



# Examining the Local Effects of Food Security Index Components Across Kalimantan Using Geographically Weighted Regression

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## Abstract

**Introduction/Main Objectives:** Food security remains a critical concern across Kalimantan Island, where substantial spatial disparities exist among its 56 regencies and cities, making conventional global regression models inadequate for capturing localized differences. **Background Problems:** This study addresses the limitation of Multiple Linear Regression in accounting for spatial heterogeneity in the relationships between Food Security Index components and the overall index, raising the question of which components exhibit spatially varying local effects across locations. **Novelty:** This study presents the first spatially explicit analysis of food security determinants at the regency and city level across Kalimantan, employing Haversine distance combined with adaptive Gaussian kernel weighting within GWR a combination not previously applied in this context. **Research Methods:** GWR was applied to cross-sectional 2024 data from the Food Security and Vulnerability Atlas, incorporating Cross Validation bandwidth selection and Weighted Least Squares parameter estimation. **Finding/Results:** The GWR model outperformed MLR with an  $R^2$  of 59.63% and MSE of 38.5241. The ratio of population per health worker and average years of schooling for women were the most spatially dominant components, significant in 45 and 43 locations respectively, supporting the need for location-specific policy interventions across Kalimantan.

## 1. Introduction

Food security is defined as a condition in which food needs are adequately met at both individual and national levels, characterized by the availability of sufficient, safe, diverse, and nutritious food that is fairly distributed, affordable, and aligned with social, cultural, and religious values, thereby enabling people to lead healthy, active, and productive lives in a sustainable manner [1]. Food security stands as one of the central objectives of the Sustainable Development Goals (SDGs), most notably under Goal 2, which is dedicated to eliminating hunger worldwide. In Indonesia, it has become a major strategic focus of the government, with President Prabowo Subianto highlighting the importance of achieving national food self-sufficiency during his administration [2].



Data published by the National Food Agency [3] show that the Food Security Index across provinces in Kalimantan Island is generally classified as food secure or highly food secure. However, at the regency and city level, notable disparities remain. Of the 56 regencies and cities in Kalimantan, six areas including Murung Raya, Mahakam Ulu, Gunung Mas, Lamandau, and Melawi fall into the vulnerable or moderately vulnerable categories, representing approximately 10.7% of all administrative units in the region. Moreover, the food security index ranges from category 2 (highly vulnerable) to category 6 (highly food secure), indicating substantial spatial variation across the island. Geographically, the more vulnerable areas tend to be concentrated in remote, inland regions, suggesting that location-specific characteristics may play a significant role in determining food security outcomes. This spatial heterogeneity implies that the relationships between food security and its determinants may not be uniform across regions some factors may exert stronger or even opposing influences in different localities underscoring the need for an analytical approach that can capture such local variation [4].

The Food Security Index has been widely studied, including research by Evalia et al. [5], which identified determinants of food security in West Sumatra using Multiple Linear Regression. However, MLR assumes that regression relationships are spatially stationary that is, constant regardless of location [6] an assumption that may be unreasonable in a geographically diverse region such as Kalimantan, where socioeconomic and geographic characteristics vary substantially across districts and cities.

GWR addresses this limitation by incorporating geographic coordinates through spatial weighting, allowing regression coefficients to vary across locations and generating local models for each observation point [7]. This makes GWR particularly suitable for detecting spatial variation in the relationships between food security and its determinants. A similar approach was applied by [8], who modelled the food security index in East Java using GWR and found that Rice Production, Adjusted Per Capita Expenditure, Poverty Line, Number of People in Poverty, and Prevalence of Food Inadequacy significantly influenced the food security index in East Java, with spatially varying coefficients. Building on this, the present study extends the application of GWR to Kalimantan Island, a region with distinct geographic and demographic characteristics that have not been previously examined under this framework.

Despite growing interest in spatial approaches to food security analysis, studies applying GWR in the context of Kalimantan Island remain absent from the literature. Previous studies have either relied on global regression models that cannot account for spatial heterogeneity, or have focused on other regions of Indonesia such as Java and Sumatra. This study therefore contributes to the literature by providing the first spatially explicit analysis of food security determinants at the regency and city level across Kalimantan. Furthermore, this study employs Haversine distance as the spatial distance measure, which accounts for the curvature of the earth and has been shown to outperform Euclidean and Manhattan distance measures in terms of accuracy [9], combined with an adaptive Gaussian kernel weighting scheme a combination that has not been previously applied in the context of food security analysis in Kalimantan.

Given the importance of spatial variation in analyzing food security, this study employs GWR to examine the local effects of food security index components at the regency and city level throughout Kalimantan Island. Specifically, this study aims to identify which components of the Food Security Index exhibit spatially varying effects across locations, to examine how the direction and magnitude of these effects differ across districts and cities, and to evaluate the performance of GWR with Haversine distance and adaptive Gaussian kernel weighting for this geographic context. The findings are expected to provide a more spatially nuanced understanding of food security conditions across Kalimantan and to support the development of more targeted and location-specific policy interventions.

## 2. Material and Methods

### 2.1. Research Data

This study utilizes cross-sectional data for the year 2024, as the primary focus is on capturing the current spatial distribution of food security conditions across Kalimantan to inform present policy needs. It is acknowledged that cross-sectional data cannot account for temporal dynamics in the relationships among variables, which constitutes a limitation of the present study.

This study examines the Food Security Index ( $Y$ ) and its eight official component indicators as published in the Food Security and Vulnerability Atlas (FSVA) by the National Food Agency [3]. These components are percentage of population below the poverty line ( $X_1$ ), percentage of households with food expenditure proportion exceeding 65% of total expenditure ( $X_2$ ), percentage of households

without access to electricity ( $X_3$ ), average years of schooling for women aged 15 years and above ( $X_4$ ), percentage of households without access to clean water ( $X_5$ ), ratio of population per health worker relative to population density ( $X_6$ ), percentage of stunted children under five ( $X_7$ ), and life expectancy at birth ( $X_8$ ). Rather than treating these components as external determinants of the Food Security Index, this study investigates how each component contributes locally to the overall index, and whether the magnitude and direction of these contributions vary across regencies and cities in Kalimantan. This approach is motivated by the recognition that food security conditions are spatially heterogeneous, and that the relative importance of each component may differ substantially across locations depending on local geographic, demographic, and socioeconomic characteristics [6].

## 2.2. Multicollinearity Detection

Multicollinearity detection is performed to identify whether interdependencies exist among predictor variables within a regression model. The existence of such dependencies may distort the estimated relationship between predictor variables and the response variable. A widely used measure for assessing multicollinearity is the Variance Inflation Factor (VIF). A predictor variable is regarded as free from multicollinearity when its VIF value does not exceed 10. The formula used to compute the VIF is given as follows [10]:

$$VIF_k = \frac{1}{1 - R_k^2} \quad (1)$$

where,  $R_k^2$  is the coefficient of determination of the MLR model with  $\mathbf{x}_j$  as the response variable and the remaining  $\mathbf{x}_i$  as the predictor variables.

## 2.3. Multiple Linear Regression

Linear regression is a statistical method employed to examine the linear relationship between one or more predictor variables and a response variable. Multiple Linear Regression (MLR) involves the use of two or more predictor variables simultaneously. The standard formulation of the MLR model, which captures the influence of predictor variables on the response variable, can be written as follows [11]:

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

Where,

$y_i$  : observed value of the response variable for the  $i$ -th observation

$\beta_0$  : intercept (constant) parameter

$\beta_k$  : regression coefficient associated with the  $k$ -th predictor variable

$x_{ik}$  : observed value of the  $k$ -th predictor variable for the  $i$ -th observation

$\varepsilon_i$  : error term for the  $i$ -th observation

The general model presented in Equation (2) can also be reformulated in matrix notation as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (3)$$

## 2.4. Parameter Estimation of the MLR

Parameter estimation in the MLR model is conducted through the Ordinary Least Squares (OLS) method. This approach determines the model parameters by minimizing the total sum of squared residuals. The estimator for the parameter  $\boldsymbol{\beta}$  is derived as follows [12]:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad (4)$$

## 2.5. Simultaneous Significance Testing of MLR Parameters

The simultaneous significance test of MLR model parameters is intended to assess whether the predictor variables collectively exert a significant influence on the response variable. The hypotheses for the simultaneous significance testing of the MLR model parameters are stated as follows:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_p = 0$$

$$H_1 : \text{at least one } \beta_k \neq 0, k = 1, 2, \dots, p$$

The test statistic employed in this test is the  $F_1$  statistic, which is formulated as follows:

$$F_1 = \frac{MSR}{MSE} = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2 / p}{\sum_{i=1}^n (y_i - \hat{y})^2 / (n - p - 1)} \tag{5}$$

Where,  $n$  is the number of observation and  $p$  is the number of predictor variables. At a given significance level  $\alpha$ , the decision criterion for the simultaneous test states that  $H_0$  is rejected when  $F_1 > F_{(1-\alpha; p; n-p-1)}$  or equivalently,  $H_0$  is rejected whenever  $p_{value} < \alpha$  [13].

### 2.6. Partial Significance Testing of MLR Parameters

The partial significance test in the MLR model is performed to identify which individual predictor variables have a significant effect on the response variable. The hypotheses for this test are expressed as follows:

$$H_0 : \beta_k = 0, k = 1, 2, K, p$$

$$H_1 : \beta_k \neq 0, k = 1, 2, K, p$$

This test utilizes the  $t_1$  statistic, which is defined as follows:

$$t_1 = \frac{\hat{\beta}_k}{SE(\hat{\beta}_k)} \tag{6}$$

Where,  $\hat{\beta}_k$  is the estimated regression coefficient and  $SE(\hat{\beta}_k)$  is the standard error of  $\hat{\beta}_k$ . At a given significance level  $\alpha$ , the decision criterion for the partial test states that  $H_0$  is rejected when  $|t_1| > t_{(\alpha/2; n-k-1)}$  or equivalently,  $H_0$  is rejected whenever the  $p_{value} < \alpha$  [14].

### 2.7. Homoscedasticity Test

The homoscedasticity test is conducted to identify whether there is variation in the error variance within a linear regression model. Such variation, known as heteroscedasticity, occurs when the error variance differs across observations [15]. One of the widely adopted methods for detecting heteroscedasticity is the Glejser test. This test follows the framework of simultaneous parameter testing in multiple linear regression, in which the absolute values of the residuals serve as the response variable [16]. The hypotheses for the homoscedasticity test are formulated as follows [17]:

$$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2$$

$$H_1 : \text{at least one } \sigma_i^2 \neq \sigma^2; i = 1, 2, K, n$$

The test statistic utilized in this test is the  $G$  statistic, which is formulated as follows:

$$G = \frac{MSR}{MSE} = \frac{(\mathbf{\beta}^T \mathbf{X}^T \boldsymbol{\varepsilon} - n\bar{\varepsilon}) / p}{(\boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon} - \mathbf{\beta}^T \mathbf{X}^T \boldsymbol{\varepsilon}) / (n - p - 1)} \tag{7}$$

At a significance level the decision rule for the homoscedasticity test is to reject  $H_0$  if  $G > F_{(1-\alpha; p; n-p-1)}$  or equivalently, to reject  $H_0$  if and only if the  $p_{value} < \alpha$ .

### 2.8. Moran's Index

Moran's Index serves as a widely adopted measure of global spatial autocorrelation, enabling the assessment of how similarly distributed a variable is among geographically neighboring areas. Through this measure, the degree of spatial randomness in the data can be evaluated, where departures from randomness may reveal underlying spatial structures such as geographic clustering or directional trends across the study area. The value of Moran's I ranges from -1 to 1, where values close to 1 indicate positive spatial autocorrelation (clustering), values close to -1 indicate negative spatial autocorrelation (dispersion), and values close to 0 indicate spatial randomness [18]. Moran's Index can be formulated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})^2} \quad (8)$$

Hypothesis testing for Moran's Index is as follows [19]:

- i. Hypothesis used for parameter testing:

$$H_0 : I = 0$$

$$H_1 : I \neq 0$$

- ii. The test statistic for Moran's Index:

$$Z(I) = \frac{I - E(I)}{\sqrt{\text{var}(I)}} \quad (9)$$

Where:

$$E(I) = l_0 \frac{1}{n-1}$$

$$\text{var}(I) = \frac{n^2 s_1 - n s_1 + 3 s_0^2}{(n^2 - 1) s_0^2} - E(I)$$

$$s_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$$

$$s_1 = \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (w_{ij} + w_{ji})^2$$

$$s_2 = \sum_{i=1}^n \left( \sum_{j=1}^n j i_{ij} + \sum_{j=1}^n w_{ji} \right)^2$$

- iii. Decision criterion:  $H_0$  is rejected if  $|Z(I)| > Z_{\frac{\alpha}{2}}$  or  $p\text{-value} < \alpha$ .

## 2.9. Geographically Weighted Regression Model

Geographically Weighted Regression (GWR) is a spatial statistical approach designed to examine the relationship between predictor variables and a response variable by accounting for spatial effects. This method is especially valuable for capturing spatial heterogeneity, in which the influence of predictor variables differs from one location to another. In GWR, spatial heterogeneity is reflected through the use of spatial weighting. Because each area may have unique characteristics, GWR produces local parameter estimates for every observation point [7]. The GWR model at the  $i$ -th location can be written as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, i = 1, 2, \dots, n, \quad (10)$$

The GWR model shown in Equation (8) can likewise be expressed in matrix form as follows [20]:

$$y_i = \mathbf{x}_i^T \boldsymbol{\beta}(u_i, v_i) + \varepsilon_i \quad (11)$$

## 2.10. Gaussian Kernel Weighting Function

Parameter estimation in the GWR model involves spatial weighting to generate local models. Spatial weights represent the influence of one location on another. In GWR, spatial weights can be calculated using kernel weighting functions, one of which is the adaptive gaussian kernel weighting function, expressed as follows [21].

$$w_{ij}(u_i, v_i) = \exp \left[ -\frac{1}{2} \left( \frac{d_{ij}}{h_i} \right)^2 \right], \quad i, j = 1, 2, \dots, n, \tag{12}$$

where  $w_{ij}$  denotes the spatial weight attributed to the  $j$ -th observation within the GWR model at a particular location, and  $h_i$  refers to the smoothing parameter or bandwidth for the  $i$ -th observation. The adaptive Gaussian kernel is selected over the fixed Gaussian kernel due to the uneven spatial distribution of regencies and cities across Kalimantan Island. Unlike fixed kernel approaches that apply a constant bandwidth across all locations, the adaptive kernel adjusts the bandwidth according to local data density narrowing in areas with closely spaced observations and expanding in sparsely distributed regions. This ensures that each local model is estimated using a sufficient and contextually appropriate set of neighboring observations, producing more reliable parameter estimates across all locations regardless of their geographic isolation [7]. The term  $d_{ij}$  refers to the distance between observation points, which is computed using the Haversine distance as defined by the following equation [22]:

$$d_{ij} = 2r \arcsin \left( \sqrt{\sin^2 \left( \frac{u_j - u_i}{2} \right) + \cos(u_i) \cos(u_j) \sin^2 \left( \frac{v_j - v_i}{2} \right)} \right) \tag{13}$$

where,  $u_i$  is the longitude coordinate of the  $i$ -th observation,  $v_i$  is the latitude coordinate of the  $i$ -th observation and  $r$  is the earth radius (6,371 km). Unlike Euclidean distance, which assumes a flat surface, Haversine distance accounts for the curvature of the earth by treating it as a sphere with a radius of 6,371 km [23]. This is particularly important for a geographically extensive region such as Kalimantan, where straight-line distance calculations on a flat plane would introduce systematic errors. Bandwidth selection is crucial for obtaining optimal parameter estimates. The optimum bandwidth value can be determined using the Cross Validation (CV) criterion. One advantage of CV is that it considers the balance between prediction error and model complexity. The CV criterion is expressed as follows:

$$CV = \sum_{i=1}^n [y_i - \hat{y}_{-i}(h_i)]^2. \tag{14}$$

Where,  $\hat{y}_{-i}(h_i)$  is the predicted value at the  $i$ -th location obtained from a model fitted without using the  $i$ -th observation and calculated using bandwidth  $h_i$  [24].

### 2.11. Estimation of GWR Model Parameters

In this research, parameter estimation is performed using the Weighted Least Squares (WLS) method. Similar to OLS, WLS operates by minimizing the sum of squared errors, but additionally incorporates a spatial weighting matrix into the estimation process. The estimator of  $\beta(u_i, v_i)$  for the  $i$ -th location is expressed as follows [20]:

$$\hat{\beta}(u_i, v_i) = (\mathbf{X}^T \mathbf{W}(u_i, v_i) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(u_i, v_i) \mathbf{Y}. \tag{15}$$

### 2.12. Model Adequacy Test for GWR

The model adequacy test is performed to assess whether there is a significant difference between the MLR model and the GWR model. The corresponding hypotheses are formulated as follows:

$$H_0 : \beta_k(u_i, v_i) = \beta_k, k = 1, 2, \dots, p \text{ and } i = 1, 2, \dots, n$$

$$H_1 : \beta_k(u_i, v_i) \neq \beta_k, k = 1, 2, \dots, p \text{ and } i = 1, 2, \dots, n$$

The test statistic for assessing the model adequacy is

$$F^* = \left( \frac{SSE_{MLR} - SSE_{GWR}}{\tau_1} \right) / \left( \frac{SSE_{GWR}}{\delta_1} \right), \tag{16}$$

The rejection region for the model adequacy test at a significance level of  $\alpha$  is defined as rejecting  $H_0$  when  $F^* > F_{1-\alpha; df_1; df_2}$ , where  $df_1 = \tau_1^2 / \tau_2$  and  $df_2 = \delta_1^2 / \delta_2$ , or equivalently,  $H_0$  is rejected whenever the  $p_{value} < \alpha$  [24].

### 2.13. Simultaneous Significance Test of GWR Model Parameters

The simultaneous significance test of the GWR model parameters is conducted to assess whether the parameters, considered jointly, have a significant effect on the response variable. The hypotheses are formulated as follows:

$$H_0 : \beta_1(u_i, v_i) = \beta_2(u_i, v_i) = \dots = \beta_p(u_i, v_i) = 0$$

$$H_1 : \text{at least one } \beta_k(u_i, v_i) \neq 0, k = 0, 1, 2, \dots, p \text{ and } i = 1, 2, \dots, n$$

The test statistic for the simultaneous significance test of the GWR model is defined as follows:

$$F_2 = \frac{SSE(X_0)}{df_1(X_0)} \bigg/ \frac{SSE(GWR)}{df_2(GWR)}. \quad (17)$$

Where,  $SSE(X_0)$  is the sum square error of the GWR model without predictor variables. The critical region for the simultaneous test at a significance level of  $\alpha$  is defined as rejecting  $H_0$  if  $F_2 > F_{(1-\alpha; n-1; \delta_1^2/\delta_2^2)}$ , or equivalently, rejecting  $H_0$  if  $p_{value} < \alpha$  [24].

### 2.14. Partial Significance Test of GWR Model Parameters

The partial significance test is used to identify which parameters have a statistically significant effect on the response variable. The hypotheses are formulated as follows:

$$H_0 : \beta_k(u_i, v_i) = 0, k = 1, 2, \dots, p \text{ and } i = 1, 2, \dots, n$$

$$H_1 : \beta_k(u_i, v_i) \neq 0, k = 1, 2, \dots, p \text{ and } i = 1, 2, \dots, n$$

The test statistic for the partial significance test of the GWR model is defined as follows:

$$t_2 = \frac{\hat{\beta}_k(u_i, v_i)}{\sigma_{GWR} \sqrt{c_{kk}}}. \quad (18)$$

The critical region for the partial test at a significance level of  $\alpha$  is defined as rejecting  $H_0$  if the test statistic exceeds the critical value, or equivalently, rejecting  $H_0$  if the  $p_{value} < \alpha$  [24].

### 2.15. Model Evaluation

The coefficient of determination ( $R^2$ ) is a measure employed to assess model performance by indicating the proportion of variability in the response variable that can be accounted for by the fitted model. It ranks among the most frequently used goodness-of-fit measures in regression analysis, owing to its straightforward interpretation and its capacity to reflect how well the model and its predictor variables explain the response variable. The coefficient of determination can be formulated as follows [25]:

$$R^2 = \left(1 - \frac{SSE}{SST}\right) \times 100\%. \quad (19)$$

Mean Square Error (MSE) is the average of the squared differences between the predicted and actual observed values. It is widely used to measure the magnitude of estimation errors produced by a model. A lower MSE value, particularly one approaching zero, signifies that the model's predictions are in close agreement with the actual observations. The MSE can be written as follows [26]:

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} \quad (20)$$

## 3. Results and Discussion

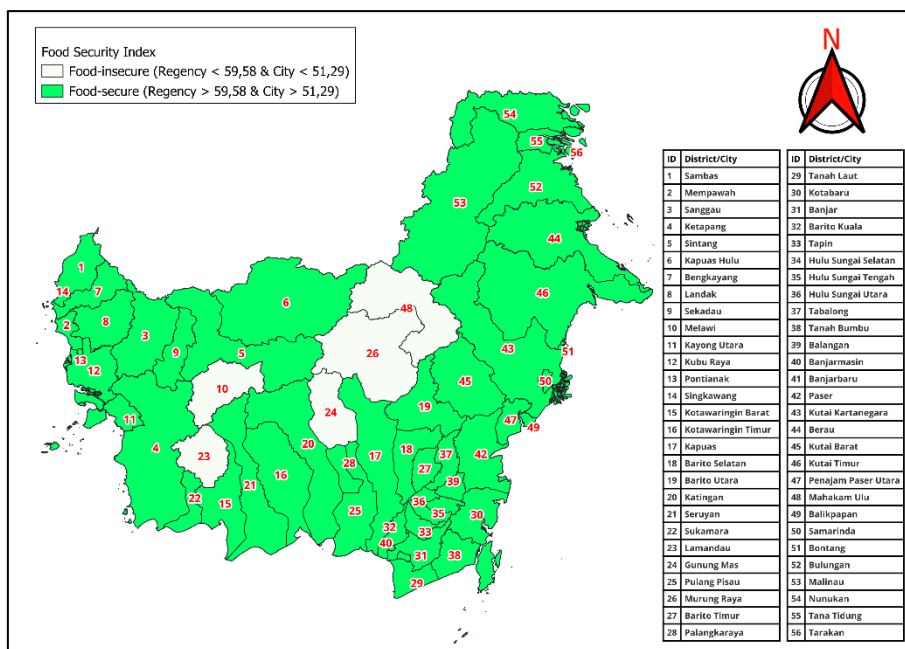
### 3.1. Data Description

The data are summarized through descriptive statistics, encompassing the mean, minimum, maximum, and standard deviation. These statistical measures were computed using R software, and the corresponding results are presented in Table 1.

**Table 1.** Descriptive statistics

Variable	Mean	Minimum	Maximum	Standard Deviation
$Y$	75.97	51.29	91.23	9.8572
$X_1$	5.8891	2.31	11.38	2.1422
$X_2$	18.4605	2.22	43.54	10.0689
$X_3$	1.1488	0	6.43	1.7808
$X_4$	30.3712	0.01	92.51	21.3225
$X_5$	8.7654	6.58	11.69	1.1170
$X_6$	8.6057	0.02	43.54	9.2876
$X_7$	71.1793	64.97	6.43	2.3129
$X_8$	22.3089	0	92.51	8.1652

Based on Table 1, the predicted food security index in Kalimantan Island is 75.97 with a standard deviation of 9.8572. The lowest food security index is 51.29 in Murung Raya Regency, while the highest index is 91.23 in Balikpapan City. The summary statistics of the other research variables are also presented in Table 1. The spatial distribution of the food security index across regencies and cities in Kalimantan Island is further depicted through a thematic map, as presented in Figure 1.



**Figure 1.** Spatial distribution of the Food Security Index across regencies and cities in Kalimantan Island

Figure 1 presents a map of Kalimantan Island, one of the major islands in Indonesia. The island consists of 56 regencies/cities. The regencies/cities in Figure 1 are classified into two categories, namely food-insecure areas, indicated by white color, and food-secure areas, indicated by green color. The classification of food security status is obtained from the National Food Agency (Badan Pangan Nasional).

Based on Figure 1, the regencies/cities in Kalimantan Island that fall into the food-insecure category include Murung Raya Regency, Melawi Regency, Mahakam Ulu Regency, Gunung Mas Regency, and Lamandau Regency. Information regarding regencies/cities with food security indices below the national average is expected to serve as a basis for government policy formulation and targeted intervention programs aimed at improving food security in these regions.

### 3.2. Detection of Multicollinearity

Multicollinearity is evaluated through the Variance Inflation Factor (VIF) following Equation (1). The VIF values are computed using R software, and the corresponding results are displayed in Table 2.

**Table 2.** Detection of Multicollinearity

Variable	VIF
$X_1$	1.6467
$X_2$	2.5913
$X_3$	1.7463
$X_4$	2.0714
$X_5$	2.4547
$X_6$	1.7069
$X_7$	2.3329
$X_8$	1.1991

Table 2 reveals that the VIF values for all predictor variables fall below 10. Consequently, it can be concluded that no multicollinearity exists among the predictor variables, and all eight predictor variables can be retained in the linear regression model.

### 3.3. MLR Modeling

The general MLR model for food security index data, based on Equation (2), is given as follows:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \varepsilon_i, \quad i = 1, 2, \dots, 56 \quad (21)$$

The parameters of the MLR model in Equation (21) are estimated using the OLS approach, as given in Equation (4). Parameter estimation is performed using R software, resulting in the MLR model in Equation (22).

$$\hat{y}_i = 67,7912 - 0,2290x_{i1} + 0,1413x_{i2} - 1,1432x_{i3} - 0,1575x_{i4} - 0,0137x_{i5} - 0,4084x_{i6} + 0,2296x_{i7} + 0,0139x_{i8} \quad (22)$$

The hypotheses for the simultaneous significance testing of the MLR model parameters are stated as follows:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

$$H_1 : \text{at least one } \beta_k \neq 0 ; k = 1, 2, 3, 4, 5$$

The test statistic  $F_1$  is defined in Equation (5), and the results derived from computations using R software are summarized in Table 3.

**Table 3.** Results of the simultaneous parameter test of the Multiple Linear Regression (MLR) Model

$F_1$	$F_{(0,9,8,47)}$	$P_{value}$	Decision
3.4596	1.8046	0.0033	$H_0$ is rejected

Table 3 shows that the calculated  $F_1$  statistic satisfies  $F_1 = 3.4596 > F_{(0,9,8,47)} = 1.8046$  and  $p_{value} = 0.0033 < \alpha = 0.1$ . Therefore, it can be concluded that the predictor variables collectively exert a statistically significant influence on the food security index. Next, a partial significance test of the MLR model parameters is carried out using the following hypotheses:

$$H_0 : \beta_k = 0 ; k = 1, 2, 3, 4, 5$$

$$H_1 : \beta_k \neq 0 ; k = 1, 2, 3, 4, 5$$

The test statistic  $t_1$  is defined in Equation (6), and the results of the calculations using R software are presented in Table 4.

As shown in Table 4, average years of schooling for women aged 15 years and above and ratio of population per health worker relative to population density are found to have a statistically significant effect on the food security index. This is evidenced by the test statistics satisfying  $|t_1| > t_{(0,95,47)} = 1.6779$  and  $p_{value} < \alpha = 0.1$ .

**Table 4.** Results of the partial parameter test of the Multiple Linear Regression (MLR) Model

Parameter	$ t_1 $	$P_{value}$	Decision
$\beta_1$	0,335	0,7390	$H_0$ is not rejected
$\beta_2$	0,775	0,4423	$H_0$ is not rejected
$\beta_3$	1,351	0,1833	$H_0$ is not rejected
$\beta_4$	2,045	0,0464	$H_0$ is rejected
$\beta_5$	0,009	0,9932	$H_0$ is not rejected
$\beta_6$	2,545	0,0143	$H_0$ is rejected
$\beta_7$	0,305	0,7619	$H_0$ is not rejected
$\beta_8$	0,091	0,9279	$H_0$ is not rejected

### 3.4. Homoscedasticity Test

The homoscedasticity assumption is tested using the Glejser test as a prerequisite for proceeding to spatial modeling. The hypotheses of the Glejser test are formulated as follows.

$$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_{56}^2 = \sigma^2$$

$$H_1 : \text{at least one } \sigma_i^2 \neq \sigma^2 ; i = 1, 2, K, 56$$

The Glejser test statistic is calculated based on Equation (7), and the corresponding results obtained from R software are shown in Table 5.

**Table 5.** Results of the Glejser Test

$G$	$F_{(0,9,8,47)}$	$P_{value}$	Decision
2,571	1.8046	0,0205	$H_0$ is rejected

Table 5 shows that the calculated statistic  $G = 2.571 > F_{(0,9,8,47)} = 1.8046$  and  $p_{value} = 0.0205 < \alpha = 0.1$ . Therefore, it can be concluded that heterogeneity exists in the error terms. The existence of heterogeneity in the error terms suggests that the response variable also exhibits heterogeneous behavior. Therefore, spatial analysis is conducted using the GWR model.

### 3.5. MLR Spatial Autocorrelation Test

The Moran's I test conducted on the MLR residuals yielded a value of -0.0009 with a  $p_{value}$  of 0.4239, indicating that the null hypothesis of no spatial autocorrelation cannot be rejected. While this suggests that the residuals are spatially random, the absence of spatial autocorrelation does not preclude the presence of spatial heterogeneity in the relationships between variables a phenomenon that global regression models such as MLR are unable to capture [6]. This provides further justification for the application of GWR in the subsequent analysis.

### 3.6. Geographically Weighted Regression (GWR) Modeling

The GWR model formulated for the food security index data, derived from Equation (10), is expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_{i1} + \beta_2(u_i, v_i)x_{i2} + \beta_3(u_i, v_i)x_{i3} + \beta_4(u_i, v_i)x_{i4} + \beta_5(u_i, v_i)x_{i5} + \beta_6(u_i, v_i)x_{i6} + \beta_7(u_i, v_i)x_{i7} + \beta_8(u_i, v_i)x_{i8} + \varepsilon_i ; i = 1, 2, \dots, 56 \quad (23)$$

The parameter estimation process in the GWR model begins with the calculation of the Haversine distance using Equation (13). Next, the optimal bandwidth is selected through the Gaussian kernel weighting function based on the CV criterion in Equation (14). Once the optimal bandwidth is obtained and the spatial weighting matrix is formed, the GWR parameters are estimated using the WLS method as specified in Equation (15). This process results in local GWR models for each regency/city in Kalimantan Island, producing a total of 56 local models. One example of the estimated GWR models is for Murung Raya Regency. ( $i = 27$ ).

$$\hat{y}_{27} = 77.4897 - 0.2611x_{27,1} + 0.1108x_{27,2} - 0.9768x_{27,3} - 0.1670x_{27,4} - 0.3322x_{27,5} - 0.4288x_{27,6} + 0.1459x_{27,7} + 0.0156x_{27,8} \quad (24)$$

### 3.7. Model Adequacy Test for Geographically Weighted Regression (GWR)

The hypotheses for testing the model adequacy of the GWR model against the MLR model can be stated as follows:

$$H_0 : \beta_k(u_i, v_i) = \beta_k ; k = 1, 2, \dots, 5 \text{ and } i = 1, 2, \dots, 56$$

$$H_1 : \beta_k(u_i, v_i) \neq \beta_k ; k = 1, 2, \dots, 5 \text{ and } i = 1, 2, \dots, 56$$

The  $F^*$  test statistic is expressed in Equation (16), and the results obtained using R software are presented in Table 6.

**Table 6.** Results of the GWR Model adequacy test

$F^*$	$F_{(0.9, 9.8430, 37.1570)}$	$P_{value}$	Decision
2.1104	1.7800	0.0493	$H_0$ is rejected

Table 6 shows that the calculated  $F^* = 2.1104 > F_{(0.9, 9.8430, 37.1570)} = 1.7800$  and the  $p_{value} = 0.0493 < \alpha = 0.1$ , indicating that the MLR model and the GWR model are not identical. Therefore, the GWR model is appropriate for modeling the food security index across regencies/cities in Kalimantan Island.

### 3.8. Simultaneous Significance Testing of GWR Model Parameters

The hypotheses for simultaneous significance testing of the GWR model parameters can be stated as follows:

$$H_0 : \beta_1(u_1, v_1) = \beta_2(u_1, v_1) = \dots = \beta_6(u_{56}, v_{56}) = 0$$

$$H_1 : \text{at least one } \beta_k(u_i, v_i) \neq 0 ; k = 1, 2, 3, 4, 5 \text{ and } i = 1, 2, \dots, 56$$

The  $F_2$  test statistic is defined in Equation (17), and the corresponding results calculated using R software are shown in Table 7.

**Table 7.** Results of the simultaneous significance testing of GWR Model parameters

$F_2$	$F_{(0.9, 54.1062, 41.8159)}$	$P_{value}$	Decision
1.8543	1.4667	0.0200	$H_0$ is rejected

As presented in Table 7, the computed  $F_2 = 1.8543 > F_{(0.9, 54.1062, 41.8159)} = 1.4667$  and the  $p_{value} = 0.0200 < \alpha = 0.05$ , indicating that the predictor variables collectively exert a statistically significant effect on the response variable.

### 3.9. Partial Significance Testing of GWR Model Parameters

The hypotheses for the partial significance test of the GWR model parameters are formulated as follows:

$$H_0 : \beta_k(u_i, v_i) = 0 ; k = 1, 2, K, 5 \text{ and } i = 1, 2, K, 56$$

$$H_1 : \beta_k(u_i, v_i) \neq 0 ; k = 1, 2, K, 5 \text{ and } i = 1, 2, K, 56$$

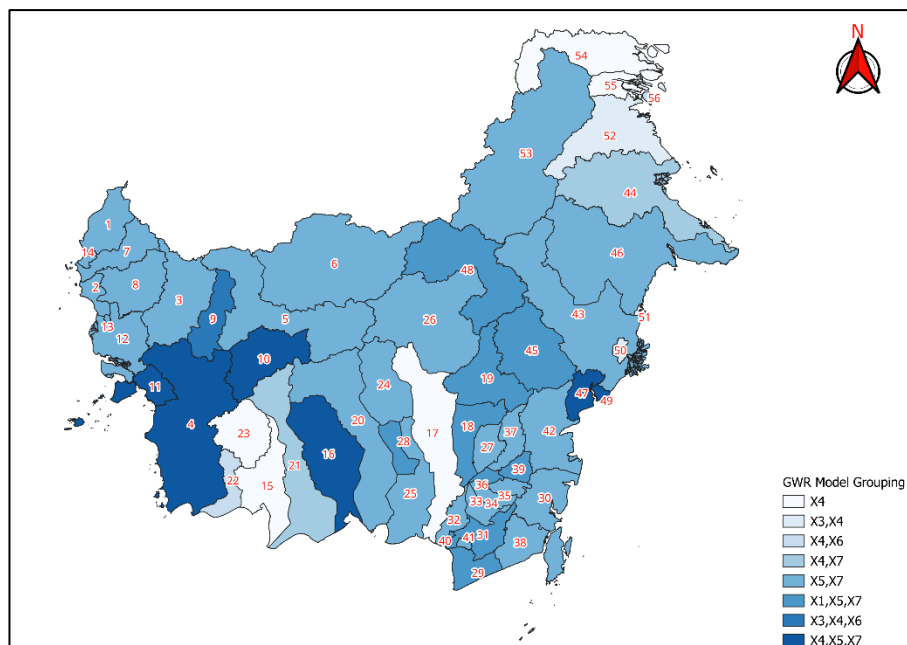
The  $t_2$  test statistic is formulated in Equation (18), and the outcomes of the partial significance test of the GWR parameters for Murung Raya Regency ( $i = 27$ ) are displayed in Table 8.

**Table 8.** Results of the partial significance testing of GWR Model parameters

Parameter	$ t_2 $	$P_{value}$	Decision
$\beta_1(u_{27}, v_{27})$	0.4206	0.6762	$H_0$ is not rejected
$\beta_2(u_{27}, v_{27})$	0.6695	0.5069	$H_0$ is not rejected
$\beta_3(u_{27}, v_{27})$	1.2671	0.2121	$H_0$ is not rejected
$\beta_4(u_{27}, v_{27})$	2.3993	0.0210	$H_0$ is rejected
$\beta_5(u_{27}, v_{27})$	0.2288	0.8202	$H_0$ is not rejected
$\beta_6(u_{27}, v_{27})$	2.9485	0.0052	$H_0$ is rejected
$\beta_7(u_{27}, v_{27})$	0.2135	0.8320	$H_0$ is not rejected
$\beta_8(u_{27}, v_{27})$	0.1126	0.9109	$H_0$ is not rejected

Based on Table 8, it can be concluded that the variables significantly influencing the food security index in Murung Raya Regency ( $i = 27$ ) are average years of schooling for women aged 15 years and above and ratio of population per health worker relative to population density.

The classification of GWR models across all observation locations, based on the significant predictor variables, is illustrated through a thematic map showed in Figure 2.



**Figure 2.** Thematic map of GWR Model grouping

As illustrated in Figure 2, the GWR models for regencies and cities across Kalimantan Island can be classified into eight groups based on the variables that exert a significant influence on the food security index. Each category is indicated by a blue color gradient, ranging from white to dark blue. For instance, regencies/cities colored in dark blue represent GWR models where the significant factors affecting the food security index include average years of schooling for women aged 15 years and above,

percentage of households without access to clean water, and percentage of stunted children under five. The representative model for this group is the GWR model of Ketapang Regency, Melawi Regency, Kayong Utara Regency, Kotawaringin Timur Regency, Penajam Paser Utara Regency, and Balikpapan City.

Three components of the Food Security Index were found to be statistically insignificant across all locations in Kalimantan, namely the percentage of population below the poverty line ( $X_1$ ), the percentage of stunted children under five ( $X_7$ ), and life expectancy at birth ( $X_8$ ), with local coefficients of -0.229, 0.230, and 0.014 and p-values of 0.739, 0.762, and 0.928 respectively.

The non-significance of  $X_1$  may be attributed to its conceptual overlap with  $X_2$ , the percentage of households with food expenditure proportion exceeding 65% of total expenditure. Both variables capture dimensions of household economic deprivation, and their high degree of conceptual similarity may have caused the contribution of  $X_1$  to be absorbed by  $X_2$  in the local model estimation, rendering  $X_1$  statistically redundant. This is consistent with the notion that poverty and food expenditure burden are closely interrelated phenomena, particularly in the context of Kalimantan where economic vulnerability tends to manifest simultaneously across multiple dimensions.

The non-significance of  $X_7$  (percentage of stunted children under five) is theoretically interpretable, as stunting is more appropriately regarded as a long-term outcome of chronic food insecurity and malnutrition rather than a direct component that drives the Food Security Index. Its relationship with the index may therefore be indirect and mediated by other variables, reducing its explanatory power in the local regression framework.

Similarly, the non-significance of  $X_8$  (life expectancy at birth) may reflect the fact that life expectancy is a broad health outcome influenced by a wide range of factors beyond food security alone, including healthcare quality, environmental conditions, and genetic factors. Its relationship with the Food Security Index may therefore be too distal and non-specific to yield statistically meaningful local estimates across all regencies and cities in Kalimantan. Nonetheless, the retention of these three components in the model is justified by their status as official indicators of the Food Security and Vulnerability Atlas [3], and their non-significance itself constitutes a meaningful finding that warrants attention in future research.

### 3.10. GWR Spatial Autocorrelation Test

To validate the GWR model, the Moran's I test was repeated on the GWR residuals, yielding a value of -0.0611 with a p-value of 0.6791. The null hypothesis of no spatial autocorrelation cannot be rejected, confirming that the GWR model has adequately accounted for the spatial structure in the data and that the residuals do not exhibit systematic spatial patterns. The GWR model is therefore considered appropriate for this study.

### 3.11. Interpretation of the GWR Model

The interpretation is conducted for a single GWR model using only the significant predictor variables. As an example, the GWR model for the observation in Murung Raya Regency ( $i = 27$ ) is presented as follows:

$$\hat{y}_{27} = 77.4897 - 0.2611x_{27,1} + 0.1108x_{27,2} - 0.9768x_{27,3} - 0.1670x_{27,4} - 0.3322x_{27,5} - 0.4288x_{27,6} + 0.1459x_{27,7} + 0.0156x_{27,8} \quad (25)$$

Murung Raya recorded the lowest Food Security Index value in Kalimantan at 51.29, placing it in the highly vulnerable category. The local GWR model for this regency identified two statistically significant components at  $\alpha = 0.1$ , namely average years of schooling for women aged 15 years and above ( $X_4$ ) and the ratio of population per health worker relative to population density ( $X_6$ ), with local coefficients of -0.167 and -0.429 respectively. The negative coefficient of  $X_6$  is consistent with theoretical expectations, suggesting that a higher population-to-health worker ratio in densely populated areas is associated with reduced food security, likely reflecting limited access to health services that support nutritional status and overall household welfare.

However, the negative coefficient of  $X_4$  contradicts the theoretical expectation that higher educational attainment among women would positively contribute to food security. This anomaly may be explained by the phenomenon of educational out-migration, whereby women with higher levels of education tend to migrate to urban centers such as Palangkaraya in search of better employment

opportunities, leaving behind households that are more economically vulnerable and food insecure. Furthermore, in a remote region such as Murung Raya, higher educational attainment does not necessarily translate into improved household income due to the severe scarcity of formal employment opportunities, resulting in a mismatch between education and local labor market conditions.

Among the non-significant components,  $X_2$  (percentage of households with food expenditure proportion exceeding 65% of total expenditure) and  $X_7$  (percentage of stunted children under five) exhibited positive coefficients of 0.111 and 0.146 respectively, contrary to theoretical expectations. The anomalous direction of  $X_2$  may reflect the unique subsistence economy of Murung Raya, where a high proportion of food expenditure does not necessarily indicate food insecurity, as households may supplement their food needs through subsistence farming and forest resources, thereby maintaining food availability despite high expenditure proportions. The positive coefficient of  $X_7$  may be attributed to the endemic nature of stunting in this region, where stunting is more closely associated with long-term sanitation and child-feeding practices rather than current food availability conditions, rendering its relationship with the Food Security Index less straightforward in this specific context.

Similar spatial variation in coefficient signs was also observed across other regencies and cities in Kalimantan, further confirming the presence of spatial heterogeneity in the relationships between food security index components and the overall index, a pattern that would not have been detectable using global regression models.

### 3.12. Model Evaluation

Model evaluation measures used in this study are the coefficient of determination ( $R^2$ ) and the Mean Squared Error (MSE). The obtained values of  $R^2$  and MSE are presented in Table 9.

**Table 9.** Model evaluation

Model	$R^2$	MSE
RLB	37.06%	60.0609
GWR	59.63%	38.5241

As shown in Table 9, it can be concluded that the GWR model demonstrates superior performance in modeling the food security index across regencies and cities in Kalimantan Island when compared to the MLR model. This is evidenced by the higher coefficient of determination ( $R^2$ ) and the lower Mean Squared Error (MSE) of the GWR model relative to the MLR model.

## 4. Conclusion

This study examined the local effects of Food Security Index components across 56 regencies and cities in Kalimantan Island using Geographically Weighted Regression with Haversine distance and adaptive Gaussian kernel weighting. The results confirm that the GWR model outperforms the MLR model, as evidenced by a higher coefficient of determination ( $R^2 = 59.63\%$ ) and a lower Mean Squared Error (MSE = 38.5241), indicating that accounting for spatial heterogeneity substantially improves model fit.

The GWR models across Kalimantan Island can be classified into eight distinct groups based on the components that significantly influence the Food Security Index at each location. Among all components, the ratio of population per health worker relative to population density ( $X_6$ ) and average years of schooling for women aged 15 years and above ( $X_4$ ) emerge as the most spatially dominant, being significant in 45 and 43 regencies and cities respectively. This finding underscores that access to health services and female educational attainment are the two most critical dimensions of food security across Kalimantan. Three components percentage of population below the poverty line ( $X_1$ ), percentage of stunted children under five ( $X_7$ ), and life expectancy at birth ( $X_8$ ) were not statistically

significant across any location, suggesting that their contributions to the Food Security Index are mediated by other components or reflect long-term outcomes rather than direct drivers.

From a policy perspective, the spatial dominance of  $(X_6)$  across 45 regencies and cities suggest that improving the distribution and availability of health workers particularly in remote inland areas should be a priority intervention for strengthening food security across Kalimantan. Special attention should be directed toward the five most vulnerable regencies, namely Murung Raya, Melawi, Mahakam Ulu, Gunung Mas, and Lamandau, where food security conditions remain critically low. In these areas, targeted programs addressing female education, healthcare access, and household economic resilience are recommended, given the unique local characteristics that distinguish these regions from the rest of Kalimantan.

This study has several limitations that should be acknowledged. First, the use of cross-sectional data limits the analysis to spatial variation at a single point in time and does not capture temporal dynamics in food security conditions. Future research is encouraged to employ spatio-temporal approaches such as Geographically and Temporally Weighted Regression (GTWR) when longitudinal data become available. Second, the retention of three statistically non-significant components warrants further investigation into alternative indicators that may better capture the dimensions of food security not explained by the current model. Third, future studies may also consider incorporating additional external variables such as agricultural productivity, infrastructure accessibility, and climate-related factors to provide a more comprehensive understanding of the determinants of food security across Kalimantan.

## Ethics approval

Not required.

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## Competing interests

All the authors declare that there are no conflicts of interest.

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## Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

## Credit Authorship

**Meirinda Fauziyah:** Conceptualization, Validation, Writing - Review & Editing, Visualization, Supervision. **Raditya Arya Kosasih:** Conceptualization, Methodology, Software, Writing - Original Draft, Visualization. **Ayu Bahriah:** Methodology, Software, Writing - Original Draft. **Suyitno:** Validation, Writing - Review & Editing, Visualization, Supervision. **Andrea Tri Rian Dani:** Writing - Review & Editing, Supervision.

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