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SPATIAL MODELING OF CHILD MALNUTRITION IN INDONESIA USING GEOGRAPHICALLY WEIGHTED MULTIVARIATE REGRESSION

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ABSTRACT

In Indonesia aspires to become a developed nation by 2045, with one of its key pillars being the improvement of human resource quality through the achievement of Sustainable Development Goal (SDG) 2. However, the prevalence of stunting, wasting, and underweight among children under five remains a critical challenge that hampers these efforts. This study aims to simultaneously analyze the determinants influencing these three forms of malnutrition among Indonesian children by incorporating spatial aspects through the Geographically Weighted Multivariate Regression (GWMR) approach. The data utilized in this study are derived from the 2023 Indonesia Health Survey Report 38 provinces across Indonesia were used as units of observation. The analysis employs nine predictor variables representing socioeconomic, demographic, and environmental factors across all provinces in Indonesia. The findings reveal that Complete Basic Immunization, Knowledge of Stunting Prevention, and Lower-Middle Economic Status consistently have significant effects on stunting and underweight. Meanwhile, Complete Basic Immunization and Complementary Feeding Practices play major roles in influencing wasting across provinces. Spatial analysis highlights varying patterns of determinants across regions. Western Indonesia (Java, Sumatra, and western Kalimantan) is more influenced by community behavior (mothers without a MCH Book, Children receiving complete basic immunizations receiving and children received complementary feeding), access to adequate sanitation, and lower-middle economic status. In contrast, Eastern Indonesia (Maluku and Papua) is more affected by structural conditions such as preterm births, low immunization coverage, knowledge of stunting prevention, and economic limitations. Central Indonesia demonstrates a more complex and varied combination of influencing factors. Furthermore, the GWMR model exhibits substantially better performance compared to the global (multivariate linear regression) model, as indicated by a significantly lower AIC value, Lower MAPE, and higher R-Square. These findings underscore the importance of spatially adaptive and decentralized nutrition policies to ensure more targeted and context-specific interventions

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1. INTRODUCTION

Indonesia has set forth a grand vision to become a developed nation by 2045 through the “Indonesia Emas 2045” initiative [1]. One of the key pillars to achieving this vision is the improvement of human resource (HR) quality, which is pursued in part by meeting the targets of the Sustainable Development Goals (SDGs), particularly Goal 2: "Zero Hunger," which includes the eradication of all forms of malnutrition by 2030 (United Nations, 2020). However, the nutritional status of young children in Indonesia still faces significant challenges toward achieving this goal. According to the Ministry of Health, in 2023 the prevalence of stunting was 21.5%, wasting was 8.5%, and underweight was 15.9% [2] indicating that Indonesia continues to struggle with meeting the nutritional needs of early childhood.

Malnutrition issues such as stunting, wasting, and underweight are not merely health problems; they are closely tied to the future development of human capital. These three conditions have long-term impacts on physical growth, cognitive development, and adult productivity [3]. Thus, evidence-based and effective interventions targeting child nutrition are crucial to strengthening the competitiveness of future generations and establishing a solid foundation for national development toward “Indonesia Emas”. Each type of malnutrition has distinct characteristics, although they are often interrelated. Stunting reflects chronic undernutrition, wasting indicates acute undernutrition, and underweight represents a combination of both [4]. The causes of malnutrition are complex, encompassing direct factors such as nutrient intake and health status, as well as indirect factors including environmental conditions, economic status, education, and food security [5]. This complexity necessitates analytical approaches capable of simultaneously capturing the interrelationships among multiple factors. In this context, relying solely on global regression models may overlook local variations and lead to biased policy recommendations, making it urgent to employ spatial multivariate approaches that can accommodate regional heterogeneity [6].

Statistical models such as multivariate linear regression are commonly employed to understand the relationships between various causative variables and malnutrition indicators simultaneously [7]. However, considering Indonesia’s diverse geographical conditions, spatial approaches are also needed. The Geographically Weighted Multivariate Regression (GWMR) model presents a promising solution as it accommodates local variations and spatial heterogeneity in the relationships among variables [8], [9].

Statistical models such as multivariate linear regression are commonly employed to understand the relationships between various causative variables and malnutrition indicators simultaneously [7]. However, this global approach, often estimated through Ordinary Least Squares (OLS), assumes spatial homogeneity and may fail to reflect local variations across different regions. To overcome this limitation, the Geographically Weighted Regression (GWR) model was developed, allowing the estimation of location-specific parameters and providing insights into spatial heterogeneity [9]. Nevertheless, GWR analyzes each dependent variable separately, which may overlook the correlations among multiple malnutrition indicators. In this regard, the Geographically Weighted Multivariate Regression (GWMR) model offers a distinct advantage by simultaneously modeling multiple response variables within a single framework [10]. GWMR not only accommodates local variations and spatial heterogeneity but also captures the interdependencies among stunting, wasting, and underweight, thus providing a more comprehensive understanding of their determinants compared to GWR. The application of GWMR is particularly urgent for Indonesia, where geographic, socioeconomic, and cultural disparities strongly influence nutritional outcomes, requiring models that not only estimate global trends but also capture localized dynamics.

Various spatial analysis methods have been applied in previous studies to examine child malnutrition. Study [11] and [12] utilized Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MGWR) to analyze spatial trends of stunting, with MGWR demonstrating superior performance. Research by [13] implemented Geographically Weighted Multivariate Poisson Regression (GWMPR) to simultaneously model stunting, wasting, and underweight cases in Southeast Sulawesi. Study [14] as well as [15] employed hotspot analysis to identify spatial clusters of malnutrition. Research by [16] and [17] applied multilevel Bayesian models to account for hierarchical regional effects. Study. [18] and [19] utilized geostatistical models to evaluate the impact of environmental factors on stunting. Study [17], [18] combined spatial analysis with regression models to explore factors influencing malnutrition. Collectively, these studies indicate that spatial modeling approaches generally outperform global models in representing malnutrition cases

Despite these advancements, several research gaps remain. First, most existing studies focus on a single malnutrition indicator (primarily stunting) or analyze multiple indicators separately, whereas multivariate analyses simultaneously addressing stunting, wasting, and underweight remain scarce. Second, although [13] applied GWMPR to all three indicators, the study was limited to a single Indonesian province and relied on census data. Third, no prior study has applied GWMR to analyze child malnutrition at the national scale in Indonesia. Therefore, this study provides novelty by being the first to employ GWMR for analyzing stunting, wasting, and underweight simultaneously across Indonesia, offering a comprehensive national-scale perspective that accounts for spatial heterogeneity while addressing multiple malnutrition dimensions at once.

This study aims to address these gaps by developing a GWMR model that integrates stunting, wasting, and underweight as response variables using provincial-level prevalence data across Indonesia. This approach is expected to provide a more comprehensive understanding of the spatial patterns and determinants of various forms of malnutrition among young children in Indonesia, as well as to identify local variations in the relationships between predictors and malnutrition indicators.

2. RESEARCH METHODS

2.1. Data and Research Variables

The data utilized in this study are derived from the 2023 Indonesia Health Survey Report (SKI) published by the Ministry of Health of the Republic of Indonesia (https://www.badankebijakan.kemkes.go.id/hasil-ski-2023/). A total of 38 provinces across Indonesia were used as units of observation. The variables employed in this research are presented in the Table 1 below.

Table 1. Research Variables [4]

Variables		Description
Responses	Y_1	Percentage of children under five experiencing stunting
	Y_2	Percentage of children under five experiencing wasting
	Y_3	Percentage of children under five experiencing underweight
Predictors	X_1	Percentage of mothers without a Maternal and Child Health (MCH) Book
	X_2	Percentage of births with gestational age less than 37 weeks
	X_3	Proportion of children aged 12–23 months receiving complete basic immunizations
	X_4	Proportion of children aged 6–23 months exclusively breastfed for six months
	X_5	Proportion of children aged >6 months routinely receiving complementary feeding
	X_6	Proportion of households with access to improved sanitation
	X_7	Prevalence of diarrhea among children under five
	X_8	Proportion of women aged >15 years with knowledge of stunting prevention
	X_9	Percentage of households with low to lower-middle economic status

Source: *Indonesia Health Survey Report 2023*

2.2 Multivariate Linear Regression

The multivariate linear regression model establishes relationships among p response variables, $Y_1, Y_2, \dots, Y_p$ and predictor variables $X_1, X_2, \dots, X_q$ The multivariate regression model for the p-th response can be expressed as follows [22]:

$$\begin{gathered} Y_1 = \beta_{01} + \beta_{11}X_1 + \cdots + \beta_{q1}X_q + \varepsilon_1, \\ Y_2 = \beta_{02} + \beta_{12}X_1 + \cdots + \beta_{q2}X_q + \varepsilon_2, \\ \vdots \\ Y_p = \beta_{0p} + \beta_{1p}X_1 + \cdots + \beta_{qp}X_q + \varepsilon_p. \end{gathered} \tag{1}$$

The residuals $\varepsilon' = [\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_n]$ satisfy $E(\varepsilon) = 0$ and $var(\varepsilon) = \Sigma$. Thus, the error terms associated with the multiple response variables are correlated. For n observations, the multivariate linear regression (MLR) model comprising m linear models simultaneously can be written as:

$$Y_{(n\times m)} = X_{(n\times(p+1))}\,\beta_{((p+1)\times m)} + \varepsilon_{(n\times m)}. \tag{2}$$

2.3 Spatial Heterogeneity

Heterogeneity testing in regression models is commonly conducted using the Breusch–Pagan (BP) test, which was originally developed to detect heteroskedasticity rather than spatial effects. In spatial applications,

the BP test is often employed to examine whether variance instability exists across spatial units, thereby serving as an indirect indication of spatial heterogeneity. The hypotheses of the BP test are:
$H_0 : \sigma_1^2 = \sigma_2^2 = \cdots = \sigma$ (homoscedasticity, no heterogeneity)
H_1 : At least one i where $\sigma_i^2 \neq \sigma$ (heterogeneity exists)

For a multivariate regression (multiple-response) framework, the BP test can be extended by constructing a joint test statistic that simultaneously evaluates variance instability across all response equations. In this case, the test statistic takes the general form [23]:

$$BP = \frac{1}{2}\boldsymbol{f}^{\boldsymbol{T}}\boldsymbol{Z}\left(\boldsymbol{Z}^{\boldsymbol{T}}\boldsymbol{Z}\right)^{-1}\boldsymbol{Z}^{\boldsymbol{T}}\boldsymbol{f} \sim \chi^2_{p-m}, \tag{3}$$

where $\boldsymbol{f}$ denotes the stacked vector of squared residuals from all m response variables, $\boldsymbol{Z}$ is the matrix of explanatory variables, and p is the number of predictors. This extension allows the BP framework to capture heteroskedasticity patterns in multiple outcomes simultaneously. The decision rule is to reject H_0 if BP > $\chi^2_{\alpha,(p+1)}$. In such cases, it can be concluded that heterogeneity exists.

2.4 Spatial Weighting Function

The optimal bandwidth in Geographically Weighted Multivariate Regression (GWMR) is determined by minimizing the Cross-Validation (CV) value, which is a function of bandwidth b. The CV value measures the model's predictive performance when each observation is excluded during model fitting. The CV formula is [6]:

$$CV = \sum_{i=1}^{n}\sum_{h=1}^{q}\left[y_{ih} - \hat{y}_{ih\neq i}\right]^2, \tag{4}$$

where y_{ih} is the observed value of the h-th response variable at the i-th location, $\hat{y}_{ih\neq i}$ is the predicted value without using the i-th observation (leave-one-out).

The kernel function defines the form of this weighting. An adaptive bisquare kernel is employed, which assigns a weight of zero for observations outside the adaptive bandwidth b_i and decreasing positive weights for observations within the bandwidth radius [9]:

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b_i}\right)^2\right)^2, & if \;\; d_{ij} \leq b_i, \\ 0, & if \;\; d_{ij} > b_i \end{cases} \tag{5}$$

where d_{ij} represents the distance between location i and location j and b_i denotes the adaptive bandwidth associated with location i. This weighting scheme ensures that observations closer to location i receive larger weights, while those beyond the bandwidth b_i receive a weight of zero.

The bandwidth b_i is determined through a cross-validation (CV) optimization procedure. Specifically, different candidate bandwidths are evaluated, and the one that minimizes the CV score is selected as the optimal bandwidth. In the adaptive scheme, b_i corresponds to the distance to the k-th nearest neighbor, where the optimal value of k is chosen based on the minimum CV criterion. This ensures that the weighting structure is both locally adaptive and statistically robust [9].

2.4 Geographically Weighted Multivariate Regression (GWMR)

GWMR is an extension of the multivariate spatial linear model, where parameter estimates are localized for each observation site. The GWMR model for the h-th response variable at location i is expressed as [10]:

$$Y_{ih} = \beta_{0h}(u_i, v_i) + \sum_{k=1}^{p}\beta_{kh}(u_i, v_i)X_{ik} + \varepsilon_{ih}. \tag{6}$$

The model parameters can be estimated using the Weighted Least Squares (WLS) method:

$$\widehat{\mathbf{B}}(u_i, v_i) = \ [\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i)\,\mathbf{X}]^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{W}(u_i, v_i)\mathbf{Y}, \tag{7}$$

with the estimator of $\widehat{\mathbf{B}}(u_i, v_i)$ is $\widehat{\mathbf{B}}(u_i, v_i) = \left[\hat{\beta}_1(u_i, v_i)\ \hat{\beta}_2(u_i, v_i)\ \ldots\ \hat{\beta}_q(u_i, v_i)\right]^T$.

The hypothesis test for model fit in Geographically Weighted Multivariate Regression (GWMR) is conducted to evaluate whether spatial heterogeneity exists in the regression coefficients. The hypotheses are defined as follows:

H_0: $\beta_{kh}(u_i, v_i) = \beta_{kh}\ \ k = 0,1,2, \ldots, p$ and $h = 1,2, \ldots, q$ (no difference between GWMR and MLR models)
H_1: $\beta_{kh}(u_i, v_i) \neq \ \beta_{kh}$ (indicating spatial variation).

The test compares the log-likelihood of the MLR model, denoted as $L(\widehat{\omega})$, with that of the GWMR model, $L(\widehat{\Omega})$ where the respective likelihoods are based on the following [10]:

$$L(\widehat{\omega}) = L\left(\widehat{\mathbf{B}}, \widehat{\mathbf{\Sigma}}_\omega\right) = (2\pi)^{\frac{nq}{2}}\left|\widehat{\mathbf{\Sigma}}_\omega\right|^{\frac{n}{2}} \exp\left(-\frac{nq}{2}\right)\ with\ \widehat{\mathbf{\Sigma}}_\omega = \frac{\left(\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{M})\mathbf{Y}\right)}{n}, \tag{8}$$

$$L\left(\widehat{\Omega}\right) = L\left(\widehat{\mathbf{B}}(u_i, v_i), \widehat{\mathbf{\Sigma}}_\Omega\right) = (2\pi)^{\frac{nq}{2}}\left|\widehat{\mathbf{\Sigma}}_\Omega\right|^{\frac{n}{2}} \exp\left(-\frac{nq}{2}\right)\ with\ \widehat{\mathbf{\Sigma}}_\Omega = \frac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S})^{\mathbf{T}}(\mathbf{I}-\mathbf{S})\mathbf{Y}}{\left(\frac{\delta_1^2}{\delta_2}\right)}, \tag{9}$$

$\delta_i = tr\left([(\mathbf{I}-\mathbf{S})^{\mathbf{T}}(\mathbf{I}-\mathbf{S})]^i\right), i = 1,2;$
$\mathbf{M} = \mathbf{X}\left(\mathbf{X}^{\mathbf{T}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathbf{T}}.$

The likelihood ratio test statistic, Wilks' Lambda, is formulated as.

$$\Lambda = \frac{L(\widehat{\omega})}{L\left(\widehat{\Omega}\right)} = \left(\frac{\left|\widehat{\mathbf{\Sigma}}_\omega\right|}{\left|\widehat{\mathbf{\Sigma}}_\Omega\right|}\right)^{-\frac{n}{2}}. \tag{10}$$

This can be expressed in terms of a test statistic U as:

$$(\Lambda)^{\frac{\mathrm{n}}{2}} = \frac{\left|\dfrac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S})^{\mathbf{T}}(\mathbf{I}-\mathbf{S})\mathbf{Y}}{\left(\frac{\delta_1^2}{\delta_2}\right)}\right|}{\dfrac{\left(\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{M})\mathbf{Y}\right)}{n}} = U. \tag{11}$$

The final decision rule involves an F-distribution approximation:

$$\left(\frac{1-U_{p,2,n}^{\frac{1}{2}}}{U_{p,2,n}^{\frac{1}{2}}}\right)\frac{(n-1-p)}{p} \sim F^*_{(p,(n-1-p))}. \tag{12}$$

Reject H₀ if $F^* > F_{(p,n-p-1)}$ indicating that the GWMR model fits the data significantly better than the standard MLR model.

Subsequently, simultaneous effects are tested using the Maximum Likelihood Ratio Test (MLRT) and approximated by Wilk's Lambda, expressed as [10]:

$$\Lambda = \frac{L(\widehat{\omega})}{L\left(\widehat{\Omega}\right)} = \left(\frac{\left|\dfrac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})^{\mathbf{T}}(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})\mathbf{Y}}{\left(\frac{\delta_{1\omega}^2}{\delta_{2\omega}}\right)}\right|}{\left|\dfrac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S})^{\mathbf{T}}(\mathbf{I}-\mathbf{S})\mathbf{Y}}{\left(\frac{\delta_1^2}{\delta_2}\right)}\right|}\right)^{-\frac{n}{2}}. \tag{13}$$

The statistic $(\Lambda)^{\frac{\mathrm{n}}{2}}$ follows an F-approximation defined as:

$$(\Lambda)^{\frac{n}{2}} = \frac{\left|\dfrac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S})^{\mathbf{T}}(\mathbf{I}-\mathbf{S})\mathbf{Y}}{\left(\frac{\delta_1^2}{\delta_2}\right)}\right|}{\left|\dfrac{\mathbf{Y}^{\mathbf{T}}(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})^{\mathbf{T}}(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})\mathbf{Y}}{\left(\frac{\delta_{1\omega}^2}{\delta_{2\omega}}\right)}\right|} \sim F_{\left(\frac{\delta_{1\omega}^2}{\delta_{2\omega}},\frac{\delta_1^2}{\delta_2}\right)}, \tag{14}$$

where $\mathbf{S}_{\boldsymbol{\omega}}$ is the smoother matrix under the null hypothesis, and the trace parameters are defined as:

$$\delta_{i\omega} = tr\left([(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})^{\mathbf{T}}(\mathbf{I}-\mathbf{S}_{\boldsymbol{\omega}})]^{i}\right), i = 1,2. \tag{15}$$

Using a significance level (α) we reject H_0 if $F > F_{\left(\frac{\delta_{1\omega}^2}{\delta_{2\omega}},\frac{\delta_1^2}{\delta_2}\right)}$.

Partial parameter testing identifies which parameters significantly affect the response variables. The hypotheses are:

$H_0 : \beta_{kh}(u_i, v_i) = 0$
$H_1 : \beta_{kh}(u_i, v_i) \neq 0$

for $i = 1,2, \dots, n; k = 0,1,2, \dots, p;$ and $h = 1,2, \dots, q$

The test statistic is [10]:

$$t = \frac{\hat{\beta}_{kh}(u_i, v_i)}{SE\left(\hat{\beta}_{kh}(u_i, v_i)\right)}, \tag{16}$$

with $SE\left(\hat{\beta}_{kh}(u_i, v_i)\right) = \sqrt{g_{kk}}$; g_{kk} is the (k+1) -th diagonal element of the matrix $(\boldsymbol{X}^T\boldsymbol{W}\boldsymbol{X})^{-1}\hat{\sigma}_h^2$. We reject H_0 at significance level α if $|t| > t_{\left(\frac{\alpha}{2};(n-rank(X))\right)}$.

2.5 Model Selection

The best GWMR model is selected based on the Corrected Akaike Information Criterion (AICc), formulated as [22]. The AICc is employed because it provides a reliable trade-off between model fit and complexity, particularly in cases with a relatively small sample size or when the number of parameters is large compared to the sample size. A lower AICc value indicates a more parsimonious model with better explanatory power. In addition to AICc, the coefficient of determination (R^2) is also used to evaluate model performance, as it measures the proportion of variance in the dependent variables explained by the predictors, thereby complementing AICc in assessing overall model goodness-of-fit. The Corrected Akaike Information Criterion (AICc), formulated as [22]:

$$AICc = |\hat{\boldsymbol{\Sigma}}| + 2p\left\{\frac{n}{n-p-1}\right\}. \tag{17}$$

where:

$\hat{\boldsymbol{\Sigma}}$: the estimated variance–covariance matrix of the residuals,
p : the number of estimated parameters in the model,
n : the sample size (number of observations).

A lower AICc value indicates a better model fit, while also accounting for model complexity and small-sample bias.

In addition to AICc, the coefficient of determination (R^2) and the Mean Absolute Percentage Error (MAPE) are also used as supplementary performance criteria. For a global regression model (MLR), the R^2 statistic is defined as [24]:

$$R^2 = \frac{\boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{y} - n\bar{y}^2}{\boldsymbol{y}^T\boldsymbol{y} - n\bar{y}^2}, \tag{18}$$

where $\boldsymbol{y}$ denotes the observed value, $\hat{y}_i$ the predicted value, and $\bar{y}$ the sample mean. For a geographically weighted multivariate regression (GWMR), the local R^2 at location i and response h is computed as [8]:

$$R_i^2 = 1 - \frac{\sum_{j=1}^{n} w_{ij}\left(y_j - \hat{y}_j\right)^2}{\sum_{j=1}^{n} w_{ij}\left(y_j - \bar{y}_i\right)^2}, \tag{19}$$

where w_{ij} denotes the spatial weight assigned to observation j relative to location i, and $\bar{y}_i$ is the locally weighted mean. Last, Mean Absolute Percentage Error (MAPE) is defined as [24]:

$$MAPE = \frac{100}{h.n} \sum_{j=1}^{m} \sum_{i=1}^{n} \left| \frac{y_{ij} - \bar{y}_{ij}}{y_{ij}} \right|. \tag{20}$$

where h is the number of response variables.

These criteria together ensure a comprehensive evaluation: AICc assesses parsimony, R^2 explains goodness-of-fit, and MAPE evaluates predictive accuracy across multiple dependent variables.

2.6 Research Stages

This research consists of three stages: Data Collection, Data Exploration, and GWMR Modeling. The detailed stages are as follows.

1. Data Collection

   The data used in this study were sourced from the 2023 Indonesian Health Survey Results (SKI) published by the Ministry of Health of the Republic of Indonesia. The units of analysis were 38 provinces in Indonesia. The dependent variables were the prevalence rates of stunting, wasting, and underweight among children under five, while the independent variables included several suspected influencing factors.

2. Data Exploration

   Exploratory analysis began with descriptive statistics to depict the distribution characteristics of stunting, wasting, and underweight prevalence rates across Indonesia in 2023, as well as the potential influencing factors. This analysis aimed to understand the data distribution and identify general patterns across provinces. Thematic maps were then created for each variable to visualize spatial disparities and support the use of spatial analysis approaches.

3. GWMR Modeling

   The modeling process was carried out in several stages as follows:

   a. Global Estimation with MLR

      The process began with parameter estimation using Multivariate Linear Regression (MLR) to obtain a general overview of the global relationships among the variables.

   b. Testing Fundamental Assumptions

      Several classical assumptions of multivariate regression were tested, including:
      Dependency among response variables; Multicollinearity among predictor variables; and
      Multivariate normality of the residuals.

   c. Testing Spatial Assumptions

      Spatial heterogeneity was tested using the Breusch–Pagan statistic to determine whether a spatial model was required.

   d. Spatial Modeling with GWMR

      i. Determination of geographic coordinates (u_i, v_i) for each province,
      ii. Calculation of Euclidean distances between observation locations,
      iii. Selection of the optimal bandwidth using the Cross Validation (CV) method,
      iv. Selection of the best kernel function based on the smallest CV value, and
      v. Construction of the weighting matrix.

e. Estimation of GWMR Parameters

GWMR model parameters were estimated and compared with the global model (MLR) through a model fit test using the F statistic, Simultaneous influence test, and Partial influence tests using the t statistic.

f. Model Selection

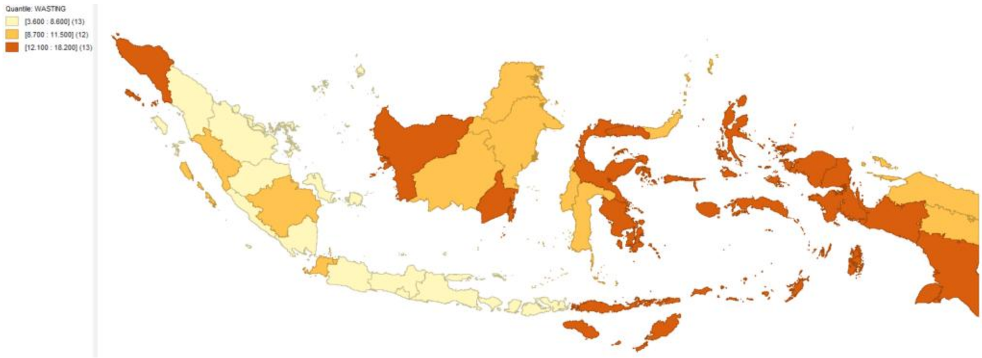
The best model was selected by comparing the corrected Akaike Information Criterion (AICc), R^2 and $MAPE$ values between the MLR and GWMR models, thereby assessing the effectiveness of the spatial approach in capturing data variation.

3. RESULTS AND DISCUSSION

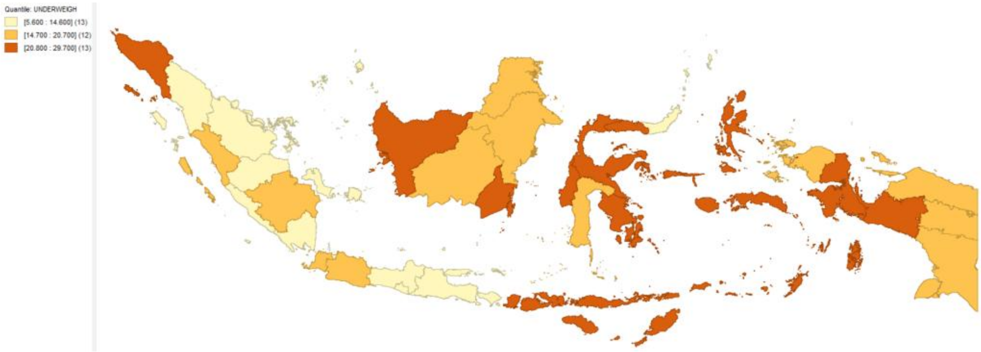
3.1 Data Exploration

As an initial stage in the Geographically Weighted Multivariate Regression (GWMR) modeling, an exploration was conducted on child malnutrition data in Indonesia, encompassing three main indicators: stunting, wasting, and underweight. Spatial visualization through thematic maps was employed to illustrate the distribution of these indicators at the provincial level. These maps provided a preliminary overview of the geographical disparities in malnutrition prevalence and served to identify regions with a high burden of nutritional problems, thereby forming the basis for subsequent spatial model development. Furthermore, to facilitate interpretation, the prevalence values of each indicator were classified into three categories based on quantile thresholds. This classification follows the principle proposed by categorical groupings are established using distributional quantiles as cut-off points, defined as: $y_i \le Q_{1/3}$ (low); $Q_{1/3} < y_i \le Q_{2/3}$ (medium); $y_i > Q_{2/3}$(high) [25].

(a)



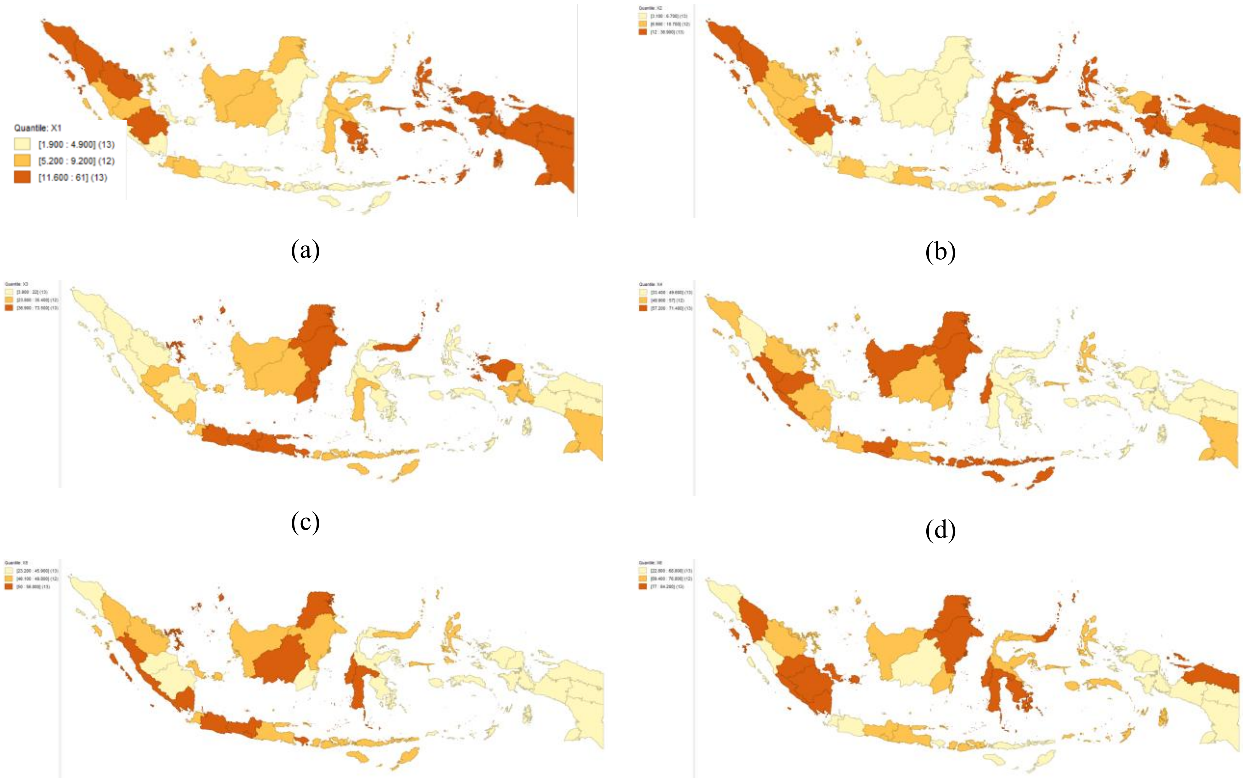
(b)



(c)

Figure 1. Distribution Maps of Stunting, Wasting, and Underweight Prevalence in Indonesia
(a) Distribution map of Stunting, (b) Distribution map of Wasting, (c) Distribution map of Underweight

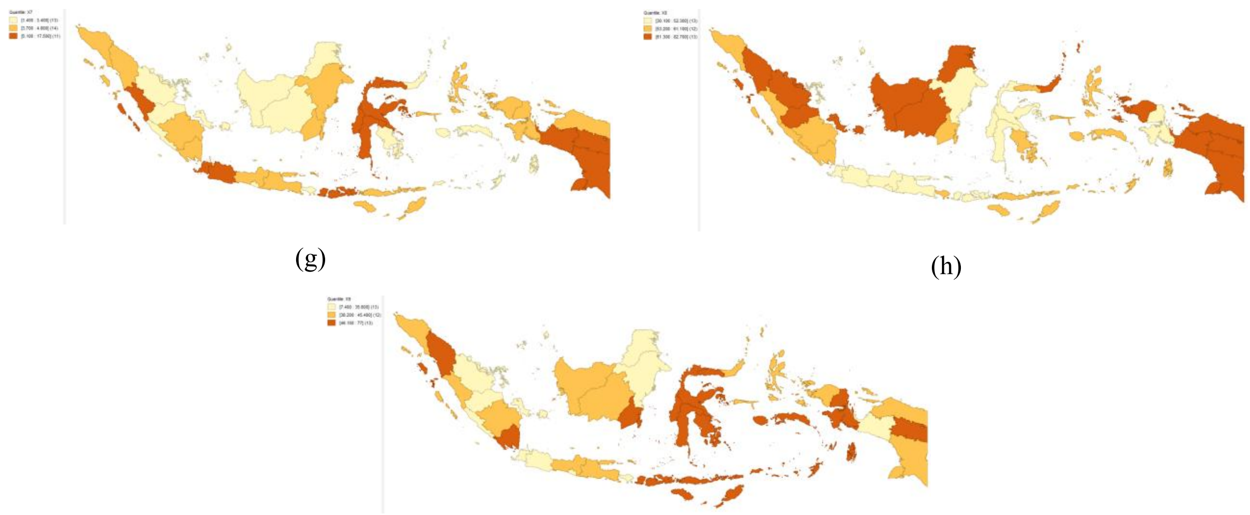
Based on Fig. 1, the distribution map of stunting, it is evident that provinces located in eastern Indonesia, such as Papua, Maluku, Sulawesi and East Nusa Tenggara (NTT), exhibit very high stunting prevalence rates (above 25%). In contrast, provinces in the western part of Indonesia, such as DKI Jakarta, Bali, and Riau Islands, display relatively low stunting prevalence rates (below 20%). Regarding the wasting indicator, the spatial distribution pattern is not entirely identical to that of stunting; however, eastern regions such as Papua and several provinces in Kalimantan show high wasting rates (above 12%). Provinces like Central Kalimantan and West Kalimantan stand out in this category, differing from the stunting trend, which is more concentrated in the eastern regions. The underweight indicator exhibits a distribution pattern somewhat similar to stunting, with a high prevalence concentrated in Papua, Sulawesi, and East Nusa Tenggara. This suggests a geographical correlation among the three forms of malnutrition, although certain provinces demonstrate pronounced differences in specific indicators, reflecting the complex and multifactorial nature of malnutrition in each region.



(a) (b)

(c) (d)

(e) (f)



(g) (h)

(i)

Figure 2. Distribution Maps of Predictor Variables
(a) Percentage of mothers without a Maternal and Child Health (MCH) Book (X1), (b) Percentage of births with gestational age less than 37 weeks (X2), (c) Proportion of children aged 12–23 months receiving complete basic immunization (X3), (d) Proportion of children aged 6–23 months exclusively breastfed for six months (X4), (e) Proportion of children aged >6 months routinely receiving complementary feeding (X5), (f) Proportion of households with access to improved sanitation (X6), (g) Prevalence of diarrhea among children under five (X7), (h) Proportion of women aged >15 years with knowledge of stunting prevention (X8), (i) Percentage of households with low to lower-middle economic status (X9)

Based on Fig. 2, which presents the distribution maps of predictor variables, it is observed that the risk factors associated with child malnutrition are unevenly distributed across the provinces of Indonesia. Several variables, such as the lack of maternal and child health (MCH) books (X_1), history of low birth weight (<37 weeks) (X_2), incidence of diarrhea in children (X_7), and lower-middle economic status (X_9), exhibit high concentrations in eastern Indonesia, particularly in Papua, West Papua, and parts of the Nusa Tenggara region. These areas also show notable deficiencies in exclusive breastfeeding coverage (X_4), access to improved sanitation (X_6), and stunting-related knowledge (X_8), which further exacerbate their vulnerability to malnutrition issues. Conversely, provinces in the western regions, such as DKI Jakarta, West Java, and Bali, generally demonstrate better conditions across most indicators, including higher coverage of complete basic immunizations (X_3) and more consistent provision of complementary feeding (X_5).

3.2 Multivariate Linear Regression

1. Assumption Diagnostics

Table 2. Response Variable Dependency Testing

Correlation	Y_1	Y_2	Y_3
Y_1	1.000		
Y_2	0.777	1.000	
Y_3	0.831	0.823	1.000
Barlett test			
χ^2	: 84.201		
P_{value}	: 0.000		

***Data source**: Processed data using R 4.3.2 (2025)*

Based on Table 2, the correlation results indicate a strong relationship among the three response variables (stunting (Y_1), wasting (Y_2), and underweight (Y_3)) with correlation values ranging from 0.777 to 0.831. This suggests a considerable degree of dependency among these variables. Furthermore, the Bartlett's test yielded a χ^2 statistic of 84.201 with a p-value of 0.000 (< 0.05), indicating statistical significance. Thus, it can be concluded that there is substantial correlation among the response variables, justifying the application of a multivariate regression approach in this study.

Table 3. Multicollinearity Diagnostic

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
VIF	6.513	2.179	1.981	2.167	3.947	5.522	3.433	2.076	1.370

***Data source**: Processed data using R 4.3.2 (2025)*

To ensure the validity of the regression model, multicollinearity among predictor variables was examined using the Variance Inflation Factor (VIF). As shown in Table 3, all predictors exhibit VIF values below the threshold of 10, indicating the absence of severe multicollinearity. However, some variables, such as X_1 (absence of maternal and child health book ownership) with a VIF of 6.513 and X_6 (adequate sanitation) with a VIF of 5.522, demonstrate moderate multicollinearity. Nevertheless, all VIF values remain within acceptable limits, thus all predictor variables were retained in the model without the need for transformation or elimination.

Table 4. Multivariate Normality Assumption

Test	**E**	**df**	P_{value}	**Description**
Doornik-Hansen	12.015	6	0.062	Accept H_0

***Data source**: Processed data using R 4.3.2 (2025)*

The assumption of multivariate normality on Table 4 was tested using the Doornik-Hansen test to determine whether the model residuals follow a multivariate normal distribution. The test yielded a statistic of 12.015 with 6 degrees of freedom and a p-value of 0.062. Since the p-value exceeds 0.05, the null hypothesis cannot be rejected, indicating no sufficient evidence against multivariate normality. Consequently, the assumption of multivariate normality is satisfied, supporting the further validity of the multivariate regression model.

2. Multivariate Linear Regression Modeling

After confirming that the fundamental assumptions of multivariate regression were satisfied, the next step involved modeling to identify the factors influencing the three response variables: stunting (Y_1), wasting (Y_2), and underweight (Y_3). The modeling approach employed Multivariate Linear Regression (MLR) method. The estimated coefficients, standard errors (SE), and p-values for each variable are presented in Table 5.

Table 5. MLR Model Effect Test Results

Response	**Stunting (y_1)**			**Wasting(y_2)**			**Underweight (y_3)**		
Predictor	$\hat{\beta}$	**SE** $\hat{\beta}$	P_{value}	$\hat{\beta}$	**SE** $\hat{\beta}$	P_{value}	$\hat{\beta}$	**SE** $\hat{\beta}$	P_{value}
Intercept	84.398	15.546	0.000	44.432	8.847	0.000	79.030	12.906	0.000
X_1	-0.118	0.128	0.365	-0.061	0.073	0.408	-0.188	0.106	**0.008**
X_2	-0.207	0.101	**0.050**	-0.065	0.057	0.271	-0.192	0.084	**0.030**
X_3	-0.194	0.054	**0.001**	-0.086	0.031	**0.009**	-0.188	0.045	**0.000**
X_4	-0.227	0.087	**0.015**	-0.118	0.050	**0.025**	-0.223	0.073	**0.005**
X_5	-0.325	0.149	**0.038**	-0.225	0.085	**0.013**	-0.336	0.123	**0.011**
X_6	-0.300	0.104	**0.008**	-0.142	0.059	**0.023**	-0.225	0.086	**0.015**
X_7	-0.722	0.402	0.083	-0.781	0.229	**0.002**	-1.319	0.334	**0.000**
X_8	-0.179	0.063	**0.008**	-0.058	0.036	0.117	-0.207	0.052	**0.000**
X_9	0.256	0.052	**0.000**	0.080	0.030	**0.011**	0.237	0.043	**0.000**
$\mathbf{R^2}$		**79.87%**			**69.12%**			**75.65%**	

***Data source**: Processed data using R 4.3.2 (2025)*

Based on Table 5, multivariate regression models were developed for each response variable. In general, most predictors exhibit statistically significant associations with at least one of the three response variables at the 5% significance level. A negative regression coefficient indicates that an increase in the predictor variable is associated with a decrease in the response variable, whereas a positive coefficient indicates the opposite relationship.

For the stunting variable (Y_1), significant predictors include X_3 (percentage of complete basic immunization), X_4 (percentage of adequate sanitation facilities), X_5 (percentage of toddlers weighed), X_6 (percentage of households with proper sanitation), X_8 (percentage of households practicing healthy living behaviors), andX_9 (household income). Most of these variables show negative coefficients, suggesting that improvements in health services, sanitation, and healthy living practices reduce the prevalence of stunting.

Conversely, X_9 (household income) shows a positive effect, which is consistent with the expectation that higher household income contributes to better child nutrition outcomes. The R^2value of 79.87% indicates that the model explains nearly 80% of the variation in stunting. It is important to note that, unlike Table 1 which showed X_2 (access to safe drinking water) as significant, in the multivariate model X_2 is not statistically significant for stunting, suggesting that its effect is absorbed by other correlated predictors.

For wasting (Y_2), significant predictors include X_3, X_4, X_5, X_7(unemployment rate), and X_9. Of particular interest, X_7 has a relatively large negative coefficient (−0.781, p=0.002), implying that higher unemployment rates are strongly associated with higher prevalence of wasting. This finding reflects the socioeconomic vulnerability of households: when unemployment rises, household income and food security decline, which in turn increases the risk of acute malnutrition among children. The model explains 69.12% of the variation in wasting.

For underweight (Y_3), almost all predictors ($X_1 - X_9$) are statistically significant. Most of them show negative effects, indicating that improvements in public health services, sanitation, and health behaviors contribute to reducing underweight prevalence. On the other hand, X_9 (household income) has a positive effect, underscoring the importance of economic capacity in addressing malnutrition. The R^2 value of 75.65% suggests that the model has strong explanatory power for underweight.

$$Y_1 = 84.398 - 0.207\mathrm{X}_2 - 0.194\mathrm{X}_3 - 0.227X_4 - 0.325X_5 - 0.300X_6 - 0.179X_8 + 0.256X_9,$$
$$Y_2 = 44.432 - 0.086\mathrm{X}_3 - 0.118\mathrm{X}_4 - 0.225\mathrm{X}_5 - 0.142\mathrm{X}_6 - 0.781\mathrm{X}_7 + 0.080\mathrm{X}_9,$$
$$Y_3 = 79.030 - 0.188\mathrm{X}_1 - 0.192\mathrm{X}_2 - 0.188\mathrm{X}_3 - 0.223\mathrm{X}_4 - 0.336\mathrm{X}_5 - 0.225\mathrm{X}_6 - 1.319\mathrm{X}_7 - 0.207\mathrm{X}_8 + 0.237\mathrm{X}_9.$$

3.3 Spatial Heterogeneity Assumption Check

Before applying spatial regression models, it is necessary to assess the spatial heterogeneity assumption to ensure that the relationships between predictors and response variables are not uniform across all observation areas. The Breusch-Pagan test was employed, with the results presented in Table 6.

Table 6. Spatial Heterogeneity Test Results (Breusch-Pagan Test)

BP_{stat}	df	P_{value}	**Conclusion**
27.756	9	0.001	Reject H_0

Data source*: Processed data using R 4.3.2 (2025)*

As shown in Table 6, the Breusch-Pagan statistic was 27.756 with 9 degrees of freedom and a p-value of 0.001. Since the p-value is less than the 5% significance level, the null hypothesis is rejected. Therefore, spatial heterogeneity is present in the data, indicating that the use of spatial regression approaches, such as Geographically Weighted Multivariate Regression (GWMR), is both appropriate and necessary for further analysis.

3.4 Geographically Weighted Multivariate Regression (GWMR)

Following the identification of spatial heterogeneity, the Geographically Weighted Multivariate Regression (GWMR) model was employed to capture local variations in the relationship between predictors and response variables. Model fit and simultaneous effect tests were conducted to evaluate the adequacy and explanatory power of the GWMR model.

Table 7. Model Fit Test Results

F_*	df_1	df_2	F_{table}	**Conclusion**
13.577	9.465	32.363	2.236	Reject H_0

Data source*: Processed data using R 4.3.2 (2025)*

The model fit test was conducted by comparing the calculated F_1 value with the critical F-table value. As presented in Table 7, the calculated F_* value of 13.577 with degrees of freedom (df_1 = 9.465; df_2 = 32.363) exceeds the F-table value of 2.236. Since F_* > F-table, the null hypothesis (H_0) is rejected. This indicates that the GWMR model is statistically adequate and capable of explaining the variation in the data.

Table 8. Simultaneous Effect Test Results of GWMR Model

F	df_1	df_2	F_{table}	**Conclusion**
3.348	35.748	32.363	1.781	Reject H_0

Data source*: Processed data using R 4.3.2 (2025)*

Subsequently, a simultaneous effect test was conducted to examine whether all predictors collectively exert a significant influence on the response variables. As shown in Table 9, the calculated F value of 3.348 ($df_1 = 35.748$; $df_2 = 32.363$) exceeds the F-table value of 1.781. Therefore, H_0 is rejected, suggesting that the predictors collectively exert a significant effect on the response variables in the GWMR model.

Partial effect analysis within the GWMR framework was carried out to assess the individual influence of each predictor on the response variables across locations. The summary of partial test results is presented in Table 9.

Table 9. Summary of Partial Test Results in the GWMR Model

Predictor	**Response**								
	Stunting (y_1)			**Wasting(y_2)**			**Underweight (y_3)**		
	Avg $\widehat{\beta}_{q1}$	**Range $\widehat{\beta}_{q1}$**	**N of sig***	**Avg $\widehat{\beta}_{q2}$**	**Range $\widehat{\beta}_{q2}$**	**N of sig***	**Avg $\widehat{\beta}_{q3}$**	**Range $\widehat{\beta}_{q3}$**	**N of sig***
X_1	-0.18	-0.60 – 0.27	21	-0.10	-0.27 – 0.21	16	-0.08	-0.30 – -0.31	9
X_2	-0.07	-0.36 – 0.25	11	-0.01	-0.08 – 0.17	0	-0.17	-0.33 – -0.06	11
X_3	-0.20	-0.23 – -0.16	38	-0.08	-0.11 – -0.01	36	-0.16	-0.22 – -0.12	38
X_4	-0.13	-0.23 – -0.01	8	-0.07	-0.13 – -0.01	10	-0.14	-0.25 – -0.02	19
X_5	-0.35	-0.64 – -0.14	17	-0.26	-0.38 – -0.09	32	-0.41	-0.65 – -0.21	32
X_6	-0.17	-0.37 – 0.03	19	-0.11	-0.18 – -0.03	19	-0.15	-0.36 – -0.07	19
X_7	-0.40	-0.40 – 0.28	1	-0.30	-0.76 – 0.69	9	-0.47	-0.92 – -0.36	11
X_8	-0.17	-0.24 – -0.11	36	-0.03	-0.05 – -0.05	1	-0.16	-0.20 – -0.09	35
X_9	0.22	0.13 – 0.34	38	0.05	0.02 – 0.07	4	0.19	0.14 – 0.25	38

***Data source**: Processed data using R 4.3.2 (2025)*

As shown in Table 9, each predictor exhibits variation in the average regression coefficient, coefficient range, and the number of locations with significant influence across the three malnutrition indicators—stunting (y_1), wasting (y_2), and underweight (y_3). Generally, predictors X_3 and X_9 demonstrate consistently significant effects across nearly all regions, particularly for stunting and underweight, each with 38 significant locations. Predictor X_5 also exhibits a relatively strong negative effect across all three malnutrition indicators, with the largest average coefficient of -0.41 for underweight. Meanwhile, predictors such as X_2 and X_7 show wide coefficient ranges, reflecting substantial spatial variation in their local impacts.

The GWMR equations for location 35 (Southwest Papua) are as follows:

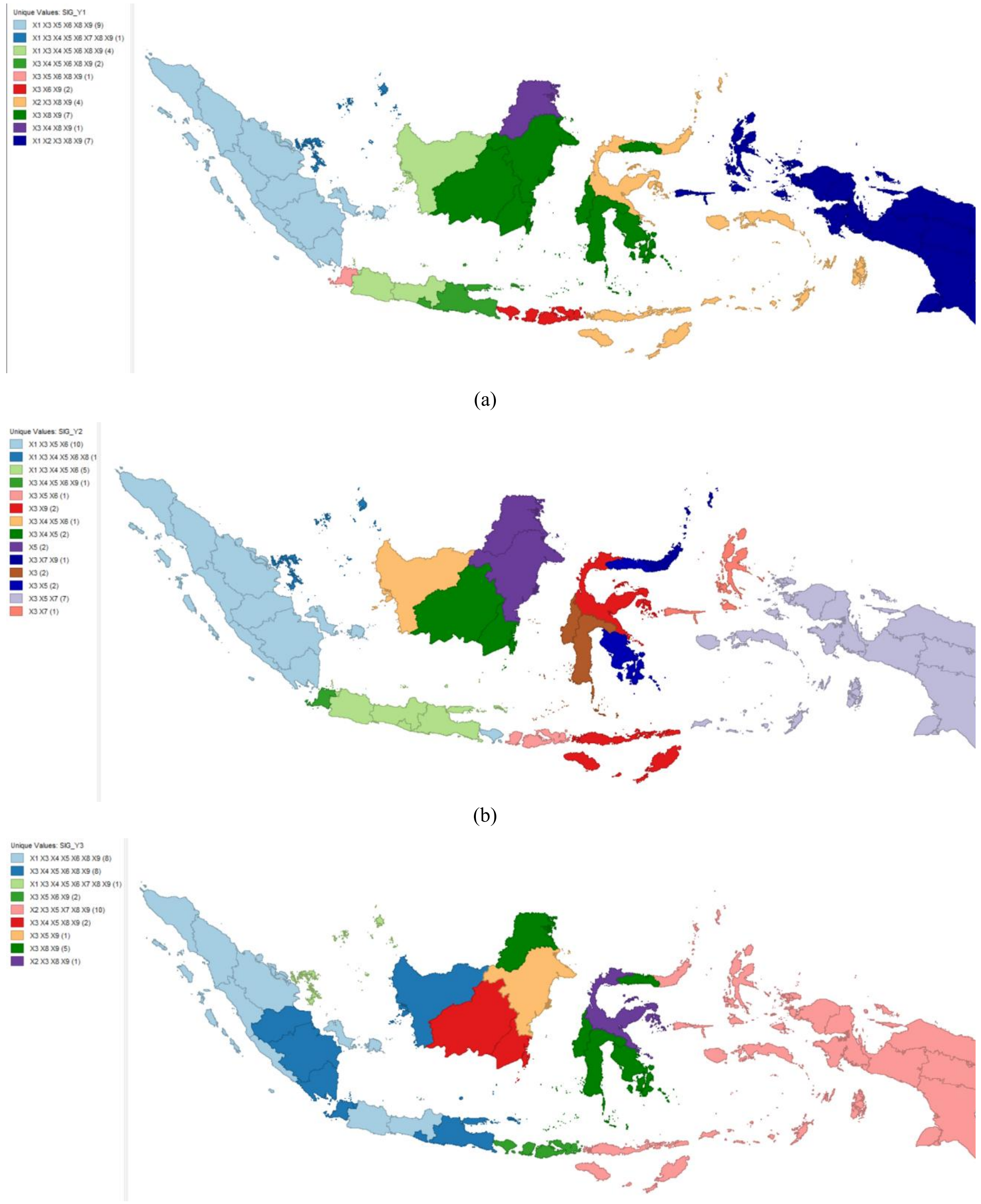
$$\hat{y}_1(u_{35}, v_{35}) = 32.85 + 0.27\mathrm{X}_1 - 0.36\mathrm{X}_2 - 0.167X_3 - 0.13X_8 + 0.34X_9,$$

$$\hat{y}_2(u_{35}, v_{35}) = 33.90 - 0.10\mathrm{X}_3 - 0.18\mathrm{X}_5 - 0.74\mathrm{X}_7,$$

$$\hat{y}_3(u_{35}, v_{35}) = 43.79 - 0.29\mathrm{X}_2 - 0.17\mathrm{X}_3 - 0.31\mathrm{X}_5 - 0.87\mathrm{X}_7 - 0.18\mathrm{X}_8 + 0.25\mathrm{X}_9.$$

These equations indicate that for stunting (y_1), a 1% increase in X_1 leads to a 0.27% increase in prevalence, while increases in X_2, X_3, and X_8 are associated with a reduction in stunting prevalence. Conversely, X_9 exerts a relatively strong positive effect. For wasting (y_2), predictors X_3, X_5, and X_7 all have negative effects, with X_7 having the largest magnitude (-0.74), suggesting its considerable role in reducing wasting. Regarding underweight (y_3), variables X_2, X_3, X_5, X_7, and X_8 negatively affect the outcome, while X_9 has a positive effect. Among all predictors, X_7 consistently contributes the most to reducing underweight prevalence.

The distribution of predictors significantly associated with the three malnutrition indicators is visualized in the figure below.



(a)

(b)

(c)

Figure 3. Map of Significant Predictors for Each Province
(a) Distribution of Significant Variables in Stunting (Y_1), (b) Distribution of Significant Variables in Wasting (Y_2), (c) Distribution of Significant Variables in Underweight (Y_3)

Fig. 3 presents the spatial distribution of significant predictors for stunting (Y_1), wasting (Y_2), and underweight (Y_3) across Indonesian provinces, as determined by the Geographically Weighted Multivariate Regression (GWMR) model. The GWMR method is a local spatial statistical technique that allows regression coefficients to vary across geographic locations. This approach is particularly suited for this analysis as it can distinguish between globally significant predictors, which are consistently influential across the entire study area, and locally significant predictors, whose influence is confined to specific regional contexts. This "mixed" modeling capability provides a nuanced understanding of the multifaceted drivers of child malnutrition.

The analysis first reveals several globally significant determinants. Notably, the proportion of children receiving complete basic immunizations (X_3) and the percentage of households with low economic status (X_9) consistently emerge as significant predictors for all three malnutrition indicators across most of Indonesia. This underscores the universal importance of fundamental public health interventions and socioeconomic stability as foundational pillars for child nutritional status, regardless of geographic location. The widespread significance of maternal knowledge in stunting prevention (X_8) further reinforces the critical role of maternal education in health outcomes nationwide.

Beyond these universal factors, the GWMR model highlights significant spatial heterogeneity in other determinants. The non-significance of certain variables in specific regions is as informative as their significance elsewhere. For example:

1. In Sumatra, the lack of a Maternal and Child Health (MCH) book (X_1) is a significant local predictor. This suggests that in this region, the MCH book is a critical gateway for maternal and child health service engagement, a factor that may be less decisive in regions with more uniformly high access to healthcare, such as parts of Java.
2. In Java, characterized by high population density, access to improved sanitation (X_6) and the prevalence of diarrhea (X_7) are key local determinants. Conversely, these variables are less frequently significant in sparsely populated regions like Papua and Maluku. In these eastern provinces, the prevalence of low birth weight (X_2) and diarrhea (X_7) become more dominant predictors, reflecting primary challenges related to neonatal health and infectious disease control in remote, less-developed settings.
3. In Kalimantan and Sulawesi, a distinct combination of factors, including infant feeding practices (X_4, X_5) and maternal knowledge (X_8), are prominent. This indicates that in these areas, behavioral and educational interventions focused on nutrition during the first two years of life may yield the greatest impact, whereas sanitation or economic interventions alone might be insufficient.

In conclusion, the findings demonstrate that while a few core factors like immunization coverage (X_3) and economic status (X_9) are universally critical, the landscape of malnutrition drivers in Indonesia is highly localized. The significance of predictors related to health service access, environmental sanitation, neonatal health, and feeding practices varies distinctly by region. This spatial heterogeneity confirms that a one-size-fits-all policy approach is inadequate. Effective programmatic interventions must be geographically tailored to address the unique combination of significant and non-significant local determinants in each province.

Table 10. Model Selection

Model	**AICc**	**MAPE**	R^2		
			Y_1	Y_2	Y_2
Global (MLR)	287.537	12.567%	79.87%	69.12%	75.65%
Local (GWMR)	44.956	8.846%	90.85%*	80.73%*	90.68%*

Notes: **average R^2 for each local estimations*

Data source*: Processed data (2025)*

Based on the calculation of the Corrected Akaike Information Criterion (AICc) at Table 10, the global model yielded an AICc value of 287.537, while the local model (GWMR) produced an AICc value of 44.956. A lower AICc value indicates a better model in terms of balancing goodness-of-fit and model complexity. Therefore, the local model (GWMR) was selected as the superior model compared to the global model, given its substantially lower AICc. This finding suggests that the local model more effectively captures significant spatial variations in the data, resulting in more accurate estimates of the factors influencing child malnutrition across different regions of Indonesia.

In addition to the AICc, the coefficient of determination (R^2) provides further insight into how well the predictors explain the variation in the response variables. For the global model, the R^2 values were 79.87% for stunting, 69.12% for wasting, and 75.65% pfor underweight. This indicates that the predictors collectively explain a relatively high proportion of the variation in the three outcomes, but with limited capacity to capture local spatial variations. In contrast, the local GWMR model demonstrated higher explanatory power, with average R^2 values of 90.85% for stunting, 80.73% for wasting, and 90.68% for underweight. These results confirm that the local model not only provides a better statistical fit but also more accurately reflects spatial heterogeneity, thereby enhancing the ability to identify region-specific determinants of child malnutrition in Indonesia.

4. CONCLUSION

This study analyzed the factors influencing three child malnutrition indicators—stunting, wasting, and underweight—in Indonesia using a Geographically Weighted Multivariate Regression (GWMR) approach. The analysis confirmed significant spatial heterogeneity, making the local GWMR model the best fit compared to the global model, with an AICc of 44.956, an R-square of 80.73% until 90.85%, and a MAPE of 8.846%. The main finding indicates that the determinants of child malnutrition are multidimensional, comprising a combination of global factors applicable nationwide and local factors unique to each region.

Nationally, three consistent determinants were identified as fundamental pillars for child nutritional status: basic immunization coverage (X_3), representing health infrastructure; household economic status (X_9); and maternal knowledge of stunting prevention (X_8) However, the GWMR model also revealed differing priorities of factors at the regional level. In western regions like Sumatra, access to maternal and child health services (X_1) is crucial. In densely populated areas like Java, environmental factors such as sanitation (X_6) and diarrhea prevalence (X_7) are more dominant. Meanwhile, in Kalimantan and Sulawesi, behavior-based interventions related to feeding practices (X_4, X_5) are more relevant. The eastern region (Papua and Maluku) faces a multidimensional challenge where various risk factors accumulate simultaneously.

These results strongly underscore that a uniform national nutrition intervention policy is likely to be ineffective. The main driver of malnutrition in one province may not be significant in another, thus requiring decentralized and geographically tailored strategies. The limitations of this study include a limited set of predictor variables and the static nature of the data. Future research is recommended to integrate longitudinal data to capture temporal dynamics and to consider using alternative geospatial methods to enrich the analysis.

Author Contributions

Teguh Susanto: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Methodology, Resources, Software, Visualization, Writing—Original Draft. Toha Saifudin: Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Supervision, Validation, Writing—Review and Editing. Nur Chamidah: Investigation, Validation, Writing—Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interest.

Declaration of Generative AI and AI-assisted Technologies

We confirm that generative AI tools were used solely for language refinement (grammar, spelling, and clarity), and that all scientific content, analysis, interpretation, and conclusions were fully developed and verified by the authors.

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