Jurnal Pendidikan Geografi:
Kajian, Teori, dan Praktik dalam Bidang Pendidikan dan Ilmu Geografi, 28(2), 2023, 228-241
ISSN: 0853-9251 (Print): 2527-628X (Online)
DOI: 10.17977/um017v28i22023p228-241

Influencing factors for the human development index in West Java using geographically and temporally weighted regression kernel functions

Anis Dyah Rahmawati[1], Aji Hamim Wigena, Muhammad Nur Aidi

IPB University, Raya Dramaga Street, Babakan, Dramaga, Bogor, West Java, 16680, Indonesia
[1]Corresponding author, Surel: anisanis@apps.ipb.ac.id

Paper received: 09-05-2023; revised: 22-05-2023; accepted: 14-06-2023

Abstract

Human Development Index (HDI) is a competitive index that serves as one of the crucial metrics for evaluating the effectiveness of enhancing the quality of human resources. HDI values from different areas can be compared. This study aims to spatially and temporally explore the HDI data from districts or cities in West Java and examine the factors that influence HDI in each of these districts or cities using the GTWR Great Circle Distance Fixed Kernels model. In this study, we used a combination of cross-sectional data from districts or cities in West Java and time series data with seven annual periods from 2015-2021. The GTWR Great Circle Distance Fixed Kernels model was expected to display coefficient values at each location and time simultaneously, providing more in-depth information and analysis results at each location and time. The analysis results using the GTWR Great Circle Distance Fixed Kernels model show that HDI in West Java carries a positive influence on the location and time. This finding should be of particular concern to the relevant government, particularly the factors presenting a natural effect on HDI based on location and time. The positive influence obtained by an area at a particular time will also have a positive impact on other regions, and if there is a negative influence, it will undoubtedly affect other regions as well. Analysis of the HDI model in West Java using the GTWR Great Circle Distance Fixed Exponential Kernel model also presents better results in comparison to the Global OLS model and the GTWR model without the Great Circle Fixed Exponential Kernel. The final parameter estimator results are displayed in the form of a geographic map to facilitate ease of understanding.

Keywords: IPM; global OLS; GTWR; spatio temporal; Kernel

1. Introduction

The Human Development Index (IPM) was initially proposed by the United Nations Development Program (UNDP) in 1990. HDI is routinely included in the annual Human Development Report (HDR) report. Meanwhile, the HDR contains various aspects of human development, including the development focusing on the growth of Gross Domestic Product (GDP), income, wealth, commodity production, and mere capital additions or development to provide more extensive access to the development of good health, proper education, and longer life expectancy (Hickel, 2020). In general, the HDI contains three indices, including the expenditure index, the education index, and the medical index. As one of the essential indicators measuring the success of development and the quality of human resources at a specific time in an area, HDI is one of the outstanding indexes. Accordingly, governments from various nations perform various measures to enhance the HDI value in their respective regions.

In addition, Geographically and Temporally Weighted Regression (GTWR) was originally a development of the Geographically Weighted Regression (GWR) model. Fotheringham, Brunsdon, and Charlton (2002) uncovered the GWR model's capacity to provide better results than the Global Ordinary Least Square Model (Global OLS) on cross-sectional data spread over several different locations. In this study, we used fixed Kernels functions, in which the optimal bandwidth selection was carried out with the minimum cross-validation technique. Fotheringham, Crespo, and Yao (2015) conducted further studies by forming a Temporally Weighted Regression (TWR) on non-stationary data and combining it with the GWR to form a Geographically and Temporally Weighted Regression (GTWR) model. That study further described the better capacity of GTWR than GWR and Global OLS. Several other studies have also measured the differences between Global OLS, GWR, and GTWR, such as the studies conducted by Aghayari, Pahlavani, and Bigdeli (2017); Chu, Kong, and Chang (2018); Conita and Purwaningsih (2020); Du, Wu, Zhang, Liu, and Zhou (2018); Feng et al. (2023); Fu and Li (2020); Harahap (2022); Haryanto, Aidi, and Djuraidah (2019); Li, Ji, and Dong (2022); Liu et al. (2017); Ma, Zhang, Ding, and Wang (2018); Shim and Hwang (2018); Sholihin, Soleh, and Djuraidah (2017); Wei, Zhang, Duan, and Zhen (2019); Xu, Luo, Ma, and Xiao (2020); Yasin, Sugito, and Prahutama (2015). These studies provide sufficient evidence that spatiotemporal variations simultaneously have a major influence and are closely related to the formation of a model.

Fotheringham, Crespo, and Yao (2015) established the GTWR model by adding local non-stationary elements from both location and time dimensions. These models used data from several different locations and years, with varying weights for each location and time in the analysis process. Therefore, the weighting matrix (W) for each location and time is different. The observation carried out in a closer location and time dimensions generates a more excellent weight value. The results of the GTWR application on this model confirm that certain parameter values are only accurate at specific locations and times. The research was conducted by calculating the authentic level from each location and time to identify the variables with a significant effect at each location and year.

Spatio temporal bandwidth and weighting matrix was used in many conditions. Pamungkas, Yasin, and Rahmawati (2016) used Fixed dan Adaptive Bandwidth; Meyer, Held, and Höhle (2014) used individual-level time-stamped geo-referenced data; Aidi et al. (2022) used fixed Gaussian kernel weighting. Additionally, Ling, Qian, Guo, and Ukkusuri (2022); Porcu, Bevilacqua, and Genton (2016) used the Great Circle Distance (GCD) concept in the Kernels function. The GCD distance concept regards the curvature of the earth in its spatiotemporal weighting matrix. This weighting matrix presents additional elements of location and time as well as in its formation. The addition of distance values that consider the earth's curvature has been proven to increase the goodness of the model.

This study explores the spatial and temporal HDI data from districts or cities in West Java between 2015-2021 and examines the influencing factors of the HDI in each district or city. In detail, the research compares the use of various Kernel functions, including Exponential, Gaussian, Bisquare, and Tricube Kernels, in the model by selecting the optimum bandwidth that was obtained based on the minimum cross-validation calibration of each function. Then, the study also examines these factors using the Global Ordinary Least model Square Model (Global OLS), as well as the Geographically and Temporally Weighted Regression (GTWR), then selects the best model for the parameter estimation and further analysis. GTWR Kernels model selection was conducted by comparing the goodness of the model established from weights with and without Great Circle Distance (GCD) from the various adopted Kernel functions.

2. Method

This study analyzed the cross-sectional data, which covers 27 districts or cities in West Java in seven-time series periods from 2015 to 2021. The study used six variables, containing the human development index as the response variable and the other five variables as explanatory variables, namely gross regional domestic product, poverty rate, high school net enrollment rate, elementary school net enrollment rate, and a number of health complaints. All data was obtained from the data published by the Central Bureau of Statistics (BPS). The data analysis was carried out with R Studio through the research procedures presented in Figure 1.

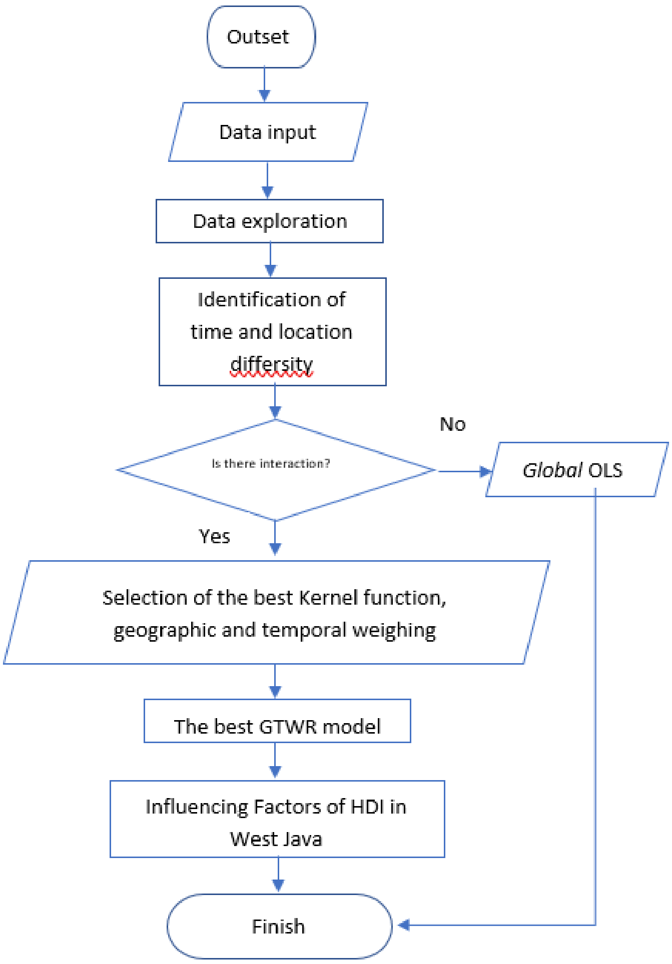

Figure 1. Research Procedure

The initial stages of research include the exploration of all variables, such as by examining the correlation between variables using Pearson correlation and assessing the multicollinearity with Variance Inflation Factors (VIF) where a lower than 10 VIF value suggested the absence of multicollinearity. Then, we identified the diversity of locations and time on the data using the Pagan Breusch test (BP) with the hypothesis of $H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ and H_1: minimum of one, with $\sigma_i^2 \neq \sigma^2$. If the BP test result showed that H_0 was accepted, then the H_0 Global OLS model was better, but if the H_0 was rejected, then it represented a variation in location and time, enabling further analysis to be carried out.

In general, the *Global* OLS model can be presented in Formula 1.

$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i \quad (1)$$

Where $y_i$is the response variable of the *i-th* observation, β_0 is the intercept, the $x_{ik}k$ – is the free variable in the i- *th* observation, β_k is the regression coefficient on the k independent variable or known as referred to as the variable parameter estimator (the estimated y_i transformation on one unit change in x_{ik}), while ε_i is the residual of *i-* observation. The data were described generally using Global OLS. For the parameter value in Global OLS, we used the same parameter for all locations, regardless of their position and time. The estimator value for all locations and times is single. The data analysis system at Global OLS was then further analyzed.

The GWR model proposed by Fotheringham et al. (2003) is presented in Formula 2.

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (2)$$

Where y_i is the observed response of i-variable, u_i dan $v_i$are two different observation locations, $\beta_0(u_i, v_i)$ is the intercept for the GWR model, x_{ik} is the k-independent variable in the i-observation, $\beta_k(u_i, v_i)$ is the regression coefficient on the k-independent variable with $\hat{\beta}(u_i, v_i) = [X^T W(u_i, v_i) X]^{-1} X^T W(u_i, v_i) y$ and ε_i is the residual from the *i*-observation.

The GWR model was further advanced into the GTWR model with an addition of location and time variations (Huang, Wu, & Barry, 2010). With the addition of the time element, the GTWR model is shown in Formula 3.

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i) x_{ik} + \varepsilon_i \quad (3)$$

Where u_i dan $v_i$is the two different observation locations at $t_i$different times, k is the independent variable of the p total with $\beta_0, \beta_1, \dots, \beta_p$is the parameters used in the model, and $\varepsilon_i$is *the error* which is assumed to have a normal distribution, with zero mean and constant variance. The linear equation to the GTWR model is presented in Formula 4.

$$y = X_i \beta_i(u_i, v_i, t_i) + \varepsilon \quad (4)$$

Further, the coefficient (β_i) for each i- *th location* in the GTWR model is obtained using Formula 5.

$$\hat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i) X]^{-1} X^T W(u_i, v_i, t_i) y \quad (5)$$

With $W(u_i, v_i, t_i)$is the geographic and temporal weighting matrices used in the model.

In the regression analysis stage, we conducted calculations using minimum Cross Validation (CV) for optimum bandwidth, as well as fixed bandwidth with and without Great Circle Distance (GCD) based on latitude and longitude data. The calculation using the GCD also regarded the curvature of the earth. Further, we compared the calculation results with and without GCD. Then, we selected the best geographic and temporal weighting matrices. The four weighting matrices used include Kernel Gaussian, Bisquare, Exponential, and Tricube with two distance approaches (latitude and longitude data or standard distances) following the Great Circle Distance (GCD).

The final stage was the parameter estimation of the Geographically and Temporally Weighted Regression Great Circle Distance Fixed Kernels model (GTWR GCD Fixed Kernel) by selecting the best model based on the coefficient of determination (R^2), Akaike Information Criterion (AIC), and Residual Sum of Square (RSS). The coefficient of determination (R^2) represents the amount of data variation that can be explained by the model. The greater R^2 value represents a better model. Meanwhile, the Akaike Information Criterion (AIC) value reflects the quality of a model relative to other models, with a smaller AIC value suggesting the better quality of the model. The residual Sum of Square (RSS) or sum of squared errors of the best model shows the model that uses the least sum of squared errors.

3. Results and Discussion

The Human Development Index is an essential indicator frequently used to measure the success of human development and people's quality of life in a specific area and period. The central purpose of HDI is to refocus general development, from its original emphasis on the economic sector and national revenue to advancements in the social sector and human resources (Hickel, 2020). Human development in the sector of health, education, nutrition, and food intake (with income as the benchmark) is reported as an essential investment for establishing greater human welfare in various fields.

The calculation of HDI in all districts or cities and provinces across Indonesia has been carried out by the Central Bureau of Statistics using the three most basic human development aspects proposed by UNDP, namely longevity (long and healthy life), knowledge (knowledge), decent living standard (decent standard of living). Consequently, the Central Bureau of Statistics has three HDI indices, namely the Expenditure Index, the Education Index, and the Health Index. All these three indices are estimated using the geometric average. Figure 2 shows the trend of HDI in West Java Province between 2015-2021.

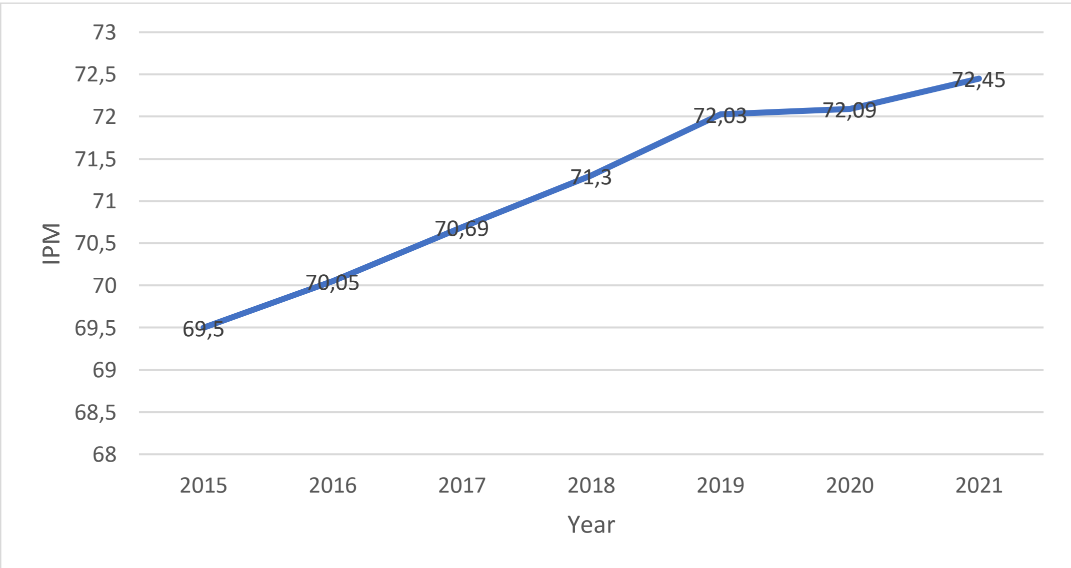

Figure 2. West Java Province HDI in 2015-2021

Generally, the HDI of West Java Province shows an increasing trend annually. As presented in Figure 2, West Java HDI has increased from 69.5 in 2015 to 72.45 in 2021. Even during the early days of the COVID-19 pandemic in 2020, West Java managed to maintain its HDI and succeeded in improving its HDI in 2021. As the first province in Indonesia to experience the COVID-19 pandemic, this outcome deserves to be commended by a number of stakeholders. Additionally, aside from being the most populated province in Indonesia, West Java managed to maintain its HDI amid the COVID-19 pandemic and successfully increased its HDI in the second year of the pandemic.

Universally, the higher HDI scores did not only occur at the province level, but it has been generally recorded from the majority of districts and cities in this province from 2015 to 2021. As presented in Figure 3 (a), the mean value of the box plot generally increases every year.

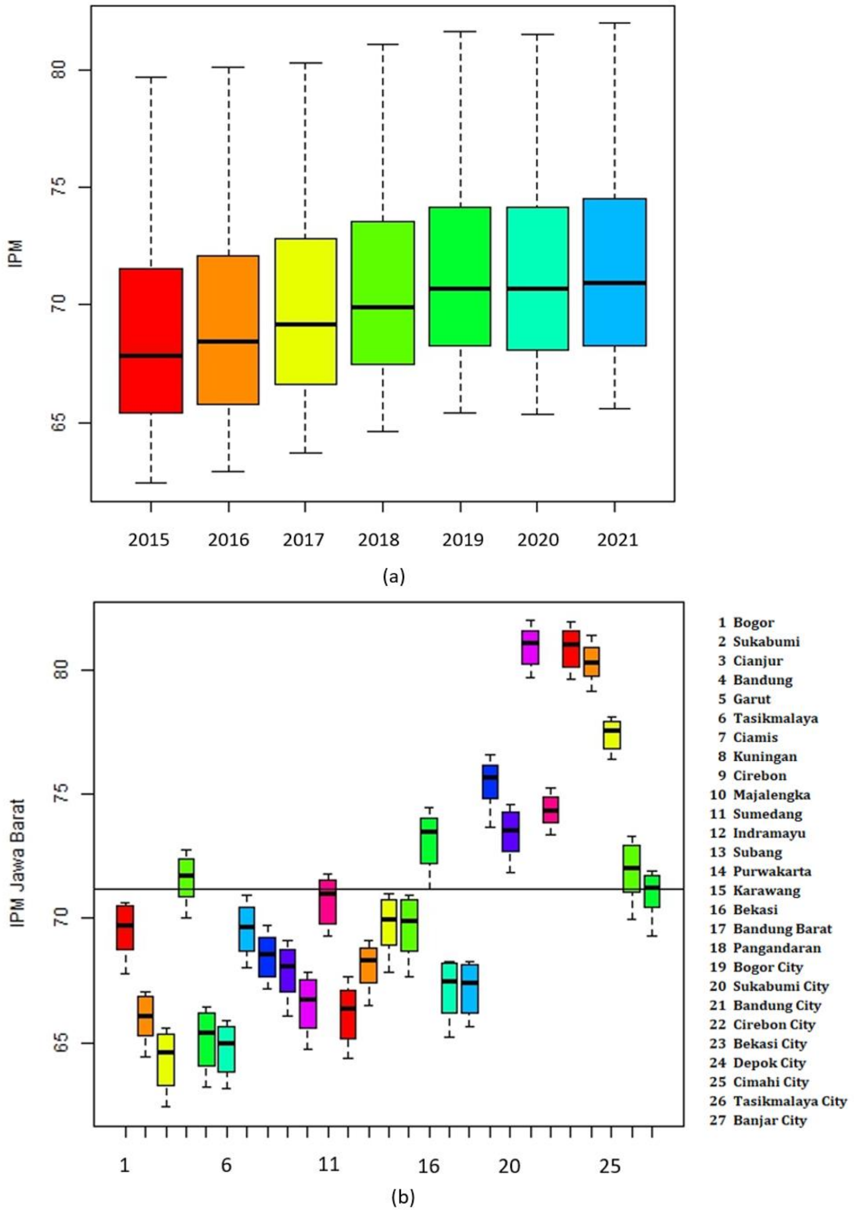

Figure 3. Box Plot HDI from Districts or Cities in West Java During 2015-2021 According to (a) Year and (b) Location

Further, in general, the provincial HDI score is higher than the district or city HDI average because the provincial-level HDI is estimated based on data collected from each district or city. In addition, Figure 3 (b) also shows several districts or cities with higher HDI than the median HDI for West Java districts or cities. Further, some of them have far higher

HDI, which enhances the West Java HDI score. Thus, the provincial HDI is generally higher than the average HDI score for each district or city. The horizontal line in Figure 3 represents the average HDI of 71.16 from 2015 to 2021. Out of the total of 27 districts or cities, four of them have similar HDI to the average West Java HDI, while 15 districts or cities have lower scores than the West Java HDI, and the remaining eight districts or cities have higher HDI than the West Java HDI.

Even though only eight districts or cities present higher HDI than the provincial HDI, the three of them have far higher HDI. These three cities are the City of Bandung, Bekasi, and Depok (marked with a red circle). The city of Bandung is the provincial capital, while the other two cities are cities bordering the national capital. Therefore, the far higher HDI in these cities is justifiable as every critical decision-making occurs at the center of government, along with developments in various fields.

Further, the five other regencies or cities attaining high HDI are Bekasi Regency, Bogor City, Sukabumi City, Cirebon City, and Cimahi City. At the same time, the regencies or cities with similar HDI to the provincial HDI are Bandung Regency, Sumedang Regency, Tasikmalaya City, and Banjar City. Consequently, the development initially occurs in the center of government and shifts to the surrounding areas. The location closest to the center of government attains more extensive effects than the areas in a relatively farther location. The map of the average district or city HDI in West Java for 2015-2021 can be seen in Figure 4.

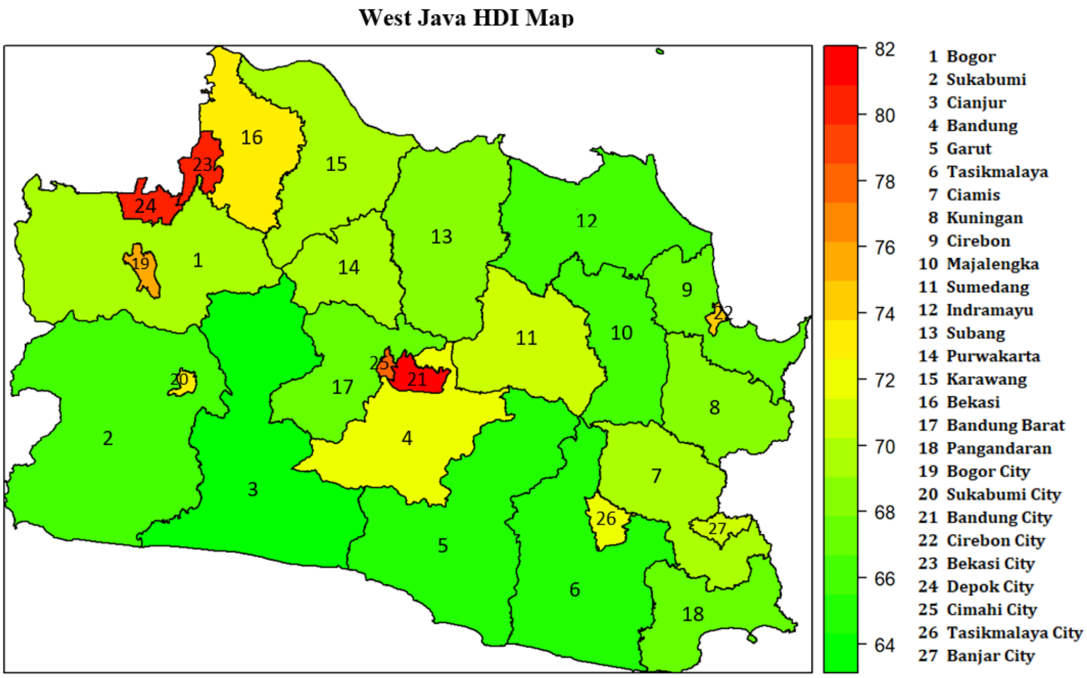

Figure 4. Map of the Average District or City HDI in West Java for 2015-2021

Figure 4 presents the correlation between locations more precisely through color gradation. Besides, the areas given red circle in Figure 3 (b) are given red gradation in Figure 4. Further, it shows that, in general, districts or cities with higher HDI than the average are located adjacent or are neighbors with the central cities and governmental areas (red areas in Figure 4).

Linear findings are also identified from the areas located away from the city center and the governmental regions. These regencies and cities are currently the focus of areas development, as shown by the construction of the southern highway route of Java. This highway is projected to connect regencies that previously had difficult access. In the long term, this construction is estimated to enhance the development of the area, including the development of its human resources.

Different from most northern areas, the southern area of West Java Province still has an HDI value graded in a relatively dark green color. This relatively darker green color represents their below 70 HDI score, on average. As presented in Figure 4, the districts with green color are located adjacent to each other, signifying their reasonably close relationship. Accordingly, the development and stimulus in one region are expected to stimulate other areas. These findings present more significant support for the indication of geographical factors influencing the HDI values of districts or cities in West Java.

3.1. Correlational Patterns between Variables

The correlational pattern between the response and explanatory variables is summarized in Table 1. The data suggested a positive relationship between HDI and two explanatory variables, namely GRDP and High School Net Participation Rate, each of which has a correlation of 29.5 and 64.2%, respectively. This data signifies that a higher value of the two descriptors signifies a more excellent HDI value. In contrast, we observed a negative relationship between HDI and three other variables, namely the poverty rate, SD Net Participation Rate, and number of health complaints, by 73.8, 17.8, and 29.5%, respectively. This shows that a higher score from the explanatory variables shows a smaller HDI value.

Table 1. Pearson Correlation, Variable p-values, and VIF

Explanatory Variable	Correlation Value	p-value	VIF
GRDP	0.295	0.000	1.38
Poverty level	-0.738	0.000	1.55
High School Pure Enrollment Rate	0.642	0.000	1.36
Primary School Pure Enrollment Rate	-0.178	0.023	1.24
Number of Health Complaints	-0.295	0.000	1.04

All of the explanatory variables have a significant correlation with HDI, with p-values of less than 5%. This finding is linear to the results reported by Ilhami, Nuryartono, and Achsani (2014) that human participation in school increases along with the increase of HDI. Further, Malau (2022) also uncovered that Gross Regional Domestic Product carries real effects on higher HDI and poverty alleviation in South Sumatra, Indonesia. Meanwhile, Lukiswati (2019) used geographically weighted panel regression on the Gender Development Index of Central Java, Indonesia, with explanatory variables for health complaints, number of elementary, junior high, and senior high school graduates, along with expenditure per capita, and the level of labor force participation, in which case the GPI is the same as the HDI, only differentiated by gender.

The multicollinearity analysis on explanatory variables was carried out based on Variance Inflation Factors (VIF). Table 1 shows that all VIF values are less than 10, both in combined data and data per year. This finding signifies the absence of multicollinearity between the explanatory variables used in the model. These variables can be used directly without the need to administer the multilinearity first.

In addition, Global OLS regression does not take into account the location and time data. This regression is commonly referred to as multiple linear regression. The Global OLS regression equation for the HDI influencing factors is shown in Equation 6.

$$\widehat{IPM} = 136.10 + 0.009\ GRDP - 0.871\ Poor + 0.2\ APMSMA - 0.688\ APMSD - 0.102\ Complaints \quad (6)$$

Based on Equation 6, the HDI is expected to increase by 0.009 and 0.2 times for every 1 unit increase in GRDP and the High School Pure Participation Rate, respectively. Conversely, the HDI is expected to decrease by 0.871, 0.688, and 0.102 for every 1 unit increase in the poverty level, the high school pure enrollment rate, and the number of health complaints, respectively. This estimation is the general formula that can be used to calculate parameters for each explanatory variable in all locations and times.

3.2. Geographically and Temporally Weighted Regression

3.2.1. Location and Time Effect Test

The Breusch-Pagan test was applied to identify the effect of location and time on the data. This test was carried out simultaneously and partially. The obtained Breusch-Pagan test result is shown in Table 2, showing a 1.3% result, lower than 5%. This finding indicates the presence of spatial and temporal variation in the HDI data and other explanatory variables.

Table 2. Breusch-Pagan Test Results

Breusch-Pagan Test Value	p-value
14,405	0.013

3.2.2. Determination of the Best Weighting Matrix

In addition, this study further examines the use of four spatiotemporal weighting matrices, namely Exponential Kernel, Gaussian, Bisquare, and Tricube weighting matrices. The four weighting matrices were used in the Fixed Kernels without the GCD effect (default) and Fixed Kernels GCD. Optimum bandwidth determination was completed by calculating the minimum Cross Validation (CV) value in calibration.

Table 3 presents the results of the various weighting matrices used in the study. Based on Table 3, the use of three measures of goodness of fit (adjusted R^2, RSS, and AIC) suggested that the GTWR models have a better measure of goodness than the Global OLS model. The adjusted R^2 *Global* OLS attains a 78.2% score suggesting that without the influence of location and time, the explanatory variables can explain the HDI condition by 78.2%. Meanwhile, all of the GTWR processing with various weighting matrices present higher adjusted results R^2 than the adjusted R^2 for Global OLS. Therefore, the inclusion of location and time data in the GTWR models better describes the HDI conditions compared to Global OLS.

The results of the goodness-of-fit measure using the RSS value suggested that the Global OLS model has the highest value of 951.964. Meanwhile, the RSS values of all GTWR models attained lower scores than the Global OLS RSS. The same result was also found in the measure of goodness using AIC, where Global OLS earned the largest value of 856,549. Thus, these two measures attained the same results, that is, apart from explanatory variables, spatiotemporal factors also affect the contributing factors of the West Java HDI, so the GTWR model is better than the Global OLS.

Table 3. Weighting Matrix, Bandwidth, and Goodness Measures

Weighting Matrix	Bandwidth	Adj R^2	RSS	AIC
Global OLS	-	0.782	951,964	856549
GTWR Gaussian without GCD	1,787	0.823	702,806	802,972
GTWR Exponential without GCD	2,916	0.812	745,561	813046
GTWR Bisquare without GCD	4.107	0.825	696,144	801290
GTWR Tricube without GCD	3,547	0.828	682,574	798,300
GTWR Gaussian GCD	2.105	0.953	127,464	521,274
GCD Exponential GTWR	1,383	0.959	62,934	421,514
GTWR Bisquare GCD	6,091	0.945	165,762	561,334
GTWR Tricube GCD	6.108	0.944	177,536	571,546

Several GTWR models were used in this study, both with the Fixed Kernels model without the Great Circle Distance (GCD) effect and the GCD. In general, models with GCD in their calculations presented better goodness-of-fit measures than the models without GCD. Consequently, the curvature of the earth also should be regarded as it has been proven capable of improving the goodness of the resulting model. As presented in Table 3, the best Great Circle Distance Fixed Kernels are the GTWR Great Circle Distance Fixed Exponential Kernel models with the highest adjusted R^2 of 95.9%, with the lowest RSS and AIC values of 62.934 and 421.514. Therefore, the GTWR Great Circle Distance Fixed Exponential Kernel Model can be used in further studies.

3.2.3. GTWR Model Parameter Estimator

The elements with a substantial impact on the yearly HDI in each district or city were identified through analysis of model parameter estimators using the GTWR Great Circle Distance Fixed Exponential Kernel. As illustrated in Figure 5, the variable presenting consistent effects on the annual HDI is the high school enrollment rate. Subsequentially, the higher high school-age children who receive education increases the HDI in an area. In other words, the success of the 12-year compulsory education implementation will significantly affect and improve human development. The second most influential variable for all areas is GRDP. The more excellent GRDP value of a region represents its better ability to develop human resources.

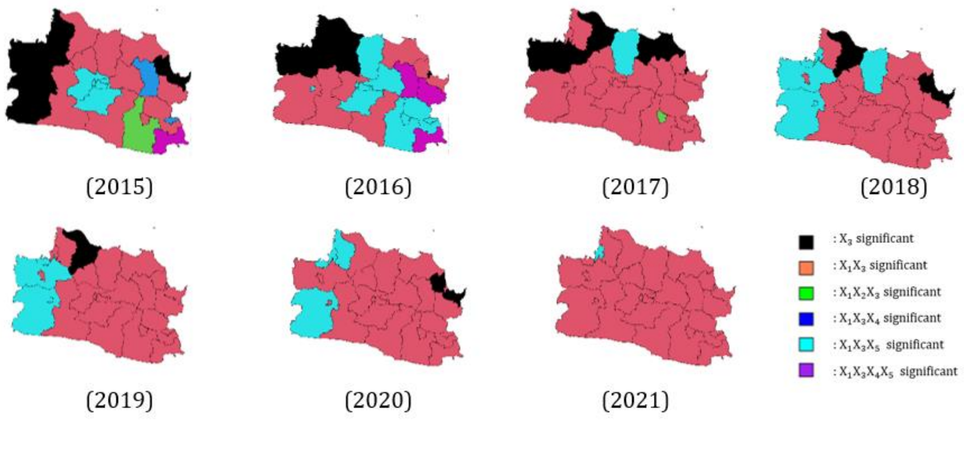

Figure 5. Map of HDI Influencing Factors Distribution

3.2.4. Distribution Map of Estimated Mean Variable by Location

The distribution of estimated variables affecting the HDI is illustrated in Figure 6 (ae), while the influence direction of all explanatory variables is shown in Figure 6 (fj). Figure 6 (a) shows a relatively different average value of the GRDP parameter estimators $\left(\bar{\bar{\beta}}_{pdrb}\right)$from districts or cities in West Java. The areas with adjacent locations tend to have similar values $\left(\bar{\bar{\beta}}_{pdrb}\right)$. Meanwhile, Figure 6 (f) presents the generally positive direction of GRDP influence on the district's or city's HDI in West Java.

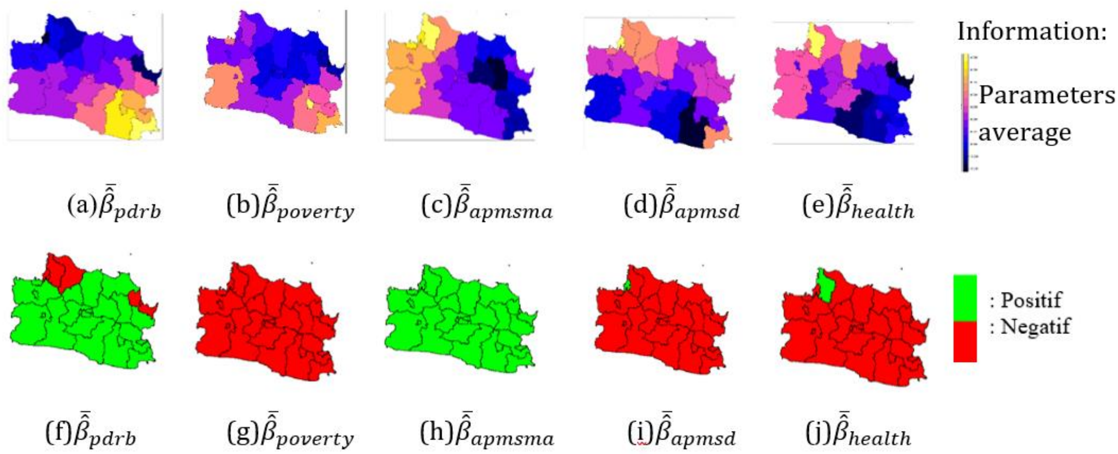

Figure 6. Distribution Map of the Mean (ae) and Direction of Influence (fj) for Estimated Explanatory Variables

Figures 6 (b) and (g) illustrate the distribution of means and direction of influence from the poverty rate parameter. The mean of the estimated poverty rate parameter ($\bar{\bar{\beta}}_{poverty}$) also tends to vary, even though its overall effect on HDI is negative. The obtained results also emphasize the similar obtained values from the areas with the adjacent location. In contrast to the poverty rate, Figure 6 (c) and (h) presents the generally positive estimated effects of the APMSMA parameter on HDI. Besides, similar to the two previous variables, the obtained $\bar{\bar{\beta}}_{apmsma}$ values are varied.

The primary school net enrollment rate and the number of health complaints in districts or cities in West Java are generally very high. Figures 6 (d) and (i) show that, in almost all regions, the primary pure enrollment rate is close to 100%. Similar to other variables, this explanatory variable also has $\bar{\bar{\beta}}_{apmsd}$different values, with a relatively negative effect on HDI, similar to the poverty rate aspect. Figures 6 (e) and (j) show that of all cities of districts, only Bekasi District has an average positive effect on the number of health complaints on HDI.

3.2.5. The Average of Estimated Variables Based on Time

Table 4 shows the average estimated value for parameter coefficients of the GTWR Great Circle Distance Fixed Exponential Kernel model based on time. The results indicate a consistent average value of coefficients every year. Further, the direction of the coefficient values in the

GTWR Great Circle Distance Fixed Kernels model is the same as the direction of the OLS Global Regression coefficient.

Table 4. Average Estimated Parameter of the GTWR Great Circle Distance Fixed Exponential Kernel Mod*el* by year

Year	$\overline{\hat{\beta}_0}$	$\bar{\hat{\beta}}_{pdrb}$	$\bar{\hat{\beta}}_{poverty}$	$\bar{\hat{\beta}}_{apmsma}$	$\bar{\hat{\beta}}_{apmsd}$	$\bar{\hat{\beta}}_{keluh}$
2015	91,847	0.006	-0.732	0.197	-0.271	-0.019
2016	94,136	0.011	-0.776	0.184	-0.289	-0.005
2017	115,319	0.010	-0.774	0.232	-0.515	-0.054
2018	138,502	0.016	-0.909	0.201	-0.727	-0.061
2019	143,611	0.014	-0.898	0.213	-0.771	-0.097
2020	159,312	0.012	-0.926	0.196	-0.912	-0.096
2021	161,754	0.014	-0.882	0.169	-0.926	-0.101

The highest average coefficient for the GRDP variable was observed in 2018 by 0.016, while the highest average coefficient for the poverty rate was in 2020 during the COVID-19 pandemic by -0.926. The highest average high school enrollment variable coefficient was identified in 2017 by 0.232, while the highest negative value was found in elementary school participation rates in 2021 by -0.926. Finally, the highest mean number of health complaints variable coefficient was in 2021 by -0.101, three years around the COVID-19 pandemic, with an increasing coefficient far above the previous years.

4. Conclusion

The results of the analysis, both descriptively and inferentially using the GTWR Great Circle Distance Fixed Kernel model, show that the Human Development Index in West Java is positively affected by location and time. Districts or cities with close locations have similar HDI values mutually influenced by location and time. Further, the closest location and time result in more closely related HDI values. This can be of particular concern to the relevant government since these variables always have a significant effect on the HDI. In addition, the HDI analysis using the GTWR Great Circle Distance Fixed Exponential Kernel model presents better results than Global OLS. This model is also able to show coefficient values at each location and time simultaneously. Therefore, this model is expected to be used by related parties. In general, HDI has a positive correlation with GRDP and high school enrollment rate., higher GRDP and high school enrollment improve the HDI value. On the other hand, HDI has a negative correlation with the level of poverty, net enrollment rate, and the number of health complaints. The smaller value of these three variables enhances the HDI value of a region. However, a more in-depth analysis of the GTWR Great Circle Distance Fixed Kernels shows that the direction $\hat{\beta}$ can vary quite a bit for each variable, location, and year. Apart from the advantages offered by the GTWR model, it also has weaknesses, including that it can only be used for non-stationary data and is very sensitive to various data conditions such as outliers, autoregressive, multicollinearity, and others. If some of these conditions are present in the data, various treatments must be carried out before the GTWR model is used.

References

Aghayari, M., Pahlavani, P., & Bigdeli, B. (2017). A geographic weighted regression for rural highways crashes modelling using the Gaussian and Tricube kernels: A case study of USA rural highways. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*(4/W4), 305–309.

Aidi, M. N., Ernawati, F., Efriwati, E., Nurjanah, N., Rachmawati, R., Julianti, E. D., … Nurfadilah, K. (2022). Spatial distribution and identifying biochemical factors affecting haemoglobin levels among women of reproductive age for each province in Indonesia: A geospatial analysis. *Geospatial Health*, *17*(2), 1118.

Bhanojirao, V. V. (1991). Human development report 1990: Review and assessment. *World Development*, *19*(10), 1451–1460.

Chu, H.-J., Kong, S.-J., & Chang, C.-H. (2018). Spatio-temporal water quality mapping from satellite images using geographically and temporally weighted regression. *International Journal of Applied Earth Observation and Geoinformation*, *65*, 1–11.

Conita, C., & Purwaningsih, T. (2020). Under-five mortality rate modeling using Geographically and Temporal Weighted Regression (GTWR). *Ahmad Dahlan International Conference on Mathematics and Mathematics Education*, *1*(1), 59–67.

Du, Z., Wu, S., Zhang, F., Liu, R., & Zhou, Y. (2018). Extending geographically and temporally weighted regression to account for both spatiotemporal heterogeneity and seasonal variations in coastal seas. *Ecological Informatics*, *43*, 185–199.

Feng, Z., Xu, C., Zuo, Y., Luo, X., Wang, L., Chen, H., … Liang, T. (2023). Analysis of water quality indexes and their relationships with vegetation using self-organizing map and geographically and temporally weighted regression. *Environmental Research*, *216*, 114587.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons.

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and Temporal Weighted Regression (GTWR). *Geographical Analysis*, *47*(4), 431–452.

Fu, Z., & Li, R. (2020). The contributions of socioeconomic indicators to global PM2. 5 based on the hybrid method of spatial econometric model and geographical and temporal weighted regression. *Science of the Total Environment*, *703*, 135481.

Harahap, R. N. (2022). *Implementasi Geographically Weighted Regression (GWR) dan Mixed Geographically Weighted Regresion (MGWR) dalam perhitungan jumlah penduduk miskin (studi kasus: Jumlah penduduk miskin Provinsi Jawa Tengah 2020)*. Universitas Islam Indonesia.

Haryanto, S., Aidi, M. N., & Djuraidah, A. (2019). Modelling of GRDP the construction sector in Java Island using Robust Geographically and Temporally Weighted Regression (RGTWR). *Repositories-Dept. of Statistics, IPB University*, *6*, 165–174.

Hickel, J. (2020). The sustainable development index: Measuring the ecological efficiency of human development in the anthropocene. *Ecological Economics*, *167*, 106331.

Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International Journal of Geographical Information Science*, *24*(3), 383–401.

Ilhami, S., Nuryartono, N., & Achsani, N. A. (2014). A*nalisis pengaruh anggaran pendidikan terhadap indeks pembangunan manusia di Indonesia.* Sekolah Pascasarjana Instutut Pertanian Bogor.

Li, W., Ji, Z., & Dong, F. (2022). Spatio-temporal evolution relationships between provincial CO_2 emissions and driving factors using geographically and temporally weighted regression model. *Sustainable Cities and Society*, *81*, 103836.

Ling, L., Qian, X., Guo, S., & Ukkusuri, S. V. (2022). Spatiotemporal impacts of human activities and socio-demographics during the COVID-19 outbreak in the US. *BMC Public Health*, *22*(1), 1466.

Liu, J., Zhao, Y., Yang, Y., Xu, S., Zhang, F., Zhang, X., … Qiu, A. (2017). A mixed geographically and temporally weighted regression: Exploring spatial-temporal variations from global and local perspectives. *Entropy*, *19*(2), 53.

Lukiswati, I. (2019). *Regresi panel terboboti geografis pada indeks pembangunan gender Jawa Tengah Tahun 2011-2015*. Institut Pertanian Bogor.

Ma, X., Zhang, J., Ding, C., & Wang, Y. (2018). A geographically and temporally weighted regression model to explore the spatiotemporal influence of built environment on transit ridership. *Computers, Environment and Urban Systems*, *70*, 113–124.

Malau, D. B. (2022). *Analisis dampak desentralisasi fiskal terhadap IPM(IPM) dan kemiskinan di Provinsi Sumatera Selatan*. Institut Pertanian Bogor.

Meyer, S., Held, L., & Höhle, M. (2014). Spatio-temporal analysis of epidemic phenomena using the R package surveillance. *ArXiv Preprint ArXiv:1411.0416*.

Pamungkas, R. A., Yasin, H., & Rahmawati, R. (2016). Perbandingan model GWR dengan fixed dan adaptive bandwidth untuk persentase penduduk miskin di Jawa Tengah. *Jurnal Gaussian*, *5*(3), 535–544.

Porcu, E., Bevilacqua, M., & Genton, M. G. (2016). Spatio-temporal covariance and cross-covariance functions of the great circle distance on a sphere. *Journal of the American Statistical Association*, *111*(514), 888–898.

Shim, J., & Hwang, C. (2018). Kernel-based geographically and temporally weighted autoregressive model for house price estimation. *PloS One*, *13*(10), e0205063.

Sholihin, M., Soleh, A. M., & Djuraidah, A. (2017). Geographically and temporally weighted regression (GTWR) for modeling economic growth using R. *Repositories-Dept. of Statistics, IPB University*, 800–805.

Wei, Q., Zhang, L., Duan, W., & Zhen, Z. (2019). Global and geographically and temporally weighted regression models for modeling PM2. 5 in Heilongjiang, China from 2015 to 2018. *International Journal of Environmental Research and Public Health*, *16*(24), 5107.

Xu, X., Luo, X., Ma, C., & Xiao, D. (2020). Spatial-temporal analysis of pedestrian injury severity with geographically and temporally weighted regression model in Hong Kong. *Transportation Research Part F: Traffic Psychology and Behaviour*, *69*, 286–300.

Yasin, H., Sugito, S., & Prahutama, A. (2015). Analisis data kemiskinan di Jawa Tengah menggunakan Metode Mixed Geographically and Temporally Weighted Regressions (MGTWR). *BIAStatistics*, *9*(1), 15–23.