JURNAL STATISTIKA DAN APLIKASINYA

e-ISSN 2620 – 8369
VOLUME 9 (ISSUE 1) JUNE 2025: 102 – 111
https://doi.org/10.21009/JSA.09109

GEOGRAPHICALLY WEIGHTED LASSO (GWL) MODELING TO IDENTIFY FACTORS INFLUENCE STUNTING INCIDENTS IN SOUTH SULAWESI

Andi Rima Novianti[1], **Aswi**[2*], **Zakiyah Mar'ah**[3]

[1,2,3]Department of Statistic, Faculty of Mathematics and Natural Sciences, State University of Makassar, Makassar, Indonesia.
Jalan Malengkeri raya, kampus parang Tambung, Makassar, 90224, Indonesia

Corresponding author's e-mail: * ***aswi@unm.ac.id***

ABSTRACT

Article History:

Received: February 3, 2025
Revised: June 28, 2025
Accepted: June 29, 2025
Published: June 30, 2025
Available online.

Keywords:

GWL; GWR; Multicollinearity; Spatial Heterogeneity; Stunting.

The Geographically Weighted Lasso (GWL) method is a technique that employs the Lasso approach within the Geographically Weighted Regression (GWR) model, which can also simultaneously select non-significant variables by shrinking the regression coefficient values to zero. Consequently, any variable assigned to a zero coefficient is considered statistically insignificant. In 2022, stunting remained a significant public health issue in South Sulawesi, ranking 10th nationwide with a prevalence of 27.2%. This underscores the urgent need for spatially sensitive analytical methods that can address regional heterogeneity and reveal key determinants at the district level. Notably, the application of GWL to analyze stunting in South Sulawesi using data from the Indonesian Nutrition Status Survey (SSGI 2022) represents a significant contribution that addresses an important research gap. This study aims to model stunting prevalence and identify its influential factors using GWL. The analysis yielded a tuning parameter λ = 0.04, achieving a model goodness of fit of $R^2 = 0.957$, demonstrating GWL's effectiveness in mitigating multicollinearity. Four primary predictors of stunting emerged: low birth weight (LBW), access to safe drinking water, the human development index (HDI), and the average length of parental schooling.

How to cite this article:
A. R. Novianti, Aswi, Z. Mar'ah, "GEOGRAPHICALLY WEIGHTED LASSO (GWL) MODELING TO IDENTIFY FACTORS INFLUENCE STUNTING INCIDENTS IN SOUTH SULAWESI", Jurnal Statistika dan Aplikasinya, vol. 9, iss. 1, pp. 102 – 111, June 2025

Journal e-mail: jsa@unj.ac.id
Research Article · Open Access

1. INTRODUCTION

Spatial heterogeneity refers to the variation in conditions across different locations within a given area, which may be observed in terms of geography, socio-cultural factors, or other elements that contribute to differences at the studied location [1]. Geographically Weighted Regression (GWR) is a method used to analyze spatial variation by applying a weighting matrix, the size of which depends on the spatial proximity of locations and produces model parameter estimates that are specific to each observation [2]. One disadvantage of GWR is the occurrence of multicollinearity, a condition in which two or more variables are highly correlated with each other at each observation location. To detect multicollinearity in spatial models, the Variance Inflation Factor (VIF) can be used, with a criterion of a VIF value greater than 10 indicating the presence of multicollinearity [3].

To address these limitations, the Geographically Weighted Lasso (GWL) method integrates the Least Absolute Shrinkage and Selection Operator (LASSO) penalty into GWR. This approach simultaneously reduces local multicollinearity and performs spatial variable selection by shrinking the coefficients of non-significant variables to zero [4], [5]. The effectiveness of GWL has been demonstrated in spatial analyses, such as its application to poverty data in Java, where it provided more stable and accurate parameter estimates compared to standard GWR [6].

According to the 2022 Indonesian Nutrition Status Survey (SSGI), South Sulawesi Province ranked 10th nationally with a stunting prevalence of 27.2%, highlighting a pressing public health issue [7]. The application of spatial analysis using GWL is particularly relevant, as stunting prevalence varies considerably across districts and cities in the province, driven by environmental factors, healthcare access, and regional characteristics. Although GWL has been applied in spatial contexts such as national-level stunting studies and analyses of unmet need for family planning in other regions, its application to stunting in South Sulawesi remains very limited, indicating a critical research gap.

Theoretically, this study aims to contribute to the spatial statistics literature by providing empirical evidence on the effectiveness of GWL in public health analysis. Practically, it will produce precise maps of stunting determinants at the district and city levels to support more effective spatially targeted interventions, such as nutritional assistance programs and maternal healthcare services. Therefore, this research aims to model stunting data at the district/city level in South Sulawesi using GWL and to identify the factors influencing stunting in the province.

2. METHODS

Material and Data

The data utilized in this study comprises stunting case records from South Sulawesi in 2022, obtained from the Indonesian Nutritional Status Survey, the South Sulawesi Provincial Health Office, and publications by the South Sulawesi Provincial Statistics Agency (BPS). The study covers 24 districts and cities within South Sulawesi Province. The dependent variable examined in this study is the prevalence of stunting (Y), while the independent variables include the percentage of low birth weight (X_1), the proportion of households with access to clean drinking water (X_2), the human development index (X_3) and the average years of parental schooling (X_4). The research procedure in this study consists of several stages, as follows:

1. Data Collection
   Data on stunting in South Sulawesi Province were collected from the South Sulawesi Provincial Health Office and publications by Statistics Indonesia (BPS) of South Sulawesi Province. The dataset includes various variables suspected to influence the prevalence of stunting.
2. Descriptive Analysis
   Descriptive analysis was conducted to examine the characteristics of each variable used in the study, including distribution, maximum and minimum values, as well as the mean.
3. Linear Regression Modeling
   A linear regression model was developed as an initial step to understand the overall relationships between variables before applying spatial models.
4. Testing for Spatial Heterogeneity

The Breusch-Pagan test was applied to detect the presence of spatial heterogeneity in the data. If the result indicates heterogeneity, spatial modeling is deemed necessary.

5. Construction of Spatial Weight Matrix
   A spatial weight matrix was constructed using the fixed exponential kernel weighting function, which is essential for both the GWR and GWL methods.
6. GWR Modeling
   GWR was employed to capture local variations in the relationships among variables across geographic locations. The local VIF was calculated to detect the presence of local multicollinearity. A VIF value greater than 10 indicates the presence of multicollinearity.
7. GWL Modeling
   GWL modeling was performed to address local multicollinearity issues identified in the GWR model and to automatically conduct variable selection by shrinking the coefficients of insignificant variables.
8. Model Evaluation
   The GWR and GWL models were compared based on the coefficient of determination (R-square). The model with the higher R-square value was considered more effective in explaining data variability. Furthermore, significant variables influencing stunting were identified based on the estimation results of the selected model.

Research Method

Spatial data

Spatial data refers to geographically oriented data that uses a specific coordinate system as a reference, enabling its representation on a map. The location of each observation facilitates its relationship with other nearby observations, which can be based on proximity or intersection between observations. A key characteristic of spatial data is the presence of spatial heterogeneity, also known as spatial effects. To detect the existence of spatial heterogeneity within a model, the Breusch-Pagan test is employed [8].

The hypotheses tested are as follows:
$H_0: \sigma_1^2 = \sigma_2^2 = \ldots = \sigma_n^2 = \sigma^2$ (no spatial heterogeneity),
$H_1: at\ least\ one\ \sigma_n^2 \neq \sigma^2$ (spatial heterogeneity exists), where $i = 1, 2, \ldots, n$.
The Breusch-Pagan (BP) test statistic is given by:

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

with vector elements

$$\boldsymbol{f} = \frac{\varepsilon_i^2}{\sigma^2}$$

where,
$\boldsymbol{f}$: vector size $(nx1)$
$\boldsymbol{Z}$: the standardized matrix of independent variables of dimension $n \times (p+1)$
ε_i: the residual for observation i and
σ^2: the residual variance of ε_i
n: the number of spatial units
p: the number of explanatory variables
The null hypothesis is rejected if $BP > \chi^2_{(\alpha;p)}$ at significant level (α) of 5%.

If the null hypothesis is accepted, it indicates no spatial heterogeneity in the model. Conversely, rejection of the null implies the presence of spatial heterogeneity, validating the inclusion of spatial aspects in further analysis.

Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is an extension of the OLS linear regression model, transforming it into a weighted regression model by incorporating spatial effects. This approach yields parameter estimates that are specific to each observation point or location, allowing for predictions at individual locations where the data is observed and conclusions are drawn [2].

The GWR equation is formulated as follows [9]:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{2}$$

In this equation, y_i represents the observed value of the *i*-th dependent variable (*i* = 1, 2, …, *n*), x_{ik} denotes the observed value of the *k*-th independent variable at the *i*-th location (*i* = 1, 2, …, *n*), $\beta_0(u_i, v_i)$ is the intercept term of the GWR model, $\beta_k(u_i, v_i)$ refers to the local regression coefficient for the k-th independent variable at the i-th location, (u_i, v_i) represents the coordinate point (longitude, latitude) at the i-th location, and ε_i is the error term for the i-th observation, assumed to follow the distribution ($\varepsilon_i \sim IIDN(0, \sigma^2)$).

Parameter coefficient estimation in GWR is performed using the Weighted Least Squares (WLS) method. This method assigns different weights to each location. The form of the parameter estimation is as follows [10]:

$$\hat{\boldsymbol{\beta}}(u_i, v_i) = (\boldsymbol{X^T W}(u_i, v_i)\boldsymbol{X})^{-1}\boldsymbol{X^T W}(u_i, v_i)\boldsymbol{Y} \tag{3}$$

with

$$\boldsymbol{X} = \begin{bmatrix} 1 x_{11} x_{12} \cdots x_{1p} \\ 1 x_{21} x_{22} \cdots x_{2p} \\ \vdots \; \vdots \; \vdots \; \ddots \; \vdots \\ 1 x_{n1} x_{n1} \cdots x_{np} \end{bmatrix} \quad \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{4}$$

$$\boldsymbol{W}(u_i, v_i) = \begin{bmatrix} w_1(u_i, v_i) & 0 & \cdots & 0 \\ 0 & w_2(u_i, v_i) \cdots & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots w_n(u_i, v_i) & \end{bmatrix} \tag{5}$$

The weighting function plays a crucial role in parameter estimation. A commonly used weighting function in the GWR model is the kernel function, which is based on distance and bandwidth magnitude [11]. In this study, the fixed exponential kernel function is employed as the weighting function. The fixed exponential kernel function between location j and location i can be systematically expressed as follows:

$$w_j(i) = \exp\left(-\frac{d_{ij}}{h}\right) \tag{6}$$

where,

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \tag{7}$$

h represents the bandwidth at the *i*-th observation location, and d_{ij} denotes the distance between the i-th and j-th locations, calculated using Euclidean distance. The method used to determine the optimal bandwidth is cross-validation (CV), as outlined below:

$$CV(h) = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(h)]^2 \tag{8}$$

Where y_i represents the i-th observation, and $\hat{y}_{\neq i}$ denotes the estimated value of the *i*-th process with bandwidth *h* (where observations at the *i*-th location are excluded from the estimation). The optimal bandwidth *h* is determined through an iterative process until the minimum CV is achieved.

Multicollinearity

Multicollinearity is a common issue in spatial data analysis. When multicollinearity occurs between two or more variables in a regression equation, the estimated coefficient values of the involved variables become infinite, rendering predictions impossible. Multicollinearity detection can be performed using the Variance Inflation Factor (VIF), with a weighting matrix applied as the collinearity detection mechanism in the GWR model. A VIF value greater than 10 indicates multicollinearity, while a VIF value less than 10 suggests the absence of multicollinearity between the predictor variables [12]. The VIF is calculated as follows:

$$VIF_k(u_i,v_i) = \frac{1}{1 - R_k^2(u_i,v_i)} \tag{9}$$

Where $R_k^2(u_i,v_i)$ represents the coefficient of determination between X_k and the other independent variables at each location (u_i,v_i), (k=1, 2, …, p).

Geographically Weighted Lasso (GWL)

The GWL model combines two concepts: GWR and lasso, which effectively address multicollinearity issues. Additionally, the GWL model can perform variable selection by shrinking insignificant regression coefficients to zero. As a result, variables with zero regression coefficients are deemed to have no significant effect [5]. The lasso method is defined as follows:

$$(\hat{\beta}_L) = \left\{ \sum_{i=1}^{n} \left(y_1 - \beta_0 - \sum_{k=1}^{p} x_{ik}\beta_k \right)^2 + \lambda \sum_{k=1}^{p} |\beta_k| \right\} \tag{10}$$

The condition $\sum_{k=1}^{p} |\beta_k| \le t$ represents the lasso constraint, where t is a parameter that controls the degree of shrinkage in the lasso coefficient estimator, with $t \ge 0$. λ denotes the optimal bandwidth value. If β_k is the smallest lasso coefficient parameter estimator and $t_0 = \sum_{k=1}^{p} |\beta_k|$, then a value of $t < t_0$ causes the MTK (Least Squares Method) solution to shrink towards zero, resulting in the coefficient being exactly zero. Conversely, if the selected value of t is greater than or equal to t_0, the lasso estimator produces the same results as the lasso coefficient estimator.

Stunting

Stunting is a condition characterized by growth failure in toddlers due to chronic malnutrition, resulting in a height that is significantly below the expected range for their age. This malnutrition often begins while the child is still in the womb and continues in the early stages after birth, but its effects are typically not evident until the child reaches 2 years old. Stunting requires special attention, as it can lead to impaired physical growth, hindered mental development, and compromised health in children. Long-term consequences of stunting may persist throughout the life cycle. It is a critical issue during the first 1,000 days of life, which marks the crucial period for a child's growth and development [13], [14, [15].

3. RESULTS

Descriptive statistics

This study utilized stunting data from 24 districts and cities in South Sulawesi Province for the year 2022. The average prevalence of stunting across these regions was 27.93%, with Jeneponto Regency exhibiting the highest stunting rate. The results of the descriptive data analysis are presented in Table 1.

Table 1. Descriptive statistics

Variable	Min	Max	Mean	Standard Deviation
Prevalence of stunting (Y)	14.10	39.80	27.93	5.73
The percentage of low birth weight (X_1)	2.21	12.93	5.73	2.38
The proportion of households with access to clean drinking water (X_2)	73.60	98.24	91.11	6.68
The human development index (X_3)	65.13	83.12	71.44	3.94
The average years of parental schooling (X_4)	6.75	11.55	8.36	1.94

Multicollinearity

The multicollinearity test is conducted by examining the VIF value. If the VIF value exceeds 10, it indicates the presence of multicollinearity.

Table 2. VIF value in the regression model

Variable	VIF
X_1	1.304
X_2	1.149
X_3	10.022
X_4	9.434

As presented in Table 2, the VIF values for each variable were obtained through the VIF test, which reveals that X_3 has a VIF value greater than 10, indicating the presence of multicollinearity. Therefore, this issue must be addressed. The spatial heterogeneity between observations was tested using the Breusch-Pagan test (Table 3).

Table 3. Results of the *Breusch-Pagan* test

Breusch-Pagan	***p-value***
7.782	0.099

The results obtained indicate a significance level of less than $\alpha = 0.10$, suggesting the presence of spatial diversity in the stunting data, which justifies proceeding to the next stage of analysis.

In spatial-based data modeling, the construction of the weighting matrix is performed prior to conducting GWR analysis. The initial step involves determining the bandwidth value using the cross-validation (CV) method. Once the Euclidean distance is calculated, the weighting for each observed location is performed using a fixed exponential kernel based on the optimal bandwidth value (Table 4).

Table 4. Optimum bandwidth value and cross-validation

***Bandwidth* Optimum**	***cross-validation (CV)***
3.926	19.493

Determining the bandwidth value is the initial step in GWR modeling. The bandwidth is calculated using a fixed exponential kernel function, indicating that the bandwidth value remains consistent across all observation locations. The obtained bandwidth value is subsequently used to construct a weighting matrix, which is then applied in parameter estimation.

As an example, the following GWR model was derived for Makassar City:

$$Y_{Makassar} = 0.040 - 1.797X_3 + 1.314X_4$$

The results indicate that the Human Development Index (IPM) (X_3) and the average length of parental schooling (X_4) significantly influence stunting in Makassar City. The GWR model obtained has an R^2 value of 0.584, or 58.4%, suggesting that the model explains 58.4% of the variance in stunting data. However, since only two variables significantly contribute to the model, it is essential to verify the underlying model assumptions to ensure its reliability and adequacy. The local VIF values are presented in Table 5.

Table 5. VIF Local Value

Districts/Cities	X1	X2	X3	X4
Barru	1.258	1.148	10.136	9.593
Bone	1.291	1.196	10.023	9.244
Bulukumba	1.383	1.140	10.118	9.695
Enrekang	1.269	1.190	9.858	9.171
Gowa	1.355	1.135	10.688	10.227
Jeneponto	1.372	1.128	10.791	10.337
Luwu timur	1.284	1.155	9.932	9.152
Luwu utara	1.295	1.208	10.038	9.248
Luwu	1.285	1.195	9.865	9.125
Makassar	1.317	1.142	11.145	10.642
Maros	1.303	1.143	10.679	10.184

Districts/Cities	X1	X2	X3	X4
Palopo	1.299	1.210	10.071	9.271
Pangkep	1.286	1.144	10.531	10.03
Pare-pare	1.255	1.169	10.073	9.466
Pinrang	1.259	1.179	9.904	9.263
Selayar	1.377	1.135	9.620	9.258
Sidrap	1.259	1.174	9.651	9.010
Sinjai	1.361	1.140	10.224	9.763
Soppeng	1.265	1.150	9.900	9.357
Talakar	1.348	1.132	10.980	10.508
Toraja utara	1.305	1.227	10.036	9.234
Toraja	1.305	1.227	10.000	9.208
Wajo	1.261	1.160	9.593	9.007
Bantaeng	1.402	1.139	10.308	9.901

Geographically Weighted Lasso (*GWL*)

Based on the local VIF values obtained for all observation locations, the variables X_3 and X_4 exhibit local VIF values exceeding 10, indicating the presence of multicollinearity. To address this issue, the GWL method is employed, as it effectively mitigates multicollinearity and produces more efficient parameter coefficient estimates, leading to more accurate prediction results. The bandwidth value obtained through the iterative process using the CV method in GWL is 0.04. The shrinkage coefficient, also determined using the CV method, along with the bandwidth value, is then applied to estimate the parameters of the GWL model.

To determine the effect of a variable on the model, the t-statistic value at each observation location is examined. The obtained t-statistic value is then compared with the critical t-table value of 1.72. If the t-statistic value is less than the t-table value, H_0 is accepted, indicating that the variable does not significantly affect the model. Conversely, if the t-statistic value exceeds the t-table value, H_0 is rejected, signifying that the variable significantly influences the model. This approach allows for the identification of variables that contribute to the model.

The R^2 value in the GWL model is 95.7%, indicating that the model effectively explains the incidence of stunting based on the analyzed variables and successfully addresses issues of spatial heterogeneity and multicollinearity. A map illustrating the distribution of regions based on the grouping of significant variables derived from the GWL model is given in Figure 1. Grouping of districts/cities based on variables that have a significant influence on the GWL model is given in Table 6.

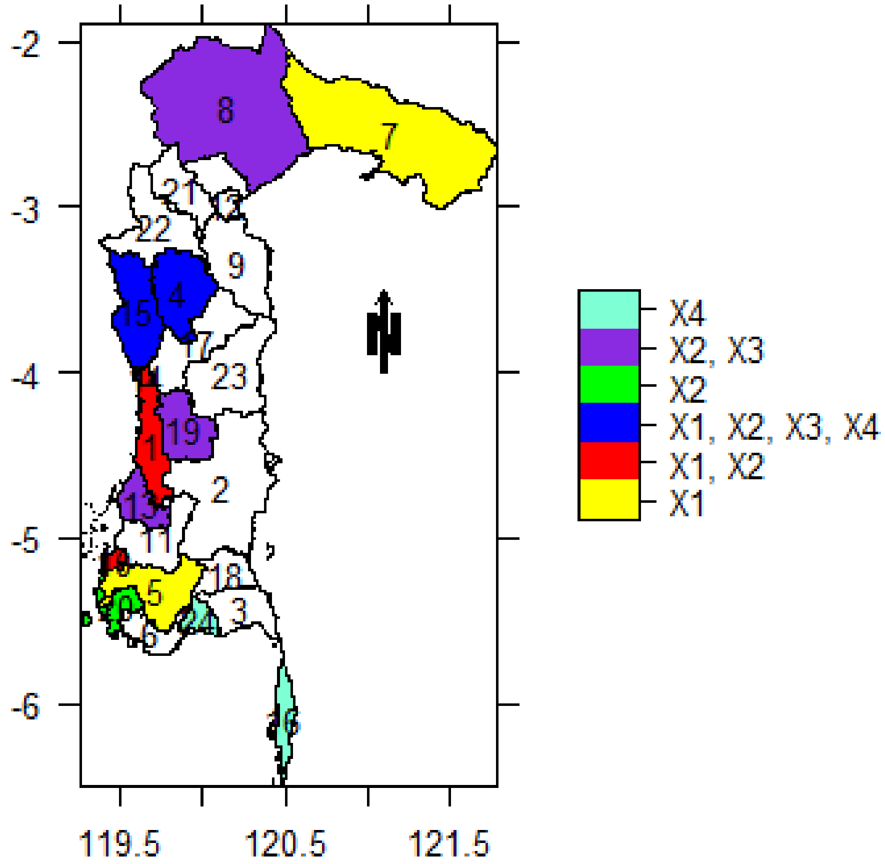

Figure 1. Map of Variable Significance Distribution

Table 6. Grouping of Districts/Cities Based on Variables that Have a Significant Influence on the GWL Model

Variable	Significant Districts/Cities
The percentage of low birth weight (X_1)	Barru, Enrekang, Gowa, Luwu Timur, Makassar, Pare-pare, Pinrang.
The proportion of households with access to clean drinking water (X_2)	Barru, Enrekang, Luwu Utara, Makassar, Pangkep, Pare-pare, Pinrang, Soppeng, Takalar.
The human development index (X_3)	Enrekang, Luwu Utara, Pangkep, Pinrang, Soppeng, Makassar.
The average years of parental schooling (X_4)	Enrekang, Pinrang, Kepulauan Selayar, Bantaeng.

For example, the following is a GWL model derived for Makassar City, demonstrating how the method addresses spatial heterogeneity and multicollinearity in the analysis of stunting incidence:

$$Y_{Makassar} = 0.323 + 0.469X_1 - 0.210X_2 - 0.644X_3$$

Based on the model presented above, the percentage of low birth weight variable has an influence of 0.469. This indicates that a one-unit increase in the percentage of low birth weight variable would result in a 0.469 increase in the prevalence of stunting. the proportion of households with access to clean drinking water variable has an influence of -0.210, suggesting that a one-unit increase in access to clean drinking water would reduce the prevalence of stunting by 0.210. Similarly, the human development index variable has an influence of -0.644, meaning that a one-unit increase in the human development index variable would decrease the prevalence of stunting by 0.644.

4. DISCUSSIONS

This study utilizes spatial data with multicollinearity issues to analyze factors influencing stunting in South Sulawesi in 2022, focusing on variables such as low birth weight, the proportion of households with access to clean drinking water, the human development index, and the average years of parental schooling. A fixed exponential kernel model was applied, with a bandwidth of 3.926 and a minimum CV of 19.493, resulting in a spatial model based on a 24x24 grid.

The GWR model, with an R^2 value of 0.584 (58.4%), was used for the initial analysis. A comparison of models involving two significant parameters indicated that the multicollinearity issue could be addressed by examining the local VIF values at each observation point. To further mitigate multicollinearity, the GWL model was applied, utilizing a shrinkage parameter (λ) to control the coefficient values. The GWL model achieved an R^2 value of 0.957 (95.7%), demonstrating a strong fit. This model reveals that the low birth weight, the proportion of households with access to clean drinking water, the human development index, and the average years of parental schooling about stunting in South Sulawesi collectively have a significant effect on the incidence of stunting.

These findings are consistent with previous studies that have demonstrated the importance of spatially varying relationships in health-related outcomes using GWR approaches [4, 5, 6]. Therefore, the results obtained in this research not only confirm the relevance of GWR and GWL models in spatial health data analysis but also reinforce the validity of local modeling techniques in addressing complex interactions and spatial heterogeneity in public health studies.

5. CONCLUSION

The model capable of addressing both heterogeneity and multicollinearity by reducing the coefficient values to zero is the GWL model. One of the models derived from the 24 models is as follows:

$$Y_{Makassar} = 0.323 + \ 0.469X_1 - 0.210X_2 - 0.644X_3$$

Factors influencing the model, as identified through GWL modeling, include the following: the percentage of low birth weight (X_1), which is significant in the areas of Barru, Enrekang, Gowa, Luwu Timur, Makassar, Pare-pare and Pinrang; the proportion of households with access to clean drinking water (X_2), which is significant in the areas of Barru, Enrekang, Luwu Utara, Makassar, Pangkep, Pare-pare, Pinrang, Soppeng and Takalar; the human development index (X_3), which is significant in the areas of Enrekang, Luwu Utara, Pangkep, Pinrang and Soppeng; and the average years of parental schooling (X_4), which is significant in the areas of Barru, Gowa, Luwu, and Pinrang.

This study recommends region-specific policies to reduce stunting, particularly in districts where key factors such as low birth weight, clean water access, education, and human development are significant. The GWL model has proven effective in addressing spatial heterogeneity and multicollinearity, making it a valuable tool for spatial health analysis. Future research could explore temporal dynamics, incorporate additional socio-environmental variables, or apply advanced spatial methods such as Bayesian models for deeper insights.

6. REFERENCES

[1] F. H. Evans, A. Recalde Salas, S. Rakshit, C. A. Scanlan, dan S. E. Cook, “Assessment of the Use of Geographically Weighted Regression for Analysis of Large On-Farm Experiments and Implications for Practical Application,” Agronomy, vol. 10, no. 11, art. 1720, 2020. doi:10.3390/agronomy10111720

[2] B. Kiani, B., Sartorius, B., Lau, C. L., & Bergquist, R., “Mastering geographically weighted regression: key considerations for building a robust model,” Geospatial Health, vol. 19, no. 1, art. 1271, Jan. 2024. doi:10.4081/gh.2024.1271

[3] Hairunnisa, H., Hadijati, M., & Fitriyani, N., “Geographically Weighted Lasso Method in Modeling the Gross Regional Domestic Product of the Bali-Nusra Region,” Jurnal Aplikasi Statistika & Komputasi Statistik, vol. 16, no. 1, pp. 58–66, Jun. 2024.

doi:10.34123/jurnalasks.v16i1.576

[4] Stewart Fotheringham & Taylor M. Oshan, "Geographically weighted regression and multicollinearity: dispelling the myth," Journal of Geographical Systems, vol. 18, no. 4, pp. 303 329, Oct. 2016, doi:10.1007/s10109-016-0239-5

[5] T. Sakai, J. Tsuchida, & H. Yadohisa, "Bayesian Geographically Weighted Sparse Regression (BGWSR) using Fused Lasso Prior," ArXiv preprint, Feb. 2024

[6] A. Setiyorini, J. Suprijadi, and B. Handoko, "Implementations of geographically weighted lasso in spatial data with multicollinearity (Case study: Poverty modeling of Java Island)," *AIP Conf. Proc.*, vol. 1827, 2017, doi: 10.1063/1.4979419.

[7] I. Ssgi, "Hasil Survei Status Gizi Indonesia (SSGI) 2022," 2023.

[8] G. Arbia, G. Espa, dan D. Giuliani, Spatial Microeconometrics, Routledge, 2021.

[9] Z. Mar'ah, A. Djuraidah, and A. Hamim, "Semi-parametric Geographically Weighted Regression Modelling using Linear Model of Coregionalization," *Int. J. Sci. Basic Appl. Res.*, vol. 34, no. 2, pp. 178–186, 2017.

[10] A. Comber, C. Brunsdon, M. Charlton, G. Dong, B. Lu, et al., "The GWR route map: a guide to the informed application of Geographically Weighted Regression," ArXiv preprint, April 2020

[11] Z. Mar'ah and S. Sifriyani, "Geographically Weighted Panel Regression (Gwpr) for Covid-19 Case in Indonesia," *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 17, no. 2, pp. 0879–0886, 2023, doi: 10.30598/barekengvol17iss2pp0879-0886.

[12] M. H. Kutner, C. J. Nachtsheim, and J. Neter, Applied Linear Regression Models, 4th ed. New York: McGraw-Hill Irwin, 2005.

[13] T. T. Pardede, B. Sumargo, and W. Rahayu, "Penerapan Regresi Least Absolute Shrinkage And Selection Operator (LASSO) Untuk Mengidentifikasi Variabel Yang Berpengaruh Terhadap Kejadian Stunting di Indonesia", JSA, vol. 6, no. 1, pp. 37–48, Jun. 2022.

[14] UNICEF, WHO, & World Bank, "Levels and trends in child malnutrition: Key findings of the 2023 edition," UNICEF, 2023. Available: https://www.unicef.org/reports/levels-and-trends child-malnutrition-2023

[15] D. Prayogi and Rini Rahani, "Determinants Analysis Of Stunting Prevalence Among Toddlers In Central Java Province In 2022", JSA, vol. 8, no. 2, pp. 152 163, Dec. 2024.