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Understanding the Spatial Distribution of Stunting in East Java, Indonesia: A Comparison of GWR and MS-GWR Models

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Abstract Stunting is a growth impairment condition in children under five years old, resulting from chronic malnutrition and repeated infections, which causes them to be shorter than expected for their age. East Java is one of twelve priority provinces, with a stunting prevalence of 17.7% in 2023. Accurate identification of the factor influencing stunting is essential to support effective and targeted interventions. Given the spatial variability in these factors, conventional regression models such as Ordinary Least Squares (OLS) are inadequate. Geographically Weighted Regression (GWR) addresses this by allowing local variation, yet it assumes a uniform spatial scale across variables. This study employs the Multiscale Geographically Weighted Regression (MS-GWR) model, which enables each explanatory variable to operate at its own optimal spatial scale. The results show that MS-GWR with an adaptive Gaussian weighting function provides the best fit, with an AICc of 67.7426 and an R^2 is 0.79. Seven variable groups significantly influence stunting, including exclusive breastfeeding, early initiation of breastfeeding (EIB), and upper respiratory tract infections (URTIs), as well as combinations of these factors. These findings highlight the importance of formulating location-specific and context-sensitive policies that reflect the dominant characteristics of each region to effectively and sustainably accelerate stunting reduction.

Keywords Spatial Analysis, Geographically Weighted Regression, Multiscale Geographically Weighted Regression, Stunting, Malnutrition.

AMS 2010 subject classifications 62H11, 62M30, 91B72, 91D25

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1. Introduction

Nutritional challenges remain a critical issue in developing countries such as Indonesia, where adequate nutrition plays an essential role in ensuring healthy growth and development [1]. Deficiencies in early childhood nutrition often lead to disruptions in both physical and cognitive development. The World Health Organization identifies three main indicators of nutritional problems: underweight (low weight-for-age), stunting (low height-for-age), and wasting [2]. Among these, stunting is a particularly pressing concern in Indonesia, and reducing its prevalence has become a national priority [3].

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A cross-sectional study was conducted by Supadmi et al. to examine factors associated with stunting among children under two years of age whose mothers are employed [4]. The study identified several significant determinants, including place of residence (urban vs. rural), maternal age, marital status, maternal education, wealth status, child's age and gender, and early initiation of breastfeeding (EIB). In a separate study, Astuti et al. explored stunting management in Indonesia from January 2023 to September 2024 by analyzing stakeholder collaboration and government policies [5]. Their research involved interviews with 60 participants and Focus Group Discussions (FGDs) to evaluate the role of social capital in stunting reduction efforts. Additionally, Lestari et al. investigated the long-term effects of childhood stunting on educational and cognitive outcomes in adulthood by analyzing pooled data from the 1993 and 1997 Indonesia Family Life Surveys [6]. Stunting status was measured using height-for-age Z-scores, and pooled regressions along with instrumental variable analysis were employed to address potential endogeneity and omitted variable bias.

Previous studies by Supadmi et al., Astuti et al., and Lestari et al. did not account for spatial effects across regions, despite the fact that spatial factors play a crucial role in understanding stunting patterns. This study aims to provide insights into factors associated with stunting incidence using spatial analysis. Variations in regional locations give rise to spatial heterogeneity [7], which can result from differences in geographic, social, cultural, and economic conditions [8]. Consequently, regression methods that incorporate spatial dimensions are necessary to examine the relationships between predictor and response variables. In this context, Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MS-GWR) are particularly suitable due to their capacity to model spatially varying relationships (GWR) and to analyze processes at multiple scales (MS-GWR) [9].

2. Material and Method

2.1. Dataset

The study utilized secondary data, with an observational unit consisting of 38 regencies/cities. The data were collected from the Directorate General of Regional Development, the East Java Provincial Health Office, and the East Java Province Central Statistics Agency. Additional spatial information, specifically the administrative map of East Java covering the 38 observations, was obtained from the Geosai website. The dataset used in this study is summarized in Table 1.

Table 1. List of Independent and Dependent Variables in the Research

Variable	Explanation
Y	Prevalence of Stunting in Toddlers/Children Under Five
X_1	Percentage of Population Below the Poverty Line
X_2	Exclusive Breastfeeding Coverage
X_3	Percentage of Pregnant Women with Chronic Energy Deficiency
X_4	Early Initiation of Breastfeeding Coverage
X_5	Percentage of Pregnant Women Consuming Iron-Folic Acid Supplements
X_6	Coverage of Toddlers/Children Under Five Affected by Acute Respiratory Infection
υ	Longitude
ν	Latitude

The dependent variable (Y) was the prevalence of stunting among children under five years old. The explanatory variables included socioeconomic and health-related factors. Poverty reflects limited access to nutritious food, sanitation, and healthcare, which has been shown to increase the likelihood of stunting [10]. Nutrition education initiatives should be strengthened to improve mothers' knowledge and to activate community health cadres in accompanying families with toddlers regarding child nutrition and health problems. In addition, healthy nursing practices and clear guidance on exclusive breastfeeding can enhance child nutrition outcomes [11]. Association of child marriage and nutritional status of mothers with under-five children in Bangladesh found that 15.2% of mothers suffered from chronic energy deficiency (BMI $< 18.5\ \mathrm{kg/m^2}$), and that maternal under-nutrition was significantly associated with stunting in their children [12], while timely initiation of breastfeeding supports infant immunity and nutrient intake [13]. Iron–folic acid supplementation during pregnancy promotes healthy fetal growth and reduces stunting [14].

2.2. *Geographically Weighted Regression (GWR)*

The Geographically Weighted Regression (GWR) model extends the classical linear regression by incorporating spatially varying coefficients, allowing localized regression effects at each observation location. In this model, parameters are estimated for each specific location, resulting in regression coefficients that differ across geographic regions. The GWR model can be expressed in Equation (1).

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i, \quad i = 1, 2, \ldots, n \tag{1}$$

where Y_i denotes the response variable for the i-th observation, $\beta_0(u_i, v_i)$ is the intercept, X_{ik} is the value of the k-th predictor for the i-th observation, $\beta_k(u_i, v_i)$ is the corresponding regression coefficient, and ε_i represents the residual. The geographic coordinates of the i-th observation are (u_i, v_i), and n is the total number of observations.

Each location has an associated diagonal weighting matrix $W(u_i, v_i)$, which assigns weights to each observation when estimating local parameters. Using the ordinary least squares approach, the GWR parameter estimates at location (u_i, v_i) are obtained in Equation (2).

$$\hat{\boldsymbol{\beta}}(u_i, v_i) = \left(X^{\mathsf{T}} W(u_i, v_i) X\right)^{-1} X^{\mathsf{T}} W(u_i, v_i) \mathbf{y} \tag{2}$$

where $\hat{\boldsymbol{\beta}}$ is the $(p+1) \times 1$ vector of estimated coefficients, and the diagonal elements of $W(u_i, v_i)$ reflect the spatial weights for observations at location (u_i, v_i).

2.3. *Multiscale Geographically Weighted Regression (MS-GWR)*

Multiscale Geographically Weighted Regression (MS-GWR) extends the GWR framework by allowing each predictor variable to operate at its own spatial scale. While GWR accounts for spatial heterogeneity by allowing relationships between variables to vary across space, it assumes that all independent variables share the same spatial scale, which may limit its ability to capture complex spatial dynamics [15]. MS-GWR overcomes this limitation by assigning different bandwidths to each predictor, enabling analysis of non-uniform spatial relationships [16]. This method is particularly useful when influencing factors exert effects at different spatial scales [17]. The MS-GWR model can be expressed in Equation (3).

$$Y_i = \beta_{bw0}(u_i, v_i) + \sum_{k=1}^{p} \beta_{bwk}(u_i, v_i) X_{ik} + \varepsilon_i, \quad i = 1, 2, \ldots, n \tag{3}$$

where bw denotes the bandwidth applied to each respective variable, $\beta_{bw0}(u_i, v_i)$ is the intercept, and $\beta_{bwk}(u_i, v_i)$ represents the regression coefficient for the k-th predictor variable.

Parameter estimation in GWR is typically performed using Weighted Least Squares (WLS). However, this approach is not directly applicable to MS-GWR, as the varying bandwidths for each covariate result in a non-uniform spatial weighting matrix. Therefore, parameter estimation in MS-GWR is conducted using a backfitting algorithm, which allows for specific bandwidth selection and combination by reformulating the GWR model within the framework of Generalized Additive Models (GAMs)[16]. MS-GWR assumes that, at each specific location (u_i, v_i), the residuals (the differences between predicted and actual values) follow a multivariate normal distribution, centered around zero, with a unique variance-covariance matrix. Equation (4) represents the form of Generalized Additive Models (GAMs) as a reformulation of GWR:

$$Y_i = f_{h_0} + f_{h_1}(X_1) + f_{h_2}(X_2) + \cdots + f_{h_p}(X_p) + \varepsilon_i \tag{4}$$

where $f_{h_k}(X_k) = h_k(\beta_k)X_k$ and h_k is a function determined by the bandwidth for the k-th predictor.
The backfitting algorithm for the MS-GWR model proceeds as follows[16]:

1. Initialize the local parameter estimates, $\hat{\beta}_{i(\text{MS-GWR})}$, using the GWR model, such that the initial local parameter values are set as $\hat{\beta}_{i(\text{MS-GWR})} = \hat{\beta}_{i(\text{GWR})}$.

2. Use these initial parameter estimates to predict the estimated values, $\hat{y}$, and calculate the residuals, $\hat{\varepsilon}$.

3. For the current values of $\hat{f}_k + \hat{\varepsilon}$, regress on X_k using GWR to obtain a tentative optimal bandwidth, h_k, for the relationship between y and X_k, and a new local parameter estimate, $\hat{\beta}_k$. These values are then used to update the previously established initial values.

4. Update the parameter estimates by using the new values, $\hat{\beta}_k$, to refine the previous local parameter estimates.

5. Terminate the iteration process when convergence is achieved, i.e., when the score of change (SOC) is less than a predefined threshold, typically 10^{-5} [18]. Two criteria for calculating SOC are commonly used.

Two criteria for calculating SOC are commonly used:

a) SOC-RSS (Proportional Change in the Residual Sum of Squares – RSS):

$$\text{SOC-RSS} = \frac{|\text{RSS}_{\text{new}} - \text{RSS}_{\text{old}}|}{\text{RSS}_{\text{new}}} \tag{5}$$

SOC-RSS examines the proportional change in the RSS value between two consecutive iterations. If this proportional change is sufficiently small, the iteration is considered to have converged. The RSS is calculated as shown in Equation (6):

$$\text{RSS} = \sum_{i=1}^{n} \big(Y_i - f(x_i)\big)^2 \tag{6}$$

b) SOC-f (Change in the GWR Smoother):

$$\text{SOC-f} = \sqrt{\frac{\sum_{j=1}^{p}\left(\sum_{i=1}^{n}\left(\hat{f}_{ij}^{\text{new}} - \hat{f}_{ij}^{\text{old}}\right)^2\right)/n}{\sum_{i=1}^{n}\left(\sum_{j=1}^{p}\hat{f}_{ij}^{\text{new}}\right)^2}} \tag{7}$$

The GWR smoother refers to the local parameter estimates (f_j) obtained from GWR at each iteration. SOC-f examines the change in the smoother values between the previous and current iterations. If the difference in smoother estimates between two iterations is sufficiently small, the iteration is considered convergent.

SOC-RSS evaluates the proportional change in RSS between iterations, while SOC-f examines changes in the local parameter estimates (GWR smoother). Convergence is achieved when these changes are sufficiently small.

3. Results

The initial step before implementing Geographically Weighted Regression (GWR) model to the stunting case in East Java Province, a multiple linear regression model was first constructed as the initial stage of the analysis. The initial step in this process involved conducting a multicollinearity test to ensure that the independent variables were not highly correlated with each other, thereby allowing the model to produce stable parameter estimates and valid interpretations. In general, a Variance Inflation Factor (VIF) value exceeding 10 is considered an indication of serious multicollinearity in the model. Based on the results of the multicollinearity test presented in Table 2.

Table 2. Variance Inflation Factor (VIF) values for independent variables

Variable	VIF Value
X_1	1.1659
X_2	1.1158
X_3	1.0668
X_4	1.0621
X_5	1.1715
X_6	1.0918

Since all VIF values in the Table 2 are below 10, it can be concluded that there is no multicollinearity problem in the regression model. Subsequently, a spatial heterogeneity test was conducted to evaluate the presence of variations caused by spatial factors. This test was performed using the Breusch-Pagan (BP) statistical test. The results of the BP Breusch-Pagan test at a significance level of $\alpha = 5\%$ (0.05) showed a p-value of $0.0408 < \alpha = 0.05$ and a calculated BP value of $13.139 > \chi^2_{(0.05;6)} = 12.592$. This result indicating the presence of spatial heterogeneity in the model. To account for this heterogeneity, modeling was conducted by constructing the weighting matrix, $W(u_i, v_i)$, which incorporates both the optimal bandwidth value and the Euclidean distance d_{ij} [19] between locations (u_i, v_i). Each element of the matrix, w_{ij}, represents the spatial influence of observation j on observation i, such that observations closer in space are assigned higher weights than those further apart. This approach allows the subsequent Geographically Weighted Regression (GWR) analysis to capture location-specific variations and spatially varying relationships between the dependent and independent variables. Following a comparison using the Akaike Information Criterion (AIC) and the coefficient of determination (R^2), the optimal bandwidth was determined to be the adaptive Gaussian kernel, which produced an AIC value of 82.514 and an R^2 value of 0.6567. In contrast, the adaptive Bisquare kernel yielded a higher AIC value of 92.628 and a lower R^2 value of 0.5004. These results indicate that the adaptive Gaussian kernel provides a better model fit and explains a greater proportion of the variability in the data compared to the Bisquare kernel. Accordingly, the Geographically Weighted Regression (GWR) analysis was carried out using the adaptive Gaussian kernel, and the estimated parameters for each variable at each location are presented in Table 3.

Table 3. Parameter Estimation Result using the MS-GWR Model

Regency/City	(Intercept)	X_1	X_2	X_3	X_4	X_5	X_6
1	-0.0570	-0.2022	-0.3598	-0.2511	-0.1643	-0.3995	-0.1855
2	0.7315	0.2079	-0.6753	-0.2006	-0.7373	0.0244	0.0181
3	-0.0150	0.0162	-0.2398	0.0924	-0.0974	-0.1294	0.0320
4	-0.2767	-0.1246	0.0452	0.1283	-0.1136	-0.3103	-0.0288
5	0.5446	0.1226	-0.6057	-0.4089	-0.6697	-0.0374	-0.0491
6	-0.2149	-0.2046	-0.2088	-0.0946	-0.1010	-0.3860	-0.1537
7	0.6418	0.1839	-0.6430	-0.3170	-0.5608	-0.1950	0.0818
8	-0.1501	-0.1077	-0.1370	0.0870	-0.1269	-0.2592	-0.0211
9	-0.1390	-0.0654	-0.1117	0.1319	-0.1069	-0.2185	0.0003
10	0.0367	-0.0011	-0.3278	0.0026	-0.1522	-0.1710	0.0221
11	-0.0521	-0.0041	-0.1955	0.1114	-0.0966	-0.1523	0.0241
12	-0.1608	-0.0726	-0.0814	0.1431	-0.1054	-0.2292	-0.0031
13	-0.2562	-0.0915	0.0351	0.1636	-0.0998	-0.2765	-0.0382
14	0.1331	0.0634	-0.4133	-0.0454	-0.1675	-0.1254	0.0497
15	-0.1094	-0.1141	-0.2054	0.0276	-0.1465	-0.2703	-0.0340
16	0.1726	-0.0005	-0.4256	-0.1982	-0.2916	-0.2575	0.0033
17	0.3631	0.0648	-0.5109	-0.3322	-0.4229	-0.2709	0.0213

Continued on next page

Table 3 Parameter Estimation Result using the MS-GWR Model

Regency/City	(Intercept)	X_1	X_2	X_3	X_4	X_5	X_6
18	-0.0528	-0.1461	-0.3049	-0.1237	-0.1875	-0.3330	-0.0889
19	-0.2321	-0.1690	-0.0955	0.0308	-0.1266	-0.3336	-0.0719
20	0.4396	0.1758	-0.5833	-0.2566	-0.3518	-0.1767	0.1006
21	-0.2495	-0.0989	0.0277	0.1612	-0.1035	-0.2781	-0.0297
22	-0.2607	-0.0756	0.0340	0.1677	-0.0945	-0.2682	-0.0525
23	0.1773	0.1050	-0.4537	-0.0515	-0.1543	-0.0782	0.0675
24	-0.0684	-0.0900	-0.2429	0.0142	-0.1538	-0.2508	-0.0221
25	-0.2183	-0.1076	-0.0227	0.1446	-0.1115	-0.2717	-0.0176
26	-0.2659	-0.0695	0.0440	0.1573	-0.0890	-0.2738	-0.0583
27	-0.2606	-0.0626	0.0089	0.1875	-0.1009	-0.2494	-0.0552
28	0.1106	-0.1729	-0.4444	-0.4971	-0.3549	-0.2144	-0.3096
29	0.1630	0.0226	-0.4247	-0.1482	-0.2565	-0.2182	0.0235
30	-0.2378	-0.0801	0.0152	0.1751	-0.0997	-0.2588	-0.0326
31	0.4395	0.0962	-0.5464	-0.3578	-0.4679	-0.2604	0.0345
32	0.0501	-0.1915	-0.4250	-0.4058	-0.2599	-0.3391	-0.2468
33	-0.0030	-0.0955	-0.3200	-0.0957	-0.2035	-0.2863	-0.0430
34	0.4819	0.0878	-0.5806	-0.4600	-0.6734	0.0033	-0.1230
35	0.1552	-0.1330	-0.4142	-0.5907	-0.5083	0.0136	-0.5963
36	-0.1966	-0.0632	-0.0162	0.1748	-0.0973	-0.2374	-0.0133
37	-0.3087	-0.1313	0.0588	0.0821	-0.1180	-0.3327	-0.0329
38	-0.1419	-0.0437	-0.0771	0.1562	-0.0947	-0.2066	0.0051

Based on Table 3 the results shows that the GWR model indicate that the influence of each explanatory variable on the prevalence of stunting among children under five varies across regions, demonstrating spatial heterogeneity. Overall, the intercept values range from approximately –0.31 to 0.73, suggesting that the baseline level of stunting prevalence (when other variables are held constant) differs across regencies. The percentage of poor population (X_1) exhibits both positive and negative coefficients. In most regions, the coefficient is positive, implying that higher poverty rates are associated with higher stunting prevalence. However, several areas show negative coefficients, indicating that poverty alone does not always strongly influence stunting without considering other interacting factors. The variables exclusive breastfeeding coverage (X_2) and early initiation of breastfeeding (X_4) consistently show negative coefficients, suggesting that improved breastfeeding practices contribute to lowering stunting prevalence across most districts. These findings emphasize the importance of maternal and child health interventions focusing on breastfeeding behavior. For the percentage of pregnant women with chronic energy deficiency (X_3), the coefficients vary from negative to positive across regions, indicating that the effect of maternal nutritional status differs spatially. Areas with positive coefficients may face broader nutritional or socioeconomic challenges that exacerbate the risk of stunting. The iron tablet consumption (X_5) variable also shows mostly negative coefficients, implying that adequate iron intake during pregnancy has a protective effect against stunting. Lastly, the children with ARI coverage (X_6) variable has small and mostly negative coefficients, indicating that improved healthcare access and treatment for respiratory infections can help reduce the prevalence of stunting, albeit with varying intensity across locations.

The GWR model for Jember Regency is expressed as follows:

$$\hat{y}_7 = 0.6418 + 0.1839X_1 - 0.6430X_2 - 0.3170X_3 - 0.5608X_4 - 0.1950X_5 + 0.0818X_6 \tag{8}$$

This equation indicates that the exclusive breastfeeding rate (X_2), early initiation of breastfeeding (X_4), and maternal nutritional status (X_3) have a negative relationship with stunting prevalence, suggesting that improvements in these factors can help reduce stunting in this region. For example in Jember Regency, a 1% increase in the percentage of the poor population (X_1) is estimated to raise the stunting prevalence by 0.1839 units, assuming other variables remain constant. Conversely, a 1% increase in exclusive breastfeeding coverage (X_2) is predicted to reduce stunting prevalence by 0.6430 units, while an increase in the proportion of pregnant women with chronic energy deficiency (X_3) decreases stunting by 0.3170 units, indicating a negative relationship in this area.

Furthermore, early initiation of breastfeeding (X_4) and iron tablet consumption (X_5) also exhibit negative effects on stunting, with coefficients of –0.5608 and –0.1950, respectively, suggesting that improvements in these maternal and child health factors contribute to reducing stunting prevalence. Meanwhile, the variable representing children with acute respiratory infections (X_6) shows a slightly positive relationship (0.0818), implying that an increase in the proportion of children with ARI slightly elevates the risk of stunting. Overall, this region demonstrates that maternal and child health interventions—such as promoting exclusive breastfeeding, early breastfeeding initiation, and preventing maternal with Chronic Energy Deficiency play a significant role in reducing stunting rates.

The regional classification according to the significant variables is provided in Table 4, and its spatial distribution is illustrated in Figure 1.

Table 4. Location Grouping Based on Significant Independent Variables Using GWR Model

Group	Location	**Significant Variables**
1	Bangkalan, Jember, Malang City, Pasuruan City, Lumajang, Malang, Pasuruan, Banyuwangi	X_2
2	Pamekasan, Sampang, Sumenep	X_2 and X_3
3	Situbondo, Bondowoso, Probolinggo City	X_2 and X_4
4	Probolinggo	X_2, X_3, and X_4

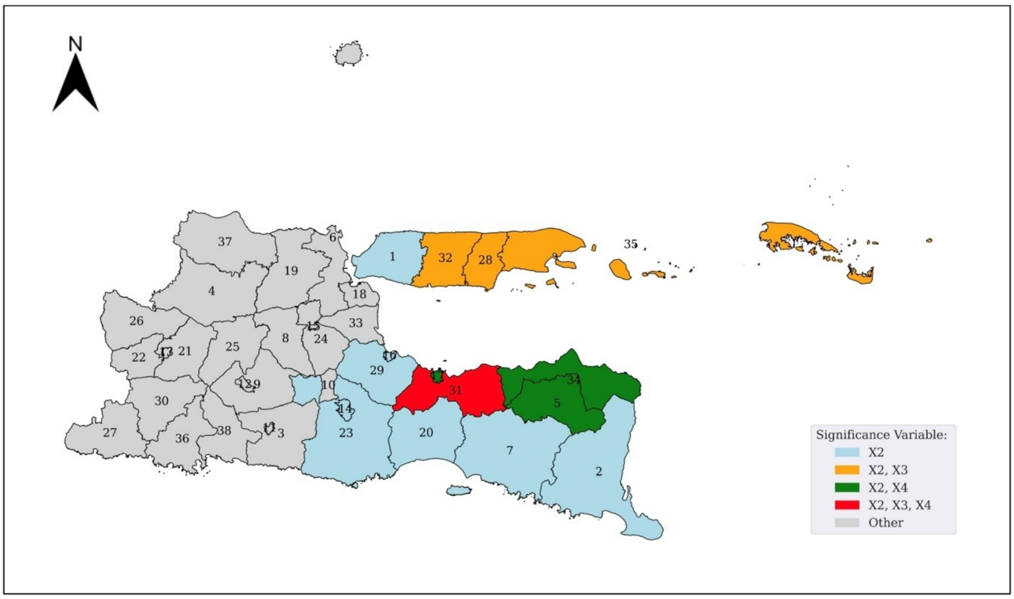

Figure 1. Visualization of Location Grouping based on Significant Independent Variables using GWR Model.

Four distinct groups were identified, each exhibiting significant parameter estimates associated with the occurrence of stunting. It can be observed that regions located in close proximity tend to share similarities in the independent variables influencing the incidence of stunting. Areas where only the variable of infants receiving exclusive breastfeeding (X_2) is significant are mainly concentrated around Lumajang Regency, covering most of the central Tapal Kuda region with a total of eight districts/cities. This indicates that exclusive breastfeeding is a key determinant in reducing stunting rates in these areas, highlighting the need for education on the importance of exclusive breastfeeding to ensure adequate infant nutrition. Meanwhile, the variables of infants receiving exclusive breastfeeding (X_2) and pregnant women with chronic energy deficiency (X_3) are significant around Pamekasan Regency, encompassing three regions, suggesting nutritional vulnerabilities occurring during both prenatal and postnatal periods. In Situbondo Regency, where the variables of exclusive breastfeeding (X_2) and early initiation of breastfeeding (X_4) are significant, postnatal breastfeeding practices are shown to play an important role in improving infant health. In Probolinggo Regency, where all three variables—exclusive breastfeeding (X_2), chronic energy deficiency in pregnant women (X_3), and early initiation of breastfeeding (X_4)—are significant, the results reflect a complex interplay of nutritional factors during both prenatal and postnatal periods. Other regions, however, do not show any significant variables affecting stunting incidence.

After modeling using GWR, the analysis proceeded to MS-GWR modeling. The MS-GWR modeling still uses Euclidean distance and an adaptive Gaussian weighting matrix. The selection of bandwidth for each covariate was carried out using the backfitting algorithm to obtain the optimal bandwidth for the overall MS-GWR model. This process produced seven bandwidth values corresponding to each covariate after five iterations, resulting in a minimum AICc value of 67.742. The bandwidth values obtained are presented in Table 5 and Table 6 presents the parameter estimation results of the MS-GWR model.

Table 5. Bandwidth for Each Parameter in the MS-GWR Model

Parameter	Bandwidth
β_0	8
β_1	38
β_2	19
β_3	38
β_4	21
β_5	34
β_6	13

The bandwidth values in the MS-GWR model indicate the degree of spatial variability for each parameter, showing how local or global the influence of each independent variable is on stunting. A smaller bandwidth value reflects a more local effect, meaning the variable's influence varies considerably across regions, while a larger bandwidth suggests a more global effect with relatively consistent influence across the study area. The smallest bandwidth is observed for β_0 (8), indicating that the intercept has highly localized variations, while β_1 (38) and β_3 (38) have the largest bandwidths, implying their effects are almost global. The variable β_2 (19) shows a moderately local effect, suggesting some spatial variation in its influence. Similarly, β_4 (21) exhibits semi-local characteristics, while β_5 (34) tends to have a more global influence. Lastly, β_6 (13) demonstrates a strong local effect, indicating that its relationship with stunting varies significantly across regions. Overall, these results reveal that some variables in the MS-GWR model have localized effects, whereas others remain relatively stable throughout the study area.

Table 6. Parameter Estimation Result using the MS-GWR Model

Regency/City	(Intercept)	X_1	X_2	X_3	X_4	X_5	X_6
1	-0.8587	0.0605	-0.3101	0.0428	-0.2521	-0.1282	-0.9433
2	0.8762	0.0679	-0.6201	0.0425	-0.3707	-0.1037	-0.0478
3	0.1297	0.0631	-0.0271	0.0518	-0.0974	-0.2053	0.0611
4	-0.3379	0.0567	-0.0712	0.0539	-0.0778	-0.2065	-0.1229
5	0.9526	0.0668	-0.6168	0.0419	-0.3601	-0.1058	-0.0919
6	-0.7381	0.0577	-0.0918	0.0471	-0.1453	-0.2212	-0.4178
7	0.9076	0.0706	-0.5958	0.0414	-0.3765	-0.1129	-0.0156
8	-0.1501	0.0605	-0.0802	0.0510	-0.1598	-0.2084	0.0176

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Table 6 Parameter Estimation Result using the MS-GWR Model

Regency/City	(Intercept)	X_1	X_2	X_3	X_4	X_5	X_6
9	0.0536	0.0607	-0.0637	0.0527	-0.0974	-0.2062	0.0254
10	0.3104	0.0649	-0.2598	0.0484	-0.1989	-0.2085	0.0853
11	0.1251	0.0624	-0.0280	0.0523	-0.0940	-0.2052	0.0580
12	-0.0654	0.0602	-0.0709	0.0532	-0.0835	-0.2059	-0.0527
13	-0.2730	0.0574	-0.0424	0.0553	-0.0572	-0.2052	-0.1478
14	0.3133	0.0671	-0.3115	0.0473	-0.2012	-0.2178	0.0890
15	-0.2712	0.0615	-0.0913	0.0488	-0.2404	-0.2103	0.0114
16	0.0828	0.0687	-0.3567	0.0417	-0.3090	-0.2230	0.0661
17	0.8312	0.0692	-0.5317	0.0410	-0.3196	-0.1278	0.0913
18	-0.8239	0.0626	-0.2561	0.0440	-0.2498	-0.2238	-0.2948
19	-0.5070	0.0580	-0.0765	0.0501	-0.2642	-0.2092	-0.1571
20	0.9734	0.0737	-0.5390	0.0410	-0.6428	-0.2221	0.1258
21	-0.2673	0.0577	-0.0415	0.0549	-0.0578	-0.2054	-0.1492
22	-0.3226	0.0571	-0.0435	0.0558	-0.0568	-0.2049	-0.1279
23	0.4411	0.0677	-0.3154	0.0477	-0.1868	-0.2183	0.0935
24	-0.1612	0.0626	-0.0887	0.0484	-0.1923	-0.2101	0.0176
25	-0.2073	0.0588	-0.0322	0.0535	-0.0729	-0.2063	-0.1580
26	-0.3188	0.0563	-0.0404	0.0557	-0.0515	-0.2052	-0.1288
27	-0.2838	0.0581	-0.0385	0.0560	-0.0555	-0.2041	-0.1312
28	-0.2450	0.0609	-0.5594	0.0422	-0.3247	-0.1080	-0.7708
29	0.2737	0.0695	-0.3534	0.0427	-0.4516	-0.2229	0.0876
30	-0.2890	0.0584	-0.0386	0.0554	-0.0591	-0.2046	-0.1317
31	0.9917	0.0696	-0.5837	0.0409	-0.3199	-0.1227	0.1117
32	-0.5856	0.0609	-0.4883	0.0422	-0.3161	-0.1134	-0.8423
33	-0.2331	0.0647	-0.2693	0.0442	-0.4604	-0.2230	-0.0025
34	0.7540	0.0654	-0.6146	0.0421	-0.3760	-0.1033	-0.4714
35	0.3395	0.0599	-0.5906	0.0434	-0.3546	-0.0972	-0.5747
36	-0.1814	0.0596	-0.0490	0.0550	-0.0684	-0.2043	-0.1246
37	-0.3698	0.0557	-0.0819	0.0529	-0.0904	-0.2071	-0.1082
38	-0.1139	0.0606	-0.0732	0.0540	-0.0659	-0.2047	-0.0754

Based on the MS-GWR parameter estimates in Table 6 and the corresponding bandwidth values, the spatial variability of each parameter can be interpreted in relation to its scale of influence. The intercept (β_0) has the smallest bandwidth (8) and exhibits wide variation across regions (-0.8587 to 0.9917), reflecting highly localized baseline stunting levels due to unobserved regional factors. Variables X_1 and X_3, with the largest bandwidths (38), show relatively stable coefficients across all regencies, indicating that these variables exert a global effect, consistent with their broad spatial influence. Variables X_2 (infants receiving exclusive breastfeeding) and X_6, with smaller bandwidths (19 and 13, respectively), demonstrate substantial local variation, with some regions showing strong negative associations with stunting, highlighting their localized impact. Variables X_4 (early initiation of breastfeeding) and X_5, with intermediate bandwidths (21 and 34), display moderate spatial variation, suggesting semi-local to global effects depending on the region. Overall, the MS-GWR results illustrate that variables with smaller bandwidths correspond to highly localized effects, while those with larger bandwidths correspond to more spatially uniform, global effects. Linking bandwidth to coefficient variation confirms that multiscale modeling effectively captures both local hotspots and global trends in stunting determinants across the study area.

The parameter estimates presented in Table 6 reveal meaningful spatial variations in the determinants of stunting across regencies and cities in East Java. Consistent with theoretical expectations, the coefficient for exclusive breastfeeding (X_2) is predominantly negative across regions, indicating that higher exclusive breastfeeding coverage contributes to lower stunting prevalence. Similarly, the coefficient for early initiation of breastfeeding (X_4) also shows a negative relationship, reinforcing the importance of postnatal care practices. In contrast, the coefficients for poverty (X_1) and chronic energy deficiency among pregnant women (X_3) are mostly positive, suggesting that higher poverty levels and maternal undernutrition increase the risk of stunting, aligning with existing public health literature. However, the magnitude and spatial variability of these effects differ across regions, implying that while some factors exert local influences (as seen in smaller bandwidths), others, such as poverty, operate more globally. Interestingly, a few areas exhibit weaker or even non-significant associations, suggesting potential confounding factors such as local food security programs or healthcare access disparities. Overall, these findings underscore that stunting reduction strategies should be spatially adaptive, focusing on enhancing breastfeeding practices in regions with negative X_2 and X_4 coefficients, and intensifying poverty alleviation and maternal nutrition interventions in areas where X_1 and X_3 exert stronger positive effects.

The grouping of regions using the MS-GWR model based on significant variables is presented in Table 7 and visually illustrated in Figure 2.

Table 7. Location Grouping based on Significant Independent Variables using MS-GWR Model

Group	Location	Significant Variables
1	Banyuwangi, Jember, Kota Probolinggo, Kota Surabaya, Kota Pasuruan	X_2
2	Blitar, Jombang, Kota Kediri, Kota Mojokerto, Kota Pasuruan, Magetan	X_4
3	Kota Madiun, Nganjuk, Pacitan, Trenggalek	X_6
4	Bondowoso, Sampang	X_2 and X_4
5	Bangkalan, Situbondo, Sumenep	X_2 and X_6
6	Pamekasan, Ponorogo	X_4 and X_6
7	Kota Malang	X_2, X_4, and X_6

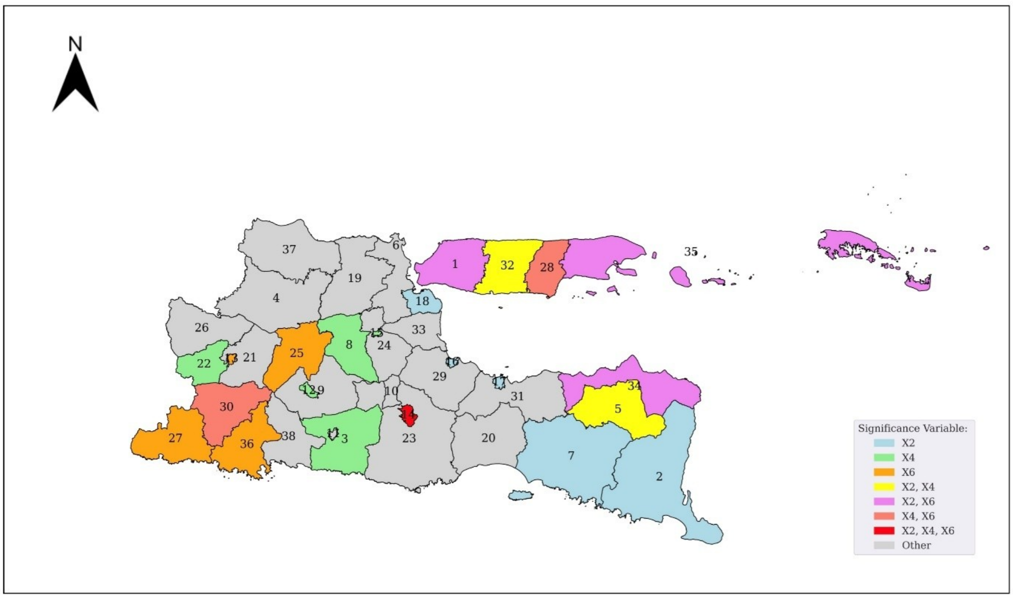

Figure 2. Visualization of Location Grouping based on Significant Independent Variables using MS-GWR Model.

There are seven distinct groups that have significant parameter estimates influencing the occurrence of stunting cases using the MS-GWR model.

The MS-GWR model identifies seven spatial groups with distinct significant determinants of stunting. In Group 1 (Banyuwangi, Jember, Probolinggo City, Surabaya City, Pasuruan City), only X_2 (infants receiving exclusive breastfeeding) is significant, indicating its primary role in reducing stunting. Group 2 (Blitar, Jombang, Kota Kediri, Kota Mojokerto City, Pasuruan City, Magetan) shows significance only for X_4 (early initiation of breastfeeding), highlighting postnatal breastfeeding practices. In Group 3 (Madiun City, Nganjuk, Pacitan, Trenggalek), X_6 is significant, reflecting strong localized influence. Groups 4 (Bondowoso, Sampang) and 5 (Bangkalan, Situbondo, Sumenep) have two significant variables each: X_2 and X_4 for Group 4, and X_2 and X_6 for Group 5, indicating combined prenatal, postnatal, and local effects. Group 6 (Pamekasan, Ponorogo) shows X_4 and X_6 as significant, while Group 7 (Malang City) exhibits significance for X_2, X_4, and X_6, demonstrating a complex interplay of factors. Overall, the results emphasize that determinants of stunting vary by region, with exclusive breastfeeding (X_2) being the most frequently significant, followed by early initiation of breastfeeding (X_4) and localized factors (X_6), highlighting the need for tailored, region-specific interventions.

The MS-GWR model reveals that the determinants of stunting vary spatially, with different regions showing significance for different combinations of variables. Overall, exclusive breastfeeding (X_2) emerges as the most consistently significant factor, indicating its crucial role in reducing stunting across most areas. Early initiation of breastfeeding (X_4) and localized factors (X_6) also show significant influence in several regions, reflecting the importance of postnatal nutrition practices and local conditions. Some regions exhibit multiple significant variables simultaneously, suggesting that stunting is influenced by a combination of prenatal, postnatal, and environmental factors. Linking these results to the MS-GWR bandwidths, variables with smaller bandwidths, such as X_2 and X_6, correspond to highly localized effects with strong regional variation, whereas variables with larger bandwidths, such as X_1, X_3, and X_5, exhibit more spatially uniform, global effects. These findings highlight the spatial heterogeneity of stunting determinants and emphasize the need for region-specific interventions and policies to effectively reduce stunting.

After modeling using the GWR and MS-GWR approaches, the goodness of fit of each model was examined. To compare the two models, the corrected Akaike Information Criterion (AICc) and R^2 were used. A good model is characterized by a low AICc value and a high R^2 [20]. Based on Table 8, the best model for this research data is MS-GWR.

Table 8. Comparison of AICc and R^2 Values for GWR and MS-GWR Models

Model	AICc	R^2
GWR	133.107	0.65
MS-GWR	67.742	0.79

Based on the model goodness-of-fit criteria presented in Table 8, the best model for modeling stunting cases in the regencies/cities of East Java Province in 2023 is the Multiscale Geographically Weighted Regression (MS-GWR) model with an adaptive Gaussian weighting function. This model was selected because it has the lowest AICc value and the highest R^2 compared to the multiple linear regression and Geographically Weighted Regression (GWR) models. This indicates that the MS-GWR model is the most suitable for representing stunting cases in East Java in 2023, as it allows for different spatial scales and accommodates variations in the local environment for each variable.

Research conducted by Rahman et al. (2021) showed that children from poor households were suffering from at least one form of malnutrition, namely wasting or stunting.Research conducted by Karina (2023) showed a significant relationship between the history of exclusive breastfeeding and the nutritional status of toddlers according to the height-to-age index.Research conducted by Mim et al. (2024) showed that the rate of child marriage among Bangladeshis was significantly associated with malnutrition among mothers and their children under five.Research conducted by Ajmal (2024) demonstrated that breastfeeding and complementary feeding affect child growth and development.Research conducted by Nisar et al. (2020) found that iron-folic acid supplementation during pregnancy was effective in reducing stunting.From the results of the analysis in this study, the variables that have a significant effect on stunting are Exclusive Breastfeeding Coverage, Early Initiation of Breastfeeding Coverage, Coverage of Toddlers/Children Under Five Affected by Acute Respiratory Infection. In

East Java, stunting is influenced significantly by the interplay of suboptimal breastfeeding practices and the high prevalence of acute respiratory infections among young children. Low rates of exclusive breastfeeding and delayed initiation deprive infants of crucial nutrients and immune protection provided by breast milk, rendering them more susceptible to infections. These infections, particularly acute respiratory infections, further compound the problem by reducing nutrient absorption, increasing metabolic demands, and diverting resources away from growth. The combined effect of compromised nutrition and increased susceptibility to infection creates a detrimental cycle that significantly hinders growth and development, ultimately contributing to elevated rates of stunting in the region. Addressing these interconnected issues through targeted interventions that promote optimal breastfeeding practices, improve sanitation and hygiene, and ensure timely access to healthcare is critical for reducing stunting prevalence in East Java.

4. Conclusion

Based on the results of the analysis described in the previous section regarding the modeling of stunting cases in each Regency/City in East Java Province using GWR and MS-GWR, two main conclusions can be drawn. First, based on the model comparison, the MS-GWR model using an adaptive Gaussian weighting kernel is the best method for modeling this research dataset, with an AICc value of 67.7426 and R^2 of 0.79. Second, the MS-GWR model identified seven groups with significant parameter estimates for stunting cases. The first group is Exclusive Breastfeeding Coverage (X_2), which includes Banyuwangi, Jember, Probolinggo City, Surabaya City, and Pasuruan City. The second group is Early Initiation of Breastfeeding Coverage (X_4), comprising Blitar, Jombang, Kediri City, Mojokerto City, Pasuruan City, and Magetan. The third group is Coverage of Toddlers/Children Under Five Affected by Acute Respiratory Infection (X_6), consisting of Madiun City, Nganjuk, Pacitan, and Trenggalek. The fourth group is X_2 and X_4, covering Bondowoso and Sampang. The fifth group is X_2 and X_6, which includes Bangkalan, Situbondo, and Sumenep. The sixth group is X_4 and X_6, comprising Pamekasan and Ponorogo. Finally, the seventh group is X_2, X_4, and X_6, which consists of Malang City.

The MS-GWR analysis highlights that determinants of stunting vary spatially across East Java, with exclusive breastfeeding, early initiation of breastfeeding, and localized factors being the most influential variables. For health planners, this implies that intervention strategies must be region-specific: programs promoting exclusive breastfeeding should target areas where X_2 is significant, while initiatives encouraging early initiation of breastfeeding should focus on regions where X_4 is significant. Regions with multiple significant factors require integrated interventions addressing both prenatal and postnatal nutrition, as well as local environmental conditions. By aligning policy actions with the spatial patterns of these determinants, health authorities can more effectively reduce stunting rates and optimize resource allocation.

5. Limitation

In this study, the amount of data was limited to only 38 regions. While MS-GWR offers the advantage of capturing spatial non-stationarity at varying scales, its performance can be compromised when applied to datasets with limited sample sizes. The increased model complexity, stemming from the estimation of numerous local parameters and bandwidths at multiple scales, demands a substantial number of observations to ensure robust and reliable parameter estimates. With small samples, MS-GWR models are susceptible to overfitting, potentially capturing noise rather than true spatial relationships, and leading to unstable or biased results. Furthermore, the estimation of appropriate bandwidths for each scale becomes challenging, potentially resulting in either oversmoothing, which obscures local variations, or undersmoothing, which amplifies the influence of individual data points and weakens the model's generalizability. Therefore, caution should be exercised when interpreting MS-GWR results derived from small datasets, and alternative methods or data augmentation techniques may be considered to mitigate these limitations.

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