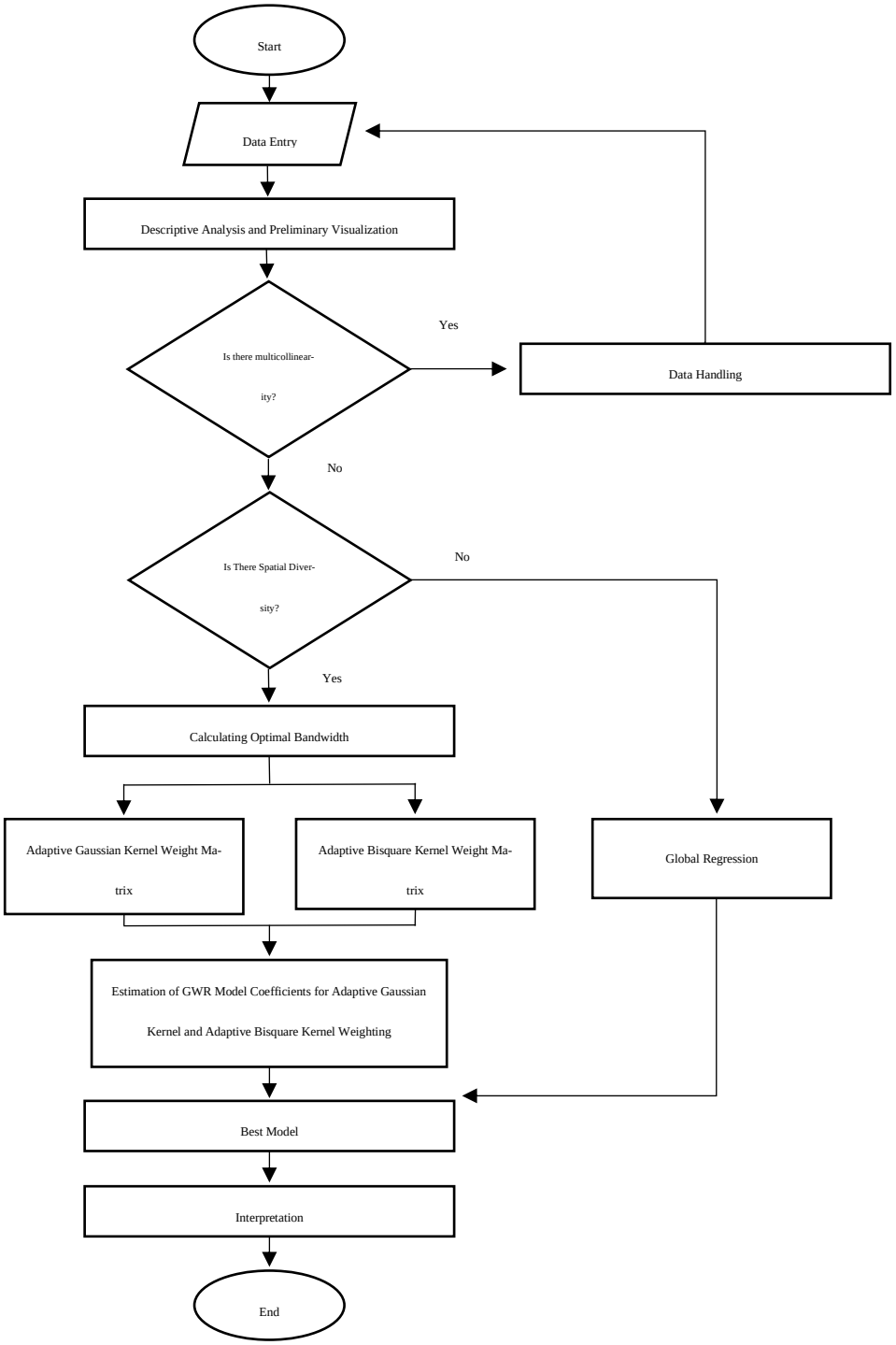


Figure 1. Data Analysis Diagram

To provide a better understanding of the research process, the following flowchart outlines the research steps.

3. Results

3.1. Data Description

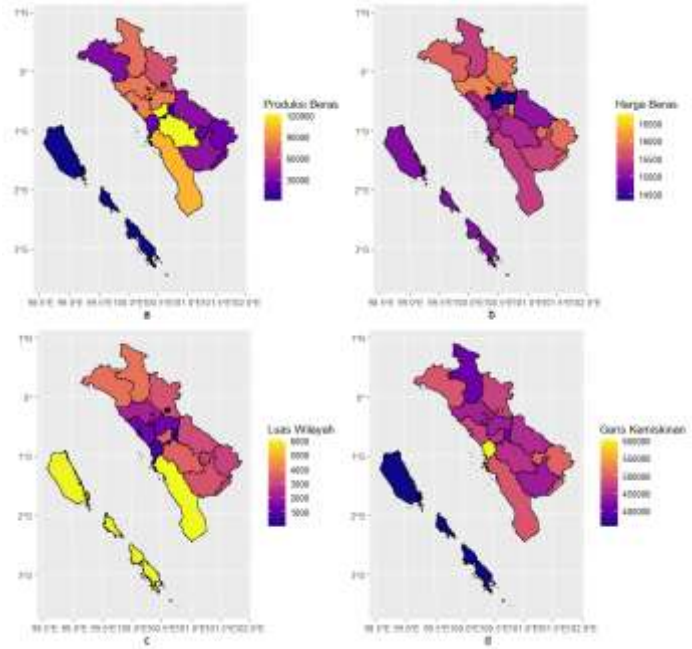


Figure 2. Visualization of Distribution Maps: (a) Rice Production; (b) Rice Prices; (c) Area; (d) Poverty Line in West Sumatra in 2025

Based on Figure 2 (a), the distribution of rice production in West Sumatra in 2025 is shown, where the yellow-colored areas indicate the highest rice production, while the dark blue-colored areas indicate very low rice production in West Sumatra. Figure 2 (b) illustrates the distribution of rice prices in West Sumatra in 2025, where the yellow-colored areas represent the highest rice prices, while the dark blue-colored areas indicate very low rice prices in the region. Figure 2 (c) shows the land area distribution in West Sumatra in 2025, where the yellow-colored areas indicate regions with larger land areas compared to the dark blue-colored regions. Figure 2 (d) illustrates the distribution of the poverty line in West Sumatra in 2025, where the yellow-colored areas indicate the highest poverty line, while the dark blue-colored areas represent very low poverty line levels in West Sumatra. The minimum, maximum, and mean values of each variable used in this study are presented in Table 1 below.

The spatial distribution maps indicate considerable regional variation in rice production, rice prices, land area, and the poverty line across districts in West Sumatra. This variation suggests that the relationships between rice production and its explanatory variables may differ geographically rather than remain constant across all districts. These observed regional differences provide preliminary evidence of spatial heterogeneity, which is later confirmed by the significant Breusch–Pagan test and supports the application of the GWR model.

Table 1. Descriptive Analysis of Variables

Variable	Minimum	Maximum	*Mean*
Y	613	122051	42138
X_1	14324	16767	15618
X_2	23,56	6045,68	2216,19
X_3	356403	602540	474713

3.2. Assumption Test

The following are the results of the assumption tests, namely the multicollinearity test on the independent variables using R Studio.

Table 2. Multicollinearity Test

Variable	VIF	Description
X_1	1,19	Free from Multicollinearity
X_2	1,52	Free from Multicollinearity
X_3	1,32	Free from Multicollinearity

It can be seen that the VIF < 10 for all independent variables, so it can be concluded that there is no multicollinearity between the independent variables used in this study.

3.3. Spatial Variability Test

The following are the results of the spatial variability test as a requirement for applying the *Geographically Weighted Regression* model using *R Studio.*

Table 3. Spatial Variability Test

Breusch Pagan	Df	p-value	Description
8,3207	3	0,03983	Reject H_0

From the test results above, a value of 0,03983 < 0,05 (α) was obtained, meaning that there is spatial diversity in the model, so that the data used can be modeled using *Geographically Weighted Regression* (GWR).

3.4. Optimum Bandwidth Results

The following are the optimum bandwidth results for each weighting function using *R Studio*.

Table 4. Optimum Bandwidth Results for Each Weighting Function

Kernel Function	Optimum Bandwidth	CV Score
Adaptive Gaussian	19	22,63479
Adaptive Bisquare	20	22,59875

The Adaptive Gaussian kernel has a bandwidth value of 19, which means that each location considers the 19 nearest points in constructing the model with weights that decrease smoothly according to distance. Meanwhile, the Adaptive Bisquare kernel has a bandwidth value of 20, which means that each location considers the 20 nearest neighbors in constructing the model with weights that decrease smoothly according to distance.

3.5. Estimated Coefficients of the GWR Model (Adaptive Gaussian)

The following are the estimated coefficients of the *Geographically Weighted Regression* (GWR) model with Adaptive Gaussian kernel weighting using *R Studio*.

Table 5. Estimated Results of the GWR Model with Adaptive Gaussian Kernel Weighting

Variable	Minimum	Quartile 1	Median	Quartile 3	Maximum
Intercept	-0,0235	0,0343	0,0457	0,0488	0,0511
X_1	-0,2993	-0,2981	-0,2970	-0,2913	-0,2550
X_2	0,3560	0,4047	0,4153	0,4307	0,4406
X_3	-0,0439	-0,0328	-0,0195	-0,0059	0,0917

The intercept values are relatively small and tend to be positive in most locations, indicating that the baseline values of the model are generally positive. Variable X_1 has entirely negative coefficients, meaning that X_1 consistently has a negative effect on the response variable in all locations. In contrast, X_2 has positive coefficients throughout the range, meaning that X_2 consistently exerts a positive effect. Meanwhile, X_3 shows varying values ranging from negative to positive. This indicates that the effect of X_3 is negative in some regions, while in other regions it is positive.

3.6. Coefficient Estimation Model GWR (Adaptive Bisquare)

The following are the estimated coefficients of the *Geographically Weighted Regression* (GWR) model with Adaptive Bisquare kernel weighting using *R Studio*.

Table 6. Estimated Results of the GWR Model with Adaptive Bisquare Kernel Weighting

Variable	Minimum	Quartile 1	Median	Quartile 3	Maximum
Intercept	-0,1702	0,1574	0,2176	0,2654	0,3359
X_1	-0,3706	-0,3573	-0,3504	-0,3486	-0,1976
X_2	0,1935	0,5716	0,5905	0,6144	0,6714
X_3	-0,3003	-0,2559	-0,1882	-0,1882	0,2011

The intercept values are relatively small and tend to be positive in most locations, indicating that the baseline values of the model are generally positive. Variable X_1 has entirely negative coefficients, meaning that X_1 consistently has a negative effect on the response variable in all locations. In contrast, X_2 has positive coefficients throughout the range, meaning that X_2 consistently exerts a positive effect. Meanwhile, X_3 shows varying values ranging from negative to positive. This indicates that the effect of X_3 is negative in some regions, while in other regions it is positive.

3.7. Best Model

To determine the best model among the GWR models with different weighting functions, the criteria used are R^2 (R-square) and *Akaike Information Criterion* (AIC). The best model is the model that has the largest R² value and the smallest AIC value. The R^2 and AIC values for both models can be seen in Table 7 below.

Table 7. AIC and R^2 Values of the GWR Models

Kernel Function	AIC	R^2
Adaptive Gaussian	47,98439	38,8%
Adaptive Bisquare	39,93070	63,3%

Table 7 shows that the model with the largest R^2 value and the smallest AIC value is the GWR model with the Adaptive Bisquare Kernel weighting function. Therefore, it can be concluded that the Geographically Weighted Regression method with Adaptive Bisquare Kernel weighting is better for modeling rice production data in West Sumatra in 2025 compared to the GWR method using Adaptive Gaussian Kernel weighting.

Although the Adaptive Bisquare kernel produced the best model performance, the coefficient of determination (R^2=63.3%) indicates that approximately 36.7% of the variation in rice production remains unexplained. This suggests that additional variables, such as rainfall, irrigation infrastructure, fertilizer use, soil quality, or agricultural technology adoption, may also contribute to regional differences in rice production. Furthermore, this study was conducted using cross-sectional data from a single province and a single year; therefore, the findings should be interpreted within this geographical and temporal context.

4. Discussion

The results of the study indicate that the Geographically Weighted Regression (GWR) model with Adaptive Bisquare Kernel weighting performs better than the Adaptive Gaussian Kernel, as reflected by the lower AIC value (39.93070 vs 47.98439) and the higher R^2 value (63.3% vs 38.8%). This finding is consistent with previous studies, which also found that the Bisquare kernel tends to provide better estimation results for data with spatial heterogeneity [7,8]. The spatial variation detected through the Breusch–Pagan test confirms that the GWR model is more appropriate than ordinary global regression for modeling rice production data in West Sumatra.

The negative effect of rice prices (X_1) on rice production indicates that an increase in rice prices does not always encourage higher production, which may be caused by limitations in production inputs at the farmer level. Land area (X_2) consistently shows a positive effect, indicating that regions with larger land areas have greater production potential. Meanwhile, the varying effect of the poverty line (X_3) across regions indicates the existence of different socio-economic dynamics in supporting rice production.

5. Conclusions

Based on the analysis conducted, it can be concluded that the *Geographically Weighted Regression* (GWR) model with the Adaptive Bisquare Kernel weighting function is a better model for modeling rice production data in West Sumatra in 2025, based on the lowest AIC value and the highest R^2 value. Therefore, the resulting model for the Solok Regency area is as follows:

$$\hat{Y}_{Solok} = 0.196 - 0.350X_1 + 0.613X_2 - 0.184X_3 \quad (8)$$

The model indicates that when rice prices increase by one unit, rice production decreases by 35%, and when the poverty line increases by one unit, rice production

also decreases by 18%. However, when land area increases by one unit, rice production increases by 61% in Solok Regency, West Sumatra, in 2025.

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