

Mapping Food Insecurity: Spatial Modelling of Undernourishment Prevalence in Indonesia using Geographically Weighted Regression

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ABSTRACT

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Undernourishment is a major global issue, with significant impact observed in Indonesia. A method of assessing the prevalence of energy deficiency resulting from inadequate nutrition is through the Prevalence of Undernourishment (PoU) index. From 2019 to 2022, Indonesia's PoU increased gradually, reaching 10.21% in 2022, indicating growing undernourishment and unstable food availability. This study aims to utilize Geographically Weighted Regression (GWR) to identify and analyze the factors contributing to undernourishment. The data were obtained from the Central Bureau of Statistics (BPS) in 2024, covering 38 provinces in Indonesia. This study examined six factors: per capita spending, access to potable water, mean years of schooling, access to adequate sanitation, college participation rate, and mean food expenditure. The findings show that the GWR model outperformed the conventional model, demonstrating greater explanatory power by accounting for 96.1% of the spatial variation in undernourishment and achieving the lowest AIC value of 176.7052. These findings highlight the need for region-specific food security policies, particularly in eastern Indonesia. The results can inform targeted government interventions and guide future spatial econometric research on food security.



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A. INTRODUCTION

Food insecurity remains a persistent challenge across Southeast Asia, especially in populous countries such as Indonesia. According to the 2022 Global Hunger Index (GHI), Indonesia ranks 77th out of 121 countries, with a moderate GHI score of 17.9. This places Indonesia as the country with the third-highest hunger level in ASEAN, following Timor Leste (30.6) and Laos (19.2) (Global Hunger Index, 2024). The Prevalence of Undernourishment (PoU), a core indicator of food security, measures the percentage of the population whose daily energy intake falls below the minimum required for a healthy and active life (Rahut et al., 2022; FAO, IFAD, UNICEF, WFP, 2021; Nzeh et al., 2024). In Indonesia, PoU has shown a concerning trend, decreasing from 8.93% in 2016 to 7.63% in 2019, only to rise sharply to 10.21% by 2022, reflecting a 2.58% increase over four years (Rahmanto et al., 2020; Suryana et al., 2021; Badan Pusat Statistik, 2024). This resurgence raises concerns about the effectiveness and sustainability of food security policies, especially post-pandemic.

Since 2024, Indonesia has launched the Free Nutritious Meal Program led by President Prabowo, aiming to reduce food insecurity and stunting by reaching over 83 million children,

toddlers, and pregnant women. However, the program faces multifaceted challenges from technical issues to operational overload. In January 2025, several students at SDN Dukuh 03 Sukoharjo experienced nausea after consuming distributed meals, signaling gaps in safety standards (Tempo.co, 2025). Moreover, menu adjustments during Ramadan 2025 raised concerns about nutritional adequacy, as substitutions like *batagor* and *pempek* lacked essential macro and micronutrients. The program's funding requirements projected to exceed Rp460 trillion annually by 2029 highlight the urgency of evidence-based evaluation of food adequacy policies (Badan Pusat Statistik, 2024; Istiqomah, 2022; Tempo.co, 2025).

Beyond policy implementation, a deeper understanding of the structural determinants of PoU is required. Several cross-national studies suggest that increases in GDP per capita, food availability, and public health investment significantly reduce PoU rates (Mejia, 2023; Rahut et al., 2022; Shareef et al., 2023). In Indonesia, provincial-level disparities reveal that PoU is not only a matter of economics but also of access to sanitation, water, and education (Badan Pangan Nasional, 2022; Otsuka et al., 2019). Therefore, localized analysis is needed to identify specific regional drivers. For instance, women's education has been shown to correlate strongly with child nutrition outcomes and overall household food sufficiency (Mumtaza, 2024).

Geographic proximity and regional characteristics contribute significantly to food insecurity. Spatial clustering of PoU in Eastern Indonesia and parts of Kalimantan suggests that food insecurity may not be randomly distributed, but rather spatially autocorrelated (Badan Pusat Statistik, 2024; Cartone et al., 2022; Nzeh et al., 2024). While income and infrastructure are commonly cited predictors, similar PoU rates among neighboring provinces suggest the presence of interregional dependence. Furthermore, high food expenditure proportions in vulnerable households do not always indicate nutritional adequacy in many cases, it reflects limited capacity to meet non-food needs, increasing vulnerability to economic shocks.

Conventional global regression models such as Ordinary Least Squares (OLS) are ill-equipped to handle such spatial heterogeneity. They assume homogeneity of relationships across regions, often masking localized variations. Models like the Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) address spatial autocorrelation, but still treat spatial effects globally (M. Zhang & Liu, 2022)(Anselin, 1988)(Baltagi & Liu, 2024). Geographically Weighted Regression (GWR), on the other hand, allows coefficients to vary across locations, capturing spatial nonstationarity and local dynamics (Brunsdon et al., 1996)(Oshan et al., 2020)(L. Zhang & Shi, 2004). This makes GWR particularly useful for modelling phenomena like food insecurity, where spatial variation is significant.

Recent studies have demonstrated the effectiveness of GWR in a range of domains, including environmental change, health outcomes, and poverty mapping (Marcella Gloria Leto Bele Hermanto et al., 2022; Rahmila et al., 2024; Suciptawati et al., 2023). In these applications, GWR consistently outperformed global models, revealing hidden spatial patterns and offering actionable local insights. This suggests that adopting GWR for food insecurity analysis in Indonesia could yield similar benefits. The method's capacity to apply localized weights enhances the sensitivity of models to regional nuances in variables such as access to clean water, educational attainment, and food expenditure (Bivand et al., 2013; Kim, 2019; Wei et al., 2019).

Based on real-world conditions, this study aims to analyze the spatial influence of food insecurity across 38 provinces in Indonesia using the Geographically Weighted Regression (GWR) method. Unlike previous studies, it introduces updated predictor variables such as Expenditure per Capita, Access to Clean Drinking Water, Average Years of Schooling, Access to Adequate Sanitation, Gross Enrollment Rate in Higher Education, and Average Food Expenditure and a more advanced spatial approach. The research aims to enhance understanding of the factors driving PoU and provide targeted policy recommendations to reduce undernourishment prevalence nationwide. Thus, the results of this study are expected to contribute to formulating integrated, contextual, and sustainable strategies to reduce PoU and support the achievement of food security in Indonesia.

B. METHODS

1. Data and Research Variable

The type of research employed in this study is quantitative research using secondary data obtained from the official website of Statistics Indonesia (BPS). This study aims to model the Prevalence of Undernourishment based on spatially varying factors that are suspected to influence it. The type of research employed in this study is quantitative research, utilizing secondary data sourced from the official website of Central Statistics Bureau (BPS).

The dataset encompasses all 38 provinces in Indonesia and consists of a response variable and six predictor variables relevant to food security and socio-economic conditions. The main instrument of this study is a data extraction and coding framework, which involves collecting, compiling, and transforming official BPS statistical indicators into a structured format suitable for quantitative analysis using Geographically Weighted Regression (GWR). The operationalization of each variable is detailed in Table 1 below.

Table 1. Research Variables

Variable	Description	Scale
Y	Prevalence of Food Insufficiency	Ratio
X_1	Expenditure per Capita	IDR
X_2	Access to Clean Water	Ratio
X_3	Average Years of Schooling	Year
X_4	Access to Adequate Sanitation	Ratio
X_5	Gross Enrollment Rate in Higher Education	Ratio
X_6	Average Food Expenditure	IDR

a. Prevalence of Undernourishment

The Sustainable Development Goals (SDGs) aim to ensure sustainable development that promotes the improvement of economic welfare and enhances quality of life (BAPPENAS., 2020). Among the 17 SDGs is the goal of Zero Hunger. One of the indicators used to measure the achievement of this goal is the Prevalence of Undernourishment (PoU). Undernourishment is defined as a condition in which an individual consumes an insufficient amount of food to provide the energy required for a normal, active, and healthy life (FAO, IFAD, UNICEF, WFP, 2021). According to the National Food Agency (2021), the formula for calculating the prevalence of undernourishment is as follows:

$$\text{PoU} = \left(\frac{\text{Number of People Experiencing Undernourishment}}{\text{Total Population}} \right) \times 100\% \quad (1)$$

b. Per Capita Expenditure

Average per capita expenditure is one of the important indicators used to measure the level of societal welfare. According to Statistics Indonesia (BPS), average per capita expenditure is the total cost incurred for the consumption of all household members during the last week, including goods obtained through donations, purchases, or self-production, divided by the number of individuals in the household. Based on Keynes' theory, when a person receives additional income, their consumption increases; however, the amount of consumption will not be as great as the increase in income (Duarsa & Wijaya, 2023). This implies that consumption behavior tends to decline proportionally with income growth, which affects the distribution of household expenditure (Puspita & Agustina, 2020). Furthermore, per capita expenditure is used as an indicator to estimate the standard of living and purchasing power, both of which are closely related to national welfare (Nizar & Arif, 2023).

$$\text{Per capita expenditure} = \frac{\text{total expenditure}}{\text{total population}} \quad (2)$$

c. Access to Safe Drinking Water

According to the Regulation of the Minister of Health of the Republic of Indonesia No. 492/MENKES/PER/IV/2010, safe drinking water is defined as water that meets physical, microbiological, chemical, and radioactive requirements. This includes water obtained through processing or unprocessed sources. Based on BPS definitions, protected sources include piped water, public taps, protected springs, protected wells, boreholes, and rainwater collection, provided they are at least 10 meters away from waste disposal facilities. These sources must either be safe for direct consumption or undergo further testing to confirm their quality. The formula for calculating the percentage of households with access to safe drinking water is as follows:

$$PRT = \left(\frac{n_a}{N} \right) \times 100\% \quad (3)$$

with PRT is Percentage of Households; n_a is Number of Households Using a Specific Water Source; and N is Total Number of Households.

d. Average Years of Schooling

Education is a fundamental aspect of development (Todaro, Michael P.; Smith, 2012). Average years of schooling represents the average number of completed years of formal education by individuals aged 25 years and older (Meilinna et al., 2023). It serves as a key indicator to assess educational attainment in a population.

$$I_{RLS} = \frac{RLS - RLS_{min}}{RLS_{max} - RLS_{min}} \quad (4)$$

with I_{RLS} is Index of average years of schooling; RLS is Average years of schooling; RLS_{min} is Minimum average years of schooling; and RLS_{max} is Maximum average years of schooling.

e. Access to Adequate Sanitation

Adequate sanitation refers to facilities that meet health standards, such as water-sealed toilets with proper waste disposal systems (e.g., septic tanks or centralized sewage systems). According to the Ministry of Health Regulation No. 829/Menkes/SK/VII/1999, adequate sanitation requires proper drainage, waste management, and food hygiene practices to prevent contamination and disease transmission.

$$\text{Access to Adequate Sanitation} = \left(\frac{\text{Number of Households with Access to Adequate Sanitation}}{\text{Total Number of Households}} \right) \times 100\% \quad (5)$$

f. Gross Enrollment Rate in Higher Education

One of the state's goals outlined in the 1945 Constitution is to improve the nation's intellectual capacity. Quality education plays a central role in achieving this goal. The Gross Enrollment Rate (GER) is a key statistical indicator used to assess participation in education. Specifically, GER in higher education refers to the percentage of the population aged 19–23 years enrolled in universities. Higher Education GER values indicate greater access to tertiary education (Istiqomah, 2022).

$$\text{GER in Higher Education} = \left(\frac{\text{Number of University Students}}{\text{Population Aged 19 – 23 Years}} \right) \times 100\% \quad (6)$$

g. Average Food Expenditure

Average food expenditure refers to the average cost incurred by households for food consumption over a specific period, including food obtained through purchase, donation, or self-production. According to BPS, this includes all food and beverages consumed both at home and outside, expressed in monetary terms and averaged across surveyed households (BPS, 2022).

$$\text{Average Food Expenditure} = \frac{\sum_{i=1}^n \text{Total Food Expenditure of Household } i}{\sum_{i=1}^n \text{Number of Family Members in Household } i} \quad (7)$$

2. Research Metodology

Data analysis was carried out in several stages, namely modelling with multiple linear regression and GWR model. The complete analysis procedure can be written as follows.

- Describe the characteristics of the Prevalence of Undernourishment in Indonesia and the factors that are thought to influence it using descriptive statistics and thematic maps.
- Modeling with multiple linear regression.

The complete analysis procedure in modelling with multiple linear regression can be written as follows.

1) Conduct a multicollinearity test by looking at the Variance Inflation Factor (VIF) value (Kim, 2019)

2) Conducting spatial effect testing.

Spatial dependency is a test conducted to determine indications of the influence of a location on observations at other locations. The existence of spatial dependency can be known by conducting several types of tests such as Lagrange Multiplier, Wald, Likelihood Ratio, and Moran's I (Baltagi & Liu, 2024).

a) Conduct Moran's I test for testing spatial autocorrelation

The Moran's I measure is stated as follows:

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

Moran index value close to -1 or 1 indicates a high autocorrelation between residuals at one location and another. Meanwhile, the Moran index value of zero indicates that there is no autocorrelation between residuals at one location and another. Hypothesis testing of spatial dependency tests using Moran's I test statistics is as follows.

$$H_0 : I = 0$$

$$H_1 : I \neq 0$$

Moran's I test statistic is expressed as:

$$Z_I = \frac{\hat{I} - E(\hat{I})}{\sqrt{Var(\hat{I})}} \quad (9)$$

The decision criteria is to reject H_0 if $|Z_I| > Z_{\frac{\alpha}{2}}$

b) Conduct Breusch-Pagan test for testing spatial heterogeneity

Spatial heterogeneity or diversity found in each location is one of the characteristics of spatial data, especially with a point approach (Anselin, 1988). This spatial heterogeneity can be caused by the condition of spatial units in an observation area which are basically not homogeneous. Spatial heterogeneity testing can be carried out using the Breusch-pagan test with the following hypothesis

$$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2 \text{ (There is no spatial heterogeneity)}$$

$$H_1 : \text{there is at least one } i \text{ where } \sigma_i^2 \neq \sigma^2 \text{ (There is spatial heterogeneity)}$$

Breusch-pagan test statistic is expressed as (Arbia, 2006)

$$BP = \frac{1}{2} f^T Z (Z^T Z)^{-1} Z^T f \sim \chi_{(k+1)}^2 \quad (10)$$

The decision criteria is to reject H_0 if $BP_{hitung} > \chi_{(k)}^2$. If there is a spatial effect, it will be continued in GWR modeling

c. Modeling with Geographically Weighted Regression (GWR).

The complete analysis procedure in modelling with GWR can be written as follows.

- 1) Determine the optimum bandwidth based on the minimum Akaike Information Criterion (AIC) value.

The AIC score (Yanagawa & Tajiri, 2018) for a model with parameter θ is as follows.

$$AIC = -2L(\hat{\theta}) + 2v_0 \quad (11)$$

- 2) Selecting the best kernel weighting function by considering the minimum AIC and maximum R^2

One method that can be used in the GWR weighting scheme is the kernel function, which plays a role in estimating model parameters (Wei et al., 2019). Some weighting functions formed from kernel functions are as follows:

- a) Fixed Gaussian Function

$$w_{ij}(u_i, v_i) = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}}{h} \right)^2 \right] \quad (12)$$

- b) Fixed Bisquare Function

$$w_{ij}(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h} \right)^2 \right)^2, & \text{for } d_{ij} \leq h \\ 0, & \text{for } d_{ij} > h \end{cases} \quad (13)$$

- c) Adaptive Gaussian Function

$$w_{ij}(u_i, v_i) = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}}{h_i} \right)^2 \right] \quad (14)$$

- d) Adaptive Bisquare Function

$$w_{ij}(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_i} \right)^2 \right)^2, & \text{for } d_{ij} \leq h \\ 0, & \text{for } d_{ij} > h \end{cases} \quad (15)$$

- 3) Testing the suitability of the GWR model.

The purpose of this test is to compare the OLS model with the GWR model (Brunsdon et al., 1996). The following is the test Testing the suitability of the GWR model hypothesis.

$H_0 : \beta_k(u_i, v_i) = \beta_k$ (There is no significant difference between the OLS model and the GWR model)

$H_1 : \beta_k(u_i, v_i) \neq \beta_k$ (There is a significant difference between the OLS model and the GWR model)

with $k = 1, 2, \dots, p$ and $i = 1, 2, \dots, n$. The following test statistics are used.

$$F_{count} = \frac{SSE(H_1)/df_1}{SSE(H_0)/df_2} \quad (16)$$

The critical region rejects H_0 if the value of $F_{count} > F_{table}$.

- 4) Calculate the estimated value of the GWR model parameters with the best kernel function

The GWR model produces local model parameter estimates for each point or location where the data is observed. In the GWR model, the y variable is predicted by predictor variables whose regression coefficients depend on the location where the data is observed (Bivand et al., 2013). The GWR model can be written as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \quad i = 1, 2, 3, \dots, n \quad (17)$$

with: y_i is Observation value of i response variable; (u_i, v_i) is Geographical coordinates of the i observation location; $\beta_0(u_i, v_i)$ is Constant or intercept at the i -th observation; β_k is Coefficient or intercept at observation i ; $\beta_k(u_i, v_i)$ is Regression coefficient or intercept of k predictor variable at the i observation location; x_{ik} is Observation value of the k th predictor variable at the i observation location; and ε_i is Error of the i -th observation which is assumed to be IID and $N(0,1)$ distributed.

- 5) Testing the significance of the GWR model parameters partially.

The purpose of testing this parameter is to determine the significant effect of predictor variables in the model on the response variable partially (Mizumoto, 2023). The hypothesis used in this test is as follows.

$H_0 : \beta_j(u_i, v_i) = 0$ (There is no effect of predictor variables on the response variable partially)

$H_1 : \beta_j(u_i, v_i) \neq 0$ (There is an effect of predictor variables on the response variable partially)

The following test statistics are used.

$$t = \frac{\hat{\beta}_j(u_i, v_i)}{\hat{\sigma} \sqrt{c_{kk}}} \quad (18)$$

The decision criteria is to reject H_0 if $|t| > t_{(\alpha/2; n-p)}$ where n is the number of observations, and p is the number of parameters to be estimated.

- 6) Interpret the parameter estimation results of the GWR model.

d. Best model selection using R^2 and AIC criteria

Selection of the best model can be measured by calculating the R^2 value of each model (Serefoglu Cabuk et al., 2024). The best model is the model with the largest R^2 value. The formula for calculating R^2 .

$$R^2 = 1 - \frac{\sum_{i=1}^n (A_i - F_i)^2}{\sum_{i=1}^n (A_i - \bar{X})^2} \quad (19)$$

Besides using R^2 , the best model selection can also be done with AIC. The magnitude of the AIC value depends on the devians of the model, where the smaller the devians value, the lower the error rate produced by the model (Sutherland et al., 2023).

e. Draw conclusions from the results obtained.

C. RESULT AND DISCUSSION

1. Descriptive Analysis

The following discussion will present the characteristics of the incidence of inadequate food consumption in Indonesia, as well as the factors believed to influence it. These factors will be presented in the form of descriptive statistics. The data is displayed in Table 2 below.

Table 2. Descriptive Statistics of Variables

Variable	N	Average	Variance	Maximum	Minimum
Y	38	10,6677	46,956	31,66	2,55
X_1	38	12014,9411	4646370,055	19953	8534
X_2	38	89,4185	44,34235372	99,96	72,1
X_3	38	9,4814	0,552794896	11,49	8,28
X_4	38	85,0223	35,19011211	96,83	72,82
X_5	38	34,9182	90,61579689	73,9	20,14
X_6	38	754778,7	13375317627	1108228	541265

Based on Table 2, the Prevalence of Undernourishment (PoU) in Indonesia is 10,6677 and the variance value is 46,956 with a minimum value in Banten and a maximum value in Maluku. As shown in Figure 1, the Prevalence of Undernourishment in Indonesia is categorized into three levels: low, medium, and high. Twelve provinces have PoU in the low category, including Banten, West Nusa Tenggara, Bali, Greater Jakarta, South Kalimantan, South Sumatra, West Java, North Sulawesi, West Sulawesi, South Sulawesi, East Kalimantan, and North Sumatra. Meanwhile, 18 provinces have medium PoU categories. Specifically, the regions under consideration are East Java, Central Kalimantan, Central Java, West Sumatra, Yogyakarta, Aceh, the Riau Islands, Bengkulu, Southeast Sulawesi, Central Sulawesi, Jambi, Bangka Belitung, Lampung, South Kalimantan, North Kalimantan, and Gorontalo. A total of four provinces have been identified as having high PoU categories: West Papua, Papua, North Maluku, and Maluku.

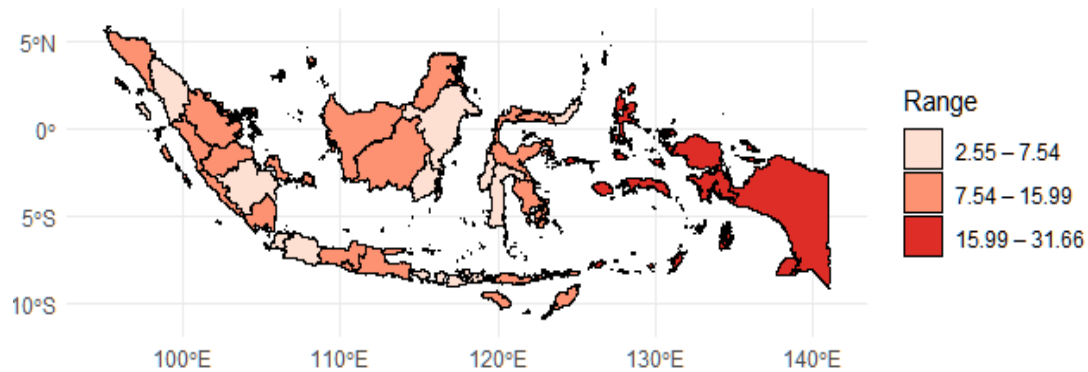


Figure 1. Thematic Map of Food Insufficiency Prevalence in Indonesia Year 2024

2. Multicollinearity Test

Multicollinearity detection using VIF value criteria is presented in Table 3.

Table 3. VIF Value

Variable	VIF
X_1	4,15
X_2	3,22
X_3	3,46
X_4	6,78
X_5	1,95
X_6	3,12

Table 3 shows that each independent variable's VIF value is less than 10. Therefore, the regression model does not show multicollinearity between the independent variables.

3. GWR Assumption Test

a. Spatial Dependency Test

Spatial dependency testing was conducted on the response variable defined as Prevalence of Undernourishment (PoU). The spatial dependency test using Moran's I test statistics uses the following hypothesis.

$$H_0 : I = 0$$

$$H_1 : I \neq 0$$

The result of the spatial autocorrelation test can be seen in Table 4 below.

Table 4. Spatial Dependence Test Result

I	E(I)	P-Value
0,85130011	-0,02702703	0,00000000000001275

The results of the spatial dependency test for the response variable (PoU) show that the p-value of Moran's I is 0,00000000000001275 less than alpha 5%, so it can be decided to reject H_0 . This indicates that the Prevalence of Undernourishment in the provinces of Indonesia has a spatial relationship. The results demonstrate that the spatial pattern is associated with positive outcomes that exceed the expected value of I. The formation of a clustered pattern is indicative of positive autocorrelation properties.

b. Spatial Heterogeneity Test

Subsequently, the spatial heterogeneity test is conducted. The objective of this test is to identify the presence of any spatial heterogeneity effect on the data by using statistics Breusch-Pagan test, the test hypothesis is obtained as follows.

$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma^2$ (There is no spatial heterogeneity)

$H_1 : \text{there is at least one } i \text{ where } \sigma_i^2 \neq \sigma^2$ (There is spatial heterogeneity)

The result of the spatial heterogeneity test can be seen in Table 5 below.

Table 5. Spatial Heterogeneity Test Result

Breusch Pagan	Degree of Freedom	P-Value
13,149	6	0,04073

The results of the spatial heterogeneity test show that the Breusch-Pagan p-value is $0.04073 < (0.05)$, so it can be decided to reject H_0 . This indicates that the spatial aspect is fulfilled, namely there is a spatial heterogeneity effect on the data.

4. Modeling With GWR

a. Optimal Weight Selection

Table 6 shows the selection of optimal weights based on the AIC and R-square values of each weight. Weights are considered optimal if they present a minimum AIC value and high R-square.

Table 6. Selection Criteria

Weight Function	Bandwidth	AIC	R ²
Fixed	Gaussian	6,638598	197,4785
	Bisquare	31,99857	212,0624
Addaptive	Gaussian	0,1101618	176,7052
	Bisquare	0,8254046	207,5731

Based on the Table 6, the results of comparing kernel functions with the reference value are as follows: The model's goodness shows that the adaptive Gaussian has the most minimum AIC value, at 176,7052. This weighting has an optimum bandwidth value of 5.347524. Another favorable value, R^2 , also indicates a high value of 0,96. This means that the model can explain the actual condition with 96%, while the remaining 4% is explained by other predictor variables not involved in the analysis. Therefore, based on the comparison results, it can be concluded that the kernel function used in this analysis is an adaptive Gaussian.

b. Spatial Variability Test

A spatial variability test determines whether the independent variable is global or local. This test represents geographic variability tests of local coefficients. An independent variable is considered global, or there is no spatial variability. If the difference in criterion value is positive. Conversely, an independent variable is a local variable, or there is spatial variability, if the difference in the criterion value is negative. The results of the spatial variability test are shown in Table 7 below.

Table 7. Spatial Variability of GWR Model with Addaptive Kernel

Variable	Diff of Criterion	Valuable	Conclusion
Intercept	-2,790787	Negative	Local Variable
X_1	-17,157441	Negative	Local Variable
X_2	-16,563400	Negative	Local Variable
X_3	-23,543053	Negative	Local Variable
X_4	-64,089889	Negative	Local Variable
X_5	-9,179085	Negative	Local Variable
X_6	-11,130510	Negative	Local Variable

Based on Table 7 all diff of criterion measures are negative, so the research variables in this regression model are considered as local variables. This indicates that the application of the GWR model is appropriate.

c. GWR Model Suitability Test

The next stage of analysis is to test whether there is a similarity between the multiple regression model and the GWR spatial regression model. The following is a test of the suitability of the GWR model in Table 8.

Table 8. Anova GWR Model

Model	DF	SSE	F-Count	P-Value
GWR	31	9,7106	9,3332	0,000446

From the calculation results obtained in Table 8, it is known that the value of Fcount is 9,3332 with p - value of 0,000446 and the value of F_{table} is $F(0,05; 31; 16,65) = 3,369382$ so that the value of $F_{count} > F_{table}$ or the p -value $(0.000446) < \alpha$. By using an α value of 0.05, the test results in a decision to reject H_0 . Thus, it can be concluded that there is a significant difference between the global regression model and the GWR model, so it can be said that the GWR model is appropriate.

d. GWR Partial Parameter Significance Test

Partial testing of GWR model parameters was conducted to determine which factors significantly influence the number Prevalence of Undernourishment (PoU) in Indonesia. This test was performed by paying attention to the p-value and t-count at each observation location. If the value of absolute t is greater than $t(0.025; 31) = 2,0395$, then H_0 is rejected, meaning that partial influence of the predictor variables on the response variable. Based on the parameters of the predictor variables that significantly affect Prevalence of Undernourishment (PoU) in each province in Indonesia, the results of GWR modeling with adaptive bisquare weighting functions form groups that are These groups are presented in Table 9.

Table 9. Significant Group of Variables in GWR Model

Significant Variables	Province
X_1	Riau Islands, West Kalimantan, Central Kalimantan, South Kalimantan, South Sulawesi, West Sulawesi
X_1, X_2	East Kalimantan
X_1, X_5	Southeast Sulawesi
X_1, X_3, X_4	East Nusa Tenggara
X_1, X_2, X_6	North Kalimantan
X_2, X_3, X_4	Papua, South Papua, Central Papua, Mountainous Papua
X_1, X_2, X_3, X_4	West Papua, Southwest Papua Barat
X_1, X_2, X_3, X_6	Central Sulawesi
X_1, X_2, X_5, X_6	North Sulawesi, Gorontalo, Maluku
X_1, X_2, X_4, X_5	North Maluku

e. GWR model interpretation

Based on the analysis of model fit testing which shows the results that there are differences between the regression results and the GWR results, then for each province has different significant variables and the magnitude of the coefficient different regression parameters. So that the shape of the resulting model is also not the same. One of the GWR models for Mountainous Papua Province is as follows.

$$\hat{y} = 16,24 + 0,618X_2 + 6,182X_3 - 1,07X_4 \quad (20)$$

Based on the model above, it can be interpreted that the clean drinking water access variable (X_2) has a positive relationship with the prevalence of food insufficiency (Y) in Mountainous Papua Province with a coefficient value of regression parameter of 0.6498. This can be interpreted that if access to clean drinking water increases by 1 unit, then the prevalence variable of food insufficiency will increase by 0.6498 units by holding other predictors constant. The variable average years of schooling (X_3) has a positive relationship with the Prevalence of Undernourishment (Y) in Mountainous Papua Province with a parameter value regression coefficient of 6.8139. This can be interpreted that every increase in the average length of schooling by 1 unit, the Prevalence of Undernourishment will increase by 6.8139 units by holding other predictors constant. The variable of access to proper sanitation (X_4) has a negative relationship with the Prevalence of Undernourishment (Y) in Mountainous Papua Province with a regression parameter value of -1.1287. This means that every increase in access to proper sanitation by 1 unit will decrease the Prevalence of Undernourishment by 1.1287 units with holding other predictors constant.

These findings are supported by Ejiohuo et al. (2024), who concluded that access to clean water and proper sanitation significantly affect a region's quality of life, given their strong links to education, environmental health, and economic inequality all of which are intertwined with food insecurity. The following section will present partial model testing results for each province in Indonesia to explore regional characteristics further. The results of this study are generally consistent with previous research findings by Mejia (2023) and Shareef et al. (2023), both of which highlight the negative relationship

between socio-economic development factors and the Prevalence of Undernourishment (PoU). In line with Mejia's conclusion that higher GDP per capita reduces PoU, this study found that expenditure per capita (X_1) is a significant factor in many provinces, such as the Riau Islands, West Kalimantan, and Southeast Sulawesi, suggesting that higher individual economic capacity contributes to better food access.

Similarly, this research supports Shareef et al.'s (2023) findings, where food supply and demand factors, as well as sanitation and education, play a key role in lowering PoU. Specifically, access to clean water (X_2), years of schooling (X_3), and adequate sanitation (X_4) emerged as significant in several undernourished provinces in Papua and Nusa Tenggara, indicating that infrastructure and education improvements directly influence food sufficiency. Overall, this study reinforces the view that multi-dimensional development, economic, educational, and infrastructural, is crucial in addressing undernourishment, and it adds a spatial dimension by showing how the influence of these factors varies geographically across Indonesia.

5. Best Model Selection

Determination of the best model between OLS and GWR in modeling the Prevalence of Undernourishment in provinces Indonesia in 2024, using criteria for the optimum AIC, and R^2 values as in Table 10 below.

Table 10. Comparison of OLS and GWR Models

Model	AIC	R^2
Model OLS (Global)	253,217	53%
Model GWR (Addaptive Gaussian)	176,7052	96%

Based on Table 10, the AIC values in the GWR model show smaller scores than the OLS model, which are 176,7052. The R^2 value in the GWR model shows a percentage that is greater than the OLS model, which is 96%. This indicates that the GWR model with adaptive gaussian weights is superior in modeling the modeling the Prevalence of Undernourishment in provinces Indonesia.

D. CONCLUSION AND SUGGESTIONS

Based on the analysis results, a multiple linear regression model and a GWR model were obtained. From the multiple linear regression analysis results, the model obtained fulfilled the assumption of residual normality and there was no multicollinearity. However, there is spatial autocorrelation and spatial heterogeneity, so an analysis was conducted using the GWR model. In selecting the kernel weight for the GWR model, it was found that the adaptive Gaussian kernel provides better model performance. Additionally, all research variables used are local in nature, making the GWR approach suitable for application. This is supported by statistical testing showing significant differences between the OLS model and the GWR model. Furthermore, the GWR model performs better than OLS because it has a smaller AIC value and a higher R-Square.

These findings underscore the importance of considering local characteristics in designing food security policies in Indonesia. The government and relevant stakeholders are encouraged

to develop more adaptive and targeted intervention strategies by focusing on key social and infrastructural factors contributing to food consumption inadequacy. Greater attention should also be directed toward Papua Mountainous Province, which exhibits the highest PoU in the country, by improving variabel yang signifikan secara local di wilayah tersebut, namely per capita expenditure, access to clean water, higher education enrollment rates, and household food expenditure.

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