JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 10, No. 2, April 2026, pp. 469-483

Understanding Spatial Variability of Human Development Index in Aceh: A Geographically Weighted Regression Approach

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Article History:
Received : 18-10-2025
Revised : 31-12-2025
Accepted : 03-01-2026
Online : 01-04-2026

Keywords:
Aceh Province;
Adaptive Gaussian Kernel;
Geographically Weighted Regression (GWR);
Human Development Index (HDI);
Spatial Heterogeneity.

ABSTRACT

The Human Development Index (HDI) is an important indicator in measuring people's quality of life, which includes education, health and economic dimensions. In Aceh Province, HDI achievements show inequality between regions, especially between coastal and inland areas. This study employs a quantitative spatial analysis to examine socio-economic determinants of HDI across districts using the Geographically Weighted Regression (GWR). The analysis utilized 2023 secondary data from the Central Bureau of Statistics (BPS), integrating HDI with key indicators of labor conditions, poverty, education, health, and regional economic performance. The global linear regression model was compared with GWR models using adaptive Gaussian and bisquare kernel weighting function, with model selection based on the Akaike Information Criterion (AIC). The results show that the GWR model with an Adaptive Gaussian Kernel weighting function outperformed the global regression model, indicating strong spatial non-stationarity in the relationships between HDI and its determinants. The average years of schooling, labor force participation rate, open unemployment rate, percentage of poverty, life expectancy, expenditure per capita, gross regional domestic product, and expected years of schooling have a significant effect on HDI in Aceh, but their contribution varies across districts. This study contributes to the literature by providing spatially explicit evidence to support region-based development policies, emphasizing the need for differentiated interventions to reduce interregional inequality and promote more equitable human development across Aceh Province.

https://doi.org/10.31764/jtam.v10i2.35734

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A. INTRODUCTION

Human resource development constitutes a significant component of the government's broader agenda for fostering a prosperous society that is aligned with the fundamental objectives of the Indonesian nation. In this context, the Human Development Index (HDI) serves as a widely accepted composite indicator for assessing quality of life through education, health, and economic dimension (Lind, 2019; Lubin, 1992; Schultz, 1961). HDI was introduced in Indonesia in 1990 by the United Nations Development Program (UNDP) and extensively used as a benchmark for evaluating development performance across provinces and districts, as well as for guiding public policy priorities (UNDP, 2007). However, improvements in HDI at the

provincial level often mask substantial disparities at the subregional scale, particularly in geographically diverse regions.

Aceh Province represents a clear example of such disparities, where HDI achievements differ markedly between coastal, inland, and island districts. Despite overall progress in HDI, several districts remain persistently below the provincial average, reflecting unequal access to education, health services, and economic opportunities (Badan Pusat Statistik, 2024). These spatial inequalities are closely linked to Aceh's complex geography, historical development patterns, and uneven infrastructure distribution. As a result, understanding the determinants of HDI in Aceh requires not only an examination of socio-economic factors but also an explicit consideration of spatial context (Badan Pusat Statistik Provinsi Aceh, 2024).

Conceptually, HDI measures three core dimensions of human development, including a long and healthy life, knowledge, and a decent standard of living. These dimensions are operationalized through life expectancy, average and expected years of schooling, and per capita expenditure, which collectively reflect human capital formation and welfare outcomes (Badan Pusat Statistik, 2024; Lubin, 1992; Mendes & Pennings, 2025). From an empirical perspective, HDI is influenced by broader socio-economic conditions such as poverty, unemployment, labor participation, and regional economic capacity, which affect household's ability to access education and health services (Faisal et al., 2025; Farida et al., 2022; Franciscus et al., 2022; Rahayu, 2025). Therefore, HDI is not merely an outcome indicator but also a function of structural economic and social processes.

In addition to socio-economic and infrastructural determinants, spatial dependence and spatial heterogeneity has been increasingly recognized as a factor influencing regional development (Fotheringham et al., 2002; Griffith & Anselin, 1989; LeSage & Pace, 2009). Studies utilizing spatial autoregressive moving average (SARMA) model highlight that persistent west-east disparities in human capital and confirm that both human capital ans spatial effects have a significant positive influence on regional economic (Windhani et al., 2023). Futhermore, uneven access to infrastructure has been shown to exacerbate regional disparities, as regions with inadequate educational and health facilities tend to exhibit lower human development outcomes compared to metropolitan areas (Syam, 2025).

Although the literature on HDI in Indonesia is extensive, previous works have predominantly employed logistic regression, panel regressions, or time-series methods, which assume parameter homogeneity (Farida et al., 2022; Leiwakabessy & Amaluddin, 2020; Sofilda et al., 2023; Wijaya et al., 2021). However, studies applying spatial statistical models remain limited, and, to date, no research has specifically examined HDI disparities in Aceh Province through such an approach (Faisal et al., 2025; S Astari, 2024; Saputro et al., 2021; Souisa et al., 2023). This gap is critical, given Aceh's pronounced interregional inequalities and heterogeneous socio-economic characteristics, which are likely to produce geographically differentiated development processes.

Given the marked interregional disparities in Aceh, the application of spatial models is particularly relevant. This study addresses the identified research gap by employing Geographically Weighted Regression (GWR), which allows regression coefficients to vary spatially across districts (Comber et al., 2023; Fotheringham et al., 2002). By capturing local variations in relationships between HDI and its socio-economic determinants, this study offers

a methodological and empirical contribution to the human development literature in Indonesia. Previous studies have shown that Geographically Weighted Regression (GWR) consistently provides better goodness of fit than global OLS models because it is able to account for spatial non-stationaroty and localized relationships among socio-economic variable (Franciscus et al., 2022; Hasibuan et al., 2023; Souisa et al., 2023)

Based on these considerations, this study aims to analyze the spatially varying determinants of the HDI in Aceh province using the Geographically Weighted Regression (GWR) approach. Specifically, this research seeks to compare global and local regression to assess the presence and extent of spatial non-stationarity in HDI determinants. By examining variations in the magnitude and significance of education, health, labor, poverty, and economic variables across regions, the analysis provides a more nuanced understanding of interregional development disparities in Aceh. The findings are expected to contribute scientifically by enriching the spatial development literature, particularly in the context of HDI analysis, while also offering practical evidence to support region-based and differentiated policy interventions aimed at reducing inequality and promoting more equitable human development outcomes.

B. METHODS

1. Data

This study employs a quantitative explanatory research design to analyze the determinants of HDI in Aceh Province. The unit of analysis is the district/city level, covering 23 districts and cities in Aceh Province, which represent the total observations in the study. The analysis uses cross-sectional secondary data for the year 2023, sourced from Aceh Province in Figures 2024 and Aceh Province People's Welfare Statistics 2023 published by Central Statistics Agency (BPS) of Aceh. The research examines district-level HDI and socio-economic characteristics, including education, health, labor market conditions, poverty, and regional economic indicators. Spatial coordinates (latitude and longitude) of districts and cities are incorporated to capture local variations in the Geographically Weighted Regression (GWR) model. The selection of variables is supported by both theory, such as human capital theory (Schultz, 1961), the basis of HDI measurement (UNDP, 2007), and some empirical studies (Faisal et al., 2025; Farida et al., 2022; Franciscus et al., 2022; Sasmita et al., 2023; Souisa et al., 2023). The variables used in this study can be seen in Table 1.

Table 1. Research Variables

Variable	Factors	Unit
Y	Human Development Index (HDI)	-
X_1	Labor Force Participation Rate	%
X_2	Open Unemployment Rate	%
X_3	Percentage of Poverty	%
X_4	Average Years of Schooling	Year
X_5	Life Expectancy	Year
X_6	Expenditure per Capita	Rupiah
X_7	Gross Regional Domestic Product (GRDP)	Rupiah
X_8	Expected Years of Schooling	Year
U	Latitude coordinate of districts	Coordinates
V	Longitude coordinate of districts	Coordinates

2. Geographically Weighted Regression (GWR)

The GWR method is used to analyze factors that significantly affect HDI in Aceh. Prior to implementing GWR, a global Ordinary Least Squares (OLS) regression model was estimated as a baseline model. Diagnostic tests were conducted to evaluate model assumptions and justify the use of GWR, including checks for multicollinearity using the Variance Inflation Factor (VIF), normality of residuals, autocorrelation, and heterogeneity using Breusch-Pagan test. GWR is based on the same principle as multiple linear regression, but it considers spatial effects within the research area. According to Fotheringham et al. (2022), GWR is a statistical method for analyzing spatial heterogeneity, which is a condition in which the same independent variable produces different responses in different locations within a study area. In GWR, each regression parameter is estimated at each geographic location point, therefore the relationship between the dependent variable (Y) and the independent variable (X) varies across locations, where the distance between observation location points is used as a weight for the observed location. The general form of the GWR model is as below (Fotheringham et al., 2002):

$$Y_i = \beta_0(u_i, v_i) + \sum_k^p \beta_k (u_i, v_i) X_{ik} + \varepsilon_i \,, \tag{1}$$

Y_i denotes dependent variable at location ith, (u_i, v_i) is longitude and latitude coordinate at location ith, $\beta_0(u_i, v_i)$ is coefficient of GWR, $\beta_k(u_i, v_i)$ is the kth GWR's coefficient for kth independent variable at location ith, X_{ik} is the kth independent variable at location ith, and ε_i is residual with assumption $\varepsilon \sim IIDN\ (0,\sigma^2)$, where $i = 1, 2, \ldots, n$ and $k = 1, 2, \ldots, p$.

The parameter estimation of the GWR model is estimated by the Weighted Least Square (WLS) method, where each location is given a different weight according to the observation point where the data is taken. The weight notation used at each location is $w_j(u_i, v_i)$ with $j = 1, 2, \ldots, n$ location. The weight matrix can be determined using a kernel function that provides weights based on the optimum bandwidth. There are two types of kernel functions, namely fixed kernel and adaptive kernel. The difference between these two types of kernel functions lies in the fact that in the fixed kernel, the bandwidth value applied is uniform for all observation areas, while in the adaptive kernel, the bandwidth value used is different for each observation area. There are two types of adaptive kernel functions that can be used as weights including Adaptive Gaussian Kernel function and Adaptive Bisquare Kernel function (Fotheringham et al., 2002; Nakaya et al., 2005).

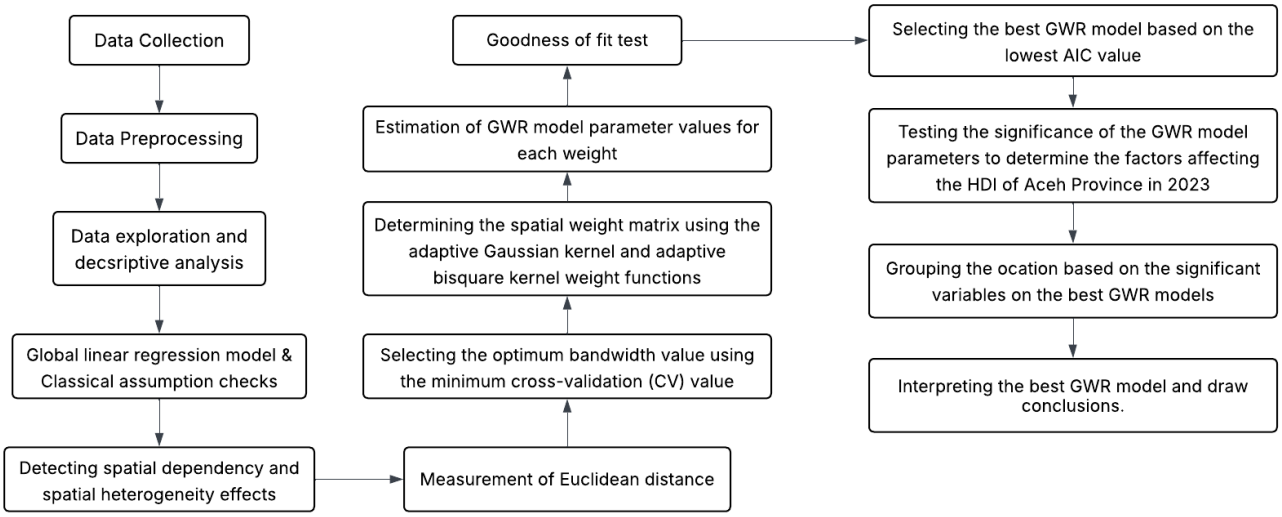


Figure 1. Data analysis stages

According to Figure 1, the initial step in GWR method is to calculate the Euclidean distance and determine the optimum bandwidth to be used in the GWR model. The optimum bandwidth for each kernel is determined using a cross-validation (CV) procedure, which minimize prediction error and ensures that local paramater estimates appropriately reflect spatial proximity. Model performance is assessed by comparing the Akaike Information Criterion (AIC) values of the global OLS model and the two GWR models. The model with the lowest AIC value is selected as the best-fitting model. After identifying the optimal GWR model, local parameter estimates are examined to identify spatial variations in the magnitude and significance of explanatory variables across districts. Data analysis was conducted using R software, employing the spgwr package to estimate GWR models and evaluate model diagnostics.

C. RESULTS AND DISCUSSION

1. Results

The descriptive statistics of the study variable are presented in Table 2. According to BPS classification, HDI is categorized as low (<60), medium (60–70), high (70–80), and very high (>80). The mean HDI value of 74.41 places Aceh in the "high" development category. A standard deviation of 4.36 suggests a moderate level of variation among districts and cities.

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation	Maximum	Minimum
Human Development Index (HDI)	74,41	4,3677	88,32	69,66
Labor force participation rate	66,01	6,8294	83,25	57,81
Open unemployment rate	5,64	1,8722	8,78	2,45
Percentage of Poverty	14,81	3,2879	19,15	7,04
Average Years of Schooling	9,67	1,1630	13,04	8,32
Life expectancy	72,11	1,7155	75,02	69,57
Expenditure per Capita	10314	2079,22	17521	7686
Gross regional domestic product	9715	7026,39	28472	1747
Expected Years of Schooling	14,66	0,9211	17,93	13,07

The mean value of 66.01% indicates that around two-thirds of the working-age population (≥15 years old) in Aceh participates in the labor market. The standard deviation of 6.83 indicates differences in labor participation between regions. The average rate of the workforce in Aceh who are not working but actively seeking employment is 5.64%, with a regional disparity of 1.87. The mean of 14.81% in poverty indicates that approximately 1 in 7 residents of Aceh live below the poverty line, with a variation between districts of 3.29%. In terms of education, residents aged 25 years and above in Aceh have spent 9.67 years pursuing formal education, which corresponds to the third grade of junior high school. The relatively minor disparity between districts, with a standard deviation of 1.16, suggests that the average resident of Aceh has not yet attained the 12-year compulsory education requirement. Meanwhile, the expected years of schooling (X_8) averages 14.66 years with standard deviation 0.92 indicates that children in Aceh have the capacity to pursue education up to the high school level.

Life expectancy (X_5) shows an average of 72.11 years with minimal variation (1.71), indicating that the health condition of the Acehnese people is satisfactory, with the average infant born during that period expected to survive until the age of 72. On the economic side, the average monthly household expenditure per person is 10,314 thousand rupiah (≈ 10.3 million rupiah per year), indicating a medium level of household consumption. The standard deviation of 2.079 indicates inequality in consumption between regions. Meanwhile, Gross Regional Domestic Product (GRDP) (X_7) has an average of 9,715 billion rupiah with a very large variation (standard deviation of 7,026.39 billion), reflecting significant differences in productivity levels between regions.

The descriptive analysis highlights notable interregional disparities across all variables, as shown by their varying standard deviations. Spatial mapping reveals that the highest labor force participation occurs in interior agricultural areas (Aceh Tengah, Gayo Lues, Bener Meriah), while open unemployment is concentrated in urban districts (Banda Aceh, Lhokseumawe, Aceh Timur). GRDP and per capita expenditure are highest in urban economies but lowest in peripheral regions (Simeulue, Aceh Singkil, Gayo Lues). Poverty remains elevated in interior and southwestern areas, reflecting a dual economic structure between prosperous urban centers and lagging rural regions. Life expectancy and education indicators are higher in urban and coastal districts but lower in rural and mountainous areas, highlighting persistent inequalities in health and educational access across Aceh. Furthermore, the distribution of HDI in Aceh Province in 2023, urban centers such as Banda Aceh, Lhokseumawe, and Langsa stand out in the very high category, indicating comparatively advanced achievements in education, health, and economic welfare. In contrast, Subulussalam and Simeulue remain in the medium category, highlighting areas that require further development efforts. Notably, no district in Aceh is classified as having a low HDI in 2023, as shown in Figure 2.



(a) Labor Force Participation Rate (b) Open Unemployment Rate (c) Percentage of poverty

(d) Average years of Schooling (e) Expected Years of Schooling (f) Life Expectancy

(g) Expenditure per Capita (h) Gross Regional Domestic Product (i) Human Development Index (HDI)

Figure 2. Spatial distribution of research variables for Aceh Province in 2023

These spatial patterns reveal that Aceh's disparities are shaped by a combination of health, education, economic, and labor market factors that vary across geography. Urban and coastal centers benefit from better infrastructure and services, while rural and remote regions face structural constraints. These findings justify the use of spatial modeling approaches such as Geographically Weighted Regression (GWR) to capture localized variations in the determinants of HDI. Spatial effect testing is conducted to determine whether there is spatial dependence and spatial heterogeneity in HDI. Spatial dependency indicates the presence of spatial autocorrelation that causes dependence between districts in Aceh Province, while spatial heterogeneity shows the diversity of districts. Spatial autocorrelation is tested using Moran test statistic, while spatial heterogeneity is calculated using the Breusch-Pagan test statistic. The result show that there is spatial dependency and spatial heterogeneity across districts.

Therefore, the GWR modeling can be proceed to analyze determination of HDI in Aceh. The adaptive Kernel function used to determine the optimum bandwidth. Adaptive Kernel function caused every district has their own optimum bandwidth. The optimum bandwidth based on the minimum CV value for the Adaptive Gaussian Kernel and Adaptive Bisquare Kernel weights can be seen in Table 3.

Table 3. Bandwidth value based on Kernel function

Districts	Adaptive Gaussian Kernel	Adaptive Bisquare Kernel	Districts	Adaptive Gaussian Kernel	Adaptive Bisquare Kernel
Aceh Barat	0.628	1.659	Bireuen	0.405	1.520
Aceh Barat Daya	0.594	2.158	Gayo Lues	0.711	1.671
Aceh Besar	0.503	2.501	Banda Aceh City	0.513	2.687
Aceh Jaya	0.592	2.029	Langsa City	0.844	1.974
Aceh Selatan	0.475	1.903	Lhokseumawe City	0.330	1.750
Aceh Singkil	0.914	2.948	Sabang City	0.667	2.881
Aceh Tamiang	0.823	1.935	Subulussalam City	0.760	2.722
Aceh Tengah	0.551	1.317	Nagan Raya	0.627	1.477
Aceh Tenggara	0.569	1.990	Pidie	0.329	1.916
Aceh Timur	0.367	1.973	Pidie Jaya	0.437	1.752
Aceh Utara	0.337	1.696	Simeulue	1.520	2.603
Bener Meriah	0.393	1.548			

The application of both global (OLS) and local (GWR) regression models provides valuable insights into the determinants of the HDI in Aceh Province. While the OLS model offers an overall picture of the relationships between socio-economic factors and HDI, the GWR approach captures spatial variations across districts, highlighting localized effects that the global model cannot detect. Building on this foundation, the following discussion interprets the role of each independent variable in shaping HDI outcomes across Aceh, as shown in Table 4.

Table 4. Parameter estimation of the GWR model

Variables	Global Model (OLS)		GWR with Adaptive Kernel Gaussian	GWR with Adaptive Kernel Bisquare
Intercept	-1.4109	Min.	-2.459	-4.116
		Q1	3.298	4.337
		Median	4.703	5.577
		Q3	6.144	6.124
		Max	13.988	8.782
Labor force participation rate (X1)	-0.0098	Min.	-0.010	-0.022
		Q1	-0.002	-0.003
		Median	0.003	0.001
		Q3	0.017	0.017
		Max	0.027	0.019
Open unemployment rate (X2)	-0.0173	Min.	-0.031	-0.103
		Q1	-0.019	-0.021
		Median	-0.007	-0.012
		Q3	0.044	0.044
		Max	0.069	0.049
	0.0344	Min.	-0.014	-0.018

Variables	**Global Model (OLS)**		**GWR with Adaptive Kernel Gaussian**	**GWR with Adaptive Kernel Bisquare**
Percentage of Poverty (X3)		Q1	0.003	-0.001
		Median	0.014	0.003
		Q3	0.031	0.023
		Max	0.044	0.034
Average Years of Schooling (X4)		Min.	0.956	1.002
		Q1	1.052	1.032
	1.0191*	Median	1.119	1.138
		Q3	1.179	1.236
		Max	1.259	1.276
Life expectancy (X5)		Min.	0.358	0.431
		Q1	0.445	0.444
	0.6217*	Median	0.464	0.457
		Q3	0.502	0.494
		Max	0.603	0.583
Expenditure per Capita (X6)		Min.	7.201×10^{-4}	7.106×10^{-4}
		Q1	7.501×10^{-4}	7.291×10^{-4}
	0.001*	Median	1.021×10^{-3}	1.015×10^{-3}
		Q3	1.070×10^{-3}	1.097×10^{-3}
		Max	1.127×10^{-3}	1.116×10^{-3}
Gross regional domestic product (X7)		Min.	-3.430×10^{-5}	-3.297×10^{-5}
		Q1	-2.781×10^{-5}	-3.126×10^{-5}
	0,00001399	Median	-4.756 x 10-6	-1.670×10^{-6}
		Q3	1.081 x 10-6	2.004 x 10-6
		Max	2.537×10^{-5}	1.034×10^{-5}
Expected Years of Schooling (X8)		Min.	0.751	0.805
		Q1	0.914	0.937
	0.7776*	Median	0.995	0.989
		Q3	1.059	1.086
		Max	1.158	1.104
AIC	15.480		-78.209	-71.921
SSR			0.018	0.026
R^2	0.999		-	-

*Significant at α = 0,1

According to Table 4, factors that significantly effect the HDI in Aceh Province globally are the average years of schooling (X_4), life expectancy (X_5), per capita expenditure (X_6), and the expected years of schooling (X_8). Thus, the global regression model obtained for this study is as follows:

$$\hat{y} = -1{,}411 + 1{,}019x_4 + 0{,}6217x_5 + 0{,}00098x_6 + 0{,}7776x_8.$$

Variable X_4 and X_5 have sizable positive coefficients (1.019 and 0.6217), indicating that, holding other factors constant, higher average years of schooling and longer life expectancy tend to have significantly higher HDI. Expenditure per capita (X_6) has a small coefficient (0.00098), indicating that its marginal effect on the HDI is relatively weak compared to other predictors. In contrast, the expected years of schooling (X_8) has a large positive coefficient (0.7776), indicating that higher educational expectations for children tend to achieve substantially higher

HDI values. This reflects the critical role of long-term investment in education in improving overall human development.

The GWR model formed must be ensured to be able to provide a better explanation than the global regression model or not by testing the goodness of fit of the model. Model selection was carried out by comparing the AIC values of the global regression with those of the two GWR specifications. From this comparison, the GWR model employing the Adaptive Gaussian Kernel was identified as the best fit, as it produced the lowest AIC value of −78.209. The goodness of fit test in Table 5 shows that the model fit test for each weighting function used can be seen in Table 5.

Table 5. Goodness of fit test

Weighted Function	$F_{statistics}$	df_1	df_2	P-value
Adaptive Gaussian Kernel	60,389	14	1,1072	0,0819*
Adaptive Bisquare Kernel	43,348	14	2,1413	0,0183*

*Significant at α = 0,1

As illustrated in Table 5, the F-statistic values of 60.389 for the Adaptive Gaussian Kernel and 43.348 for the Adaptive Bisquare Kernel indicate that, in both cases, the GWR models provide a statistically significant improvement over the global OLS model. Thus, confirming the existence of spatial variability in the relationships between the independent variables and the HDI. A comparison of the two models indicates that the Adaptive Gaussian Kernel demonstrates a marginally elevated F-statistic, thereby signifying its superior capacity to explain the variability in HDI across geographical locations, as shown in Figure 3.

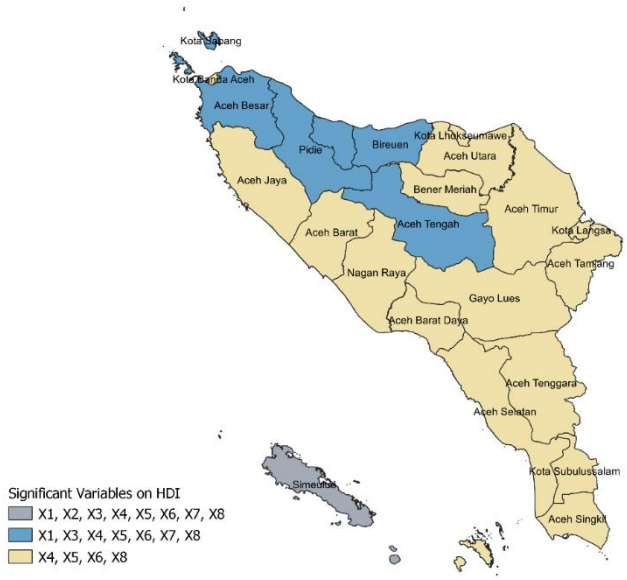


Figure 3. Group of significant variables on HDI in the best GWR model

The distribution of significant variables across Aceh Province, as illustrated in Figure 3, reveals three distinct regional patterns. Districts shaded in gray (Simeulue) are influenced by all eight variables, including labor force participation, unemployment, poverty, education, health, expenditure, and GRDP. This indicates that Simeulue's HDI is highly sensitive to changes

in every socio-economic factor, reflecting the vulnerability of island regions where development challenges are multidimensional.

2. Discussion

The local model (GWR) results reveal the determinants of HDI in Aceh operate through three interrelated dimensions, namely human capital, labor-poverty dynamics, and economic welfare, whose relative importance varies spatially across districts. This synthesis clariefies that HDI disparities in Aceh cannot be understood through isolated variables, but rather through the interaction of these dimensions within distinct regional contexts. The human capital dimension, represented by education and health variables, emerges as the most consistent driver of HDI across Aceh. Both average years of schooling (X_4) and expected years of schooling (X_8) show strong and stable positive effects across all districts, confirming the central role of human capital in improving welfare. Similarly, life expectancy (X_5) exerts a consistently positive influence, although the magnitude varies slightly by district. These findings are in line with human capital theory, which emphasizes education and health as key drivers of productivity and development (Schultz, 1961), and also in line with previous studies where life expectancy have a positive influence on HDI (Permai et al., 2016). These results are also consistent with previous studies demonstrating that average years of education, expected years of education, and life expectancy have a positive correlation and impact on the HDI in several countries (Faisal et al., 2025; Firmansyah et al., 2023).

The labor-poverty dimension, capture by the labor force participation rate (X_1), open unemployment (X_2), and poverty rate (X_3), exibits more heterogeneous and spatially contingency effects. Labor forces participation and unemployment show mixed signs across districts. In some regions, high labor participation reflects productive employment, while in others it may indicate informal or low-quality work. These seemingly contradictory effects do not indicate model instability, but rather reflect spatial non-stationarity, where the same socio-economic variables operated differently depending on local structural conditions. These findings are in line with previous studies that document varied impacts of labor rate and unemployment on HDI across Indonesian regions (Farida et al., 2022; Franciscus et al., 2022). Similarly, the poverty variable presents the most complex results. While theory suggests a negative relationship, the global OLS model shows a counterintuitive positive coefficient, and the GWR results vary across space. This inconsistency may arise from overlap with other variables such as expenditure, or from structural differences in how poverty interacts with education and health at the district level. For example, study conducted in 2023 - 2024 show a negative effects of poverty rate on HDI (Hasibuan et al., 2023; Rahayu et al., 2020).

The economic welfare dimension, represented by expenditure per capita (X_6) and Gross Regional Domestic Product (X_7), plays a supportive but envious role. Expenditure per capita consistently shows a small positive effect, indicating that household consumption contibutes to welfare improvement, although its influence is weaker than that of education or health. In contrast, GRDP displays weak and spatially inconsistent effects, suggesting that economic growth in Aceh does not automatically translate into improved human development due to structural disparities. These findings highlight the need for district-specific policies aligned with local socio-economic and geographic contexts. Similar pattern have been reported in

earlier studies, which highlight the limited trickle-down effect of regional growth on human development (Prajanati et al., 2022).

The spatially explicit results provide important insights for regional policy formulation. The northern and central regions (Banda Aceh, Aceh Besar, Pidie, Bireuen, Lhokseumawe, Aceh Utara, Bener Meriah, and Aceh Tengah) show a wide range of significant variables, excluding unemployment. Here, HDI is driven by labor, poverty, education, health, expenditure, and GRDP, suggesting that development in these districts is shaped by a complex interaction of human capital and economic structures. These areas represent Aceh's growth centers, where policies must address both social and economic dimensions simultaneously. In contrast, the southern and eastern parts of Aceh (such as Aceh Selatan, Aceh Tenggara, Subulussalam, Aceh Singkil, and Gayo Lues) are characterized by a narrower set of significant factors primarily education, life expectancy, and expenditure per capita. This indicates that in more peripheral or interior regions, human development is most strongly driven by basic human capital and household welfare rather than by labor market dynamics or regional economic output. Policy priorities should focus on expanding access to educational and healthcare services and strengthening targeted social assistance programs, rather than relying solely on

D. CONCLUSION AND SUGGESTIONS

This study applied Geographically Weighted Regression (GWR) to model the Human Development Index (HDI) in Aceh Province, comparing its performance against the global OLS model. In line with the research objective of identifying spatially varying determinants of HDI, the results show that the GWR model provides a substantially better fit, as indicated by lower AIC values, and more importantly, reveals significant spatial heterogeneity in the relationship between HDI and its determinants across districts. This spatial heterogeneity underscores that a single global relationship does not adequately capture the complexity of human development in Aceh. The analysis shows that education (average and expected years of schooling) and life expectancy consistently have strong positive effects on HDI across Aceh. However, the GWR results further demonstrate that the magnitude and significance of socio-economic variables vary geographically. In the northern coastal districts (Banda Aceh, Lhokseumawe, Bireuen), HDI is shaped by a broader mix of factors including labor participation, poverty, and GRDP, while in inland and southern regions (Gayo Lues, Aceh Tenggara, Subulussalam), it is mainly driven by education, health, and household expenditure. Simeulue stands out as highly sensitive to all socio-economic variables. These findings refine the global model results by showing that HDI determinants are not spatially uniform, but context-dependent across districts.

From a scientific perspective, this study contributes to the literature by providing the first district-level spatial analysis of HDI determinants in Aceh using the GWR approach, thereby addressing a methodological gap in previous non-spatial studies. These results refine the global model by showing that the magnitude and significance of each factor change across space, meaning HDI determinants are geographically specific. Hence, policy efforts should be area-based comprehensive programs integrating labor, economy, and welfare for coastal growth centers, and focused improvements in education, healthcare, and household welfare for inland areas. In Simeulue, multi-sectoral approaches are crucial to strengthen connectivity, services,

and economic diversification. Despite these contributions, this study has several limitations. The analysis relies in cross-sectional data for a single year, which limits the abaility to capture temporal dynamic in human development. In addition, the set of explanatory variables is constrained by data availibility and does not explicitly incorporate institutional or environmental factors. Future research is encouraged to employ panel spatial models, include broader development indicators, and explore multiscale spatial effects to further enrich the understanding of HDI dynamics in Aceh.

ACKNOWLEDGEMENT

The authors thank the editor and reviewers for their insightful comments and suggestions, which have greatly improved the quality of this paper.

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