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Machine Learning-Enhanced Geographically Weighted Regression for Spatial Evaluation of Human Development Index across Western Indonesia

Gustian Angga Firmansyah[1,*], Junta Zeniarja[1], Harun Al Azies[1,2] , Sri Winarno[1], Syuhra Putri Ganiswari[1]

[1]*Study Program in Informatics Engineering, Faculty of Computer Science, Universitas Dian Nuswantoro, Jl. Imam Bonjol No.207, Pendrikan Kidul, Kec. Semarang Tengah, Kota Semarang, Jawa Tengah 50131, Indonesia.*
[2]*Research Center for Materials Informatics, Faculty of Computer Science, Universitas Dian Nuswantoro, Indonesia*
*Corresponding author e-mail: gustiananggaf@gmail.com

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Abstract

The HDI (Human Development Index) is one of the important components to measure the level of success in efforts to improve the quality of human life. The human development index is built with three dimensions, namely the longevity and health dimension, the knowledge dimension and the decent standard of living dimension. The longevity and health dimension is measured using Life expectancy at birth. The knowledge dimension is measured using expected years of schooling and average years of schooling. Meanwhile, the decent standard of living dimension is measured using Adjusted per capita expenditure. This study aims to find factors that influence HDI (Human Development Index) in Western Indonesia Region using machine learning models. The results obtained are that HDI is influenced by average years of schooling, expected years of schooling, Life expectancy at birth, and Adjusted per capita expenditure which are sorted from the most significantly influential. The model used in this study is GWR (Geographically Weighted Regression) with evaluation results including, AIC of 215.3162, AICc of 226.5107, and the accuracy level in the form of R-square of 99.38% which means this model is good to use.

Keywords: *Human Development Index, Geographically Weighted Regression, Machine Learning, Western Indonesia Region, Spatial, Regression*

1. Introduction

The success of a country can be measured using the HDI (Human Development Index) (Marizal & Atiqah, 2022). HDI is a measuring tool to evaluate and monitor progress in building human quality of life (Maulana et al., 2019; Nur Amiroh & Avianto, 2023). This index was introduced by the UNDP (United Nations Development Programme) in 1990 and published in an annual report known as the HDR (Human Development Report) (Marizal & Atiqah, 2022; Maulana et al., 2019).

HDI consists of three main dimensions that include longevity and health, knowledge, and a decent standard of living (Nur Amiroh & Avianto, 2023). The dimension of longevity and health can be measured by the indicator of Life Expectancy (LE). The knowledge dimension uses two indicators, namely Expected Years of Schooling (EYS) and Mean Years of Schooling (MYS). Furthermore, the dimension of a decent standard of living uses the indicator of Gross National Income (GNI) per capita (Marizal & Atiqah, 2022). These dimensions reflect efforts to improve public access to income, health, and education (Marizal & Atiqah, 2022; Maulana et al., 2019; Nur Amiroh & Avianto, 2023; Tambunan et al., 2022; Tjodi et al., 2021). HDI is also an important indicator by governments in determining General Allocation Funds in several countries, including Indonesia (Marizal & Atiqah, 2022; Maulana et al., 2019; Nur Amiroh & Avianto, 2023).

Although HDI originally consisted of four dimensions, namely life expectancy, expected years of schooling, mean years of schooling, and gross national income per capita, in 2010, UNDP changed it to three dimensions to accommodate changes in society (Badan Pusat Statistik Indonesia, 2022; Nur Amiroh & Avianto, 2023). Using HDI as a measuring tool for human development is essential for planning and evaluating government (Wardhana et al., 2021). However, there are challenges in the validity of HDI data due to different data sources from various government agencies, which can confuse the policy-making process (Nona, 2022).

In the context of Indonesia, HDI plays a strategic role as it is not only a measure of government performance but also used as a consideration in allocating funds for public services and community welfare (Ade Onny Siagian, 2022; Nur Amiroh & Avianto, 2023). By considering HDI and its dimensions, the government can expand people's choices and create an environment supporting longevity, health, and productivity (Maulana et al., 2019). This approach is important in improving people's quality of life globally and sustainably, as well as creating social harmony (Marizal & Atiqah, 2022).

One method used to predict HDI is GWR (Geographically Weighted Regression) which is a spatial regression model that calculates each parameter for each observation location so that each location will have a different interpretation (Amarrohman et al., 2023; Putri et al., 2022). GWR modelling requires a weighting function, and the Fixed Gaussian Kernel is one of the functions used in the study (Suryowati et al., 2021). In a study on HDI modelling in Indonesia, GWR was used to model HDI using independent variables such as Length of Schooling Expectancy, Average Years of Schooling, Life Expectancy, and Per Capita Expenditure (Maulana et al., 2019). The study found that all independent variables affected HDI, and the GWR model was the best compared to linear regression (Marizal & Atiqah, 2022).

Several studies discuss the GWR method, including research conducted by Sukanto et al., (Sukanto et al., 2019) on Spatial Analysis of Poverty with a Geographically Weighted Regression Approach: Case Study of Pandeglang and Lebak Regencies. Research using the GWR method was also conducted by Amalia and Sari (Amalia & Sari, 2019) with the title Spatial Analysis to Identify Open Unemployment Rate Based on Regency / City in Java Island in 2017. Another research using the GWR method for modeling the factors that cause poverty in North Sumatra Province in 2018 was conducted by Daulay and Simamora (Daulay & Simamora, 2023).

Overall, HDI is an important indicator used to measure the quality of human life, and GWR is a method used to predict HDI based on various independent variables. This study compares MLR (Multiple Linear Regression), RR (Ridge Regression), and GWR (Geographically Weighted Regression) on the new HDI data by districts/cities in Western Indonesia in 2022, using fixed Gaussian kernel and fixed bi-square kernel as the weights in the GWR model.

2. Related Works

Understanding regional variations in various socioeconomic parameters relies heavily on spatial analysis. In this review, we will look at works on GWR and the application of machine learning techniques to the HDI in Western Indonesia. The research we evaluate emphasizes the relevance of utilizing spatial models to capture heterogeneity across geographic regions, allowing us to gain insight into HDI spatial variation and its drivers. Previous study has shed light on the application of GWR in the geographical analysis of HDI in various regions of Indonesia.

Permai et al., (Permai et al., 2016) found that GWR helps to comprehend the distinct geographical implications of HDI in various locations, and the results outperform global linear regression models. Another study conducted in Central Java by Mahara and Fauzan (Mahara & Fauzan, 2021) looked at the impact of HDI and population percentage on poverty levels. In this investigation, they employed GWR to account for spatial effects and discovered that the GWR model beat the OLS model in estimating these influences. In her work, Kopczewska (Kopczewska, 2022) discusses the prospects provided by machine learning in geographical analysis. Machine learning, both supervised and unsupervised, has enormous potential in regional research, and these methods can assist in overcoming spatial analytical issues. Wu et al., (Wu et al., 2021) work on COVID-19 demonstrates the necessity of geographical analysis in the context of a pandemic. They employed geographical visualization, spatial regression, and machine learning to uncover parameters impacting disease distribution, yielding crucial insights for epidemic control. Finally, Littidej et al., (Littidej et al., 2022) integrated GWR with artificial neural network-based machine learning to anticipate sugarcane land burning in Northeast Thailand. The findings suggest recommendations for decreasing the impact of such burning.

Based on these findings, it appears that using GWR in spatial analysis by considering spatial aspects and creating models with machine learning methods is a promising approach for understanding and overcoming major spatial variations in HDI research in western Indonesia. Using a machine learning approach, this study extends the concept of the GWR model, which has been employed in previous studies. We hope to better understand the spatial influence on the HDI in Indonesia's western area by constructing the GWR model using a machine learning approach. This approach tries to find more complicated patterns and elements that standard spatial analysis may miss, so making a substantial contribution to understanding spatial disparities in human development levels in the region. In the context of HDI in western Indonesia, this study bridges the knowledge gap between traditional spatial analysis and the development of machine learning technologies.

3. Materials and Methods

Based on the research objectives, the analysis method used in this research is inferential analysis. Data processing in this study used tools in the form of RStudio and Arcview software.

3.1 Data Sources and Research Variables

This study uses cross-section secondary data from Statistics Indonesia. The observations of this study are districts/cities in Western Indonesia in 2022, as many as 282 districts/cities. Then, the data is split by 80:20, 80% for training data and 20% for test data. The research variables used in this study are described in the following table.

Table 1. Research Variable

Variable	Scale
HDI (Human Development Index) (Y)	Ratio
Life expectancy at birth (X1)	Ratio
Expected years of schooling (X2)	Ratio
Average years of schooling (X3)	Ratio
Adjusted per capita expenditure (X4)	Ratio

3.2 Analysis Steps

The stages of analysis in this study can be seen in the following flowchart.

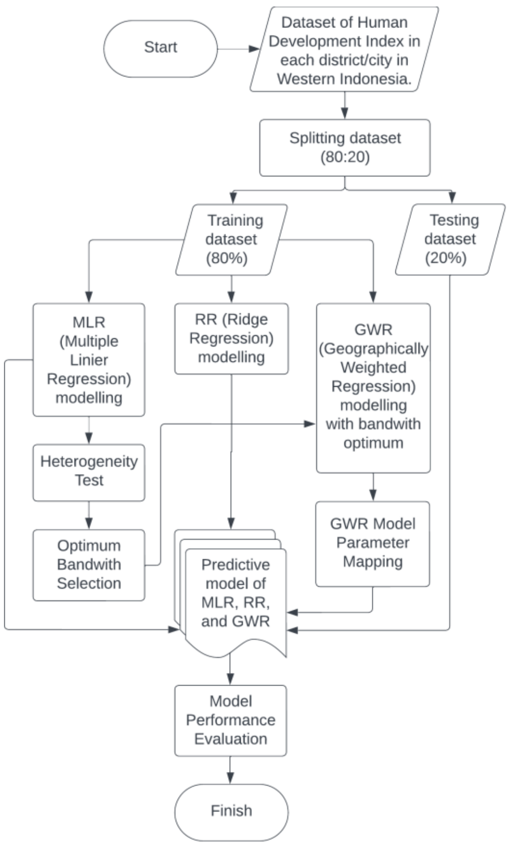

Figure 1. Research Flowchart

The stages of analysis carried out to see the effect of independent variables on HDI are as follows.

1) Data preparation by splitting data on the dataset with a ratio of 80:20 (training data: testing data).
2) Modelling the HDI of residents in Western Indonesia with the MLR (multiple linear regression) algorithm includes testing the assumptions of classical regression models and spatial diversity (heterogeneity test) using the BP-test (Breusch-Pagan test) (Nuramaliyah et al., 2019) with the following hypotheses:
   a) H0: the residual variation (error) in the model is homogeneous (no heterogeneity between regions)
   b) H1: the model's residual variation (error) is not homogeneous (there is heterogeneity between regions). The decision will reject H0 if the p-value < α (5%).
3) Modelling the HDI of residents in Western Indonesia with the RR algorithm.
4) While the stages in the spatial model use GWR, the GWR method was first introduced by Fotheringham in 1967 and is a development of the MLR method (Oshan et al., 2020). The concept in GWR modelling is to estimate the parameter value at each observation location point so that each observation point has a different parameter value (Li et al., 2020). The stages of GWR analysis in this study include:
   a) Determining the optimum bandwidth value based on cross-validation (CV) criteria using fixed Gaussian kernel and fixed bi-square kernel.
   b) Creating a GWR model with optimum bandwidth.
   c) Mapping the results of GWR model parameters using Arcview software.
5) Evaluate the performance of MLR, RR, and GWR models using AIC, AICC, and R-square criteria.

4. Results and Discussion

A GWR spatial analysis is conducted to analyze the factors influencing the HDI. The procedure in GWR analysis includes MLR modelling, heterogeneity test, optimum bandwidth selection, RR modelling, optimum bandwidth selection, GWR modelling, mapping the results of GWR model parameters, and all performance evaluation of all models.

4.1 MLR (Multiple Linear Regression) modelling

The results and discussion of the MLR model can be used to see the relationship between the HDI in each district/city in Western Indonesia with influencing factors. MLR testing is carried out regression on the HDI response variable so that a summary of the MLR model formed can be seen in the following table:

Table 2. Parameter Estimation of MLR Model

Predictor Variable	Coefficient	Std. Error	t-statistik	Probability
Intercept	4.906	7.300e-01	6.72	1.51e-10
Life expectancy at birth (X1)	0.4943	9.793e-03	50.47	< 2e-16
Expected years of schooling (X2)	0.9290	3.718e-02	24.99	< 2e-16
Average years of schooling (X3)	1.268	3.179e-02	39.90	< 2e-16
Adjusted per capita expenditure (X4)	0.0007848	1.507e-05	52.07	< 2e-16

Based on the model summary obtained, all predictor variables significantly affect the HDI in Western Indonesia in 2022 with a significance level of 5%. The results obtained are that HDI is influenced by average years of schooling, expected years of schooling, Life expectancy at birth, and Adjusted per capita expenditure which are sorted from the most significantly influential.

4.2 HeterogeneityTest

Furthermore, classical assumption testing is carried out, which includes heterogeneous test. The Heterogeneity test is conducted to determine the homogeneity of the variance in the residuals with the test used is Breush-Pagan (Al Azies & Dewi, 2021), the Breusch Pagan test results with the equation produces a p-value of 0.001433 which is smaller than the 5% significance level so it can be concluded that there is a violation of the homogeneity assumption in the MLR model. Violating this assumption indicates that the error variance in the model is not identical, so it is necessary to conduct an analysis considering spatial or regional aspects. This indicates that the analysis using the MLR model is no longer feasible. Violating the assumption of homogeneity indicates the existence of spatial diversity, so it is necessary to approach spatial effects in the model. The GWR (Geographically Weighted Regression) model is good if heterogeneity occurs (Purwaningsih & Noraprilia, 2018).

4.3 RR (Ridge Regression) modelling

The results and discussion of the RR model can be used to see the relationship between HDI in each district/city in Western Indonesia and the factors that influence it. The RR model uses the optimal lambda value as one of its parameters, in this case, the optimal lambda value is 0.4217482. So that the summary results of the RR model formed can be seen in the following table:

Table 3. Parameter Estimation of RR Model

Predictor Variable	Coefficient
Intercept	7.0353239141
Life expectancy at birth (X1)	0.4726779719
Expected years of schooling (X2)	0.9566315798
Average years of schooling (X3)	1.2029079004
Adjusted per capita expenditure (X4)	0.0007513387

Based on the model summary obtained, all predictor variables significantly affected the HDI in Western Indonesia in 2022. The results obtained are that HDI is influenced by average years of schooling, expected years of schooling, Life expectancy at birth, and Adjusted per capita expenditure which are sorted from the most significantly influential.

4.4 GWR (Geographically Weighted Regression)

Based on the results of classical assumption testing and spatial dependence effects, there are differences in characteristics between observation areas, while the MLR and RR models only produce global estimates. Therefore, a model is needed to consider spatial effects and diversity, one of which uses GWR, which produces local parameters for each observation area. The stages of preparing the GWR Model are as follows (Azies, 2022).

4.4.1 Optimum Bandwidth Selection

The GWR model uses weights based on the geographical location of each district/city. The first step is to determine the geographical location (longitude and latitude) of each district/city in Western Indonesia, then calculate the Euclidean distance based on the geographical location for each district/city in Western Indonesia. An area can be determined by the order of other adjacent areas based on the Euclidean distance so that the order of the closest area for the entire observation area will be obtained. Next, choose the optimum bandwidth for each district/city in Western Indonesia with a kernel function. To choose the best kernel method, modelling is done for each weight to get the cross-validation (CV) value of the weight. The weight with the smallest CV value is the best to build the model(Azies, 2022) .

Table 4. Bandwidth and CV of the Weight Function

Weight Type	Bandwidth	CV Score
Fixed Gaussian Kernel	14.2963686	37.77748
Fixed Bi-square Kernel	116.4930700	40.40228

Weighting can be said to be optimal if the CV value is low. The table above shows that the fixed Gaussian kernel weighting type is optimal for GWR modelling because it has a smaller CV value than the fixed bi-square kernel weighting method. Analysis using the fixed Gaussian kernel obtained an optimal bandwidth value of 14.2963686 from a minimum CV of 37.77748, which means that points with a radius of 14.2963686 are considered to have an optimal effect on formatting the localization model parameters. With the weights used in the model, parameter estimates are applied locally, resulting in different parameter values for each district/city. The next GWR modelling will use a weight matrix with a fixed Gaussian weight function.

4.4.2 GWR Modelling with Bandwith Optimum

The GWR model is built using optimum bandwidth with fixed Gaussian weighting function. The following is the parameter estimation of the GWR model that describes the relationship between the Human Development Index (Y) and the factors that influence it, namely life expectancy at birth (X1), expected years of schooling (X2), average years of schooling (X3) and adjusted per capita expenditure (X4) globally in Western Indonesia:

Table 5. Parameter Estimation of GWR Model

Variable	Global Coefficient
Intercept	4.9056
Life expectancy at birth (X1)	0.4943
Expected years of schooling (X2)	0.9290
Average years of schooling (X3)	1.2685
Adjusted per capita expenditure (X4)	0.0008

Based on the model summary obtained, it can be seen that all independent variables have a positive effect on the dependent variable. The most influential independent variable on the dependent variable is X3 which is the average years of schooling. And the least influential independent variable is X4 which is the adjusted per capita expenditure. The R-squared (R^2) value in this model is 0.9938, which means that the four factors influencing the HDI can explain 99.38% of the variation in the HDI in Western Indonesia globally.

4.4.3 GWR Model Parameter Mapping

The GWR model that has been built previously is still global, where the model still represents all districts/cities in Western Indonesia. Furthermore, the GWR model parameters are mapped for each independent variable in each district/city in Western Indonesia to see the significance of the influence of factors that affect the HDI by district/city. The GWR modelling results will be mapped for each independent variable, namely life expectancy at birth (X1), expected years of schooling (X2), average years of schooling (X3), and adjusted per capita expenditure (X4). The following are the results of the mapping of the four independent variables:

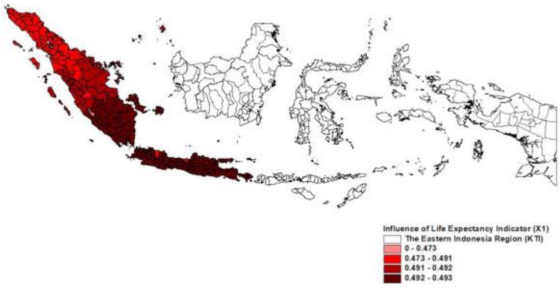

Figure 2. Significance Map of Life Expectancy at Birth (X1)

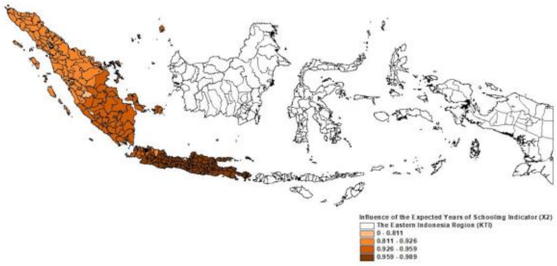

Figure 3. Significance Map of Expected Years of Schooling (X2)

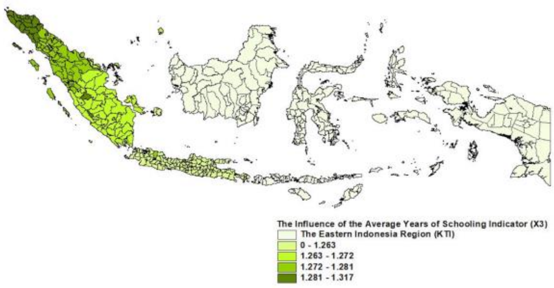

Figure 4. Significance Map of Average Years of Schooling (X3)

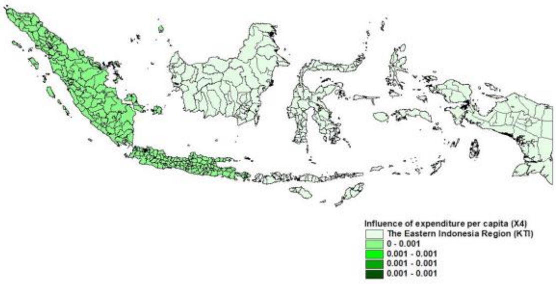

Figure 5. Significance Map of Adjusted Per Capita Expenditure (X4)

The GWR model is a model that can be used effectively to describe the factors that influence HDI. The following are some examples of GWR models built for each district/city, where each district/city has different models and parameters for each variable which can be seen in the following table.

Table 6. Example of GWR Modelling Results

District/city	GWR Model in Each Area
Simeulue	Y = 5.320379 + 0.4899229263(X1) + 0.8950878532(X2) + 1.283739961(X3) + 0.0008022086944(X4)
Aceh Singkil	Y = 5.258486 + 0.4904852016(X1) + 0.9019493215(X2) + 1.280559214(X3) + 0.0007987338973(X4)
Aceh Selatan	Y = 5.307948 + 0.490035591 (X1) + 0.8973750291 (X2) + 1.282349156 (X3) + 0.0008011063251 (X4)

Based on the GWR model of the Simeuleu region, it is known that the relationship between HDI and Life expectancy at birth (X1), Expected years of schooling (X2), Average years of schooling (X3), and Adjusted per capita expenditure (X4) is positive, which means that the relationship between HDI and Life expectancy at birth (X1), Expected years of schooling (X2), Average years of schooling (X3), and Adjusted per capita expenditure (X4) have an effect on the HDI. The GWR model provides different impacts for each zone of change.

4.5 Model Performance Evaluation

The best spatial regression model is determined using the values of the Coefficient of Determination (R^2), AIC, and AICc. If the R^2 value is greater than other models, it indicates that the model is better than other models. Meanwhile, absolute values of AIC and AICc that are smaller than other models indicate that the model is better than other models. The performance of the three models can be seen in the following table (Lutfiani & Scolastika Mariani, 2017).

Table 7. Model Performance Evaluation with Training Data

Model	Training Data		
	R^2	AIC	AICc
MLR	0.9934	236.668	236.668
RR	0.9919562	-365.4463	-365.1761
GWR	0.9938718	215.3162	226.5107

Table 8. Model Performance Evaluation with Testing Data

Model	Testing Data		
	R^2	AIC	AICc
MLR	0.9955	55.58137	55.58137
RR	0.9941458	-88.56808	-87.36808
GWR	0.9960601	41.62554	51.8253

Based on these tables, the R^2 value generated by the GWR model is greater than the MLR and RR models. In addition, based on the absolute values of AIC and AICc, the GWR model is smaller than the MLR and RR models. This applies equally to both using training data and test data. So, it can be concluded that the GWR model is better used to model the influence of the Human Development Index.

5. Conclusion

Based on the analysis that has been done, it can be concluded that the GWR model with the Gaussian kernel weighting function (for example: in western Indonesia) is as follows:

$$Y = 4.9056 + 0.4943(X1) + 0.9290(X2) + 1.2685(X3) + 0.0008(X4)$$

The best model among the MLR, RR, and GWR models is determined by the R^2, AIC, and AICc values. The R^2 value obtained in the MLR model is 99.34%, the AIC value obtained is 236,668, and the AICc value obtained is 236,668. While the R^2 value obtained in the RR model is 99.19%, the AIC value obtained is -365.4463, and the AICc value obtained is -365.1761. The R^2 value obtained in the GWR model is 99.38%, the AIC value obtained is 215.3162, and the AICc value obtained is 226.5107. The largest R^2 value and the smallest absolute value of AIC and AICc are owned by the GWR model. So the GWR model is better than the MLR and RR models for modelling HDI in western Indonesia in 2022.

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