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ESTIMATION OF GEOGRAPHICALLY WEIGHTED PANEL NONPARAMETRIC REGRESSION MODELS WITH SPLINE ESTIMATORS

LULU KURATA AYUN*, ANNA ISLAMIYATI, GEORGINA MARIA TINUNGKI

Department of Statistics, Faculty of Mathematical and Natural Sciences, Hasanuddin University, Makassar, 90245, Indonesia

Abstract: Geographical regression modeling approaches have developed rapidly in addressing spatial variation in data analysis. Geographically Weighted Regression (GWR) and Geographically Weighted Panel Regression (GWPR) models are widely used to accommodate spatial heterogeneity, but they still have limitations in capturing nonlinear relationships between variables. Therefore, this study proposes a Geographically Weighted Panel Nonparametric Regression approach with a truncated spline estimator (GWPRS) as an extension of the GWPR model. This model integrates nonparametric regression with spatial and temporal weighting in panel data. The selection of optimal knot points is performed using Generalized Cross Validation (GCV). The case study was applied to Human Development Index (HDI) data in South Sulawesi Province for the period 2019–2023 with a Fixed Gaussian Kernel weighting function and a Fixed Effect Model approach. The results show that the optimal model is obtained at order m=1 with two knot points, and the independent variables that affect HDI differ between districts/cities, forming seven regional groups based on significant variables.

Keywords: geographically weighted panel nonparametric regression; truncated spline; spatial panel data; human development index; GCV.

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*Corresponding author

E-mail address: lulukurataayun2001@gmail.com

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1. INTRODUCTION

Geographic regression modeling has developed rapidly in addressing spatial variation in data analysis. One widely used method is Geographically Weighted Regression (GWR), which was developed to accommodate spatial heterogeneity between observation areas [7]. However, the GWR model only considers spatial aspects without incorporating temporal dynamics [9]. To overcome these limitations, the Geographically Weighted Panel Regression (GWPR) model was developed, which is capable of integrating spatial and temporal dimensions in panel data [17,18]. Nevertheless, the GWPR model still assumes a linear relationship between variables, making it less flexible in capturing nonlinear patterns.

Spline-based nonparametric approaches have been widely developed to improve the flexibility of regression models. Islamyati (2022) introduced the use of truncated splines on longitudinal data to smooth the regression curve and improve the accuracy of parameter estimation [11]. The integration of spline techniques into the geographic regression framework resulted in the GWR Spline model, which is capable of capturing nonlinear patterns between variables at various locations [13]. Several previous studies, such as Sifriyani et al. [15], showed that the Nonparametric-Geographically Weighted Spline Regression (NGWSR) model was able to map spatial variations more accurately based on the coefficient of determination and RMSE. Further development by Sifriyani et al. [14] used the Cross Validation (CV) and Generalized Cross Validation (GCV) approaches to determine the optimal knot points in geographic spline models.

The Human Development Index (HDI) is the main indicator used to measure the quality of regional development based on the dimensions of health, education, and living standards [2]. HDI data in South Sulawesi Province has panel characteristics that include spatial and temporal dimensions, thus requiring a modeling approach that can accommodate regional heterogeneity and time dynamics [1–6].

Based on the research by Zhao et al. [21], the fixed Gaussian kernel spatial weighting function is effective in capturing spatial variations in geographic modeling. Therefore, this study developed a Geographically Weighted Panel Regression Spline (GWPRS) model with a truncated spline estimator and a fixed Gaussian kernel weighting to model the nonlinear relationship in spatial panel data. This study aims to estimate the GWPRS model and identify significant variables that affect the HDI in each district/city in South Sulawesi for the period 2019–2023.

2. PRELIMINARIES

2.1 Panel Data Regression

The panel data regression model can generally be expressed by the following equation:

$$y_{it} = \beta_{0it} + \boldsymbol{\beta}\boldsymbol{x}_{it} + \varepsilon_{it}\ , \quad i = 1,2,3,\dots,N, \qquad t = 1,2,3,\dots,T \qquad (1)$$

Where y_{it} is the observation unit i in period t, β_{0it} is the intercept representing the individual/unit effect for the first unit in period t, $\boldsymbol{x}_{it}^T = (x_{1it}, x_{2it}, \dots, x_{pit})$, is the observation vector of predictor variables of size $1 \times p$, $\boldsymbol{\beta}^T$ is $(\beta_1, \beta_2 \dots, \beta_p)$, is the regression parameter vector of size $1 \times p$ (regression coefficients) and ε_{it} is the regression residual of individual i in period t

2.2 Geographically Weighted Panel Regression (GWPR)

GWPR is an extension of cross-sectional GWR for estimating spatially varying parameters in panel data [20]. The GWPR model used in this study is fixed effect GWPR, which is a combination of fixed effect panel data regression models with GWR. The model equation is as follows:

$$\ddot{y}_{it} = \sum_{j=1}^{p} \beta_j(u_i, v_i)\, \ddot{x}_{itj} + \ddot{\varepsilon}_{it} \qquad (2)$$

where

$$\ddot{y}_{it} = y_{it} - \bar{y}_i;\ \ddot{x}_{itj} = x_{itj} - \bar{x}_{ij};\ \ddot{\varepsilon}_{it} = \varepsilon_{it} - \bar{\varepsilon}_i$$

Where (u_i, v_i) is the coordinate point for location i in the form of latitude and longitude, $\beta_j(u_i, v_i)$ is the corrected average regression coefficient of independent variable j for location i, p is the number of independent variables, and $\ddot{\varepsilon}_{it}$ is the corrected average error for location i and t.

2.3 Truncated Spline

The truncated spline regression approach is used to model the nonlinear relationship between the response variable and the predictor variable. In this study, it is necessary to select the optimal knot points in the truncated spline analysis using the GCV criterion:

$$GCV = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\left(1 - \frac{df}{n}\right)^2} \tag{3}$$

where y_i is the value of the response variable at the nth point (i), $\hat{y}_i$ is the model prediction the nth point (i), n is the number of observation, and df is degree of freedom of the spline model.

2.4 Fixed Gaussian Kernel

The spatial weighting in this study uses the Fixed Gaussian Kernel function, which is expressed as:

$$w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right) \tag{4}$$

where w_{ij} is the weight value between location *i* and locatin *j*, d_{ij} is the Euclidean distance between observation points *i* and *j*, b is the *bandwidth* (smoothing parameter) [19].

2.5 Model Parameter Significance Test

In this study, to determine the independent variables that influence the dependent variable, a T-test or partial test was performed:

$$T_j(u_i, v_i) = \frac{\hat{\beta}_j(u_i, v_i)}{\hat{\sigma}\sqrt{c_{jj}}}, j = 1,2, \ldots, p \tag{5}$$

where $T_j(u_i, v_i)$ is the value T for independent variable j at location i $\hat{\beta}_j(u_i, v_i)$ is the parameter estimate for independent variable j at location i, c_{jj} is the j diagonal element in the matrix $\boldsymbol{C}_i\boldsymbol{C}_i'$ of parameter covariance**,** and $\hat{\sigma}$ is the model residual standard. The decision rule used in making decisions is based on the test statistic$\left[T_j(u_i, v_i)\right] > t_{\frac{\alpha}{2}, df = \frac{\delta_1^2}{\delta_2}}$ or $p - value < \alpha$ [13]

2.6 Research design

The analysis stages in this study included several main steps. First, descriptive statistical analysis was performed to describe the characteristics of the data. Next, multicollinearity testing was performed using the Variance Inflation Factor (VIF). The selection of the best panel data model was performed using the Chow test and the Hausman test.

The next stage is to determine the optimal knot point using the Generalized Cross Validation (GCV) criteria. A spatial heterogeneity test is performed using the Breusch–Pagan test to identify spatial variations between regions. The parameters of the Geographically Weighted Panel Regression Spline (GWPRS) model were then estimated using the truncated spline approach with Fixed Gaussian Kernel weighting. Finally, a partial parameter significance test was conducted to determine the significant independent variables at each observation location.

3. MAIN RESULTS

3.1 Descriptive Statistics

Descriptive statistics were used to provide an initial overview of the characteristics of the Human Development Index (HDI) data and predictor variables in districts/cities in South Sulawesi Province for the 2019–2023 (n = 120) panel observations. Table 1 presents a summary of descriptive statistics for all research variabels

Table 1. Descriptive Statistics of Research Variables

Variable	Minimum Value	Median	Mean	Maximum Value
HDI	64.00	70.35	71.06	83.52
LFPR	55.49	65.71	65.96	85.11
EGR	-10.87	4.615	4.077	15.45
GRDP	25696	47895	52330	155952
LE	66.24	69.10	69.69	73.99

Table 1 presents a summary of descriptive statistics for all research variables. The average HDI of 71.06 with a range of 64.00–83.52 indicates differences in development levels between regions. The EGR variable has a minimum negative value of −10.87, indicating economic contraction in a certain period, while the large variation in per capita GRDP ( ) indicates economic inequality between regions. In addition, LFPR and LE also show relatively high variation. These conditions indicate spatial heterogeneity, making the Geographically Weighted Panel Regression Spline (GWPRS) approach relevant for use in modeling.

3.2 Selection of Optimal Knot Points

The selection of optimal knot points in truncated spline nonparametric regression is done using the Generalized Cross Validation (GCV) criterion. The model with the minimum GCV value is selected as the best model. In this study, the number of knot points is limited to two points. Table 2 shows the smallest GCV values for each model.

Table 2. Minimum GCV Values for Each Optimal Knot Point

Number of Optimal Knot Points	Minimum GCV value
One knot point	4.760
Two knot point	4.358

Table 2 presents the minimum GCV values for each model. The results show that the model with two knot points produces a smaller GCV value than the model with one knot point, namely 4.358. Therefore, the nonparametric regression model with a truncated spline estimator using two knot points is selected as the optimal model.

3.3 Formation of the Spatial Weight Matrix

The spatial weight matrix in the Geographically Weighted Panel Regression Spline (GWPRS) model in this study is a diagonal matrix of size 24×24, which represents the spatial weights between districts/cities in South Sulawesi Province. The weighting function used is a fixed Gaussian kernel that requires the determination of the optimum bandwidth value. The bandwidth value is determined using the Cross Validation (CV) criteria.

After obtaining the optimum bandwidth, the spatial weight matrix is formed for each observation location. In GWPRS modeling, the spatial weight matrix used is the same for each time period so that the matrix is repeated for each year of observation. As an illustration, the spatial weight matrix at location 1, namely Selayar Islands Regency, can be written as follows:

$$\boldsymbol{W}(u_{\mathbf{1}}, v_{\mathbf{1}}) = diag[w_{1\,1}(u_{\mathbf{1}}, v_{\mathbf{1}}), w_{2\,1}(u_{\mathbf{1}}, v_{\mathbf{1}}), w_{3\,1}(u_{\mathbf{1}}, v_{\mathbf{1}}), \dots, w_{24\,3}(u_{\mathbf{1}}, v_{\mathbf{1}})$$
$$= diag[1, \quad 6.578 \times 10^{-6}, 0.050 \quad , \dots, 3.140 \times 10^{-3} \ ]$$

The fixed Gaussian weight matrix shows that the weight value between Selayar Islands Regency and itself is one. Meanwhile, the weight between Selayar Islands Regency and Bulukumba Regency is very small, namely 6.578×10^{-6}, which indicates a relatively long spatial distance. The same procedure is applied to calculate the weight between Selayar Islands Regency and other regencies/cities.

3.4 Estimation of Geographically Weighted Panel Regression with Truncated Spline (GWPRS) Model Parameters

The GWPRS parameter estimators produced will vary at each location, so that each district/city has different regression coefficients. The following is an example of a GWPRS model $i = 1$, namely the Selayar Islands, as follows.

$$\hat{Y}_{1t} = -2.12x10^{-13} - 0.832X_{1,1t} + 0.874(X_{1,1t} - 57.533)_+ - 0.014(X_{1,1t} - 73.875)_+ -$$
$$0.022X_{2,1t} - 0.006\left(X_{2,1t} - (-9.055\,)\right)_+ - 0.028(X_{2,1t} - 5.467)_+ +$$
$$1.41x10^{-4}X_{3,1t} - \ 4.32x10^{-5}(X_{3,1t} - 34679.17)_+ - \ 8.90x10^{-5}(X_{3,1t} -$$
$$106544.6)_+ + 0.219X_{4,1t} + 0.693(X_{3,1t} - 66.77)_+ + 0.677(X_{3,1t} - 71.050)_+$$

With $t = 2019, 2020, 2021\ 2022, 2023$

The following is an interpretation of the GWPRS model in the Selayar Islands

1. The effect of the LFPR variable (X_1) on the HDI in districts/cities in South Sulawesi Province, assuming other variebles are constant, is as follows:

$$\hat{Y}_{1t} = -2.12x10^{-13} - 0.832X_{1,1t} + 0.874(X_{1,1t} - 57.533)_+ - 0.014(X_{1,1t} - 73.875)_+$$

The LFPR variable shows a nonlinear relationship with the HDI. At low LFPR values, an increase in LFPR is followed by a decrease in the HDI. After passing the first knot point, the relationship becomes positive so that an increase in LFPR is followed by an increase in the HDI. At higher LFPR values, the HDI continues to increase but at a slower rate.

2. The effect of the EGR variable (X_2) on the HDI in districts/cities in South Sulawesi Province, assuming other variables remain constant, is as follows:

$$\hat{\hat{Y}}_{1t} = -2.12x10^{-13} - 0.022X_{2,1t} - 0.006\left(X_{2,1t} - (-9.055\,)\right)_+ - 0.028\left(X_{2,1t} - 5.467\right)_+$$

EGR shows a negative relationship with HDI in several spline segments. An increase in EGR is not always followed by an increase in HDI in fact, at certain values, the relationship becomes increasingly negative.

3. The effect of the GRDP (X_3) on the HDI in districts/cities in South Sulawesi Province, assuming other variables remain constant, is as follows:

$$\hat{\hat{Y}}_{1t} = -2.12x10^{-13} + 1.41x10^{-4}X_{3,1t} - 4.32x10^{-5}\left(X_{3,1t} - 34679.17\right)_+ - 8.90 \times 10^{-5}\left(X_{3,1t} - 106544.6\right)_+$$

The GRDP per capita variable has a positive relationship with the HDI in all spline segments. However, the slope of the relationship decreases as the GRDP value increases. This indicates the phenomenon of diminishing returns, whereby an increase in economic welfare continues to increase the HDI but with an increasingly smaller additional effect.

4. The effect of the LE varieble (X_4) on the HDI in districts/cities in South Sulwesi Province, assuming other variables remain constant, is as follows:

$$\hat{\hat{Y}}_{1t} = -2.12x10^{-13} + 0.219X_{4,1t} + 0.693\left(X_{4,1t} - 66.77\right)_+ + 0.677\left(X_{4,1t} - 71.050\right)_+$$

Life expectancy (LE) shows a strong positive relationship with HDI. An increase in LE is followed by an increase in HDI across all spline segments, even with an increasing slope after passing a certain knot point. These results indicate that health factors contribute significantly to improving the quality of human development.

3.5 Parameter Significance Test

The results of the GWPR model parameter estimation with a truncated spline estimator were tested partially to determine the significance of each independent variable parameter on the Human Development Index (HDI) in each district/city. The testing was conducted using a t-test with the following hypothesis:

$H_0: \beta_j(u_i, v_i) = 0$

$H_1: \ \beta_j(u_i, v_i) \neq 0$

where j denotes the spline parameter index and i denotes the observation location. The test decision is based on the value $[T_j(u_i, v_i)] > t_{\frac{\alpha}{2}, df = \frac{\delta_1^2}{\delta_2}}$ or $p - value < \alpha$ then H_0 is rejected, At a significance level of $\alpha = 0.05$ and $t_{\frac{\alpha}{2}}$ = 2.179. The results of the GWPR model parameter significance test with the spline estimator for Selayar Regency $(i = 1)$ presented in Table 3

Table 3. Results of the Significance Test of the GWPR Model Parameters with Spline Estimator for Selayar Islands Regency

Parameter	Estimator	Test Statistics	Decision
$\beta_0(u_1, v_1)$	-2.12E-13	-2.116	Accept H_0
$\beta_1(u_1, v_1)$	-0.832	-1.768	Accept H_0
$\beta_2(u_1, v_1)$	0.874	1.847	Accept H_0
$\beta_3(u_1, v_1)$	-0.014	-0.500	Accept H_0
$\beta_4(u_1, v_1)$	-0.022	-0.180	Accept H_0
$\beta_5(u_1, v_1)$	-0.006	-0.047	Accept H_0
$\beta_6(u_1, v_1)$	-0.028	-1.140	Accept H_0
$\beta_7(u_1, v_1)$	1.41E-04	5.106	Reject H_0
$\beta_8(u_1, v_1)$	-4.32E-05	-1.773	Accept H_0
$\beta_9(u_1, v_1)$	-8.90E-05	-7.099	Reject H_0
$\beta_{10}(u_1, v_1)$	0.219	0.334	Accept H_0
$\beta_{11}(u_1, v_1)$	0.693	1.118	Accept H_0
$\beta_{12}(u_1, v_1)$	0.677	2.902	Reject H_0

Table 3 shows that in the Selayar Islands district, there are two significant variable parameters that influence the human development index, namely gross regional domestic product (GRDP) and life expectancy (LE). This was obtained through the decision rule, namely $|T_{hitung}| > 2{,}179$, which shows that H_0 is rejected, or in other words, the independent variable parameters have a significant influence on the dependent variable. Similar testing and interpretation were conducted in all districts/cities in South Sulawesi Province. The statistical test values T for all district/city observations can be seen in Appendix 8.

The GWPRS model produces local parameter estimators, so that significant variables may differ between districts/cities. Based on the results of the parameter significance test, districts/cities were grouped based on the combination of independent variables that significantly affect the HDI. The grouping results are presented in Figure 1.

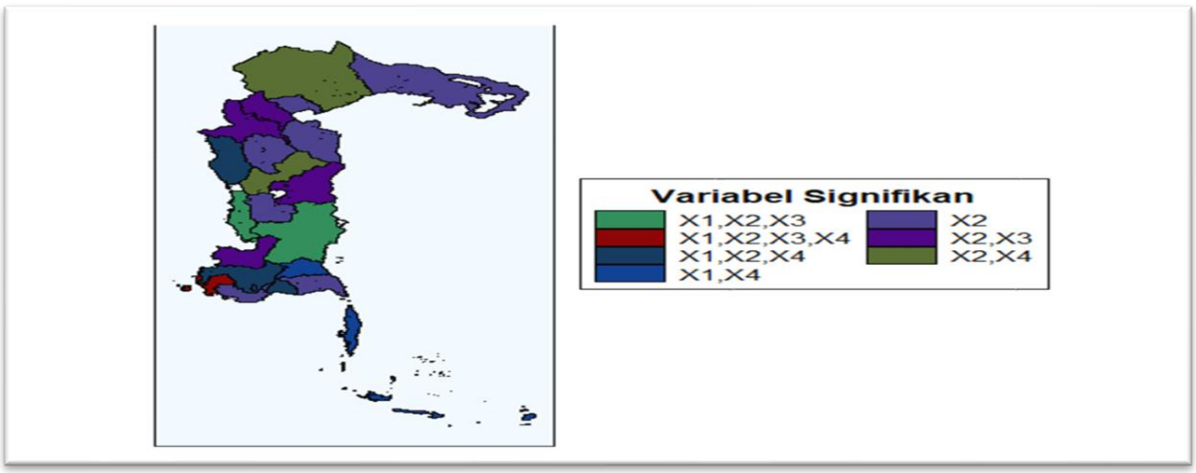

Figure 1. Map of Significant Independent Variable Grouping

Figure 1 shows that districts/cities in South Sulawesi Province can be classified into seven groups based on significant independent variables. The first group consists of Selayar Islands and Sinjai, where the Labor Force Participation Rate (LFPR) and Life Expectancy (LE) variables have a significant effect on the Human Development Index (HDI). The second group consists of Pinrang, Bantaeng, and Gowa, with LFPR, Economic Growth Rate (EGR), and LE variables being significant. The third group includes Barru and Bone, where LFPR, EGR, and LE are also significant variables. The fourth group consists of Takalar, in which all independent variables in the model have a significant effect on HDI. The fifth group includes Bulukumba, Enrekang, Luwu, Jeneponto, Soppeng, East Luwu, Parepare, and Palopo, with EGR as the only significant variable. The sixth group consists of Sidenreng Rappang and North Luwu, where EGR and LE variables are significant. The seventh group includes Pangkajene and Islands, Wajo, Tana Toraja, Makassar, Maros, and North Toraja, with EGR and Gross Regional Domestic Product (GRDP) being significant determinants of HDI.

These grouping results indicate spatial variation in the factors influencing HDI in South Sulawesi Province during the 2019–2023 period. This supports the use of the Geographically Weighted Poisson Regression (GWPR) model with spline estimators as an appropriate approach to capture local characteristics in each district/city.

4. CONCLUSIONS

The Geographically Weighted Panel Regression (GWPR) model with spline estimators has proven to be capable of accommodating spatial variations and non-linear relationships between the Human Development Index (HDI) and explanatory variables in each district/city in South Sulawesi Province. Parameter estimation was performed locally at each location by considering distance-based spatial weights and spline functions that allow changes in the form of the relationship at certain knot points. The results of the analysis show that the Labor Force Participation Rate (LFPR), Economic Growth Rate (EGR), Gross Regional Domestic Product (GRDP) per capita, and Life Expectancy (LE) have a significant effect on the HDI, with different patterns of influence between regions. The significance of the spline parameters indicates that the relationship between these variables and the HDI is non-linear and varies spatially. Based on the similarity of the parameter significance patterns, the study area was divided into seven groups that reflect the dominance of certain variables. Thus, the local approach through GWPR with spline estimators is effective in describing the heterogeneous dynamics of the HDI at the district/city level.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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