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LOCATION-BASED STUNTING MODELING USING GEOGRAPHICALLY WEIGHTED PANEL REGRESSION IN BLITAR REGENCY

Henny Pramoedyo[1*], Wigbertus Ngabu[2], Atiek Iriany[3]

[1,2,3]Department Statistics, Faculty of Mathematics and Science
Brawijaya University, Indonesia
[1]hennyp@ub.ac.id
(**corresponding author*)

ABSTRACT

Stunting remains a significant public health issue in Blitar Regency, Indonesia, particularly in rural areas where chronic malnutrition and inadequate access to healthcare services persist as major challenges. This study aims to explore the spatial and temporal factors influencing stunting using the Geographically Weighted Panel Regression (GWPR) method. By integrating cross-sectional and time-series data from 2021 to 2023, the study evaluates various factors, including the stunting prevalence rate and independent variables such as maternal education level, per capita income, the number of postpartum mothers receiving Vitamin A supplements, immunization coverage, and the availability of healthcare personnel. The findings reveal that stunting prevalence is significantly influenced by location-specific variables, with healthcare access and nutrition being dominant factors in rural areas, while economic conditions exert a greater influence in urban areas. The GWPR model provides deeper insights into spatial heterogeneity and offers valuable guidance for designing targeted and region-specific policies to reduce stunting rates in Blitar Regency. The results indicate that the R-Square value of the GWPR model is 0.9123, meaning that 91.23% of the stunting prevalence in Blitar Regency can be explained by the independent variables in this study.

Keywords : Stunting, Geographically Weighted Regression (GWR) Panel, Spatial Variation

I. INTRODUCTION

Stunting is a significant public health issue in Indonesia, especially in rural areas like Blitar Regency. Stunting, or short stature, refers to a condition where children are shorter than the standard height for their age due to chronic malnutrition and repeated infections during growth periods (Beal et al., 2018). Data from Indonesia's Ministry of Health shows that the prevalence of stunting in Blitar Regency remains high. This issue is complex and multifaceted, requiring innovative and holistic approaches to understand and address it (Budiastutik & Nugraheni, 2018).

Various factors contribute to the high stunting rates, including socioeconomic conditions, parenting practices, access to healthcare services, and the availability and quality of food (Prendergast & Humphrey, 2014). Each of these factors may vary spatially across different areas within Blitar Regency. Therefore, an analysis that considers spatial variation is crucial for a more comprehensive understanding of the distribution and determinants of stunting (Sipahutar et al., 2022). In this context, location-based statistical modeling, such as Geographically Weighted Regression (GWR), offers a more accurate approach to analyzing data with spatial dimensions (Iriany et al., 2023) (Sulekan & Jamaludin, 2020).

GWR is a statistical method that accounts for geographic variation by assigning greater weight to data that are geographically closer (Wheeler, 2021). The innovation of this study lies in the use of GWR to more accurately identify the factors influencing stunting in various locations, as compared to conventional regression models that assume uniform relationships between variables across the entire study area (Anismuslim et al., 2023). This approach provides new insights into the local variations of stunting determinants, which in turn can assist in designing more effective and targeted interventions.

This research also introduces the use of panel data, which combines cross-sectional and time series data, to capture both the temporal dynamics and spatial variations of stunting. The innovation in using panel data enables a deeper analysis of changes in the determinants of stunting over time and how the interaction between these factors evolves across different locations (Pramoedyo et al., 2020). This approach offers a more comprehensive and dynamic understanding of the stunting phenomenon and its determinants in Blitar Regency.

Moreover, the approach that integrates GWR and panel data provides additional value in the policy context (Mar'ah & Sifriyani, 2023). This study's findings are anticipated to provide a basis for local governments to develop more precise and localized policies. By considering regional variations, evidence-based policy innovations are expected to more effectively reduce stunting rates and improve the quality of life for children in Blitar Regency.

Overall, this study aims to make a significant contribution to the efforts to combat stunting in Blitar Regency through an innovative analytical approach. By gaining a deeper understanding of the local factors influencing stunting through GWR and panel data methods, it is hoped that more targeted and sustainable interventions can be implemented, Ultimately, this approach aims to enhance the health and overall well-being of children in the region. (Muche et al., 2021).

II. METHODS

2.1. Data

This study utilizes panel data, encompassing cross-sectional and time-series data from all sub-districts in Blitar Regency during the 2021–2023 period. The data were obtained from official sources, such as the Blitar Regency Health Office, for stunting prevalence. The variables analyzed include the dependent variable, namely the stunting prevalence rate, and independent variables such as maternal education level, per capita income, the number of postpartum mothers receiving Vitamin A supplements, immunization coverage, and the availability of healthcare personnel.

2.2. Panel Regression

Panel data integrates cross-sectional and time-series elements, with each unit in the cross-sectional dataset being observed repeatedly over a defined time frame. The panel data regression model is generally represented by the following equation:(Ngabu, Pramoedyo, et al., 2023)

$$Y_{it} = \alpha_{it} + \sum_{k=1}^{n} \beta_k X_{kit} + \varepsilon_{it} \quad (1)$$

where :

y_{it} : Response variable

α_{it} : Intercept coefficient

β : Panel regression parameter

x_{kit} : Predictor variable

ε_{it} : Residual/error

2.3. Geographically Weighted Regression

Geographically Weighted Regression (GWR) is a statistical technique designed to examine spatial heterogeneity. This phenomenon arises when the same predictor variable generates varying responses across different locations within the same study area (H. Yu et al., 2020). The GWR model is an extension of simple linear regression. While simple linear regression uses the same parameters for all locations, GWR assigns different parameters to each location. The GWR model can be expressed as follows: (Pramoedyo et al., 2024).

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

where:

y_i : Response variable

β : Panel regression parameter

u_i, v_i : Coordinate points (longitude and latitude)

x_{ik} : Predictor variable

ε_i : Residual/error

2.4. Estimation of GWR Parameters

The parameters in the Geographically Weighted Regression (GWR) model can be estimated using the Weighted Least Squares (WLS) method by applying specific weights to each location. The parameter estimation for the GWR model at each observation point can be represented as follows: (Iriany et al., 2024).

$$\widehat{\boldsymbol{\beta}}(u_i, v_i) = [\boldsymbol{X^T W}(u_i, v_i)\boldsymbol{X}]^{-1}\boldsymbol{X}^T W(u_i, v_i)\boldsymbol{y} \tag{3}$$

Where:

$\boldsymbol{W}$: weight matrix

with $\boldsymbol{W}(i)$ representing a spatial weight matrix of size $n \times n$

$$\mathbf{W}(\mathrm{i}) = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & w_{in} \end{bmatrix}$$

2.5. Geographically Weighted Panel Regression (GWPR)

The Geographically Weighted Panel Regression (GWPR) integrates the characteristics of the GWR model with the principles of panel data regression. The equation for the GWPR model is formulated as follows: (Du et al., 2020).

$$\ddot{y}_{it} = \beta_0(u_{it}, v_{it}) + \sum\nolimits_j \beta_j(u_{it}, v_{it})\,\ddot{x}_{itj} + \ddot{\varepsilon}_{it}$$

The GWPR model can be written in matrix form as follows.

$$\ddot{\boldsymbol{y}} = \ddot{X}\beta\,(u_{it}, v_{it}) + \ddot{\varepsilon} \tag{4}$$

Where :

$$\ddot{\boldsymbol{y}} = \begin{bmatrix} \ddot{y}_{11} \\ \ddot{y}_{21} \\ \vdots \\ \ddot{y}_{N1} \\ \ddot{y}_{12} \\ \ddot{y}_{22} \\ \vdots \\ \ddot{y}_{N2} \\ \vdots \\ \ddot{y}_{1T} \\ \ddot{y}_{2T} \\ \vdots \\ \ddot{y}_{NT} \end{bmatrix} \quad \ddot{\boldsymbol{X}} = \begin{bmatrix} 1 & \ddot{x}_{111} & \ddot{x}_{112} & \cdots & \ddot{x}_{11p} \\ 1 & \ddot{x}_{211} & \ddot{x}_{212} & \cdots & \ddot{x}_{21p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \ddot{x}_{N11} & \ddot{x}_{N12} & \cdots & \ddot{x}_{N1p} \\ 1 & \ddot{x}_{121} & \ddot{x}_{122} & \cdots & \ddot{x}_{12p} \\ 1 & \ddot{x}_{221} & \ddot{x}_{222} & & \ddot{x}_{22p} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & \ddot{x}_{N21} & \ddot{x}_{N22} & \cdots & \ddot{x}_{N2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \ddot{x}_{1T1} & \ddot{x}_{1T1} & \cdots & \ddot{x}_{1Tp} \\ 1 & \ddot{x}_{2T1} & \ddot{x}_{2T2} & \ddots & \ddot{x}_{2tp} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & \ddot{x}_{NT1} & \ddot{x}_{NT2} & & \ddot{x}_{NTp} \end{bmatrix} \quad \ddot{\varepsilon} = \begin{bmatrix} \ddot{\varepsilon}_{11} \\ \ddot{\varepsilon}_{21} \\ \vdots \\ \ddot{\varepsilon}_{N1} \\ \ddot{\varepsilon}_{12} \\ \ddot{\varepsilon}_{22} \\ \vdots \\ \ddot{\varepsilon}_{N2} \\ \vdots \\ \ddot{\varepsilon}_{1T} \\ \ddot{\varepsilon}_{2T} \\ \vdots \\ \ddot{\varepsilon}_{NT} \end{bmatrix}$$

$$\boldsymbol{\beta}\,(\boldsymbol{u_{it}}, \boldsymbol{v_{it}}) = \begin{bmatrix} \beta_0(u_{it}, v_{it}) \\ \beta_1(u_{it}, v_{it}) \\ \beta_2(u_{it}, v_{it}) \\ \vdots \\ \beta_p(u_{it}, v_{it}) \end{bmatrix} \tag{5}$$

2.6. Estimation of GWPR Parameters

The parameters of the GWR model can be estimated through the Weighted Least Squares method, which involves assigning specific weights to each location and observation time. (D. Yu et al., 2021). The parameters in the GWPR model vary across different locations and times (Chotimah, 2019). The weight element $w_{it}(u_{it}, v_{it})$ is incorporated into equation (4), resulting in the following GWPR model equation (Iriany et al., 2023).

$$w_{it}^{\frac{1}{2}}(u_{it}, v_{it})\ddot{y}_{it} = w_{it}^{\frac{1}{2}}(u_{it}, v_{it})\beta_0(u_{it}, v_{it}) + w_{it}^{\frac{1}{2}}(u_{it}, v_{it})\sum_{k=1}^{p}\beta_k(u_{it}, v_{it})\ddot{x}_{itj} + w_{it}^{\frac{1}{2}}(u_{it}, v_{it})\ddot{\varepsilon}_{it}$$

Next, the sum of squared errors is minimized.

$$\sum_{t=1}^{T}\sum_{i=1}^{N}\boldsymbol{w}(u_{it}, v_{it})\,\varepsilon_{it}^2 = \sum_{t=1}^{T}\sum_{i=1}^{N}\boldsymbol{w}(u_{it}, v_{it})\left[\ddot{y}_{it} - \beta_0(u_{it}, v_{it}) - \sum_{j}\beta_j(u_{it}, v_{it})\,\ddot{x}_{itj}\right]^2$$

$$= \sum_{t=1}^{T}\sum_{i=1}^{N}w(u_{it}, v_{it})\left[\ddot{y}_{it} - \beta_0(u_{it}, v_{it}) - \beta_1(u_{it}, v_{it})\,\ddot{x}_{it1} - \cdots - \beta_p(u_{it}, v_{it})\,\ddot{x}_{itp}\right]^2$$

It can be written in matrix form as follows.

$$\begin{aligned}
\varepsilon^T\boldsymbol{W}(u_{it}, v_{it})\varepsilon &= [\ddot{\boldsymbol{y}} - \ddot{\boldsymbol{X}}\boldsymbol{\beta}(u_{it}, v_{it})]^T\boldsymbol{W}(u_{it}, v_{it})[\ddot{\boldsymbol{y}} - \ddot{\boldsymbol{X}}\boldsymbol{\beta}(u_{it}, v_{it})] \\
&= \ddot{\boldsymbol{y}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{y}} - \ddot{\boldsymbol{y}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{X}}\boldsymbol{\beta}(u_{it}, v_{it}) - \boldsymbol{\beta}^{\boldsymbol{T}}(u_{it}, v_{it})\ddot{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{y}} \\
&\quad + \boldsymbol{\beta}^{\boldsymbol{T}}(u_{it}, v_{it})\ddot{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{X}}\boldsymbol{\beta}(u_{it}, v_{it}) \\
&= \ddot{\boldsymbol{y}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{y}} - 2\boldsymbol{\beta}^{\boldsymbol{T}}(u_{it}, v_{it})\ddot{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{y}} + \boldsymbol{\beta}^{\boldsymbol{T}}(u_{it}, v_{it})\ddot{\boldsymbol{X}}^{\boldsymbol{T}}\boldsymbol{W}(u_{it}, v_{it})\ddot{\boldsymbol{X}}\boldsymbol{\beta}(u_{it}, v_{it})
\end{aligned}$$

2.7. Spatial Heterogeneity

Spatial heterogeneity refers to a condition in a region where there are differences between one location and another, whether in terms of geography, socio-cultural conditions, or other factors that can create spatial heterogeneity in the studied area (Putra et al., 2022). Testing for spatial heterogeneity can be performed using the Breusch-Pagan test statistic, with the following hypotheses applied.

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

$H_1 : \sigma_i^2 \neq \sigma^2$ (spatial heterogeneity exists)

The test statistic used is as follows.

$$BP = \left(\frac{1}{2}\right)f'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-\boldsymbol{1}}\boldsymbol{Z}'\boldsymbol{f} + \left(\frac{1}{T}\right)\left[\frac{e'\boldsymbol{W}\boldsymbol{e}}{\sigma^2}\right]^2 \sim \chi^2_{\alpha(k+1)}$$

If the value of $BP > \chi^2_{k+1}$ or the $p - value < \alpha$, If H_0 is rejected, it indicates the presence of spatial heterogeneity.

2.8. Spatial Autocorrelation

Spatial autocorrelation refers to the correlation of a variable based on its geographic location (Ngabu, Fitriani, et al., 2023). The hypotheses used are as follows:

$H_0 : I = 0$ (No spatial effect)

$H_1 : I \neq 0$ (spatial effect exists)

The test statistic used is as follows.

$$Z_{hitung} = \frac{I - E(I)}{\sqrt{Var(I)}}$$

where:

I : Moran's I Index

$E(I)$: Expected value of Moran's I test

$Var(I)$: Variance of Moran's I Index

$$Var(I) = \frac{n^2 S_1 - nS_2 + 3\left(\sum_i \sum_j \boldsymbol{W}_{ij}\right)^2}{\left(\sum_i \sum_j \boldsymbol{W}_{ij}\right)^2 (n^2 - 1)}$$

$$S_1 = \frac{\sum_i \sum_j \left(\boldsymbol{W}_{ij} + \boldsymbol{W}_{ji}\right)^2}{2}$$

$$S_2 = \sum_i (\boldsymbol{W}_{i.} + \boldsymbol{W}_{.i})^2$$

The equation for Moran's I is as follows:

$$I = \frac{n \sum_i \sum_j \boldsymbol{W}_{ij}(X_i - \bar{X})((X_j - \bar{X})}{\boldsymbol{W} \sum_j (X_i - \bar{X})^2}$$

With:

$$E(I) = \frac{-1}{(n-1)}$$

The decision-making criteria are as follows: if $|Z_{hitung}| > Z_{(\frac{\alpha}{2})}$ atau $p - value < \alpha$, then H_0 is rejected, and it can be concluded that there is a relationship between the characteristics of different regions. The value of Moran's I index ranges between -1 and 1. If I > E(I) then there is positive autocorrelation, and if I < E(I), then there is negative autocorrelation.

2.9. Spatial Weights

The role of spatial weighting represents the relative location of one observation point to another (Chotimah, 2019). The farther the distance between two points, the smaller the weight compared to points that are closer together. The weighting function will provide different parameter estimates at each location. Weighting in the GWR model uses spatial coordinate variables, specifically longitude and latitude (Getis, 2009). Longitude refers to the meridians that extend from the North Pole to the South Pole, used to determine a point's east-west position on the Earth's surface. Latitude, on the other hand, refers to the parallels that encircle the Earth horizontally, used to measure a point's north-south position.

In GWR modeling, one commonly used weighting function is the adaptive kernel weighting function. This function adjusts the bandwidth dynamically for each location being analyzed. Several types of adaptive kernel functions include the following: (Fotheringham et al., 2017)

1. Adaptive Kernel Gaussian

$$\boldsymbol{w_{ij}} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_i}\right)^2\right)$$

2. Adaptive Kernel Bisquare

$$\boldsymbol{w_{ij}} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_i}\right)^2\right)^2 \\ 0 \end{cases}$$

With d_{ij} representing the Euclidean distance between observations at point I and point j, the formula to calculate the Euclidean distance is as follows:

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

with:

(u_i, v_i) : coordinates of location i

$\left(u_j, v_j\right)$: coordinates of location j

The variable h_i denotes the bandwidth at the i-th observation location. To determine the optimal bandwidth, the Cross Validation (CV) method is commonly employed. The optimal bandwidth is identified by minimizing the CV value (Wheeler, 2021). The Cross Validation (CV) formula is expressed as follows (Fotheringham et al., 2024):

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

where:

y_i : response variable at observation i-th

$\hat{y}_{\neq i}(h)$: estimated value of y_i with bandwidth h where the estimator at location i-th is excluded from the estimation process.

III. RESULTS AND DISSCUSSION

3.1. Model Selection

To determine the most suitable panel regression model among the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM), a series of tests is conducted. The process begins with the Chow test to compare the CEM and FEM, followed by the Hausman test to decide between the FEM and REM models.

Table 1 : Model Selection

Test	F-count	χ^2	P-Value	Decision
Uji Chow	31,618	-	$3.6\text{x}10^{-12}$	fixed effect
Uji Hausman	-	578.48	$3.5\text{x}10^{-11}$	fixed effect

From Table 1, it is shown that the p-values from both the Chow and Hausman tests are less than 0.05. Based on the results of the Chow test and the Hausman test, both confirm that the Fixed Effect Model (FEM) is the most suitable. Consequently, the Lagrange Multiplier test is unnecessary.

3.2. Spatial Heterogeneity Test

Spatial heterogeneity tests the variability between observation locations. The Breusch-Pagan test is used to perform the spatial heterogeneity analysis. The results are as follows:

Table 2 : Spatial Heterogeneity Test

BP	P-Value
28.354	0.0078

As shown in Table 2, the test results yield a p-value of 0.0078, which is $p - value$ < α (0.05), indicating the presence of spatial heterogeneity in the data. To address this, spatial analysis is applied, utilizing the GWPR method.

3.3. Testing the Significance of Parameters

The estimation of parameters in the GWPR model using the adaptive bisquare kernel employs the WLS method, producing a unique model for each district. Parameter significance is tested at each location using the t-test, where a $p{-}value$ < α (0.05) indicates that the predictor variable significantly influences the response variable. The table below presents the results of the parameter significance test for location 1 using the adaptive bisquare kernel weighting.

Table 3 : Parameter Significance for Wlingi Subdistrict

Variable	Coefficient	t_{count}	P-value	R-Square
X_1	0.356	-6.562	0.000	0.9123
X_2	0.492	3.625	0.000	
X_3	1.362	2.365	0.013	
X_4	-0.365	0.562	0.462	
X_5	0.025	1.002	0.158	

Based on Table 3, it is shown that the variables influencing the prevalence of stunting in Wlingi Subdistrict, Blitar Regency, are X_1,X_2,X_3, as their p-values are less than < α (0,05). Next, the predictor variables influencing the prevalence of stunting in each subdistrict of Blitar Regency will be determined using the adaptive bisquare kernel weighting function. The coefficient of determination results indicate that the R-Square value of the GWPR model is 0.9123, meaning that the stunting modeling in Blitar Regency can be explained by the independent variables in this study by 91.23%.

3.4. Model Interpretation

The optimal model for the Geographically Weighted Panel Regression (GWPR) in analyzing stunting prevalence cases in Blitar Regency is based on the adaptive bisquare kernel weighting function. This approach produces a unique GWPR model for each subdistrict, resulting in 38 distinct models across Blitar Regency.

$$\hat{y}_{1t} = 0.786 + 0.325X_{1t1} + 0.855X_{2t1} - 3.689X_{3t1} + 0.456X_{4t1} + 0.325X_{5t1}$$

$$\vdots$$

$$\hat{y}_{30t} = 0.897 + 0.345X_{1t1} + 0.743X_{2t1} + 3.271X_{3t1} + 0.542X_{4t1} + 0.552X_{5t1}$$

Based on the obtained models, the following is an explanation of one model, namely the GWPR model for Wlingi Subdistrict. In the GWPR model equation for Wlingi Subdistrict, it is observed that the predictor variables $X_1, X_2,$ and X_3 significantly influence the number of stunting prevalence cases. Specifically, for X_1 in Wlingi Subdistrict, its impact is statistically significant, indicating a strong relationship with the response variable, representing the percentage of the population with stunting prevalence, a 1% increase in X_1, assuming other variables remain constant, will increase the number of stunting prevalence cases in Wlingi by 0.010 individuals. Furthermore, a 1% increase in X_1, assuming other variables remain constant, will decrease the number of X_2 in Wlingi Subdistrict by 0.855 percent.

IV. CONCLUSION

From the analysis and discussion carried out, the following conclusions have been reached:

1. There is a spatial effect on the number of stunting prevalence cases in Blitar Regency from 2021 to 2023. The spatial effect in this analysis refers to spatial heterogeneity, which indicates that the predictor variables provide varying responses in each subdistrict of Blitar Regency.
2. The factors X_1 and X_2 significantly influence the stunting prevalence cases in Blitar Regency.

In addition to the GWPR method, future research can integrate other approaches, such as Machine Learning techniques like Recurrent Neural Networks, to detect more complex patterns or identify interactions between variables.

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