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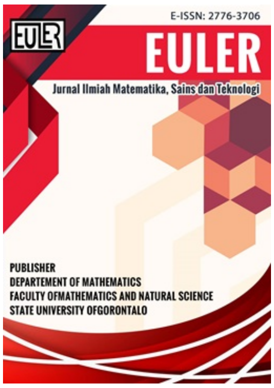

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Research Article

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Evaluating Kernel Weighting Functions in Geographically Weighted Logistic Regression for Spatial Modelling of Stunting in East Lombok

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ABSTRACT. *Stunting remains a major public health concern in Indonesia, with East Lombok Regency recording the highest prevalence in West Nusa Tenggara Province in 2022. This study aims to identify factors influencing stunting while accounting for spatial heterogeneity across regions. The Geographically Weighted Logistic Regression (GWLR) method was applied, comparing three kernel weighting functions: Fixed Gaussian, Adaptive Gaussian, and Adaptive Bisquare, to determine the best-fitting model. Parameter estimation was conducted using Maximum Likelihood Estimation with the Newton–Raphson iterative procedure. The results show that the Adaptive Gaussian kernel provided the best model performance, indicated by the lowest Corrected Akaike Information Criterion (AICc) value of 28.346. Spatial mapping identified two regional clusters: one where vitamin A supplementation significantly affected stunting, and another where no explanatory variables were significant. These findings emphasize the importance of incorporating spatial effects in public health modeling to support more targeted and context-specific interventions for stunting reduction at the local level.*

1. Introduction

Stunting is a condition of impaired child growth caused by nutritional deficiencies beginning in the womb [1]. According to [2], stunting has serious impacts on children, including hindering cognitive, motor, and verbal development, causing metabolic disorders, reducing immune function, increasing the risk of obesity, making children more susceptible to illness, and decreasing their learning capacity, work performance, and productivity. At the national level, the average stunting rate is 30.8%, while in West Nusa Tenggara (NTB) it is 33.49% [3]. According to data from “Satu Data NTB,” the number of stunted children under five in NTB reaches 81,015, with the highest number found in East Lombok Regency at 22,062. The high prevalence of stunting in East Lombok Regency serves as the basis for this study, which aims to identify the factors influencing stunting in the region. Before preventive measures can be implemented, it is important to first determine the causal factors of stunting.

Rusliani et al. [4] classify the causes of stunting into two categories: direct and indirect. Direct causes include inadequate nutritional intake and infectious diseases, while indirect causes involve household-level food availability, parental caregiving practices, and healthcare services. According to [5, 6], the factors contributing to stunting may vary across regions due to differences in the characteristics of each area, a phenomenon known as regional or spatial heterogeneity. Spatial heterogeneity occurs when the same independent variable exerts different effects across different locations within the study area [7]. The presence of spatial heterogeneity renders conventional regression analysis inadequate, thus necessitating the use of spatial regression approaches [8]. These approaches help model the spatial distribution of count-based diseases, such as stunting, and understand the relationship between environmental and socioeconomic factors and the disease at the local level [9].

One widely used spatial regression method is Geographically Weighted Regression (GWR). GWR is an extension of the Ordinary Least Squares (OLS) theory into a weighted regression model that takes into account spatial heterogeneity, allowing predictions at each location where data are observed and analyzed [10]. However, since the data in this study are binary or follow a Bernoulli distribution, the appropriate method is Geographically Weighted Logistic Regression (GWLR). GWLR is an extension of logistic regression that incorporates spatial location factors and assumes that the response variable follows a Bernoulli distribution [11].

Several studies have applied the GWLR method. Ulhaq et al. [12] applied GWLR in a study of malnutrition among toddlers in Indonesia using three kernel functions. The results show that the Adaptive Gaussian Kernel function provided the best model with the smallest AICc value of 31.908. Soliha et al. [13] compared the Fixed Gaussian GWLR model with a global binary logistic regression model in analyzing factors explaining AIDS cases in East Java. They concluded that the GWLR model with the Fixed Gaussian Kernel outperformed the global logistic regression model with an AIC of 44.178. Similarly, Solekha et al. [11], in their study of GWLR for poverty in East Nusa Tenggara, found that the Adaptive Gaussian Kernel GWLR model was more effective in modeling poverty in NTT in 2019 compared to binary logistic regression.

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To address research gaps in prior GWLR-based studies, the present study compares three different kernel functions: Fixed Gaussian Kernel, Adaptive Gaussian Kernel, and Adaptive Bisquare Kernel, to identify the optimal model. Additionally, the observational unit used in this study is the subdistrict level, which represents the case study area for stunting—an aspect underexplored in previous GWLR research. Using a smaller observational unit, such as the subdistrict, provides a more detailed understanding of the stunting issue and allows for a more accurate interpretation of spatial effects influenced by proximity between areas [14]. This enables local governments to design more targeted interventions aligned with specific local conditions. Therefore, the objectives of this study are to:

1. Model GWLR using Fixed Gaussian Kernel, Adaptive Gaussian Kernel, and Adaptive Bisquare Kernel weighting functions for stunting cases in East Lombok.
2. Identify the best model among the three kernel functions for stunting cases in East Lombok.
3. Map the areas influenced by factors affecting stunting levels in East Lombok based on the best-performing model.

The findings of this research are expected to benefit the community, particularly in East Lombok Regency, by supporting efforts to prevent and address stunting.

2. Methods

The methods employed in this study consist of descriptive analysis and inferential analysis based on spatial analysis. Descriptive analysis was conducted to visually explore the data through mapping techniques. The spatial analysis method used was Geographically Weighted Logistic Regression (GWLR), as the stunting data in this study are binary, with values of 0 and 1 (0 representing the high stunting category and 1 representing the low stunting category).

In addition, this study compared three types of kernel functions: Fixed Gaussian Kernel, Adaptive Gaussian Kernel, and Adaptive Bisquare Kernel, to determine the best GWLR model based on the lowest Corrected Akaike Information Criterion (AICc) value.

2.1. Data Description

The data used in this study are secondary data obtained from the East Lombok District Health Office regarding the prevalence of stunting in East Lombok Regency in 2022. The unit of analysis used is sub-district-level data for all sub-districts in East Lombok Regency.

This study employs two types of variables: dependent and independent variables. The dependent variable is the 2022 stunting prevalence, categorized into high stunting and low stunting. The independent variables consist of three indicators. Table 1 presents the variable definitions.

Table 1. Definition of research variables

Variable	Data Type	Definition
Stunting (Y)	Categorical	Low stunting = 1 (rate < 20%); High stunting = 0 (rate > 20%). Described as chronic malnutrition caused by prolonged insufficient nutrient intake [15]. WHO sets 20% as the threshold.
Children under five receiving Vitamin A (X_1)	Numerical (Percent)	Vitamin A supports immunity, vision, and growth [16].
Pregnant women consuming IFA tablets (X_2)	Numerical (Count)	Iron–folic acid supplementation reduces anaemia among pregnant women.
Early initiation of breastfeeding (EIB) (X_3)	Numerical (Percent)	Breastfeeding initiated within first hour after delivery [17].

2.2. Spatial Weight Matrix

The construction of the spatial weight matrix begins with calculating the Euclidean distance between locations. If location j has coordinates (u_j, v_j), the distance between location i and j is given by [12]:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}, \tag{1}$$

where d_{ij} is the Euclidean distance between observation location i and observation location j, u_i represents the latitude of observation location i, and v_i represents the longitude of observation location i.

The next step is to determine the optimal bandwidth value, which is a non-negative parameter that functions as a smoothing parameter. This value is obtained using the Cross Validation (CV) method based on the Least Squares approach through the following formula [11]:

$$CV(h) = \sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq i}(h)\right)^2, \tag{2}$$

where $\hat{y}_{\neq i}(h)$ is the estimated value of y_i when the observation at location u_i, v_i is omitted during the estimation process. The optimal bandwidth value is the value of h that yields the smallest CV value. Once the Euclidean distance and the optimal bandwidth value are obtained, the spatial weight matrix can be calculated.

1. Fixed Gaussian Kernel [18]:

$$w_i(u_i, v_i) = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right]. \tag{3}$$

2. Adaptive Gaussian Kernel [12]:

$$w_i(u_i, v_i) = -\left(\frac{1}{2}\frac{d_{ij}}{h_{(q)}}\right)^2. \tag{4}$$

3. Adaptive Bisquare Kernel [18]:

$$w_i(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_q}\right)^2\right]^2, & d_{ij} \leq h_q, \\ 0, & d_{ij} > h_q, \end{cases} \tag{5}$$

where where w_i is the weight of the i-th data point, (u_i, v_i) are the latitude and longitude coordinates, d_{ij} is the distance between location i and location j, and h is the bandwidth.

2.3. Geographically Weighted Logistic Regression (GWLR)

Geographically Weighted Logistic Regression (GWLR) is a combination of the Geographically Weighted Regression (GWR) method and logistic regression [12, 19]. GWLR is a non-parametric method used to estimate regression parameters by taking spatial factors into account. This method is an extension of GWR that enables the modeling of categorical data and non-stationary parameters. Mathematically, the GWLR model can be expressed as:

$$\pi(x_i) = \frac{\exp\left(\sum_{j=0}^{p} \beta_j(u_i, v_i)\, x_{ij}\right)}{1 + \exp\left(\sum_{j=0}^{p} \beta_j(u_i, v_i)\, x_{ij}\right)},$$

where x_{ij} is the observed value of the predictor variable at location $(u_i v_i)$; $\beta_j(u_i, v_i)$ is the regression coefficient for each location $(u_i v_i)$; p is the number of predictor variable parameters; u_i represents the latitude and v_i represents the longitude. One method for estimating parameters in GWLR is Maximum Likelihood Estimation (MLE). The likelihood function of the logistic model is:

$$L(\beta(u_i, v_i)) = \prod_{i=1}^{n} \pi(x_i)^{y_i} \left[1 - \pi(x_i)\right]^{1-y_i}.$$

The log-likelihood function can be written as:

$$\ln L^*(\beta) = \sum_{i=1}^{n} w_i(u_i, v_i) \left[y_i\, \beta^T x_{G,i} - \ln\left(1 + \exp(\beta^T x_{G,i})\right)\right]. \tag{6}$$

The first derivative with respect to the regression parameters is:

$$\frac{\partial \ln L^*}{\partial \beta^T} = \sum_{i=1}^{n} w_i(u_i, v_i) \left[y_i - \pi(x_{G,i})\right] x_{G,i},$$

while the second derivative is:

$$\frac{\partial^2 \ln L^*}{\partial \beta^T \partial \beta} = -\sum_{i=1}^{n} w_i(u_i, v_i)\, \pi(x_{G,i}) \left[1 - \pi(x_{G,i})\right] x_{G,i} x_{G,i}^T.$$

Since the above function is implicit, the parameters are estimated iteratively using the Newton-Raphson method through the Iteratively Reweighted Least Squares (IRLS) procedure. The Newton-Raphson update equation is:

$$\boldsymbol{\beta}^{(m+1)}(u_i, v_i) = \boldsymbol{\beta}^{(m)}(u_i, v_i) - \left[\mathbf{H}^{(m)}\right]^{-1} \mathbf{g}^{(m)}, \tag{7}$$

where $\mathbf{g}^{(m)}$ is the first derivative (gradient vector) at the m-th iteration, and $\mathbf{H}^{(m)}$ is the second derivative (Hessian matrix) at the m-th iteration.

According to [18], there are two types of parameter testing conducted in modeling data using the Geographically Weighted Logistic Regression (GWLR) method, namely:

1. Simultaneous Test
   This test aims to determine whether all independent variables jointly have a significant effect on the dependent variable, with the following hypotheses:

$$H_0 : \beta_1(u_i, v_i) = \cdots = \beta_p(u_i, v_i) = 0,$$
$$H_1 : \text{At least one } \beta_j(u_i, v_i) \neq 0.$$

   The test statistic used is the Likelihood Ratio Test (LRT):

$$G = -2 \ln \left[\frac{\left(\frac{n_1}{n}\right)^{n_1} \left(\frac{n_0}{n}\right)^{n_0}}{\prod_{i=1}^{n} \hat{\pi}^{y_i} (1 - \hat{\pi})^{1-y_i}}\right], \tag{8}$$

   where $n_1 = \sum_{i=1}^{n} y_i,\ n_0 = \sum_{i=1}^{n} (1 - y_i),\ n = n_0 + n_1$. The null hypothesis H_0 is rejected if the $p - value < \alpha$ or $G > \chi^2_{(\alpha,p)}$, where p is the degrees of freedom (the number of predictor variables).
2. Partial Test
   This test is conducted to determine which independent variables have a significant partial effect on the dependent variable, with the following hypotheses:

$$H_0 : \beta_j(u_i, v_i) = 0,$$
$$H_1 : \beta_j(u_i, v_i) \neq 0.$$

   The test statistic used is the Wald test:

$$W = \frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}. \tag{9}$$

   The null hypothesis H_0 is rejected if $|W| > Z_{(\alpha/2)}$.

2.4. Selection of the Best Model

The purpose of selecting the best model is to determine the most appropriate method for modeling the data. According to [20], one commonly used approach is to compare the values of the Corrected Akaike Information Criterion (AICc). AICc is used to measure the relative quality of a statistical model based on the available data. The smaller the AICc value, the better the model quality. The formula for AICc is:

$$AICc = AIC + \frac{2k^2 + 2k}{n - k - 1}, \tag{10}$$

where

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

where n is the number of observations, k is the number of parameters estimated in the regression model, and L is the maximum value of the likelihood function. If AICc is used as the criterion for selecting the best model, the model interpretation is carried out using the Odds Ratio (OR). The Odds Ratio is used to interpret the results of both logistic regression and GWLR models [20]. The formula for the Odds Ratio is:

$$OR_{(u_i,v_i)} = \frac{\dfrac{\pi^{(1)}_{(u_i,v_i)}}{1 - \pi^{(1)}_{(u_i,v_i)}}}{\dfrac{\pi^{(0)}_{(u_i,v_i)}}{1 - \pi^{(0)}_{(u_i,v_i)}}} = \exp\left(\hat{\beta}_{(u_i,v_i)}\right). \tag{11}$$

2.5. Analysis Stages

The following steps and stages of analysis were carried out in this study:

1. Conduct an exploration of the collected data. The exploration was performed for each variable used in the study..
2. Detect multicollinearity among independent variables using the Variance Inflation Factor (VIF) [13].

3. Perform a spatial heterogeneity test using the Breusch-Pagan Test [11].
4. Calculate the Euclidean distance for each sub-district based on geographic coordinates (longitude and latitude).
5. Determine the optimal bandwidth using Cross Validation (CV).
6. Calculate the spatial weight matrix for each kernel function.
7. Estimate the parameters of the GWLR model using the Maximum Likelihood Estimation (MLE) method and numerical iteration through the Newton-Raphson method in the Iteratively Reweighted Least Squares (IRLS) procedure.
8. Test the significance of parameters both simultaneously and partially.
9. Compare the AICc values for each kernel function to obtain the best GWLR model.
10. Perform mapping to obtain grouping/clustering based on significant factors affecting stunting levels in East Lombok Regency using the selected best model.
11. Interpret the results and draw conclusion.

3. Results and Discussion

3.1. Data Exploration

The stunting data in this study were classified into two categories: high and low stunting. This classification follows the World Health Organization (WHO) standard, which defines areas with a stunting prevalence rate exceeding 20% as high-stunting regions. Areas below this threshold are categorized as low-stunting regions, indicating relatively better child nutrition and health conditions.

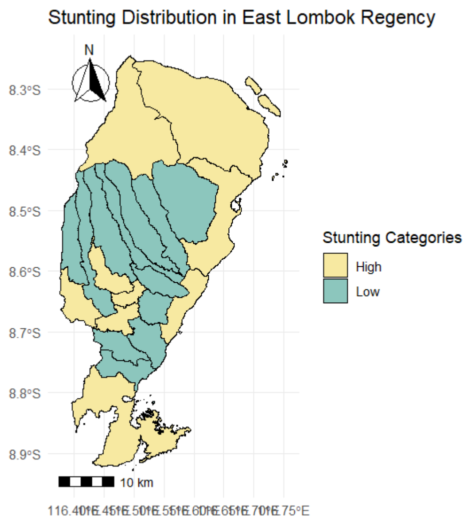

Figure 1. Map of stunting distribution in East Lombok

Figure 1 presents the spatial distribution of stunting prevalence in East Lombok Regency in 2022. The map reveals a heterogeneous pattern across subdistricts, with high-stunting areas concentrated in the northern, southern, eastern, and western parts of the regency, while low-stunting areas are generally located in the central and partially western regions. The highest prevalence was recorded in Sikur Subdistrict (30.57%), whereas the lowest occurred in East Sakra Subdistrict (6.81%). This spatial variation indicates that stunting in East Lombok does not occur uniformly across regions but is influenced by local environmental and socio-economic characteristics. Similar findings have been reported by Bele et al. [5] in East Nusa Tenggara and Hariani et al. [6]in North Lombok, where spatial disparities were associated with differences in health service accessibility and maternal nutrition programs. The observed pattern supports the assumption of spatial heterogeneity, suggesting that location-specific factors play an essential role in shaping stunting prevalence. Therefore, a spatial modeling approach such as Geographically Weighted Logistic Regression (GWLR) is necessary to capture these localized variations more accurately than global models.

3.2. Multicollinearity

Before conducting the GWLR analysis, a multicollinearity test was performed on the independent variables using the Variance Inflation Factor (VIF). A VIF value greater than 10 indicates the presence of multicollinearity among explanatory variables, which can reduce the stability and interpretability of regression coefficients.

Table 2. VIF values for multicollinearity

Variable	VIF
X_1	1.279
X_2	1.009
X_3	1.289

As shown in Table 2, all variables have VIF values below 10, indicating that there is no multicollinearity among the predictors. This result suggests that the explanatory variables, namely vitamin A supplementation for children under five (X_1), iron-folic acid consumption among pregnant women (X_2), and early initiation of breastfeeding (X_3), are independent and suitable for inclusion in the GWLR model.

The absence of multicollinearity supports the validity of the model since the estimated coefficients are not biased by redundant information between variables. Similar findings were reported by Solekha and Qudratullah [11] and Hariani et al. [6], who also found low VIF values in modeling stunting and poverty, confirming that health and socio-economic factors contribute distinct effects. Therefore, the independence among variables ensures that each predictor uniquely explains spatial variations in stunting prevalence across East Lombok.

3.3. Spatial Heterogeneity Test

After confirming the absence of multicollinearity, the Breusch–Pagan (BP) test was performed to examine whether spatial heterogeneity exists in the data. This test evaluates whether the variance of the residuals is constant across regions. If the residual variance differs significantly between locations, it indicates the presence of spatial heterogeneity, suggesting that model parameters may vary spatially.

Table 3. Spatial heterogeneity test

Test	p-value
BP Test	0.043

As shown in Table 3, the BP test yields a p-value of 0.043, which is below the significance level of 0.05. Therefore, the null hypothesis of homogeneity is rejected, confirming the existence of spatial heterogeneity in the dataset. This finding implies that the relationship between explanatory variables and stunting prevalence varies across subdistricts in East Lombok.

The presence of spatial heterogeneity provides strong justification for applying a local modeling approach such as GWLR instead of a global logistic regression model. Similar evidence was reported by Bakri et al. [7] in East Java, where spatially varying relationships were observed in regional health indicators. These studies, together with the present findings, reinforce the argument that accounting for spatial heterogeneity improves model accuracy and enables a better understanding of localized determinants of stunting. Hence, GWLR is considered an appropriate analytical framework for this study.

3.4. Spatial Weight Matrix

The construction of the spatial weight matrix began with the calculation of Euclidean distances between subdistricts based on eq. (1), which measures the proximity among spatial units and helps identify the sequence of nearest neighbors for each region i [12]. These distances serve as the foundation for determining how spatial dependence is quantified within the model.

Table 4. Eucliedan distances

	Aikmel	Jerowaru	...	Wanasaba
Aikmel	0.000	10.219	...	10.178
Jerowaru	10.219	0.000	...	1.405
⋮	⋮	⋮	⋱	⋮
Wanasaba	10.178	1.405	...	0.000

The next step was determining the optimal bandwidth value using the least squares approach through the Cross Validation (CV) method as defined in eq. (2). The optimal bandwidth controls the smoothness of spatial weighting and affects how local relationships are captured in the GWLR model.

For the Fixed Gaussian weighting function, the optimal bandwidth value obtained was 6.667, which is applied uniformly to all locations. Conversely, the Adaptive weighting functions allow for variable bandwidths that adjust according to the density of neighboring observations in each subdistrict. This flexibility enables better modeling of areas with unequal data distributions, particularly when observation density varies across space [18].

Table 5. Adaptive kernel bandwidth

Sub-district	Bandwidth
Aikmel	10.793
Jerowaru	5.046
⋮	⋮
Wanasaba	6.232

The differences in bandwidth values shown in Table 5 reflect variations in spatial structure and data density among subdistricts. Subdistricts with higher population or spatial clustering tend to have smaller bandwidths, allowing the model to capture finer local variations. This finding aligns with Ulhaq [12] and Aliu et al. [20], who emphasized that adaptive kernel functions can more effectively represent spatial heterogeneity by adjusting the weighting range based on the distribution of spatial units. The construction of the spatial weight matrix, therefore, ensures that the GWLR model accounts for both spatial proximity and local variability, improving its accuracy in identifying region-specific effects related to stunting prevalence.

After obtaining the Euclidean distances and the optimal bandwidth values, the spatial weight matrices were computed for each kernel weighting function based on eq. (3)–eq. (5). These matrices define how spatial influence decays with increasing distance, ensuring that closer regions exert a greater effect on local parameter estimation compared to those farther away. For the Fixed Gaussian kernel, the weights are applied uniformly within a fixed distance threshold, as shown below:

$$W_{ij} = \begin{bmatrix} 1 & 0.309 & \cdots & 0.312 \\ 0.309 & 1 & \vdots & \vdots \\ 0.389 & 0.959 & \ddots & 0.951 \\ \vdots & \vdots & \ddots & 0.993 \\ 0.312 & 0.978 & \cdots & 1 \end{bmatrix}.$$

In contrast, the Adaptive Gaussian kernel adjusts the bandwidth dynamically according to the density of spatial observations. This allows each location to have a specific neighborhood size, improving sensitivity to local variations:

$$W_{ij} = \begin{bmatrix} 1 & 0.799 & \cdots & 0.801 \\ 0.359 & 1 & \vdots & \vdots \\ 0.589 & 0.977 & \ddots & 0.984 \\ \vdots & \vdots & \ddots & 0.997 \\ 0.513 & 0.987 & \cdots & 1 \end{bmatrix}.$$

Meanwhile, the Adaptive Bisquare kernel assigns higher weights to nearby observations and reduces the influence of distant ones to zero beyond a certain distance, resulting in a more localized spatial structure:

$$W_{ij} = \begin{bmatrix} 1 & 0.011 & \cdots & 0.012 \\ 0 & 1 & \vdots & \vdots \\ 0 & 0.823 & \ddots & 0.874 \\ \vdots & \vdots & \ddots & 0.974 \\ 0 & 0.901 & \cdots & 1 \end{bmatrix}.$$

These differences in the weighting structure highlight the varying degrees of spatial dependence modeled by each kernel. The Fixed Gaussian kernel assumes uniform spatial influence, which may overlook local variability, while the Adaptive Gaussian and Adaptive Bisquare kernels better accommodate spatial heterogeneity by adjusting weights according to neighborhood structure.

Overall, constructing the spatial weight matrix is a crucial step in GWLR modeling, as it determines how spatial relationships among subdistricts are represented mathematically. The appropriate kernel selection ensures that the model accurately captures localized effects of environmental and socio-economic factors influencing stunting in East Lombok.

3.5. Estimation and Significance Testing of GWLR Model Parameters

After constructing the spatial weight matrices, the parameters of the GWLR model were estimated using the Maximum Likelihood Estimation (MLE) method with the Newton–Raphson iterative procedure, as defined in eq. (6) and eq. (7). The estimated coefficients in GWLR vary across locations because the model incorporates spatial weighting, allowing parameter values to reflect local effects rather than assuming spatial uniformity.

The significance of the parameters was tested for each kernel function using the Likelihood Ratio Test (LRT) for simultaneous testing and the Wald test for partial testing, as described in eq. (8) and eq. (9). These tests determine whether the explanatory variables significantly influence stunting prevalence at both the global and local levels.

Table 6. Simultaneous test of GWLR with fixed Gaussian kernel

Deviance Value (G)	$\chi^2_{(\alpha,p)}$
15.834	6.251

As shown in Table 6, the deviance value (G = 15.834) exceeds the critical χ^2 value (6.251), indicating that at least one explanatory variable significantly affects stunting prevalence in East Lombok Regency. The partial test results show that the variable X_1 (vitamin A supplementation for children under five) has a significant effect in several subdistricts, including Aikmel, Sakra, East Sakra, and Sambalia.

The significance of X_1 highlights the role of nutritional interventions in influencing local stunting rates, particularly in areas where access to healthcare and supplementation programs is relatively stronger. This localized effect is consistent with the findings of Solekha and Qudratullah [11], who also identified vitamin A as a key determinant of child nutrition in spatial models of poverty and health outcomes.

Table 7. Simultaneous test of GWLR with adaptive Gaussian kernel

Deviance Value (G)	$\chi^2_{(\alpha,p)}$
15.800	6.251

Table 7 shows that the deviance value (G = 15.800) is greater than $\chi_((\alpha,p))^2 = 6.251$, confirming that at least one predictor variable significantly influences stunting prevalence. Partial testing indicates that variable X_1 (vitamin A supplementation) is significant in a wider range of subdistricts, including Aikmel, Labuhan Haji, Lenek, Masbagik, Montong Gading, Pringgabaya, Sakra, West Sakra, East Sakra, Sambalia, Selong, Sembalun, Sikur, Sukamulia, and Suralaga. In contrast, X_2 (iron-folic acid consumption among pregnant women) and X_3 (early initiation of breastfeeding) show no significant effect in any location.

The broader significance of X_1 under the Adaptive Gaussian kernel demonstrates the advantage of using adaptive weighting in capturing spatially varying relationships. Adaptive kernels account for uneven spatial distributions of data, allowing more accurate identification of localized determinants.

Based on Table 8, the deviance value (G = 12.502) exceeds $\chi_((\alpha,p))^2 = 6.251$, indicating that at least one predictor variable has a significant effect on stunting cases in East Lombok Regency. The partial test shows that X_1 (vitamin A supplementation) is significant in only three subdistricts, namely Aikmel, Sakra, and East Sakra.

Table 8. Simultaneous test of GWLR with adaptive Bisquare kernel

Deviance Value (G)	$\chi^2_{(\alpha,p)}$
12.502	6.251

The smaller number of significant regions in the Adaptive Bisquare kernel suggests that this kernel produces a more localized weighting structure with sharper cutoffs in spatial influence. Consequently, it may be less effective for regions with overlapping or continuous spatial interactions. These findings reinforce the argument that the Adaptive Gaussian kernel provides the most balanced and accurate representation of spatial heterogeneity in stunting data, offering superior sensitivity without overfitting.

Overall, the results across the three kernel functions demonstrate that while all models identify vitamin A supplementation as an influential factor, the Adaptive Gaussian kernel provides the best balance between model fit and spatial interpretability. Its ability to capture broader yet locally adaptive spatial relationships makes it the most suitable kernel for modeling stunting distribution in East Lombok.

3.6. Selection of the Best Model

The selection of the best-fitting model was based on the Corrected Akaike Information Criterion (AICc), as defined in eq. (10). This criterion evaluates model performance by considering both goodness of fit and model complexity. A smaller AICc value indicates a model that provides a better balance between accuracy and parsimony, reducing the risk of overfitting while ensuring reliable spatial interpretation.

Table 9. Best model

Kernel Weight on GWLR	AICc
Fixed Gaussian	28.419
Adaptive Gaussian	28.
Adaptive Bisquare	36.263

As shown in Table 9, the GWLR model employing the Adaptive Gaussian kernel weighting function yields the smallest AICc value (28.346), indicating superior model performance compared to the Fixed Gaussian and Adaptive Bisquare kernels. The lower AICc suggests that the Adaptive Gaussian kernel more effectively captures spatial heterogeneity by dynamically adjusting the bandwidth according to the density of local observations.

This result aligns with previous studies by Ulhaq [12] and Wardhani et al. [18], which also found that adaptive kernels tend to outperform fixed kernels in modeling spatially non-stationary health and socio-economic data. The flexibility of the Adaptive Gaussian kernel allows the model to represent both densely and sparsely populated subdistricts more accurately, ensuring that local relationships between predictors and stunting prevalence are better reflected.

Consequently, the GWLR model with the Adaptive Gaussian kernel is identified as the most suitable model for explaining spatial variations in stunting across East Lombok Regency. This finding reinforces the importance of accounting for spatial dependence and varying local conditions when modeling public health phenomena in geographically diverse regions.

3.7. Mapping

After identifying the best-fitting model from the GWLR analysis, mapping was performed based on the results of the Adaptive Gaussian kernel model. This mapping aimed to visualize the spatial distribution of significant and non-significant variables affecting stunting across subdistricts in East Lombok Regency in 2022. By presenting spatial patterns, this stage enhances the interpretability of the GWLR model and provides practical insights for local-level policy formulation.

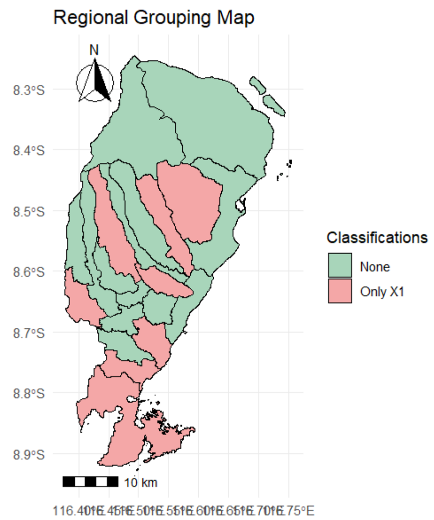

Figure 2. Regional grouping map

Figure 2 illustrates the spatial distribution of statistically significant parameters. The results show that only one variable, X_1 (vitamin A supplementation for children under five), exhibits a significant relationship with stunting in several subdistricts, including Keruak, Jerowaru, East Sakra, Terara, Suralaga, Pringgasela, Wanasaba, Suela, and Pringgabaya. The remaining subdistricts show no significant relationship with any of the predictor variables. Both X_2 (iron-folic acid tablet consumption among pregnant women) and X_3 (early initiation of breastfeeding) were not significant in any location.

The spatial heterogeneity of X_1 indicates that the impact of vitamin A supplementation varies geographically. Subdistricts located in the southern and eastern regions, such as Jerowaru and East Sakra, show stronger associations, suggesting that health and nutritional programs in these areas may be more effective or better targeted. In contrast, northern and central regions, such as Sembalun and Selong, display weaker associations, which could be attributed to differences in healthcare accessibility, socio-economic conditions, or local implementation of public health programs. This finding aligns with Hariani et al. [6], who reported that nutritional and maternal health factors tend to exhibit spatially non-stationary effects across Lombok.

At the subdistrict level, the model for Suralaga (u_{18}, v_{18}), derived using the Adaptive Gaussian weighting function, can be expressed as follows:

$$g(x) = -30.499 + 0.008X_1 + 0.098X_2 + 0.189X_3.$$

The interpretation of the GWLR model is conducted using the odds ratio based on eq. (11), obtained by exponentiating the regression coefficients [18]. For Suralaga, the coefficient of X_1 (vitamin A supplementation) is 0.008, corresponding to an odds ratio of 1.008. This means that each unit increase in the proportion of children under five who receive vitamin A increases the likelihood of lower stunting prevalence by 1.008 times.

The spatial mapping underscores the importance of geographically targeted nutrition policies. Identifying subdistricts where vitamin A supplementation significantly influences stunting allows policymakers to prioritize interventions in areas with lower program performance. Moreover, this spatially differentiated evidence supports the argument that local conditions should guide the design and implementation of health interventions, consistent with the principle of place-based public health strategies.

4. Conclusion

This study employed Geographically Weighted Logistic Regression (GWLR) to analyze factors influencing stunting in East Lombok Regency in 2022, utilizing Fixed Gaussian, Adaptive Gaussian, and Adaptive Bisquare weighting functions. Stunting cases were classified into two categories: high stunting and low stunting. Of the 21 subdistricts, 12 were identified as having low stunting, indicating that significant regional variation exists across East Lombok.

The analysis revealed that the provision of vitamin A to children under five (X_1) significantly affected stunting in several subdistricts, while the variables of iron-folic acid tablet consumption by pregnant women (X_2) and early initiation of breastfeeding (X_3) were not significant in any subdistrict. These findings highlight the critical role of vitamin A supplementation in reducing stunting, a factor that warrants more targeted public health efforts, particularly in areas where its impact is most pronounced.

The GWLR model using the Adaptive Gaussian weighting function emerged as the best model, as indicated by its smallest AICc value of 28.346. This model's ability to adaptively weight spatial data based on local variation in predictor variables allows for a more nuanced understanding of the spatial dynamics of stunting. Mapping based on the best model revealed two distinct clusters: one where vitamin A supplementation had a significant effect on stunting, and another where no significant variables were identified. This spatial differentiation underscores the importance of localized interventions in addressing public health challenges such as stunting.

While this study provides valuable insights into the spatial distribution of stunting, it is not without limitations. Future research should integrate additional socio-economic factors, such as household income and access to healthcare, as well as explore temporal data to better understand the evolving patterns of stunting over time. The findings of this study are expected to inform local government policy and contribute to more targeted and context-specific public health interventions in East Lombok Regency.

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