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# Geographically Weighted Regression Model of Stunting Determinants in Indonesia

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## ABSTRACT

**Background:** Stunting is a chronic condition resulting from malnutrition during early growth, potentially affecting physical and cognitive development in children into adults. According to the 2023 Indonesian Health Survey (SKI), stunting in Indonesia remains at 21.5%. This figure is still far from the government's target for 2024, which was below 14%. This study aims to identify the determinants of stunting caused by spatial conditions in Indonesia in 2024.
**Subjects and Method:** This study employed an ecological design with a spatial approach, utilizing aggregate data from the 2023 SKI and 2024 Central Bureau of Statistics (BPS) across 38 provinces in Indonesia. The dependent variable was stunting prevalence, and the analysis included eight independent variables using descriptive statistics, spatial analysis (Moran's I and Local Moran's I), multiple linear regression (OLS), and Geographically Weighted Regression (GWR). Data was processed between November 2024 and January 2025 using SPSS, Geoda, and R Studio.
**Results:** Results show that the average stunting prevalence in Indonesia in 2024 was 23.56% (Standard Deviation: 6.80), which unmet the government's target in the same year. The provinces with the lowest and highest stunting prevalence were Bali (7.2%) and Central Papua (39.3%). Meanwhile, Papua, West Papua, South Papua, Central Papua, and Highlands Papua were provinces with high stunting prevalence and surrounded by similarly high prevalence (high-high) provinces. In contrast, Banten and West Sumatra had high stunting prevalence but were surrounded by provinces with low prevalence (High-Low). Finally, factors influencing stunting across geographical areas included stunting knowledge, completion of immunization coverage, and poverty rates.
**Conclusion:** Efforts to reduce stunting in Indonesia should focus on improving communication, information, and education, particularly in provinces with high prevalence. In addition, increasing coverage and access to complete basic immunization and enhanced family welfare should also be highlighted.

**Keywords:** stunting, geographically weighted regression, spatial.

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## BACKGROUND

One of the critical global nutrition challenges is addressing stunting in children under five. Stunting is a chronic condition caused by early-life malnutrition, with long-term consequences on physical growth and cognitive development (BKPK, 2023). Sustainable Development Goal (SDG) 2.2 aims to eliminate all forms of malnutrition, ensuring adequate nutrition for adolescent girls, pregnant and lactating mothers, and the elderly (BKPK, 2023).

Globally, the 2022 stunting prevalence was 22.3%, with 148.1 million children affected. Over half of stunted children worldwide reside in Asia (76.6 million), while approximately 42% (63.1 million) live in Africa. The 2022 Association of Southeast Asian Nations (ASEAN) Snapshot Report showed declining stunting prevalence in Cambodia, the Philippines, Vietnam, and Myanmar, whereas Malaysia, Thailand, and Indonesia experienced increases (ASEAN Stats, 2022).

Stunting remains a major health issue in Indonesia. According to the 2023 Indonesian Health Survey (SKI), approximately one (1) in five (5) children aged 0-59 months in Indonesia experienced stunting (BKPK, 2023). The national stunting prevalence was 21.5%, beyond the government's 2024 target, below 14%. Figure 1 shows a significant regional disparity, with stunting prevalence ranging from 7.2% (Bali) to 39.3% (Central Papua). Fifteen out of 38 provinces had stunting prevalence below the national average, with Bali (7.2%), Jambi (13.5%), and Riau (13.6%) having the lowest rates. However, 23 provinces reported stunting prevalence above the national average, with Central Papua (38.4%), East Nusa Tenggara (37.9%), and Highlands Papua (37.3%) having the highest rates (BKPK, 2023).

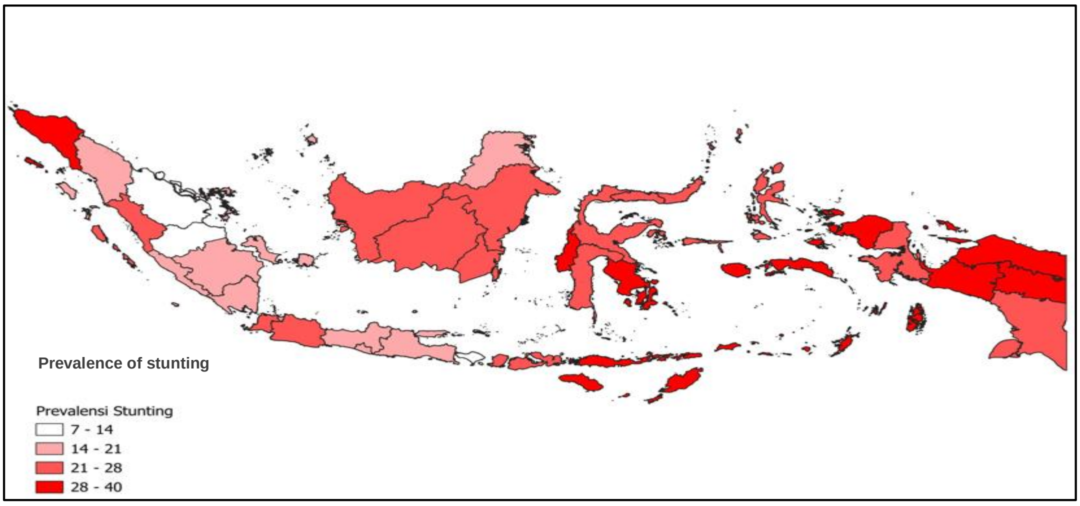


**Figure 1. Map of Stunting Prevalence Distribution in Indonesia**
(Source: SKI 2023, processed by researchers)

Stunting is influenced by various factors occurring during prenatal, birth, and post-natal stages, encompassing maternal and infant-related factors.

Given that stunting impacts both child growth and cognitive development, long-term health, and productivity in adulthood (Soliman A et al., 2021; Yadika ADN et al., 2019), addressing these critical stages is essential to reduce stunting prevalence.

An appropriate statistical modeling approach is necessary to identify key determinants of stunting in Indonesia. Traditional Multiple Linear Regression using the Ordinary Least Squares (OLS) method may produce invalid results if spatial effects are present, leading to non-independent errors and inaccurate model interpretation (Grekousis, 2020). The Geographically Weighted Regression (GWR) method is widely applied to overcome spatial heterogeneity, as it can capture spatial variations by generating local regression coefficients for each region studied (Grekousis, 2020).

Despite numerous studies on stunting determinants in Indonesia, limited research has accounted for spatial heterogeneity. Understanding spatial heterogeneity is crucial, as each district/city has unique characteristics that may be overlooked in conventional analyses (Pramono et al., 2012). Therefore, this study aims to analyze the spatial distribution and model the determinants of stunting in Indonesia in 2024.

## SUBJECTS AND METHOD

### 1. Study Design

This study employed an ecological study design with a spatial approach, utilizing aggregate data from the 2023 SKI and 2024 BPS across 38 provinces in Indonesia. We further analyzed the aggregated data between November 2024 and January 2025.

### 2. Population and Sample

This study utilized secondary data derived from aggregate data published publicly by BPS in 2024, and from the 2023 SKI report. The 2023 SKI data covered all regions of Indonesia, with households as the observation unit. The survey sample comprised 315,646 households and 1,191,692 household members, distributed across 38 provinces and 514 districts/ cities. The sampling in the 2023 SKI was conducted using a systematic sampling technique.

### 3. Study Variables

The dependent variable was stunting prevalence, while the independent variables were population density, poverty levels, stunting awareness, sanitation access, access to drinking water, exclusive breastfeeding, complete neonatal visits, and complete basic immunization.

### 4. Operational Definition of Variables

Stunting prevalence was the proportion of children aged 0–59 months with a height-for-age Z-score below -2.0, aggregated at the provincial level. Population density was defined as the number of individuals per square kilometer ($Km^2$) of land area, while the poverty rate indicated the proportion of individuals living below the poverty line. Furthermore, stunting awareness reflected the percentage of individuals with accurate knowledge of stunting. Access to sanitation and drinking water represented the proportion of households with access to improved sanitation services and safe drinking water, respectively. In addition, exclusive breastfeeding referred to the percentage of children aged 6–23 months who were exclusively breastfed for the first six months. Complete neonatal visits indicated the proportion of children aged 0–59 months who received all recommended neonatal check-ups, whereas complete basic immunization was the proportion of children aged 12–23 months who received the full schedule of basic vaccinations.

### 5. Study Instruments

The 2023 SKI used three instruments: the individual, and Household with and without Children under 5 years old.

### 6. Data analysis

Data processing was conducted using SPSS for descriptive analysis, Geoda for spatial analysis and geographic data visualization, and R Studio for GWR modeling. No study sample was required since the design was ecological and the data was aggregated (Gerstman BB, 2013). The entire population dataset served as the study sample.

We conducted the following analysis. First, a descriptive analysis was conducted to provide an overview of each variable. Second, neighborhood definitions were established based on proximity using the queen contiguity method, where a region is considered neighboring if it shares either a corner or a side with another region (Akolo IR, 2022). This step was necessary before conducting spatial analysis. Third, Global spatial autocorrelation analysis using Moran's I was performed on the stunting variable, with values ranged from -1 to 1, where higher values indicated stronger positive spatial autocorrelation. The Moran's I value was then compared with the expected value (E[I]) to determine the clustering pattern of the data. Local spatial autocorrelation was also assessed using Local Moran's I, identifying spatial clustering patterns of stunting prevalence in specific provinces. The clustering results were classified into four groups:

1. High-High: Locations with high stunting prevalence surrounded by neighbors with similarly high stunting prevalence.
2. Low-Low: Locations with low stunting prevalence surrounded by neighbors with similarly low stunting prevalence.
3. Low-High: Locations with high stunting prevalence but surrounded by neighbors with low stunting prevalence.
4. High-Low: Locations with low stunting prevalence but surrounded by neighbors with high stunting prevalence.

Fourth, multiple linear regression using the OLS method was conducted, which consisted the following steps:

1. Classical assumption tests to check for strong correlations between independent variables.
2. Backward stepwise variable selection, including normality, homoscedasticity, and independence tests.

Finally, the GWR modeling used independent variables with the highest adjusted R-square value from the multiple linear regression analysis with the OLS method. The steps for spatial regression analysis using GWR included:

1. Determining weights using adaptive Gaussian, adaptive exponential, and adaptive bisquare kernel functions, with the cross-validation (CV) method, to obtain the optimal bandwidth.
2. Comparing GWR models generated from adaptive Gaussian, exponential, and bisquare kernel functions. The selected model had the lowest Akaike Information Criterion (AIC) value.
3. Estimating GWR model parameters.
4. Obtaining the GWR model for stunting determinants in each province.
5. Selecting the best model based on AIC and R-square values, where the best model had a lower AIC and a higher R-square.

## RESULTS

### 1. Descriptive analysis and determinants of stunting

Table 1 presents the descriptive analysis of one dependent and eight independent variables. The average stunting prevalence was 23.56% (SD: 6.80). The mean population density was 667.08 people/km$^2$ (SD: 2,579.87 people/km$^2$). The average poverty rate was 11.15% (SD: 6.67%), knowledge stunting 43.06% (SD: 8.32%), complete basic immunization 30.62% (SD: 15.14%), and complete neonatal visits 33.46% (SD: 12.92%). The average proportion of proper sanitation access was 81.14% (SD: 15.07%), proper drinking water access was 87.00% (SD: 11.82%), and exclusive breastfeeding was 70.57% (SD: 8.34%).

**Table 1. Descriptive analysis and determinants of stunting**

| Variable | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|
| Population Density (people/km$^2$) | 667.08 | 2,579.87 | 9.00 | 15.978.00 |
| Stunting prevalence (%) | 23.56 | 6.80 | 7.20 | 39.30 |
| Proverty rate (%) | 11.15 | 6.75 | 4.00 | 32.97 |
| Stunting knowledge (%) | 43.06 | 8.32 | 31.38 | 64.92 |
| Complete basic immunization (%) | 30.62 | 15.14 | 3.90 | 73.50 |
| Complete neonatal visits (%) | 33.46 | 12.92 | 8.80 | 63.80 |
| Sanitation access (%) | 81.14 | 15.07 | 12.61 | 96.83 |
| Drinking access (%) | 87.00 | 11.82 | 30.64 | 99.96 |
| Exclusive breastfeeding (%) | 70.57 | 8.34 | 44.64 | 83.07 |

### 2. Stunting Spatial Autocorrelation Test

The global spatial autocorrelation analysis of stunting using Moran's I is shown in Table 2. The Moran's I index was 0.4661, higher than the expected value E(I) of -0.0270, indicating a clustered distribution of stunting in Indonesia. This suggests that stunting prevalence in Indonesia was spatially dependent, forming clusters in specific areas. The pseudo p-value of 0.0010 confirmed the statistical significance of spatial autocorrelation. Stunting prevalence in neighboring provinces was similar to distant provinces (Table 2).

**Table 2. Results of spatial autocorrelation testing using Moran's I**

| Test Type | p |
|---|---|
| Morans'I | 0.466 |
| E [I] | -0.027 |
| Pseudo p value | 0.001 |

### 3. Cluster map stunting autocorrelation test

The results of the spatial autocorrelation analysis using The Local Moran's I cluster map indicated that out of 38 provinces, 16 had a significance value of less than 0.05. The remaining 22 provinces had a significance value greater than 0.05. Among these 16 provinces, five were classified as High-High, meaning they had a high stunting prevalence and were surrounded by neighboring provinces with similarly high stunting prevalence. Nine provinces fell into the Low-Low category, with low stunting prevalence clustered together with similarly low-prevalence neighbors. Additionally, two provinces were categorized as High-Low, indicating that they had low stunting prevalence but were surrounded by provinces with high stunting prevalence. No provinces were classified in the Low-High category. The provinces categorized as High-Low were West Sumatra and Banten, indicating that these regions had a high stunting prevalence despite being surrounded by provinces with low stunting prevalence (Figure 2).

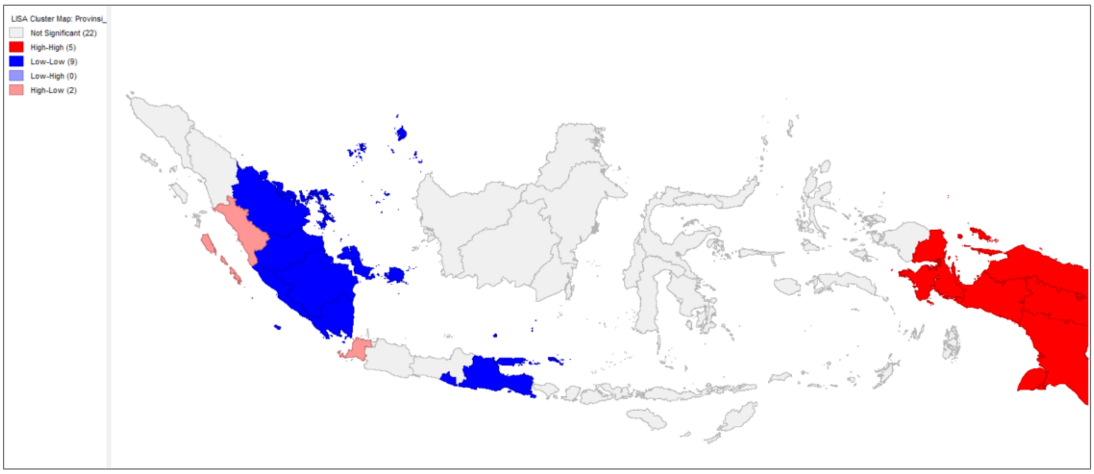


**Figure 2. Cluster map autocorrelation test results with Morans'I**

### 4. Multiple linear regression analysis

Backward stepwise multiple linear regression yielded a model with the highest R-squared value. Three variables were eliminated from the model (e.g. population density, complete neonatal visits, and proper drinking water access). The final model showed 68% of the variation in stunting prevalence ($R^2$ = 0.6809), while the remaining 32% was explained by other variables not included in the study (Table 3).

**Table 3. Final modeling of stunting determinants with multiple linear regression**

| Variable | Coefficient | Standard Error | p |
|---|---|---|---|
| Intercept | 56.46 | 16.42 | 0.001 |
| Proverty rate (%) | 0.59 | 0.17 | 0.001 |
| Stunting knowledge (%) | -0.36 | 0.12 | 0.005 |
| Complete basic immunization (%) | -0.16 | 0.05 | 0.005 |
| Sanitation access (%) | -0.11 | 0.09 | 0.231 |
| Exclusive breastfeeding (%) | -0.14 | 80.09 | 0.140 |
| R Square= 0.6809 | | | |
| AIC= 223.1354 | | | |

### 5. Assumption tests for multiple linear regression

The assumption testing results indicated that the assumptions of normality, homoscedasticity, linearity, and independence were met (p-value > 0.05). Additionally, the linearity assumption was satisfied (p-value < 0.05). Multicollinearity testing showed that all independent variables had a Variance Inflation Factor (VIF) value of less than 10, indicating no significant correlation between independent variables. As a result, all five independent variables were deemed suitable for inclusion in the regression model.

**Table 4. Test assumptions in multiple linear regression**

| Assumptions | Test Type | p | Conclusion |
|---|---|---|---|
| Normality | Shapiro-Wilk | 0.834 | The normality assumption was met |
| Homoscedasticity | Breusch-Pagan | 0.579 | The homoscedasticity assumption was met |
| Independence | Durbin- | 0.199 | The independence assumption was met |

| Assumptions | Test Type | p | Conclusion |
|---|---|---|---|
| Linearity | Watson Anova | <0.001 | The linearity assumption was met |
| Multicollinearity | VIF | VIF values for all variables <10 | Multicollinearity did not occur |

**6. Selection of optimal bandwidth and weighting function**

The bandwidth selection was conducted using cross-validation with three kernel functions: bisquare, exponential, and Gaussian. The optimal kernel function was determined based on the lowest Akaike Information Criterion (AIC) value. The results indicated that the exponential kernel function had the lowest AIC value, making it the most suitable choice (Table 5).

**Table 5. Comparison of the best weighting functions**

| Kernel Function | AIC Value |
|---|---|
| Bisquare | 214.26 |
| Exponential | 208.96 |
| Gaussian | 214.81 |

**7. GWR model of stunting determinants**

Table 6 presents the parameter estimation results for the GWR model using the exponential kernel function. The analysis yielded an R-square value of 75%, indicating that the variation in stunting prevalence can be explained by combining five independent variables in the GWR model. In comparison, the remaining 25% was attributed to other unexamined factors. Since the estimated parameters in the GWR model were spatially localized, the model provides parameter estimates specific to each province. Additionally, the GWR model allowed for the evaluation of the significance of each variable at the provincial level. Among the five analyzed variables, three were found to have a statistically significant impact on stunting ($p<0.050$), namely poverty rate, stunting-related knowledge, and complete basic immunization.

**Table 6. GWR model results for stunting determinants**

| Variable | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|
| Intercept | 47.59 | 50.16 | 55.21 | 62.53 | 66.07 |
| Proverty rate (%) | 0.52 | 0.54 | 0.57 | 0.59 | 0.67 |
| Stunting knowledge (%) | -0.39 | -0.38 | -0.35 | -0.32 | -0.31 |
| Complete basic immunization (%) | -0.19 | -0.18 | -0.17 | -0.15 | -0.13 |
| Access sanitation (%) | -0.17 | -0.14 | -0.11 | -0.08 | -0.06 |
| Exclusive breastfeeding (%) | -0.19 | -0.18 | -0.12 | -0.10 | -0.08 |
| R Square=0.7516 | | | | | |
| AIC=208.8114 | | | | | |

**8. GWR model of stunting determinants by province**

The results of the Geographically Weighted Regression (GWR) model When using an exponential weighting function, the result indicated that all 38 provinces in Indonesia exhibited significant associations with three independent variables related to stunting:

stunting-related knowledge, complete basic immunization, and poverty rate (p-value < 0.05). Whereas, two variables (access to proper sanitation and exclusive breastfeeding) otherwise (Table 7). The significance values for each province are detailed in Table 7.

**Table 7. Significance values from GWR by province**

| Province | Intercept | Proverty rate | Stunting knowledge | Complete basic immunization | Access to sanitation | Exclusive breastfeeding |
|---|---|---|---|---|---|---|
| Aceh | 0.011 | 0.004 | 0.021 | 0.006 | 0.423 | 0.368 |
| North Sumatra | 0.009 | 0.004 | 0.016 | 0.006 | 0.397 | 0.333 |
| West Sumatra | 0.010 | 0.003 | 0.017 | 0.005 | 0.445 | 0.359 |
| Riau | 0.013 | 0.006 | 0.031 | 0.013 | 0.432 | 0.279 |
| Jambi | 0.011 | 0.007 | 0.027 | 0.012 | 0.366 | 0.304 |
| South Sumatra | 0.010 | 0.004 | 0.022 | 0.007 | 0.398 | 0.364 |
| Bengkulu | 0.002 | 0.011 | 0.009 | 0.033 | 0.108 | 0.090 |
| Lampung | 0.017 | 0.005 | 0.034 | 0.013 | 0.522 | 0.297 |
| Bangka Belitung | 0.004 | 0.005 | 0.010 | 0.008 | 0.238 | 0.140 |
| Riau | 0.002 | 0.013 | 0.009 | 0.031 | 0.110 | 0.088 |
| DKI Jakarta | 0.003 | 0.008 | 0.009 | 0.004 | 0.175 | 0.096 |
| West Java | 0.012 | 0.005 | 0.026 | 0.009 | 0.410 | 0.376 |
| Central Java | 0.002 | 0.012 | 0.009 | 0.025 | 0.118 | 0.079 |
| Yogyakarta | 0.002 | 0.010 | 0.009 | 0.020 | 0.136 | 0.080 |
| East Java | 0.013 | 0.006 | 0.033 | 0.015 | 0.449 | 0.258 |
| Banten | 0.003 | 0.008 | 0.010 | 0.016 | 0.149 | 0.161 |
| Bali | 0.008 | 0.003 | 0.012 | 0.005 | 0.398 | 0.290 |
| West Nusa Tenggara | 0.002 | 0.012 | 0.009 | 0.027 | 0.114 | 0.084 |
| East Tenggara Timur | 0.005 | 0.003 | 0.010 | 0.005 | 0.324 | 0.222 |
| West Kalimantan | 0.004 | 0.005 | 0.010 | 0.006 | 0.272 | 0.173 |
| Central Kalimantan | 0.011 | 0.007 | 0.027 | 0.011 | 0.374 | 0.319 |
| South Kalimantan | 0.002 | 0.012 | 0.009 | 0.032 | 0.115 | 0.099 |
| East Kalimantan | 0.011 | 0.003 | 0.018 | 0.005 | 0.478 | 0.382 |
| North Kalimantan | 0.012 | 0.002 | 0.015 | 0.005 | 0.510 | 0.402 |
| North Sulawesi | 0.005 | 0.006 | 0.012 | 0.007 | 0.256 | 0.211 |
| Central Sulawesi | 0.002 | 0.012 | 0.009 | 0.032 | 0.130 | 0.101 |
| South Sulawesi | 0.004 | 0.008 | 0.011 | 0.008 | 0.209 | 0.177 |
| Southeast Sulawesi | 0.015 | 0.005 | 0.033 | 0.014 | 0.486 | 0.270 |
| Gorontalo | 0.002 | 0.010 | 0.009 | 0.019 | 0.141 | 0.092 |
| West Sulawesi | 0.002 | 0.011 | 0.009 | 0.023 | 0.125 | 0.080 |
| Maluku | 0.003 | 0.009 | 0.009 | 0.015 | 0.166 | 0.092 |
| North Maluku | 0.011 | 0.005 | 0.023 | 0.008 | 0.399 | 0.361 |
| West Papua | 0.006 | 0.006 | 0.015 | 0.009 | 0.257 | 0.253 |
| Southwest Papua | 0.006 | 0.006 | 0.015 | 0.008 | 0.280 | 0.265 |
| Papua | 0.004 | 0.006 | 0.010 | 0.009 | 0.228 | 0.135 |
| South Papua | 0.011 | 0.006 | 0.025 | 0.009 | 0.388 | 0.350 |
| Central Papua | 0.003 | 0.008 | 0.010 | 0.011 | 0.176 | 0.158 |
| Papua Mountains | 0.003 | 0.007 | 0.010 | 0.012 | 0.197 | 0.105 |

## 9. Model selection

Table 8 compares the performance of multiple linear regression and GWR models. The GWR model demonstrated superior performance, with a higher R-squared value (0.7516) and a lower AIC value (208.8114) compared to multiple linear regression ($R^2$= 0.68, AIC= 223.13). Based on these criteria, the GWR model with an exponential weighting function was identified as the best model for analyzing stunting determinants in Indonesia.

**Table 8. Best model selection**

| Model | R Square Value | AIC Value |
|---|---|---|
| Multiple Linear Regression | 0.68 | 223.13 |
| GWR | 0.75 | 208.81 |

## DISCUSSION

The global spatial autocorrelation analysis results indicate a positive spatial autocorrelation with a clustered pattern. This finding suggests that the prevalence of stunting in neighboring provinces tends to be similar compared to geographically distant provinces. These results align with previous studies by (Tahangnacca and Muntahaya, 2023) and (Sipahutar et al., 2022), which also reported that stunting in Indonesia exhibits spatial autocorrelation with a clustered pattern. The clustering of stunting cases may be attributed to the tendency of neighboring regions to share similar characteristics. Lifestyle, beliefs, and cultural factors can influence this clustering pattern and access to healthcare facilities, which tend to be comparable across adjacent areas (Tahangnacca and Muntahaya, 2023).

The spatial autocorrelation cluster map analysis results using Local Moran's I identified five provinces categorized as High-High clusters, namely Papua, West Papua, South Papua, Central Papua, and Highland Papua. These provinces exhibit a high prevalence of stunting and are surrounded by other provinces with similarly high stunting prevalence. Parenting practices, energy intake, and protein intake are key risk factors for stunting among both indigenous Papuans and non-Papuan populations. Energy intake has been identified as the dominant factor influencing stunting among indigenous Papuans, while protein intake is the primary factor among non-Papuans (Ramadhani et al., 2019).

Additionally, two provinces were classified as Low-High clusters, meaning they have a high prevalence of stunting despite being surrounded by provinces with low stunting prevalence. These provinces are Banten and West Sumatra. The high stunting rates in Banten are attributed to poor environmental conditions, inadequate clean water facilities, and poor sanitation, which worsened during the COVID-19 pandemic (BPD Provinsi Banten, 2022). Meanwhile, the high stunting prevalence in West Sumatra is associated with human development index disparities and income inequality (Resfaliza et al., 2024).

The spatial regression modeling using GWR produces a model with an R-squared value of 75.16% and an Akaike Information Criterion (AIC) of 208.81, demonstrating a better fit compared to the Multiple Linear Regression (MLR) model (R-squared= 68.09%, AIC = 223.13). These results confirm that spatial models effectively capture local variations that global models cannot explain. In this context, spatial analysis provides deeper insights into local factors influencing stunting, which is crucial for evidence-based intervention planning. The provincial classification using the GWR model and the exponential weighting function revealed that all 38 provinces demonstrated statistical significance ($p < 0.05$) for Three independent variables associated with stunting: poverty, knowledge of stunting, and complete basic immunization across 38 provinces ($p < 0.05$), with the following explanations. The explanations for these relationships are as follows:

First, poverty. Stunting is predominantly found in impoverished communities, where low income restricts access to nutritious food and affects overall quality of life. Consistent with (Karyati, 2021), poverty levels, economic growth rates, and education levels contribute significantly to stunting prevalence in the ten highest-affected regions of Indonesia. Economic constraints hinder families from meeting balanced nutritional needs, making poverty a dominant driver of stunting (Sutarto et al., 2018).

Second, knowledge of stunting. A body of literature suggests that knowledge is crucial in shaping health behaviors. Knowledge is acquired through sensory perception of specific subjects, influencing individuals' attitudes toward health. A study by (Ningtyas et al., 2020) found that maternal knowledge of nutrition is significantly associated with stunting prevalence. This finding aligns with research by (Juniantari et al., 2024), which indicates a significant relationship between maternal knowledge of stunting and stunting incidence.

Third, complete immunization status. Immunization stimulates the production of antibodies and strengthens immunity, effectively preventing the transmission of certain diseases. The primary objective of childhood immunization is to reduce morbidity and mortality risks associated with vaccine-preventable diseases. Research by (Wanda et al., 2021) demonstrated a significant association between a child's immunization history and stunting occurrence. Similarly, Kurniawati (2020) found that incomplete immunization is one of the risk factors for stunting, with children lacking full immunization being 2.9 times more likely to experience stunting (Kurniawati, 2020).

These findings highlight the importance of addressing poverty, enhancing knowledge about stunting, and promoting complete immunization coverage as key strategies for stunting prevention in Indonesia. A spatial approach, such as GWR, allows for a more localized and targeted intervention strategy, optimizing public health efforts to reduce stunting prevalence.

The average prevalence of stunting in Indonesia is 23.56%, with a standard deviation of 6.80, which remains significantly higher than the government's 2024 target of 14%. The province with the lowest stunting prevalence is Bali (7.2%), while the highest prevalence is observed in Central Papua (39.3%). Spatial autocorrelation analysis indicates that, across 38 provinces, stunting prevalence exhibits a statistically significant positive spatial autocorrelation with a clustered pattern. The Local Moran's I cluster map analysis identifies five provinces categorized as High-High clusters—Papua, West Papua, South Papua, Central Papua, and Highland Papua—where stunting prevalence is high and surrounded by provinces with similarly high prevalence. Meanwhile, two provinces, Banten and West Sumatra, fall into the Low-High category, indicating a high stunting prevalence despite being surrounded by provinces with lower prevalence.

The estimation of GWR model parameters using an exponential kernel function yields an R-squared value of 75%, indicating that the variation in stunting prevalence can be explained by a combination of five independent variables: poverty rate, stunting awareness, basic immunization coverage, access to adequate sanitation, and exclusive breastfeeding. The remaining 25% is attributed to other factors not included in the study. Poverty rate, stunting awareness, and basic immunization coverage are identified as the most significant determinants of stunting at the provincial level.

To reduce stunting, the Indonesian government should prioritize interventions in the High-High cluster provinces—Papua, West Papua, South Papua, Central Papua, and Highland Papua. These efforts should ensure a continuous and comprehensive approach to child development, beginning from pregnancy through early childhood. Key measures include ensuring maternal nutrition during pregnancy, childbirth, and breastfeeding and providing adequate nutrition for infants and young children. Additionally, enhancing the monitoring and evaluation system is crucial to assess the effectiveness of policies aimed at reducing stunting.

Adopting successful strategies from surrounding regions could be beneficial for Low-High provinces such as Banten and West Sumatra, where stunting prevalence remains high despite neighboring provinces having lower rates. These strategies may include supplementary feeding programs for pregnant women, iron and calcium supplementation, and improved water and sanitation facilities. Strengthening nutrition and healthcare services, ensuring high-quality interventions, and enhancing accountability in service delivery are also critical.

Further interventions should focus on improving education, communication, and public awareness regarding stunting, particularly among pregnant women, breastfeeding mothers, and households with young children. Strengthening the role of community health posts (Posyandu) can help increase public knowledge and awareness about stunting prevention. Additionally, ensuring universal access to basic immunization, especially in remote and underserved areas, is essential. Addressing poverty through targeted economic and social policies—such as improving education and skill development for low-income families—can also contribute to reducing stunting rates in Indonesia. By implementing these strategies, significant progress in stunting reduction can be achieved.

## AUTHORS CONTRIBUTION

Dini Kurniawati served as the principal investigator, responsible for developing the research concept, designing the methodology, managing the research process, conducting data analysis, and drafting the initial version of the manuscript. Wiji Wahyuningsih contributed as a co-author by editing and revising the manuscript and refining the research methodology. Iko Safika and Sutanto Priyo Hastono contributed to ensuring the integrity of the research, interpreting the findings, formulating the conclusions, and supervising the final revision of the manuscript prior to publication.

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## CONFLICT OF INTEREST

There was no conflict of interest.

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