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GEOGRAPHICALLY WEIGHTED PANEL REGRESSION WITH ADAPTIVE BISQUARE KERNEL ON STUNTING DATA IN SOUTHEAST SULAWESI PROVINCE

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Abstract. Stunting is a public health problem that shows spatial and temporal variations between regions. Differences in health, nutrition, environment, and human development characteristics cause the relationship between determinants and the number of stunting cases to be not homogeneous. This study aims to model the number of stunting cases in Southeast Sulawesi Province using Geographically Weighted Panel Regression (GWPR) with the weighting function of Adaptive Bisquare Kernel. The data used is secondary panel data for 17 districts/cities during the 2019–2023 period with the number of stunting cases as dependent variables and six independent variables representing health, nutrition, environment and human development factors. The results show that the GWPR model with the Adaptive Bisquare Kernel is able to accommodate spatial and temporal heterogeneity through estimating different local parameters in each district/city. The difference in local coefficients indicates that the influence of the determinants of stunting varies between regions. Thus, the GWPR approach provides more specific information about the characteristics of each region so that it can support the formulation of stunting control policies that are more targeted.

Keywords: adaptive bisquare kernel; data panel; geographically weighted panel regression; heterogenitas spasial; stunting

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1. INTRODUCTION

Stunting is a condition of toddlers who have a lower height than their age standard, due to chronic malnutrition in the critical growth and development phases [1]. Data from the Southeast Sulawesi Provincial Health Office shows that the number of stunting cases in districts/cities is still relatively high during the 2019–2023 period [2, 3, 4, 5, 6]. In addition, the 2023 Indonesian Health Survey (SKI) reported that the prevalence of stunting in Southeast Sulawesi was 30.0%, placing this province among the ten highest in Indonesia [7]. The variation in the number of stunting cases between regions is influenced by differences in environmental, socio-economic, and health service characteristics [8]. Therefore, the relationship between the determinants and the number of stunting cases cannot be assumed to be spatially homogeneous [9].

Stunting data has a panel structure that covers 17 districts/cities during the 2019–2023 period. This characteristic allows simultaneous analysis of region and time variations [10]. However, conventional panel models assume homogeneous regression parameters between regions so that they do not accommodate spatial heterogeneity [11].

Geographically Weighted Regression (GWR) was developed to produce regression parameters that vary at each location. However, GWR only considers spatial variation and has not accommodated temporal dimensions [12]. As a development, Geographically Weighted Panel Regression (GWPR) integrates spatial and temporal dimensions in modeling relationships between variables [13]. GWPR provides better modeling performance than conventional panel models [14].

GWPR performance is influenced by kernel function selection and bandwidth in the formation of spatial weights [15]. Adaptive Bisquare Kernel is one of the kernel functions that uses adaptive bandwidth so that the weights are adjusted to the spatial conditions at each location [16]. This supports a more representative estimation of local parameters.

Based on this, this study applied GWPR with the Adaptive Bisquare Kernel to model the number of stunting cases and identify variations in the influence of determining factors between regions in Southeast Sulawesi Province for the 2019–2023 period.

2. PRELIMINARIES

This study uses secondary panel data for the 2019–2023 period obtained from the Central Statistics Agency (BPS) and the Southeast Sulawesi Provincial Health Office. The data covered 17 districts/cities for five years ($N=17$, $T=5$), resulting in 85 observations. The dependent variables and six independent variables used are presented in Table 1.

TABLE 1. Data and Data Sources

Variabel	Symbols	Variable Name	Data Source	Units
Dependent	Y	The number of stunting	Southeast Sulawesi Provincial Health Office	People
Independent	X_1	Low Birth Weight (BBLR)	Southeast Sulawesi Provincial Health Office	Per 1,000 live births
	X_2	Exclusive breastfeeding	Southeast Sulawesi Provincial Health Office	People
	X_3	Complete basic immunizations	Southeast Sulawesi Provincial Health Office	People
	X_4	Households with decent sanitation	Southeast Sulawesi Provincial Health Office	Household
	X_5	Toddlers get vitamin A	Southeast Sulawesi Provincial Health Office	People
	X_6	Human Development Index	Statistics Indonesia (BPS)	Percent (%)

2.1. Regresi Data Panel. Panel data regression combines cross section and time series dimensions to produce more efficient estimates, with a common model

$$(1) \quad y_{it} = \alpha_i + \beta_j x_{ijt} + \varepsilon_{it} \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T$$

By y_{it} stating that the dependent variable in the unit to- i and time to- t , α_i is the intercept for the unit to- i , x_{ijt} is the value of the independent variable to- j in the unit to- i and time to- t , the β_j regression coefficient for the independent variable to- j , and ε_{it} is an error.

The data regression model panel consists of Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). The model selection was carried out using the Chow test and the Hausman test, then continued with the test of classical assumptions which included normality, multicollinearity, autocorrelation, and homocedasticity.

2.2. Geographically Weighted Regression (GWR). GWR is the development of a regression model that allows the regression coefficient to vary at each observation location so that it is able to accommodate spatial heterogeneity [17, 18]. The GWR model is stated as

$$(2) \quad y_i = \beta_0(u_i, v_i) + \sum_{j=1}^p \beta_j(u_i, v_i) x_{ij} + \varepsilon_i$$

with (u_i, v_i) is the geographic coordinate of the location to- i .

The proximity between regions is measured using Euclidean distances,

$$(3) \quad d_{ij} = \sqrt{(u_i, u_j)^2 + (v_i, v_j)^2}$$

whereas, the optimum bandwidth is obtained by minimizing the Cross Validation (CV) function,

$$(4) \quad CV = \sum_{i=1}^n (y_i - \hat{y}_{\neq i}(b))^2$$

with the $\hat{y}_{\neq i}(b)$ value of the approximate location to- i after being excluded from the estimation (avoiding the degenerate solution $CV = 0$). The b optimal value is searched through the Golden Section Search algorithm.

Spatial weights are calculated using the Adaptive Bisquare Kernel, which is a kernel function that adjusts bandwidth based on the density of the observation location,

$$(5) \quad w_{ij} = \left[1 - \left(\frac{d_{ij}}{b_i} \right)^2 \right]^2, \quad d_{ij} < b_i, \quad w_{ij} = 0, \quad d_{ij} \geq b_i$$

2.3. Geographically Weighted Panel Regression (GWPR). GWPR is a GWR development that combines GWR with panel data models so that it is able to estimate local parameters and capture spatial and temporal variations [13]. The GWPR model is formulated as follows.

$$(6) \quad y_{it} = \beta_0(u_{it}, v_{it}) + \sum_{j=1}^p \beta_j(u_{it}, v_{it}) x_{ijt} + \varepsilon_{it}$$

Since the geographic coordinates of each district/city remain constant throughout the observation period, the weighting on the GWPR model uses the Adaptive Bisquare Kernel function

that takes into account spatial and temporal distance information simultaneously, which is formulated as follows [19].

$$(7) \quad d_{itjh} = \sqrt{(u_{it} - u_{jh})^2 + (v_{it} - v_{jh})^2}$$

The model parameters are estimated using the Weighted Least Square (WLS) method by minimizing the number of weighted error squares,

$$(8) \quad \sum_{h=1} \sum_{j=1} w_{jh}(u_{it}, v_{it}) \varepsilon_{jh}^2$$

so that the suspect is obtained,

$$(9) \quad \hat{\beta}(u_{it}, v_{it}) = [X^T W(u_{it}, v_{it}) X]^{-1} X^T W(u_{it}, v_{it}) y$$

with $W(u_{it}, v_{it})$ a measured diagonal matrix $nT \times nT$ containing weights to the point, location, and time (u_{it}, v_{it}) .

2.4. Model Evaluation. The selection of the best model is carried out based on the Corrected Akaike Information Criterion (AICc) value, with a smaller AICc value indicating a better model,

$$(10) \quad AIC = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n \left(\frac{n + \text{tr}(S)}{n - 2 - \text{tr}(S)} \right)$$

with $\hat{\sigma} = \frac{RSS}{n}$, S the projection matrix (hat matrix, $\hat{y} = Sy$), and the $\text{tr}(S)$ effective degree of freedom of the model. The smallest AICc value indicates the best balance between the similarity and complexity of the model.

3. MAIN RESULTS

3.1. Descriptive statistics. On average, the prevalence of stunting showed a decline until 2022, but increased again in 2023, with the maximum value between regions recorded the highest that year. This condition shows an uneven decline in prevalence in all districts/cities during the 2019-2023 period (Table 2).

The BBLR variable (X_1) was relatively stable during the observation period, while exclusive breastfeeding (X_2), complete basic immunization (X_3), and toddlers who received vitamin A (X_5), tended to decrease. In contrast, households with decent sanitation (X_4), and HDI (X_6),

TABLE 2. Descriptive Statistics of Research Variables

Variabel	Year	Average	Standard Deviation	Minimum Score	Maximum Value
Y	2019	509	671	11	2.557
Y	2020	1.142	774	221	2.883
Y	2021	1.156	739	198	2.980
Y	2022	796	522	176	1.803
Y	2023	1.038	800	163	3.436
X ₁	2019	76	54	7	186
X1	2020	88	73	16	305
X1	2021	93	70	0	266
X1	2022	91	63	6	274
X1	2023	83	44	0	148
X ₂	2019	1.435	1.756	110	7.448
X2	2020	1.127	910	357	3.484
X2	2021	1.320	1.078	314	3.630
X2	2022	1.015	888	162	3.345
X2	2023	927	958	108	3.828
X ₃	2019	3.158	2.011	671	8.481
X3	2020	2.976	1.714	648	6.919
X3	2021	2.619	1.536	555	5.996
X3	2022	2.723	1.523	665	6.237
X3	2023	2.537	1.487	498	5.620
X ₄	2019	28.949	18.340	4.727	70.642
X4	2020	37.271	31.025	5.181	133.929
X4	2021	46.235	48.132	6.771	179.436
X4	2022	37.458	22.383	4.853	78.578
X4	2023	35.659	19.718	10.674	80.343
X ₅	2019	12.609	9.645	3.027	44.147
X5	2020	10.591	6.750	2.002	24.802
X5	2021	10.687	7.350	2.604	27.969
X5	2022	9.790	6.842	2.115	27.175
X5	2023	9.851	6.353	2.935	26.009
X ₆	2019	69	5	64	83
X6	2020	69	5	64	84
X6	2021	70	5	65	84
X6	2022	70	5	65	85
X6	2023	71	5	66	85

showed an increasing trend. The spatial distribution of the number of stunting cases in each district/city during the 2019-2023 period is then presented in Figure 1.

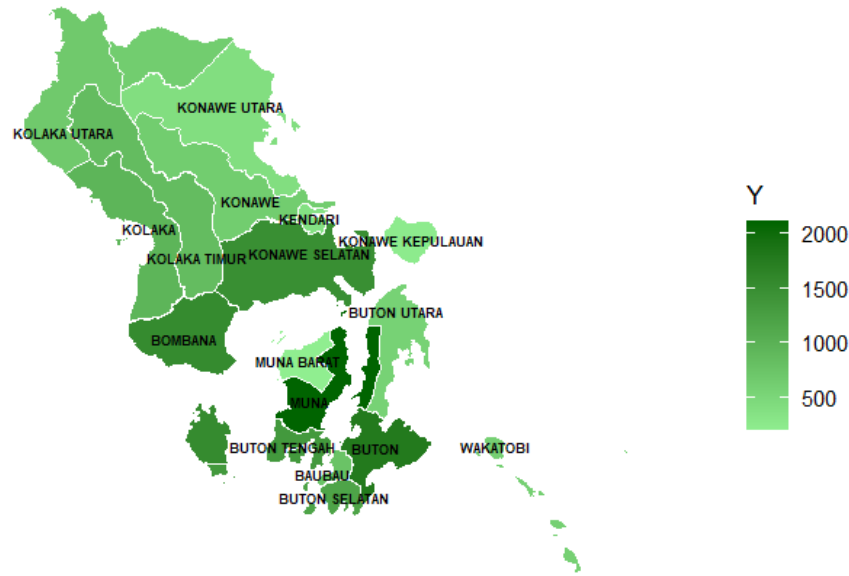


FIGURE 1. Distribution of the Number of Stunting Cases in Southeast Sulawesi Province, 2019–2023

Based on Figure 1, the number of stunting cases shows spatial variation between districts/cities in Southeast Sulawesi Province. West Muna, Muna, South Konawe, Baubau City, and South Buton districts have a relatively higher number of cases, while Konawe Islands, Wakatobi, North Buton, North Kolaka, and North Konawe tend to have a lower number of cases. This uneven distribution pattern is the empirical basis for the need for a model approach that accommodates spatial heterogeneity such as GWPR.

3.2. Panel Data Regression Model Selection. Determining the best global panel model that will be a benchmark for GWPR

TABLE 3. Descriptive Statistics of Research Variables

Testing	p-value	Selected models
Chow Test	0,0002392	FEM
Hausman Test	0,0002189	FEM

Based on Table 3, Chow and Hausman's test obtained that the appropriate panel model is the Fixed Effect Model (FEM).

TABLE 4. Results of the Classical Assumption Test of the Global FEM Model

Assumption Test	Test Statistics	p-value	Verdict
Normalitas (Jarque–Bera)	1,59	0,4509	Normally distributed residual
Multikolinearitas (VIF)	1,87–6,68	–	No indication of multicollinearity
Autokorelasi (Wooldridge)	AR(1)	0,1813	No autocorrelation
Homoskedastisitas (Breusch–Pagan)	16,078	0,0003	There is heteroscedasticity

3.3. Classic Assumption Testing. Based on Table 4, the global FEM model meets all classical assumptions except homocedasticity. Together with the existence of spatial heterogeneity, it is the basis for the application of the GWPR approach to accommodate spatial heterogeneity between regions.

3.4. Optimal Bandwidth and Spatial Penetrator Matrix. The optimal bandwidth for each district/city is determined by minimizing the Cross Validation (CV) value using the Golden Section Search algorithm based on the Euclidean distance between locations. The optimal bandwidth results for each observation are presented in Table 5.

The optimal bandwidth value ranges from 1.95–3.70, indicating variations in spatial influence between regions. The value is then substituted along with the Euclidean distance in the Adaptive Bisquare Kernel function to form a measured diagonal spatial weighting $W(u_{it}, v_{it})$ matrix $nT \times nT$. Because the location coordinates are fixed all the time, the resulting spatial weights are identical at all times.

3.5. Estimated GWPR Model Parameters. The estimation of the local parameters of the GWPR model was carried out using the Weighted Least Squares method using Equation (9), calculated separately for each district/city based on the Adaptive Bisquare Kernel weighting matrix. The results of the local parameter estimation are presented in Table 6.

Based on Table 6, each district/city has a different local regression coefficient, resulting in a GWPR model that is specific to each region. As an illustration, the GWPR model in several districts/cities is written as follows.

TABLE 5. Optimal Bandwidth of Districts/Cities

Regency/City	Bandwidth
Buton	2,25
Muna	2,23
Konawe	2,74
Kolaka	2,71
Konawe Selatan	2,18
Bombana	2,36
Wakatobi	3,70
Kolaka Utara	3,70
Buton Utara	2,43
Konawe Utara	2,82
Kolaka Timur	2,47
Konawe Kepulauan	2,12
Muna Barat	1,95
Buton Tengah	2,29
Buton Selatan	2,70
Kendari	2,27
Baubau	2,58

$$\hat{Y}_{Buton} = 0,144 + 4,744X_1 - 0,401X_2 + 0,294X_3 + 0,003X_4 - 0,046X_5 + 9,280X_6$$

$$\hat{Y}_{Muna} = 0,129 + 4,116X_1 - 0,402X_2 + 0,392X_3 + 0,003X_4 - 0,064X_5 + 8,311X_6$$

$$\hat{Y}_{Konawe} = 0,111 + 2,708X_1 - 0,319X_2 + 0,409X_3 + 0,004X_4 - 0,075X_5 + 7,237X_6$$

The model in other districts/cities has the same shape with different coefficient values according to the characteristics of each region. These differences show that the influence of each independent variable on the number of stunting cases is spatially inhomogeneous, so each district/city has a different local model.

TABLE 6. GWPR Model Local Parameter Estimation

Regency/City	Intercept	X_1	X_2	X_3	X_4	X_5	X_6
Buton	0,144	4,744	-0,401	0,294	0,003	-0,046	9,280
Muna	0,129	4,116	-0,402	0,392	0,003	-0,064	8,311
Konawe	0,111	2,708	-0,319	0,409	0,004	-0,075	7,237
Kolaka	0,110	2,680	-0,320	0,414	0,004	-0,076	7,191
Konawe Selatan	0,126	3,249	-0,355	0,388	0,004	-0,069	8,200
Bombana	0,155	4,206	-0,363	0,268	0,003	-0,048	10,003
Wakatobi	0,120	4,919	-0,399	0,397	0,000	-0,060	7,723
Kolaka Utara	0,120	3,096	-0,306	0,349	0,004	-0,066	7,849
Buton Utara	0,124	4,166	-0,401	0,410	0,002	-0,067	8,021
Konawe Utara	0,112	2,772	-0,317	0,399	0,004	-0,074	7,346
Kolaka Timur	0,125	3,192	-0,337	0,372	0,004	-0,068	8,132
Konawe Kepulauan	0,112	3,021	-0,389	0,481	0,004	-0,083	7,237
Muna Barat	0,141	4,070	-0,399	0,338	0,004	-0,056	9,070
Buton Tengah	0,144	4,809	-0,401	0,291	0,003	-0,045	9,274
Buton Selatan	0,136	5,075	-0,403	0,320	0,001	-0,047	8,692
Kendari	0,118	2,950	-0,345	0,413	0,004	-0,075	7,667
Baubau	0,134	4,876	-0,403	0,338	0,001	-0,051	8,611

4. CONCLUSION

This study shows that Geographically Weighted Panel Regression (GWPR) with Adaptive Bisquare Kernel is able to model the number of stunting cases in Southeast Sulawesi Province by considering spatial and temporal variations simultaneously. The results of the local parameter estimation showed that the influence of the determinants of stunting was different in each district/city, which indicated that there was spatial heterogeneity so that the local model was more suitable than the global panel model. Thus, the GWPR approach produces more specific information about the characteristics of each region and has the potential to be the basis for the formulation of stunting control policies that are more targeted according to local conditions.

CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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