Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 10, Number 2, 2026
DOI: 10.30829/zero.v10i2.30987
Page: 756-767

Comparing Adaptive Kernels in Geographically and Temporally Weighted Regression for Stunting in East Nusa Tenggara, 2021–2023

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Article Info

Article history:

Accepted : 13 August 2026

Keywords:

Adaptive Kernel;
East Nusa Tenggara;
Geographically and Temporally Weighted Regression;
Spatiotemporal Modeling;
Stunting.

ABSTRACT

Stunting remains a major public health challenge in East Nusa Tenggara, Indonesia. This study compares Gaussian, Bisquare, and Exponential adaptive kernels in Geographically and Temporally Weighted Regression (GTWR) to model spatiotemporal variation in stunting determinants. District-level panel data from 22 districts/municipalities during 2021–2023 were used, yielding 66 space-time observations. Models were evaluated using R^2, RMSE, spatial-temporal parameter tests, and a spatial-only GWR baseline. The Bisquare adaptive GTWR produced the strongest in-sample fit ($R^2 = 98.58\%$; RMSE = 0.7647), improving over the Bisquare GWR baseline ($R^2 = 46.98\%$; RMSE = 4.6703), although this high fit should be interpreted cautiously. GRDP per capita, poverty rate, and maternal education showed significant spatial-temporal variability, while the sanitation and clean water access variable was not significant ($F_3 = 1.0938$; p = 0.4771). GTWR may serve as an exploratory tool for identifying local stunting patterns.

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1. INTRODUCTION

Stunting continues to be an important public health issue in Indonesia, particularly in East Nusa Tenggara (NTT), which has repeatedly shown one of the highest prevalence levels relative to other provinces [1]. As a manifestation of impaired linear growth caused by prolonged undernutrition, stunting carries lasting implications for cognitive development, later-life productivity, and overall human capital formation [2], [3]. Its underlying drivers are multidimensional, spanning economic, social, educational, and health-related domains. For this reason, a clearer understanding of regional determinants is needed to support the development of more effective and locally tailored interventions.

This study uses GRDP per capita, poverty rate, maternal educational attainment, and sanitation and clean water access as explanatory variables because they represent key socioeconomic and environmental dimensions commonly associated with child nutrition outcomes. GRDP per capita reflects regional economic capacity and potential access to resources, while poverty captures household-level constraints that may limit food security and healthcare utilization. Maternal education is linked to caregiving knowledge, health-seeking behavior, and child-feeding practices, whereas sanitation access reflects environmental conditions that may influence infection-related growth faltering [4], [5], [6]. These variables were also selected because they are consistently available at the district/municipality level for the 2021–2023 study period.

Most existing research on stunting in NTT and similar regions has relied on global models or spatial-only techniques, such as conventional linear regression and Geographically Weighted Regression (GWR). While these approaches can describe overall effects and spatial variation, they tend to pay limited attention to temporal processes, including shifts in the strength or direction of associations between stunting and its explanatory factors across time. Given that socioeconomic conditions and public health interventions evolve from year to year, ignoring the temporal dimension may result in an incomplete understanding of stunting patterns [7], [8].

Given that stunting prevalence varies across both space and time, a spatial–temporal analytical approach is particularly relevant [7]. Geographically and Temporally Weighted Regression (GTWR) is one method designed to accommodate this variability. As an extension of Geographically Weighted Regression (GWR), GTWR incorporates spatial and temporal dimensions simultaneously within a single modelling framework. This allows the analysis to capture local heterogeneity and temporal dynamics in the relationships between predictors and the outcome variable [8], [9]. Consequently, GTWR offers a more refined assessment of how socioeconomic influences on stunting differ not only across districts/cities, but also across distinct time periods.

Recent studies on Indonesian stunting have increasingly used spatial methods to show that stunting determinants vary geographically across regions [4], [10], [11]. These studies are useful for detecting spatial variation, but they generally do not explicitly model changes in local relationships over time. Spatiotemporal modelling approaches have also been applied in related epidemiological studies to capture changes across both space and time [6], [7]. However, limited attention has been given to how different adaptive local weighting schemes affect GTWR parameter estimation and model performance. Therefore, a systematic comparison of Gaussian, Bisquare, and Exponential adaptive kernels within the GTWR framework remains relevant, especially for East Nusa Tenggara, where stunting prevalence varies across districts and years[1], [12], [13]. Accordingly, this study compares Gaussian, Bisquare, and Exponential adaptive kernels in GTWR for modeling stunting prevalence in East Nusa Tenggara during 2021–2023, with spatial-only GWR used as a supporting benchmark. Model performance is evaluated using R^2 and RMSE, while spatial–temporal coefficient variation is examined to identify locally varying socioeconomic determinants.

2. RESEARCH METHOD

2.1 Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is a local modelling extension of linear regression that applies spatial weights to estimate location-specific parameters. Under this framework, regression coefficients are not assumed to be constant; instead, they are estimated separately at each location using geographically weighted neighbouring observations. Therefore, the response variable is predicted using predictors with spatially varying effects. The resulting parameter estimates are local in nature and are most valid for interpretation within the vicinity of each observation location [14], [15] In the Geographically Weighted Regression (GWR) model, the relationship between the response variable Y and the predictor variables at location i can be expressed as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i) X_{ij} + \varepsilon_i, \qquad i = 1,2,\dots,n \text{ and } j = 1,2,\dots,k \tag{1}$$

The estimation of GWR parameters is carried out using the Weighted Least Squares (WLS) method, which assigns varying weights to each observation location. The form of the parameter estimation for the GWR model at each location can be formulated as follows [16].

$$\hat{\boldsymbol{\beta}}(u_i, v_i) = (\boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{W}(u_i, v_i)\, \boldsymbol{X})^{-\mathbf{1}} \boldsymbol{X}^{\boldsymbol{T}} \boldsymbol{W}(u_i, v_i)\, \boldsymbol{Y} \qquad i = 1,2,\dots,n \tag{2}$$

$\boldsymbol{W}_{ij}(u_i, v_i)$ is a spatial weighting matrix of dimension $n \times n$, defined as follows[17], [18]:

$$\boldsymbol{W}_{\boldsymbol{ij}}(u_i, v_i) = \begin{bmatrix} \boldsymbol{w}_{i1} & 0 & \cdots & 0 \\ 0 & \boldsymbol{w}_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{w}_{in} \end{bmatrix}$$

The weight for the data at point n in the model evaluation around point i is denoted as $\boldsymbol{w}_{in}$. The weighting matrix at location i is constructed based on a weighting function determined through a kernel function [19], [20]. Three types of weighting functions are used, as follows:

a. Gaussian Kernel

Gaussian Kernel assigns smaller weights as the distance between locations increases. Its formula is expressed as follows:

$$w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_i}\right)^2\right) \tag{3}$$

b. Bisquare Kernel

Bisquare Kernel assigns a weight of zero to points that lie outside the bandwidth range. Its formula is given as:

$$w_{ij} = \begin{cases} \left(1-\left(\frac{d_{ij}}{h_i}\right)^2\right)^2 & \text{, for } d_{ij} \le h_i \\ 0 & \text{, for } d_{ij} > h_i \end{cases} \tag{4}$$

c. Exponential Kernel

Exponential Kernel produces weights that decrease exponentially with distance. The equation is formulated as:

$$w_{ij} = exp\left(-\frac{d_{ij}}{h_i}\right) \tag{5}$$

where h_i is the adaptive bandwidth and d_{ij} is the distance between location i and j

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

One approach to determine the optimal bandwidth is the cross-validation method, which can be mathematically formulated as follows:

$$CV(h) = \sum_{i=1}^{n} (y_i - \hat{y}_{\neq i}(h))^2 \tag{6}$$

The optimal bandwidth is obtained by minimizing equation (6). The adaptive bandwidth is implemented using a nearest-neighbor approach, in which the bandwidth scale varies spatially while maintaining a constant number of observations within each local regression. The bandwidth at location *i* corresponds to the distance to the (h) nearest neighbor. The optimal value of (h) is selected by minimizing the cross-validation function in Equation (6), ensuring an optimal trade-off between bias and variance in the local parameter estimates [8].

2.2 Geographically and Temporally Weighted Regression (GTWR)

Geographically and Temporally Weighted Regression (GTWR) is an extension of GWR designed to address data instability across both spatial and temporal dimensions simultaneously [21], [22], [23]. In contrast to conventional GWR, GTWR embeds spatial and temporal components within the weighting matrix, allowing parameter estimates to vary across locations and over time. The GTWR models were estimated using R software, with calibration carried out through a customised procedure designed to accommodate adaptive kernel specifications. The GTWR model with p independent variables and a dependent variable y_i at location $\{(u_i, v_i, t_i)\}$ for each observation can be formulated as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i).x_{ik} + \varepsilon_i \tag{7}$$

The parameter estimation in the GTWR model for each variable k at the observation point $\{(u_i, v_i, t_i)\}$ can be expressed as follows:

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = (\boldsymbol{XTW}(u_i, v_i, t_i)\boldsymbol{X})^{-1}\boldsymbol{XTW}(u_i, v_i, t_i)\boldsymbol{Y} \tag{8}$$

In the GTWR model, the weight matrix is defined as $\boldsymbol{W}(u_i, v_i, t_i) = \text{diag}(\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{in})$, where n denotes the number of observations. Each diagonal element α_{ij} $(1 \le j \le n)$ represents a spatial-temporal distance function at the observation point (u_i, v_i, t_i). It is assumed that observations closer to point i in the space-time coordinate system exert a greater influence on the parameter estimate $\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$ than those farther away. GTWR defines local weights using a combined spatial–temporal distance. Observations that are closer in both geographic and temporal dimensions receive larger weights in the local parameter estimation. The concept of spatial–temporal distance is illustrated in Figure 1 [24], [25].

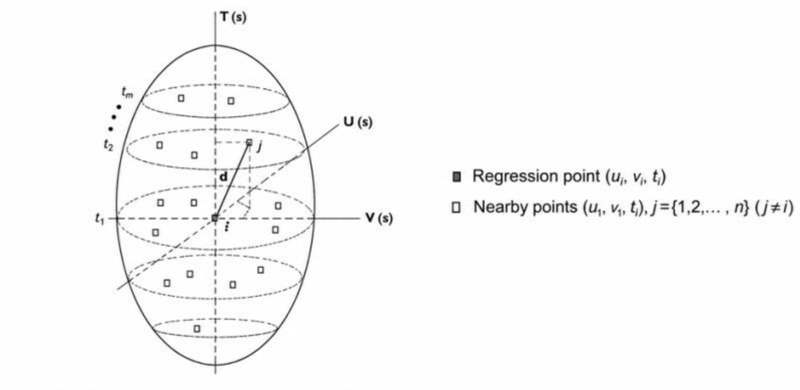


Figure 1. Illustration of spatial-temporal distance

The spatial-temporal distance function is defined as a combination of the spatial distance function and the temporal distance function. By employing the spatial distance d^S and the temporal distance d^T, the equation can be expressed as follows:

$$(d^{ST})^2 = \lambda(d^S)^2 + \mu(d^T)^2 \tag{9}$$

The parameters λ and μ represent scaling factors used to balance the differing effects in measuring spatial and temporal distances. Hence, the Euclidean distance is formulated as follows [9], [24]:

$$\left(d_{ij}^{ST}\right)^2 = \lambda\left\{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right\} + \mu\left(t_i - t_j\right)^2 \tag{10}$$

Based on the spatial–temporal distance in Equation (10), the GTWR weighting function is constructed by replacing the spatial distance d_{ij} in the kernel function with the spatial–temporal distance d_{ij}^{ST}. Thus, the Gaussian, Bisquare, and Exponential adaptive kernels were applied within the spatial–temporal distance framework. The temporal-to-spatial scaling ratio is defined as $\tau = \mu/\lambda$, where τ adjusts the relative contribution of temporal distance. Its value was selected using the minimum cross-validation (CV) criterion [24].

Because the dataset is structured as a district-level panel, each district/municipality appears repeatedly across three years. Thus, the spatial coordinates (u_i, v_i) are identical for observations from the same district but differ in the temporal coordinate t_i. In the GTWR distance function, repeated observations from the same district are distinguished by the temporal distance component. For two observations from the same district in different years, the spatial distance is zero, but the temporal distance remains positive. Therefore, these observations are not treated as duplicates in the weighting process [25].

2.3 Spatial Heterogeneity Test

Spatial heterogeneity is the condition where the influence of independent variables on the dependent variable differs across locations. Evaluating spatial heterogeneity helps determine whether the relationships captured by the regression model are constant across space or differ by location. This aspect can be examined using tests such as the Breusch–Pagan test [16].

2.4 Goodness of Fit Test GTWR

Hypothesis testing in the GTWR model encompasses two components: model adequacy testing (goodness of fit) and parameter testing. The assessment of model adequacy in GTWR is essentially analogous to that in GWR, which can be formulated under the following hypotheses:

H_0: $\beta_k(u_i, v_i, t_i) = \beta_k$ for each $k = 0,1,2, \dots, p$, and $i = 1,2, \dots, n$
(There is no significant difference between the global regression model and the GTWR model)
H_1: At least one $\beta_k(u_i, v_i, t_i) \neq \beta_k$ for $k = 0,1,2, \dots, p$
(There is a significant difference between the global regression model and the GTWR model)

The test statistic is determined by comparing the residual sum of squares from the global regression model under H_0 and the GTWR model under H_1 [18]. The goodness-of-fit statistic can be expressed as follows:

$$F_1 = \frac{[RSS(H_0) - RSS(H_1)]/df_1}{RSS(H_1)/df_2} \tag{11}$$

where $RSS(H_0)$ denotes the residual sum of squares under the global regression model, whereas $RSS(H_1)$ denotes the residual sum of squares under the GTWR model. Furthermore, df_1 represents the difference in model complexity between the global and GTWR models, and df_2 represents the residual degrees of freedom of the GTWR model. When the effective number of parameters is used, these degrees of freedom can be approximated by $df_1 = ENP_{GTWR} - (p+1)$ and $df_2 = n - ENP_{GTWR}$. At significance level α, H_0 is rejected if $F_1 > F_{\alpha, df_1, df_2}$, indicating that the GTWR model provides a significantly better fit than the global regression model.

2.4.1 Partial Test GTWR

A statistically significant difference between the GTWR model and the global regression model indicates the need for a partial test to assess whether the effect of predictor x_k varies across locations and time. The partial test evaluates whether each local coefficient is constant or varies significantly over the space–time observations, following the spatial nonstationarity testing framework of Leung et al. [18]. The hypotheses are:
$H_0: \beta_k(u_1, v_1, t_1) = \beta_k(u_2, v_2, t_2) = \ldots = \beta_k(u_n, v_n, t_n)$
H_1: at least one local coefficient differs across space–time observations.
At significance level α, H_0 is rejected if $F_3 > F_{\alpha, df_1, df_2}$, or equivalently if the p-value is less than α [18].

2.5 Model Evaluation

According to [24], [25], several methods can be employed to evaluate and identify the most appropriate model, including:

2.5.1 Coefficient of Determination ($\boldsymbol{R^2}$)

The coefficient of determination reflects the extent to which variation in the dependent variable is explained by the independent variables, as specified in the model. This measure is typically applied to regression models involving more than two variables.

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}\right) \times 100\% \tag{12}$$

2.5.2 Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is used to assess the accuracy of the model by calculating the square root of the average squared differences between the observed and predicted values. This measure indicates the average magnitude of prediction errors in the same units as the dependent variable [26].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

The strongest in-sample specification is determined based on the highest R^2, the lowest RMSE, and supporting diagnostics such as adaptive bandwidth and ENP.

2.6 Research Procedure

The analysis was conducted in four stages. First, district-level panel data for 22 districts/municipalities in East Nusa Tenggara during 2021–2023 were compiled from official BPS publications [27]. Second, multicollinearity and heterogeneity diagnostics were performed using VIF and the Breusch–Pagan test. Third, GTWR models with Gaussian, Bisquare, and Exponential adaptive kernels were estimated using R software. Finally, model performance was evaluated using R^2, RMSE, bandwidth, ENP, and comparison with a spatial-only GWR baseline.

3. RESULT AND ANALYSIS

3.1 Data Description and Descriptive Statistics

Before conducting the GTWR analysis, the operational definition, source, unit, reference year, and completeness of each variable were examined. The dataset consists of district-level panel data for 22 districts/municipalities in East Nusa Tenggara observed over three years, from 2021 to 2023, resulting in 66 district-year observations. The dependent variable is child stunting prevalence, defined as the percentage of children under five classified as stunted at the district/municipality level. The stunting data were obtained from official BPS Nusa Tenggara Timur publications, which report the number and percentage of stunted children under five by district/municipality. Because published stunting figures in Indonesia may originate from different reporting systems, such as SSGI and e-PPGBM, the temporal pattern in this study is interpreted cautiously as variation in officially published district-level data rather than as a direct comparison of measurement-equivalent survey estimates [27].

Table 1. Operational Definition and Source of Data

Variable	Operational Definition	Unit	Reference Years	Source
Stunting prevalence (Y)	Percentage of children under five classified as stunted at district/municipality level	%	2021–2023	BPS Nusa Tenggara Timur publications
GRDP per capita (X_1)	Gross Regional Domestic Product per capita at district/municipality level	million IDR/person	2021–2023	BPS Nusa Tenggara Timur and BPS district/municipality publications
Poverty rate (X_2)	Percentage of population below the poverty line	%	2021–2023	BPS Nusa Tenggara Timur and BPS district/municipality publications
Maternal education (X_3)	Percentage of mothers with at least junior high school education	%	2021–2023	BPS Nusa Tenggara Timur and BPS district/municipality publications
Sanitation and clean water access (X_4)	Percentage of households with access to proper sanitation and clean water	%	2021–2023	BPS Nusa Tenggara Timur and BPS district/municipality publications
Coordinates (u, v)	Longitude and latitude of district/municipality centroid	decimal degrees	Fixed by district	BIG administrative boundary data; centroids generated using QGIS

All explanatory variables were aligned by district/municipality and reference year. The final dataset contains 66 complete district-year observations, and no interpolation was applied. Maternal education is consistently defined as the percentage of mothers with at least junior high school education. The spatial coordinates (u, v)represent district/municipality centroid coordinates. Euclidean centroid-to-centroid distance was used in the spatial weighting process; however, because East Nusa Tenggara is an archipelagic province, this distance represents geometric proximity and may not fully reflect actual inter-island accessibility or transport connectivity.

Table 2. Descriptive Statistics of Variables (2021-2023)

Variable	Unit	Mean	Variance	Minimum	Maximum
Stunting Prevalence (Y)	%	16.79	41.14	7	32
GRDP per Capita (X_1)	million IDR/person	21.35	140.60	12.18	59.47
Poverty Rate (X_2)	%	21.05	46.33	8.61	34.27
Maternal Education (X_3)	%	27.89	66.33	16.42	65.55
Sanitation and Clean Water Access (X_4)	%	74.10	202.04	42.15	93.06

Table 2 shows that stunting prevalence ranges from 7.00% to 32.00%, with a mean of 16.79%, indicating variation across districts and years. The explanatory variables also show considerable variation, particularly GRDP per capita and sanitation and clean water access, suggesting heterogeneous socioeconomic and infrastructure conditions across East Nusa Tenggara. These descriptive patterns support the use of a local spatial–temporal model to examine whether the associations between stunting and its determinants vary across districts and years.

3.2 Multicollinearity Diagnosis

Before estimating the GTWR model, multicollinearity among explanatory variables was examined using the Variance Inflation Factor (VIF). This diagnostic step was conducted because socioeconomic variables, particularly GRDP per capita and poverty rate, may be correlated and may affect the stability of regression coefficient estimates. A VIF value below 10 is generally considered acceptable, indicating that severe multicollinearity is not present.

Table 3. Multicollinearity Test

Variable	VIF	Description
GRDP per Capita (X_1)	1.765	No severe multicollinearity
Poverty Rate (X_2)	1.668	No severe multicollinearity
Maternal Education (X_3)	1.945	No severe multicollinearity
Sanitation and Clean Water Access (X_4)	1.635	No severe multicollinearity

The VIF results showed that all explanatory variables had VIF values below the commonly used threshold. Therefore, the selected predictors were retained in the model. This indicates that the estimated effects of GRDP per capita, poverty rate, maternal education, and household sanitation and clean water access are not seriously affected by multicollinearity.

3.3 Spatial Data Test

The Breusch–Pagan test was applied to evaluate heterogeneity in the regression model. The test produced a BP statistic of 17.218 (df = 4) with a p-value of 0.001753. Because the p-value is below 0.05, the null hypothesis of homoskedasticity is rejected, indicating heterogeneity in the error variance. This implies that the residual variance is not constant across observations, which supports the use of a spatial–temporal modelling approach such as GTWR to better accommodate heterogeneity in the data.

3.4 GTWR Modeling

The GTWR model was estimated using three adaptive kernel functions: Gaussian, Bisquare, and Exponential. Table 4 summarizes the local coefficients from the Bisquare Adaptive kernel, which was the strongest in-sample specification. The coefficient ranges indicate that the effects of GRDP per capita, poverty rate, maternal education, and sanitation and clean water access vary across districts and years, suggesting spatial–temporal heterogeneity in the relationships between stunting prevalence and its predictors. For illustration, the local model for Southwest Sumba Regency under the Bisquare Adaptive kernel is:

$$\hat{y}_{17} = 238.6491 + 3.8893X_1 - 4.8758X_2 - 3.6041X_3 - 0.8845X_4$$

In the Southwest Sumba local model, the intercept value of 238.65 should not be interpreted as an observed stunting prevalence. It is a model-based local baseline term when all predictors are set to zero. Because the predictors are not centered and the Bisquare Adaptive kernel applies localized weighting, the intercept may fall outside the observed range of stunting prevalence. The positive coefficient of GRDP per capita also should not be interpreted as evidence that higher regional income directly increases stunting. At the district level, this association may reflect ecological aggregation, unequal distribution of economic gains, omitted variables such as food security or health-service access, or sectoral economic activity that does not directly translate into household nutrition.

Table 4. Parameter Statistic GTWR Bisquare Adaptive

Variable	Mean	Std	Minimum	Maximum
Intercept	37.94	158.00	-823.84	429.03
GRDP per Capita ($\mathbf{X_1}$)	-1.04	2.32	-5.08	7.20
Poverty Rate ($\mathbf{X_2}$)	0.12	4.54	-12.97	27.25
Maternal Education ($\mathbf{X_3}$)	0.15	1.79	-5.31	5.17
Sanitation and Clean Water Access ($\mathbf{X_4}$)	-0.18	0.81	-2.62	2.09

The wide range of local intercept estimates, from -823.84 to 429.03, indicates local coefficient instability under the Bisquare Adaptive kernel. Therefore, the Bisquare GTWR coefficients should be interpreted as exploratory spatial–temporal associations rather than firm causal or policy signals.

3.5 Testing the GTWR Model Hypothesis

Hypothesis testing in the GTWR model is conducted to evaluate the validity and significance of the estimated model, both as a whole and for each predictor variable. This process includes a goodness-of-fit test to ensure that the GTWR model applied is statistically appropriate, along with a partial test to assess the influence of each predictor variable on the response variable individually.

3.5.1 Model Goodness of Fit Test for GTWR

The GTWR goodness-of-fit evaluation is performed to examine whether the estimated model provides an adequate representation of the observed data and can be used for further analysis. It is carried out by contrasting model-explained variability with the overall variability in the response, which reflects the extent to which the GTWR model describes the association between the predictors and the response variable.

Table 5. ANOVA for GTWR

Kernel Function	F	F_{table}	P -Value
Gaussian Adaptive	6.3935	1.7497	0.0000
Bisquare Adaptive	67.3676	1.5293	0.0000
Exponential Adaptive	7.0467	1.6984	0.0000

Based on the results presented in Table 5, the F_1 **test** was employed to compare the global regression model (OLS) with the Geographically and Temporally Weighted Regression (GTWR) model. The results indicate that, for all types of kernel functions used, the obtained F_1 values were greater than the critical F-table value at the 5% significance level. In addition, all p-values were 0.0000 $(< \alpha = 0.05)$, which means that H_0 is rejected for all kernels. A significant improvement in model performance under GTWR, compared with the global regression model, indicates the presence of spatial–temporal variation in the analysed data.

3.5.2 Partial Test in GTWR

If the GTWR model is found to be significantly different from the global regression model, the next step is to conduct a partial test to examine whether there are differences in the effects of predictor variables x_k across locations. The partial test in the GTWR model aims to evaluate the significance of each predictor variable's influence while taking spatial and temporal variation into account.

Table 6 presents the spatial–temporal variability test for the predictor coefficients. Under the Gaussian and Exponential adaptive kernels, none of the predictor coefficients show significant spatial–temporal variability, with p-values reported as 1.0000. These values are interpreted cautiously because they may indicate that the smoother Gaussian and Exponential weighting structures produced relatively stable coefficient surfaces in this small space–time dataset. In contrast, under the Bisquare Adaptive kernel, GRDP per capita, poverty rate, and maternal education have p-values below 0.05, indicating significant coefficient variability across districts and years. Sanitation and clean water access is not significant, suggesting that its coefficient is relatively more stable across space and time.

Table 6. Spatial-Temporal Factor Test for Predictor Variables

Kernel Function	Variabl	F3 Stat	P -Value	Description
Gaussian Adaptive	X_1	0.0072	1.0000	Insignificant
	X_2	0.0301	1.0000	Insignificant
	X_3	0.0217	1.0000	Insignificant
	X_4	0.0046	1.0000	Insignificant
Bisquare Adaptive	X_1	9.0386	0.0041	Significant
	X_2	34.6616	0.0001	Significant
	X_3	5.4035	0.0177	Significant
	X_4	1.0938	0.4771	Insignificant
Exponential Adaptive	X_1	0.0028	1.0000	Insignificant
	X_2	0.0184	1.0000	Insignificant
	X_3	0.0075	1.0000	Insignificant
	X_4	0.0023	1.0000	Insignificant

3.6 Comparison of GTWR Models

The optimal GTWR model was selected by comparing three adaptive bandwidth weighting functions, evaluated using R^2 and RMSE, to obtain the most accurate estimation with minimal prediction error. Before comparing model performance, the selected adaptive bandwidth and spatiotemporal scaling parameters were examined to assess the degree of localization in each GTWR specification. As shown in Table 7, the Gaussian and Exponential adaptive kernels selected 10 nearest neighbours and produced moderate ENP values of 15.6668 and 15.6564, respectively. The Bisquare Adaptive kernel selected 14 nearest neighbours and produced a higher ENP value of 34.4989, indicating a more flexible local model.

Table 7. Selected Adaptive Bandwidth and Spatiotemporal Scaling Parameters

Kernel Function	Selected Adaptive Bandwidth (h)	λ	μ	τ	ENP	Residual df
Gaussian Adaptive	10	1.000	0.001	0.001	15.6668	50.3332
Bisquare Adaptive	14	1.000	0.100	0.100	34.4989	31.5011
Exponential Adaptive	10	1.000	0.001	0.001	15.6564	50.3436

Note: λ was fixed at 1 for identifiability, so $\mu = \tau$. ENP denotes the effective number of parameters, and residual df is calculated as $n - ENP$, with $n = 66$.

The higher ENP of the Bisquare Adaptive model indicates that this specification captures stronger local variation, but it also implies greater sensitivity to bandwidth selection and potential overfitting. Therefore, the high R^2 obtained by the Bisquare GTWR model should be interpreted as strong in-sample local fit rather than evidence of out-of-sample predictive superiority. Model performance was then compared between the spatial-only GWR baseline and the GTWR model using R^2 and RMSE. The GWR baseline was included as a supporting benchmark to evaluate whether incorporating temporal distance improves in-sample model fit.

Table 8. Comparison between GWR Baseline and GTWR Model

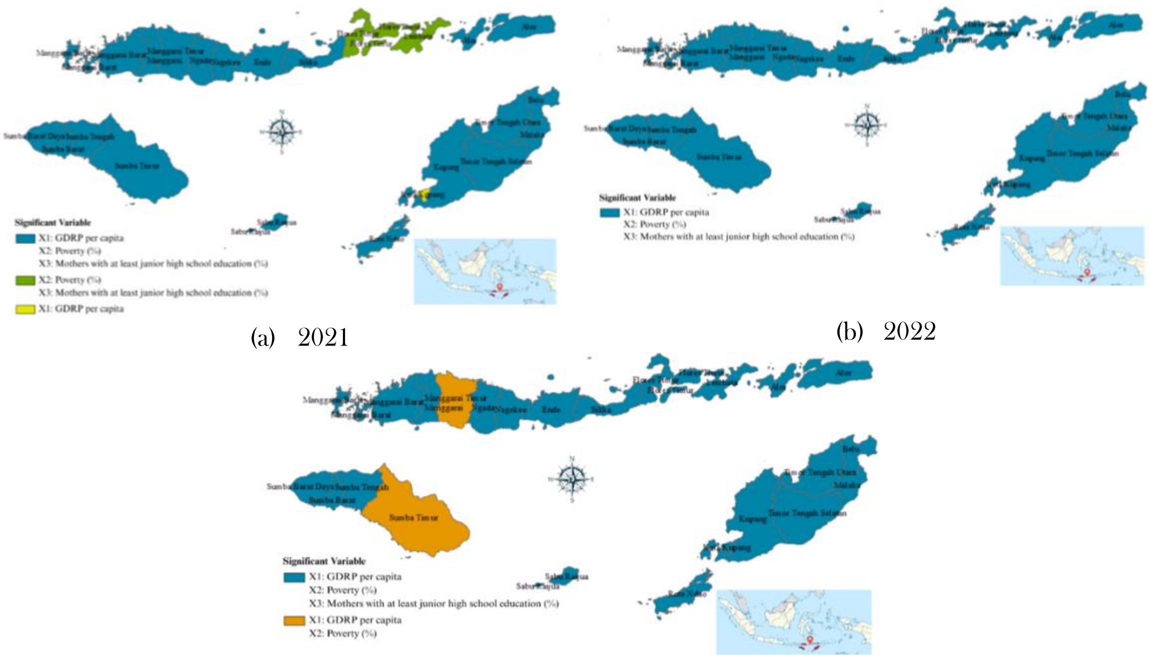
Model	Kernel Function	R^2(%)	RMSE
GWR	Gaussian Adaptive	14.62	5.9266
	Bisquare Adaptive	46.98	4.6703
	Exponential Adaptive	26.10	5.5138
GTWR	Gaussian Adaptive	69.11	3.5644
	Bisquare Adaptive	98.58	0.7647
	Exponential Adaptive	74.76	3.2220

As shown in Table 8, GTWR consistently improves the in-sample fit over the spatial-only GWR baseline across all adaptive kernels. The largest improvement is observed for the Bisquare Adaptive kernel, where R^2 increases from 46.98% in GWR to 98.58% in GTWR, while RMSE decreases from 4.6703 to 0.7647. Similar improvements are found for the Gaussian and Exponential kernels, indicating that incorporating temporal distance into the local weighting scheme adds explanatory value beyond spatial weighting alone.

Among the GTWR specifications, the Bisquare Adaptive kernel provides the strongest in-sample performance. However, this result should be interpreted cautiously because the Bisquare model also has the highest ENP, indicating greater model flexibility and sensitivity to adaptive bandwidth selection. Therefore, the high R^2 of the Bisquare GTWR model is interpreted as strong in-sample local fit rather than evidence of out-of-sample predictive superiority. In addition, the archipelagic geography of East Nusa Tenggara should be considered, as inter-island separation may influence spatial weighting and produce sharper local estimates under adaptive kernels.

3.7 Interpretation of Results

This section presents the spatial distribution of stunting-related patterns across districts/municipalities in East Nusa Tenggara (NTT) for the years 2021–2023. Interpretation focuses on the variables that show significant associations with stunting prevalence under the GTWR framework. The reported patterns are derived from the GTWR model fitted with a Bisquare adaptive kernel, which demonstrated the strongest overall performance. The map in Figure 2 was constructed from the local significance test of GTWR coefficients. For each district-year observation, predictors with local p-values below 0.05 were classified as significant. The colors indicate the combination of significant predictors in each district for the corresponding year.



(a) 2021 (b) 2022

(c) 2023

Figure 2. Local significance patterns of GTWR predictor coefficients in East Nusa Tenggara under the Bisquare Adaptive kernel: (a) 2021, (b) 2022, and (c) 2023. Colours indicate combinations of locally significant predictors based on p-value < 0.05, as shown in the legend. The map was generated using QGIS with WGS 84 coordinate reference system (EPSG:4326) and exported at 300 dpi.

Figure 2 summarizes the local significance patterns of GTWR coefficients under the Bisquare Adaptive kernel for 2021–2023. In 2021, significant predictors varied across districts. Most districts showed simultaneous significance of GRDP per capita (X_1), poverty rate (X_2), and maternal education (X_3), while several districts showed fewer significant predictors, particularly (X_2, X_3) or X_1 alone. In 2022, the pattern became more uniform, with (X_1, X_2, X_3) appearing significant across districts. In 2023, spatial differentiation reappeared, with most districts remaining associated with (X_1, X_2, X_3), while several districts showed significance mainly for (X_1, X_2).

These maps should be interpreted as exploratory visualizations rather than definitive policy zoning. With only three annual observations and no formal convergence test, the apparent uniformity in 2022 should be viewed as a descriptive pattern rather than evidence of convergence. The positive local coefficient of GRDP per capita in Southwest Sumba also should not be interpreted as evidence that higher regional income directly increases stunting. At the ecological district level, this association may reflect unequal distribution of economic gains, omitted variables such as food security or health-service access, or sectoral economic activity that does not directly translate into household nutrition.

4. CONCLUSION

This study compared Gaussian, Bisquare, and Exponential adaptive kernel specifications in the GTWR framework to model district-level stunting prevalence in East Nusa Tenggara during 2021–2023. The results show that the Bisquare Adaptive kernel produced the strongest in-sample performance among the evaluated GTWR specifications, with the highest R^2 and the lowest RMSE. However, this result should be interpreted cautiously because the dataset contains only 66 space–time observations and the Bisquare model has a relatively high effective number of parameters (ENP), indicating greater local model flexibility and sensitivity to adaptive bandwidth selection. Therefore, the Bisquare Adaptive model is best understood as the strongest in-sample GTWR specification, not as definitive evidence of superior out-of-sample predictive performance. The comparison with the spatial-only GWR baseline suggests that incorporating temporal distance into the local weighting scheme improves in-sample model fit. Nevertheless, this comparison is used as a supporting benchmark rather than a full predictive validation exercise, because the GWR model does not explicitly account for temporal separation among repeated district observations. The GTWR results also indicate that GRDP per capita, poverty rate, and maternal education show spatial–temporal coefficient variability under the Bisquare Adaptive kernel, whereas sanitation and clean water access does not show significant spatial–temporal variation. These findings suggest that stunting-related socioeconomic associations in East Nusa Tenggara are not spatially or temporally uniform.

Overall, adaptive-kernel GTWR can be used as an exploratory tool for identifying local spatial–temporal patterns in stunting determinants. However, the local coefficient estimates should not be interpreted as firm causal or policy signals because several estimates show instability and the analysis is based on ecological district-level data over a short observation period. Future research should use longer and more measurement-consistent panel data, apply cross-validated or out-of-sample prediction measures, examine alternative distance metrics for archipelagic regions, and further evaluate bandwidth and ENP diagnostics to strengthen the predictive and substantive interpretation of GTWR results.

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