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Spatial Modelling of Child Malnutrition in East Java using Geographically Weighted Regression

Syifa' Azizah Putri Gunawan[1]*, Regina Fortunata[1], Elly Ana[1]
[1]Department of Mathematics, Airlangga University, Indonesia
syifa.azizah.putri-2022@fst.unair.ac.id

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ABSTRACT

Child malnutrition is a persistent public health issue in East Java, Indonesia, characterized by uneven spatial distribution across its 38 regencies and cities. This study aims to model the prevalence of malnutrition among children under five using Geographically Weighted Regression (GWR) to identify locally significant determinants. Secondary data used in this study is prevalence of child nutritional status by regencies/cities in East java, taken from the 2023 Indonesian Health Survey, incorporating seven predictor variables: low birth weight prevalence, complete immunization coverage, exclusive breastfeeding, access to improved sanitation, number of community health posts (*Posyandu*), access to clean water, and poverty rate. Spatial dependence and heterogeneity were confirmed through Moran's I (p = 0.009) and Breusch-Pagan tests (p = 0.024), validating the application of GWR. Spatial dependence and heterogeneity were confirmed through Moran's I (p = 0.009) and the Breusch-Pagan test (p = 0.024), indicating the relevance of a spatial modelling approach. The best-performing model used an adaptive bi-square kernel (CV = 0.133; R^2 = 94.15%). All predictors exhibited spatial variability with statistically significant effects in specific regions ($p < 0.05$). In Tuban Regency, for instance, five variables including low birth weight, breastfeeding practices, and sanitation were significantly associated with malnutrition rates. These findings suggest that the relationship between predictors and malnutrition is not uniform across regions. GWR enables the identification of local patterns often overlooked by global models, offering a more accurate understanding of spatial disparities. The results provide strong evidence for developing targeted, region-specific public health strategies to address child malnutrition more effectively in East Java

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A. INTRODUCTION

Malnutrition is a major contributor to child illness and death. While various interventions exist, their uptake among children and mothers especially across different socio-economic groups remains unclear (Tette et al., 2015). It results from an imbalance between nutritional needs and intake, covering both undernutrition and obesity (Ghosh, 2020). WHO (2010) classifies undernutrition into protein-energy malnutrition and micronutrient deficiency (Karmakar et al., 2010), with the former often affecting children aged 6–24 months due to poor breastfeeding, low-protein diets, and infections (Goals, 2004). Factors such as economic status, household culture, consumption habits, sanitation, and gender bias especially against girls play significant roles. Socio-economic conditions like income, ethnicity, location, and family dynamics are crucial (Ghosh, 2020). Despite government programs, child malnutrition remains a persistent challenge.

In Indonesia, child malnutrition persists as a critical issue within the public health landscape. The country ranks 27th globally and 5th in Asia in terms of the highest stunting rates (Luh et al., 2024). Although the Indonesian Nutrition Status Survey (SSGI) reported a downward trend in national stunting rates from 27.7% in 2019, 24.4% in 2021, 21.6% in 2022, to 21.5% in 2023 this condition continues to affect millions of children. East Java stands out as one of the provinces contributing significantly to national malnutrition figures. In 2018, the region experienced a sharp increase in toddler malnutrition, from 16.47% in 2017 to 38.3% (Azkia & Setiawan, 2022; BPS, 2023). Despite recent improvements, the province's stunting rate in 2023 was 17.7%, slightly below the national average. However, due to its large population, even this modest rate has a substantial national impact (Luh et al., 2024).

The 2023 Indonesian Health Survey (SKI) reported the highest stunting rates in Probolinggo Regency (35.4%), Probolinggo City (31.8%), and Lumajang Regency (29.9%) (BPS, 2023). Meanwhile, Malang City recorded 0.00% malnutrition, contrasting sharply with Tuban Regency (2.5%). Determinants such as low birth weight (0.02% in Tulungagung vs. 5.92% in Jember) and immunization coverage (30.66% in Probolinggo City) further highlight regional inequalities (BPS, 2023). These findings show that malnutrition is a multifaceted, region-specific issue (Muche et al., 2021).

The complexity of these spatial patterns implies that conventional statistical approaches, such as global regression, may not adequately explain localized disparities (Andresen, 2022). Therefore, spatial analytical methods that account for heterogeneity such as Geographically Weighted Regression (GWR) are essential. Unlike global models, GWR enables parameter variation across locations, revealing local influences (Griffith & Anselin, 1989).

Previous studies, both local and international, have shown that spatially adaptive models like Geographically Weighted Regression (GWR) are effective in capturing localized patterns and spatial heterogeneity in child malnutrition (Azkia & Setiawan, 2022; Hutabarat et al., 2016; Siswanto et al., 2022). International evidence further supports this, with studies in Ethiopia revealing spatial clusters and region-specific factors influencing nutritional outcomes (Kitaw et al., 2024; Muche et al., 2021; Seboka et al., 2022). Compared to global models, GWR allows coefficients to vary by location, making it better suited for identifying local drivers of malnutrition (Andresen, 2022; Griffith & Anselin, 1989). Despite these advantages, its application in East Java remains limited, especially in studies that integrate multiple determinants such as low birth weight, immunization, exclusive breastfeeding, sanitation, and poverty.

In addition to GWR, clustering algorithms such as K-Means have been used to group regions with similar malnutrition characteristics based on multidimensional indicators, supporting targeted, region-based interventions (Chandra et al., 2021). However, unlike GWR, clustering methods do not model causal relationships. GWR offers greater flexibility by allowing regression coefficients to vary by location, enabling more accurate analysis of spatially varying associations (Siswanto et al., 2022). Studies by Azkia & Setiawan (2022) and Hutabarat et al. (2016) show that GWR outperforms global models in capturing local determinants of malnutrition, particularly in the context of East Java.

This study aims to examine the spatial distribution of child malnutrition in East Java, identify locally significant determinants using GWR, and evaluate the model's performance against global regression. The results are expected to contribute methodologically by demonstrating the use of GWR in regional health analysis and practically by informing targeted policy interventions to address child malnutrition more effectively.

B. METHODS

This study employs a quantitative approach using secondary data sourced from the 2023 Indonesian Health Survey (SKI), covering all 38 regencies and cities within East Java Province. The analysis uses centroid coordinates (latitude and longitude) of each district/city, based on the administrative boundary shapefile (shp) format, which serves as the spatial reference for the GWR analysis. The analysis aims to model the prevalence of child malnutrition based on spatially distributed determinants. One response variable and seven predictor variables were used, as summarized in Table 1. These predictors were selected based on their relevance in previous malnutrition studies and their availability in the regional health database.

Table 1. Research Variables

Variable	Description	Scale	Unit
Y	Prevalence of Child Malnutrition	Ratio	Percentage (%)
X_1	Prevalence of Low Birth Weight (LBW)	Ratio	Percentage (%)
X_2	Coverage of Complete Basic Immunization	Ratio	Percentage (%)
X_3	Coverage of Exclusive Breastfeeding	Ratio	Percentage (%)
X_4	Households with Access to Improved Sanitation	Ratio	Percentage (%)
X_5	Number of Integrated Health Posts (*Posyandu*)	Numeric	Number
X_6	Households with Clean Water Access	Ratio	Percentage (%)
X_7	Percentage of Poor Population	Ratio	Percentage (%)

Table 1 lists the response variable (prevalence of child malnutrition) and key predictors, including low birth weight prevalence, immunization coverage, exclusive breastfeeding, access to improved sanitation, number of *Posyandu* (integrated health posts), clean water access, and poverty rate. All variables are measured at the district level and expressed in ratio or numerical form, allowing for consistent comparison across regions.

The analytical method used is Geographically Weighted Regression (GWR), a spatial regression technique that extends Ordinary Least Squares (OLS) by incorporating geographical location in parameter estimation. GWR is particularly suitable for spatial data with evidence of spatial dependence and heterogeneity, as it allows regression coefficients to vary across locations. This flexibility enables more accurate modelling of local variations in the relationship between malnutrition and its determinants. Unlike global models that assume uniformity, GWR captures localized effects that are critical in public health research, especially in geographically diverse regions such as East Java (Griffith & Anselin, 1989; Wicaksono et al., 2023). The analysis was conducted in several stages, which are briefly outlined in the flowchart presented in Figure 1 below.

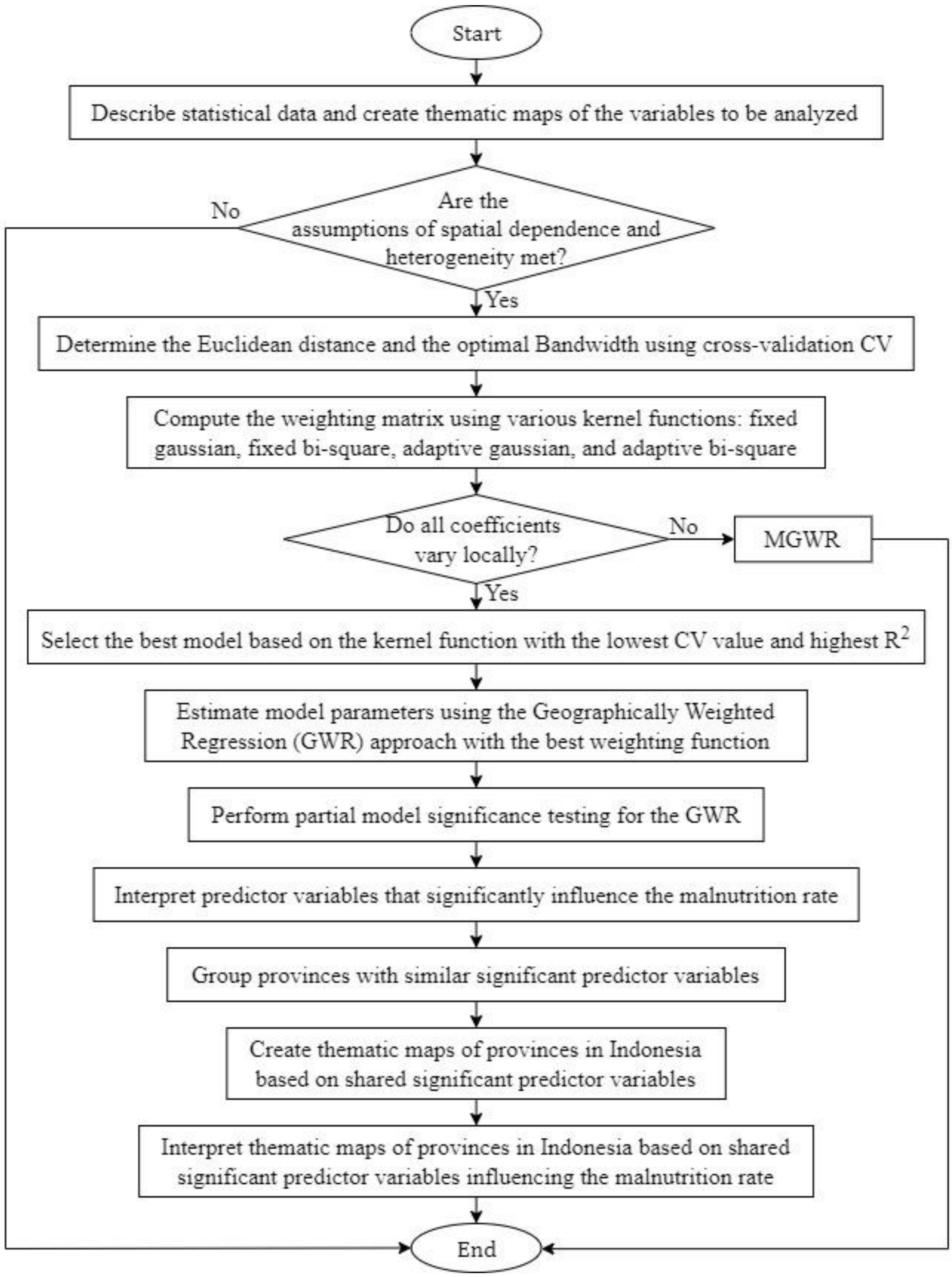

Figure 1. Research Flowchart

The research procedure, illustrated in Figure 1, follows a structured sequence beginning with statistical description and thematic mapping, followed by spatial assumption testing including spatial dependence (using Moran's I) and spatial heterogeneity to determine whether location influences malnutrition patterns. Once spatial criteria are met, the model is estimated using the optimal kernel weighting function through a series of model fit evaluations. The final stages involve interpreting the GWR results, drawing conclusions, and visualizing regional groupings to support localized recommendations. This comprehensive flow ensures that the analysis is grounded in both theoretical rigor and empirical validity.

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{1}$$

where:
$\hat{I}$: Moran's Index, range $-1 \leq \hat{I} \leq 1$
N : total number of locations
w_{ij} : spatial weight element (Queen continguity)
y_i : observed value at spatial unit *i*
y_j : observed value at spatial unit *j*
$\bar{y}$: mean of the observations across all N regions

A Moran's I value that nears -1 or 1 suggests a high degree of autocorrelation (ρ) among residuals between one location and another. Conversely, a value near zero suggests the absence of such spatial dependence. The hypothesis test for spatial dependence using Moran's I is mathematically expressed as follows.
$H_0: I = 0$ (no spatial dependence)
$H_1: I \neq 0$ (spatial dependence exists)

The test statistics for Moran's I is expressed by following the Formula (2), with the decision rule reject H_0 if $|Z_1| > Z_{\frac{\alpha}{2}}$.

$$Z_I = \frac{\hat{I} - E(\hat{I})}{\sqrt{Var(\hat{I})}} \tag{2}$$

Spatial heterogeneity, or the variation present in each location, is a key characteristic of spatial data, particularly with point-based approaches, and may arise due to the inherently non-homogeneous nature of spatial units. Spatial heterogeneity may be examined through the Breusch-Pagan test, using the following hypotheses. (Wicaksono et al., 2023).
$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (no spatial homogeneity)
$H_1: \exists i$ such that $\sigma_n^2 \neq \sigma^2$ (spatial homogeneity exists)

The Breusch-Pagan test statistic is expressed by the following formula, with the decision rule reject H_0 if $BP > \chi^2_{(k)}$ (Griffith & Anselin, 1989).

$$BP = \frac{1}{2} f^T Z (Z^T Z)^{-1} Z^T f \sim \chi^2_{(k)} \tag{3}$$

where:
f : $(f_1, f_2, \dots, f_n)^T$ with $f_i = \left(\frac{e_i^2}{\hat{\sigma}^2} - 1\right)$
e_i : $y_i - \hat{y}_i$ where $\hat{y}_i$ is obtained using the ordinary least square (OLS) method
$\hat{\sigma}^2$: estimated variance of y
Z : an $n \times k$ matrix containing standardized vectors for each observation

Next, the optimal bandwidth is based on the lowest CV value. Bandwidth measures how distance reduces influence the farther the distance, the smaller the weight. It defines the radius where observations still affect estimates at point i (Agustina et al., 2015). A larger bandwidth gives smoother results but increases bias. The core idea of the cross-validation (CV) approach is to minimize CV(k). Its core concept is the leave-one-out approach, in which the regression function is evaluated by excluding the i-th observation in turn. The best bandwidth is selected based on the smallest prediction error (i.e., the smallest sum of squared errors) for the response variable. The cross-validation method is defined as follows (Chamidah et al., 2023).

$$CV = \sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq 1}(h)\right)^2 \tag{4}$$

Subsequently, the optimal kernel weighting function is chosen by considering the minimum CV value and the maximum R-squared value. The weighting in the GWR model reflects the spatial relationship between observations. The weighting scheme in GWR can be implemented using various methods, one of which is the kernel function, which serves to estimate the parameters within the GWR model. The following are several weighting functions derived from kernel functions (Siti Hartina Daulay & Elmanani Simamora, 2023).

a. Fixed Gaussian Kernel

$$w_{ij}(u_i, v_i) = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^2\right] \tag{5}$$

b. Fixed Bi-square Kernel

$$w_{ij}(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2 & ;\ d_{ij} \le h \\ 0 & ;\ d_{ij} > h \end{cases} \tag{6}$$

c. Adaptive Gaussian Kernel

$$w_{ij}(u_i, v_i) = \exp -\frac{1}{2}\left(\frac{d_{ij}}{h_i}\right)^2 \tag{7}$$

d. Adaptive Bi-square Kernel

$$w_{ij}(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2 & ;\ d_{ij} \le h \\ 0 & ;\ d_{ij} > h \end{cases} \tag{8}$$

where:

h : non-negative/smoothing parameter (bandwidth)

d_{ij} : Euclidean distance between locations (u_i, v_i)

C. RESULT AND DISCUSSION

1. Descriptive Statistics

Descriptive statistics refer to statistical methods that encompass the processes of data collection, processing, and presentation to generate meaningful insights (Walpole et al., 2011). The primary function of descriptive statistics is to depict the characteristics of the subject under study, thereby making the presented data more accessible and informative for readers, whether drawn from a sample or an entire population (Nasution, 2020). Its purpose is to provide a general overview of the data without aiming to draw deeper or inferential conclusions (Nuryadi et al., 2017). The characteristics of child malnutrition in East Java and its suspected influencing factors are presented in Table 2.

Table 2. Characteristics of Child Malnutrition Incidence in East Java

Variable	N	Mean	Maximum	Minimum
Y	38	0.634	0.00	2.50
X_1	38	5.424	1.60	15.60
X_2	38	93.71	63.30	106.00
X_3	38	72.47	34.70	137.20
X_4	38	92.35	69.74	100.00
X_5	38	96.79	77.00	100.00
X_6	38	90.46	48.78	100.00
X_7	38	104.8	6.60	240.10

2. GWR Assumption Test

Before conducting the analysis using GWR, spatial dependency and spatial heterogeneity assumptions were first tested. The dependency test was applied to the response variable, namely the prevalence of child malnutrition.

a. Spatial Dependency

Spatial dependency was assessed using Moran's I test, under the following hypotheses.

$H_0: I = 0$

$H_1: I \neq 0$

The outcome of the spatial autocorrelation test is shown in Table 3.

Table 3. Moran's I Statistic Results

$\boldsymbol{I}$	$\boldsymbol{E(I)}$	$\boldsymbol{P_{value}}$
0.10449846	-0.02702702	0.00909986

The results of the spatial dependency test for the responses variable (the rate of malnutrition among toddlers) show that the significance value of Moran's I is 0.00909986 which is less than the 5% alpha level, thus H_0 can be rejected. This indicates that the rate of malnutrion among toddlers in East Java Province has a spatial relationship. Viewed from the positive Moran's I value, which is greater than the expected value of I, it was found that the formed spatial pattern is a clustered pattern with positive autocorrelation characteristics.

b. Spatial Heterogeneity

Next is the spatial heterogeneity test. This test is conducted to assess the presence of spatial heterogeneity effect on the data. Based on the Breusch-Pagan test statistic, the following hypotheses are evaluated was obtained.

H_0: $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_{38}^2 = \sigma^2$ (the absence of spatial heterogeneity

H_1: at least one is present I where $\sigma_i^2 \neq \sigma^2$ (there is spatial heterogeneity)

Critical area rejects H_0 if $p_{value} < \alpha$ (0.05).

The results of the spatial heterogeneity test can be seen in Table 4 below.

Table 4. Breusch-Pagan Test Result

Breusch Pagan Test	$\boldsymbol{DF}$	$\boldsymbol{P_{value}}$
14,237	7	0,02437

The Breusch-Pagan test confirmed the presence of spatial heterogeneity (p = 0.024), validating the need for a spatial modelling approach such as GWR. This finding highlights that the relationship between malnutrition and its determinants is not uniform across East Java. It suggests that localized policy strategies rather than province-wide interventions may be more effective in addressing child malnutrition.

3. Selection of Optimum Weight

The selection of optimal weights using the criteria of CV and R-Square values for each weight can be seen in Table 5. The weighting is considered optimal if the CV values is small and the R^2 value is large.

Table 5. Selection Criteria

Model	**Kernel Weighting Function**	**CV**	$\boldsymbol{R^2}$
OLS	-	0.504915	0.898332
GWR	Fixed Gaussian	0.505360	0.918901
GWR	Fixed Bi-Square	0.510918	0.908300
GWR	Adaptive Gaussian	0.505360	0.918901
GWR	Adaptive Bi-Square	0.133596	0.941520

Based on Table 5, the comparison of kernel functions with reference to the model goodness values shows that the Adaptive Bi-Square kernel function yields the lowest CV value 0.133596. this weight has an optimum bandwidth value of 3.0. another goodness-of-fit measure is the R^2, which shows a high value of 94.15%, meaning that the model can explain the actual condition by 94.15%, whereas the remaining 5.85% is attributed to other independent variables not accounted for in this analysis. Therefore, it can be concluded that by comparing all regarding the model's fit, the Adaptive Bi-Square kernel function is applied.

4. Spatial Variability Test

Next, a spatial variability test is conducted to determine whether the independent variable is a global variable or a local variable. This test is represented by geographically variability test of local coefficients. Independent variables are said to be global variables or, in the other words, there is no spatial variability. If the value of the DIFF of criterion is positive. Conversely, an independent variable is said to be a local variable or to have spatial variability if the DIFF of criterion value is negative. The results of the spatial variability test are shown in Table 6 below.

Table 6. Spatial Variability of the GWR Model with an Adaptive Kernel

Variable	DIFF of Criterion	Value	Remarks
Intercept	-2.99534	Negative	Local Variable
X_1	-0.57989	Negative	Local Variable
X_2	-1.40743	Negative	Local Variable
X_3	-2.63918	Negative	Local Variable
X_4	-0.77903	Negative	Local Variable
X_5	-3.98734	Negative	Local Variable
X_6	-1.31255	Negative	Local Variable
X_7	-5.75366	Negative	Local Variable

Based on Table 6, all DIFF of criterion measures are negative, indicating that the research variables in this regression are considered local variables. This indicates that the application of the GWR model is appropriate.

5. GWR Model Fit Test

The next stage of analysis s to compare the GWR model with global regression (OLS) in explaining the cases of malnutrition rates among toddlers in the regencies/cities of East Java Province. Table 7 displays the goodness of fit test results for the GWR model.

Table 7. ANOVA GWR Model

Source	SS	df	MS	F
Global Residuals	9.177	30.000		
GWR Improvement	8.429	27.456	0.307	
GWR Residuals	0.749	2.544	0.294	10.42861

The suitability of the GWR model is indicated when H_0 is rejected ($F > F_{\alpha,df_1,df_2}$) and it is concluded that GWR is not the same as the global model (OLS). The F test statistics obtained is 2.04286 with degrees of freedom df_1 and df_2 of 30.000 ($\approx$ 30) and 27.456 ($\approx$ 27), respectively, the F value for $\alpha = 5\%$ is $F_{\alpha(df_1,df_2)} = F_{0.05,30,27} = 6{,}416$ (see the F table). Therefore, the F test result $F(10.42861) > 6.416$ leads to the decision to reject H_0. it can be concluded hat the GWR model is superior in explaining the level of malnutrition among toddlers in East Java regencies compared among toddlers in East Java regencies compared to the global regression model.

6. Significance Test Partial Local Parameter of the GWR Model

Partial significance testing is used to determined predictor variables that have a significant influence on the Malnutrition Rate in Toddlers in Regencies/cities of East Java Province. In this test, the hypothesis is formulated as follows.

$H_0: \beta_k (u_i, v_i) = 0$ (The k-th predictor variable at the i-th location does not have a significant effect on the response variable)

$H_1: \beta_k (u_i, v_i) \neq 0$ (The k-th predictor variable at the i-th location has a significant effect on the response variable)

where $k = 1,2, \dots, p$ dan $i = 1,2, \dots, n$. With statistic test as follows below.

$$t_{i,k} = \frac{\hat{\beta}_k (u_i, v_i)}{s\left(\hat{\beta}_k (u_i, v_i)\right)} \tag{9}$$

The rejection region for the significance test of the partial significance level (α) is H_0 rejected if the value $\left|t_{i,k}\right| > t_{\frac{\alpha}{2(df)}}$. Based on the parameter estimation results, it was found that each region exhibits different sets of significant predictors. To illustrate these spatial differences, two regencies Tuban and Trenggalek were selected for comparison. Tuban Regency was chosen as one of the examples because it had five predictor variables that showed significant effects on the under-five child malnutrition rate. Accordingly, the partial significance testing for this regency is formulated as follows.

$H_0: \beta_k (u_{23}, v_{23}) = 0$ (The k-th predictor variable at the i-th location does not have a significant effect on the response variable)

$H_1: \beta_k (u_{23}, v_{23}) \neq 0$ (The k-th predictor variable at the i-th location has a significant effect on the response variable)

The results of the partial significance test of local parameters for Tuban Regency were obtained using the OSS-GWR4 software and are briefly summarized in Table 8.

Table 8. Uji Significant Parsial Test Local Parameter GWR Model Tuban Regency

Parameter	$\left\|t_{23,k}\right\|$	$t_{0,05(30)}$	Decision
β_1	2.15151		H_0 rejected
β_2	-0.61320		H_0 accepted
β_3	-0.33378		H_0 accepted
β_4	2.98558	2.04227	H_0 rejected
β_5	3.65762		H_0 rejected
β_6	2.55339		H_0 rejected
β_7	2.39619		H_0 rejected

As shown in Table 8, the parameter $\beta_1, \beta_4, \beta_5, \beta_6$, and β_7 were found to be statistically significant, leading to the rejection of H_0, in contrast, β_2 and β_3 were not significant, resulting in a failure to reject H_0. These findings indicate that the predictor variables Prevalence of Low Birth Weight (LBW), Households with Access to Improved Sanitation, Number of Integrated Health Posts (Posyandu), Households with Clean Water Access, and Percentage of Poor

Population have a significant influence on the prevalence of child malnutrition in regencies/cities across East Java.

In addition to Tuban Regency, Trenggalek offers a meaningful contrast in terms of significant predictors. While child malnutrition in Tuban is primarily influenced by infrastructural and environmental factors, these variables were found to be significant at Location 3 within the regency-level analysis in East Java Province. Accordingly, the hypothesis for the partial significance test at this location can be formulated as follows.

$H_0: \beta_k\,(u_3, v_3) = 0$ (The k-th predictor variable at the i-th location does not have a significant effect on the response variable)

$H_1: \beta_k\,(u_3, v_3) \neq 0$ (The k-th predictor variable at the i-th location has a significant effect on the response variable)

The results of the partial significance test of local parameters for Trenggalek Regency were obtained using the OSS-GWR4 software and are briefly summarized in Table 9.

Table 9. Uji Significant Parsial Parameter Lokal Model GWR Kabupaten Trenggalek

Parameter	$\lvert t_{33,k} \rvert$	$t_{0{,}05(30)}$	Decision
β_1	0.51259		H_0 accepted
β_2	-0.62546		H_0 accepted
β_3	2.16103		H_0 rejected
β_4	0.45914	2.04227	H_0 accepted
β_5	-2.72802		H_0 accepted
β_6	2.91724		H_0 rejected
β_7	0.1952		H_0 accepted

Spatially, these two regencies are located in different parts of East Java Tuban in the northern region and Trenggalek in the southern coastal area indicating regional diversity in malnutrition drivers. These findings emphasize the importance of localized strategies tailored to the unique determinants present in each area, as opposed to one-size-fits-all programs.

7. Grouping 38 Regencies/Cities Based on Similarity of Significant Variables Visualized Graphically

The visualization results are presented in Figure 3 below.

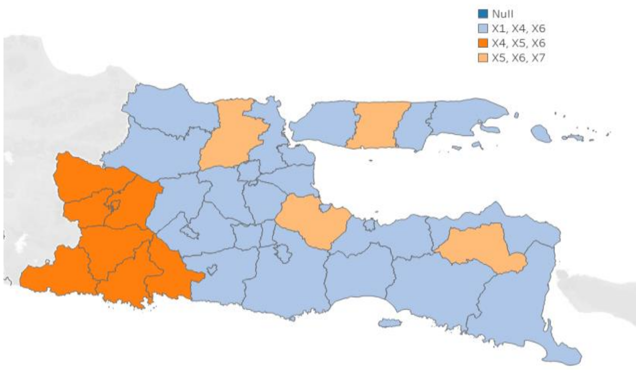

Figure 3. Clustering of Regencies/Cities Based on Signficant Variables

This study reveals that East Java's regencies and cities can be grouped based on similarities in significant predictor variables of under-five child malnutrition identified through GWR modelling. Regions within the same cluster often share key influencing factors particularly low birth weight (X_1), access to sanitation (X_4), and access to clean water (X_6) which reflect common underlying causes and spatial autocorrelation. These findings highlight the importance of spatially informed, region-specific health policies. The results are consistent with previous studies by Azkia & Setiawan (2022) and Hutabarat et al. (2016), both of which demonstrated the superiority of GWR in capturing regional variations in malnutrition determinants. The observed spatial patterns further affirm GWR's effectiveness in uncovering localized health risks and guiding more targeted interventions.

D. CONCLUSION AND SUGGESTIONS

This study concludes that spatial modelling using Geographically Weighted Regression (GWR) effectively identifies local variations in the determinants of child malnutrition across regencies in East Java. In alignment with the research objectives, the model reveals that the prevalence of low birth weight, access to sanitation, the number of *Posyandu*, clean water access, and poverty rate are significant predictors, each varying in influence across regions. These findings emphasize the importance of region-specific health policies: infrastructure-focused interventions in areas like Tuban and behavioral health education in regions such as Trenggalek. The study contributes to public health planning by offering localized, evidence-based insights for policymakers. However, these conclusions are limited to the selected variables and the spatial context of East Java, and further research is needed to generalize the results to broader settings.

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