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Analysis of Factors Affecting the Human Development Index in Papua Province Using the Geographically Weighted Panel Regression Model

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Abstract

The level of human quality development between regions or countries can be measured using the Human Development Index (HDI) value. The higher the value of the HDI, the better the quality of human development in the region. Some variables affect the value of the HDI. This study will test six independent variables using the Geographically Weighted Panel Regression (GWPR) method. This GWPR method combines panel data regression with the Geographically Weighted Regression (GWR) method. This GWPR method combines the dimensions of location and time to determine the effect of the independent variable on the dependent variable. Therefore, the purpose of this study is to see which variables have a significant effect on the value of the HDI in Papua Province. By using panel data regression, the best model that can be formed is the Fixed Effect Model (FEM). However, the FEM model that was formed did not meet the heteroscedasticity assumption test on the residuals, so further modeling was carried out using the GWPR model. GWPR modeling on this data uses a kernel weighting function, whereas previously, data transformation was carried out by the concept of the FEM model. The GWPR model with the best kernel weighting function is fixed exponential. In selecting the best model based on the coefficient of determination (R^2), the GWPR model is better than the FEM model. Regarding the significance of model parameters, nine groups of districts/cities based on independent variables significantly affect the HDI. In all districts/cities of Papua Province, the per capita expenditure variable significantly affects the HDI's value.
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INTRODUCTION

The Human Development Index (HDI) is a measure of the quality of human development in a region by combining three primary dimensions, namely longevity, knowledge (education), and a decent standard of living[1]. The HDI divides the level of human development classification into four status categories, low (< 60), medium $(60 \leq IPM \leq 70)$, high $(70 \leq IPM \leq 80)$, and very high ($\geq$ 80) [1]. The higher the value of the HDI, the more it shows that human development in a region is excellent. Human development emphasizes that community involvement is significant in the development process stage because the community plays a direct role in increasing the HDI figure.

According to the Central Statistics Agency (BPS), it was recorded that in the last five years, the highest and lowest HDI positions have not changed significantly, with DKI Jakarta occupying the highest HDI position, while Papua Province occupies the lowest HDI position[2]. Papua Province occupies the lowest position in the HDI value because development in the province is still facing various problems, such as the implementation of special autonomy that has not been optimal, inadequate infrastructure and connectivity development, development of superior potential based on natural resources, and limitations in essential services and vulnerability to social inequality and poverty[2]. In this case, the HDI is also referred to as a composite index because the HDI value is formed from several variable indicators that represent aspects of human development[3]. Therefore, the HDI value will be relevant if the variable indicator selection is correct. Statistical analysis is needed to identify the variables that significantly affect the HDI.

The value of the HDI in the Regency/City of Papua Province can be influenced by spatial aspects or geographical conditions. Spatial heterogeneity is one of the influences caused by spatial aspect problems that contribute to differences in HDI values in the Regency/City of Papua Province. To handle this problem, the Geographically Weighted Regression (GWR) method is needed[4]. This GWR model can produce local estimated regression coefficient values[5]. The GWR method is built using a point approach, which means that the regression model parameters will produce different values in each location based on the latitude and longitude positions[6]. This method only uses one observation period, while if you want to analyze the factors that influence the HDI value in the Regency/City of Papua Province in general, you can use data with several periods (panel data). However, the GWR method is unsuitable for panel data use, so it is necessary to approach it with another method.

One method suitable for analyzing the factors that influence the HDI value in the Regency/City of Papua Province on panel data that pays attention to spatial aspects is the Geographically Weighted Panel Regression (GWPR) analysis. The GWPR method is a combined method of panel data regression with the GWR method[7]. The GWPR method will estimate model parameters based on the value of the selected kernel weighting and the optimum *bandwidth value* calculated with the *cross-validation* (CV) value. This method is suitable for analyzing the factors that influence the HDI value because it can produce a model for each region on data that depends on time and has high heterogeneity.

Previous research on the factors influencing HDI in Indonesia has been conducted by Retno Mayapada et al. [8]. This study used the *random forest regression method* to determine the factors influencing the HDI in Indonesia. The study results determined that per capita expenditure is the factor that most influences HDI in Indonesia. In addition, other research has been conducted by Kenny Dwi Lorenza et al. [9]. In this study, an analysis of the factors influencing the HDI in the Regency/City of Lampung Province was carried out using the Spatial Autoregressive (SAR) method. The study results showed that the factors influencing the HDI in the region were the average length of schooling and adjusted per capita expenditure.

Then, the research was conducted by Rahmat Hafizatul Fajri [10]. Using the panel data regression method, this study analyzed factors influencing the Human Development Index in

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Riau Province. The selected model is the Random Effect Model (REM), which results in the average length of schooling being a significant variable influencing the Human Development Index. Previous research that considered spatial and time aspects was conducted by Dia Cahya et al. [11]. In this study, an analysis of factors influencing the Human Development Index in East Java was conducted using the GWPR method. The study results obtained three groups of Regency/City based on factors that influence the Human Development Index value.

Based on the explanation above, this study analyzed the factors influencing the HDI value in Papua Province by considering spatial and time aspects. The GWPR method can be used in this study. The results of this study will produce several groups of Regency/City based on independent variables that significantly affect the HDI value. The analysis results of the factors that influence the HDI value in Papua Province can be used as a strategy for making policies related to increasing the HDI value in Papua Province.

METHODS

1. Data

The data used in this study are quantitative data obtained from the Central Statistics Agency (BPS) and the Papua Province Human Development Index Publication Book in 29 Regencies/Cities in 2019-2023. The data used are Human Development Index data (Y) in percent, with six independent variables, namely, the average length of schooling (X_1) In years, the percentage of poor population (X_2), life expectancy (X_3) in years, expected length of schooling (X_4) in years, per capita expenditure (X_5) in thousand rupiahs, and life expectancy (X_6) in years. Regency/City location data in the form of longitude and latitude are also used, obtained from the location point of the Mayor's or Regent's office in each Regency/City.

2. Detecting Multicollinearity

Multicollinearity testing is performed to determine whether there is a strong correlation between two or more independent variables in the regression model. To determine whether or not there is multicollinearity, the value of the Variance Inflation Factors (VIF) is looked at [12]. If the value is $VIF < 10$ high, then it can be concluded that there is no multicollinearity between the independent variables. However, if the value of $VIF > 10$ then it can be concluded that there has been multicollinearity between the independent variables.

3. Forming a Panel Data Regression Model

The formation of panel data regression models is carried out after conducting multicollinearity tests on the data. Panel data regression combines *cross-section* and *time series data* [13]. This means data is collected at various times and from different observation units. In other words, panel data collects information from similar observation units repeatedly in different periods, allowing for a more in-depth analysis of changes in variance between times and observation units [11]. Three approach models can be used to estimate the model, namely *the Common Effect Model* (CEM), *the Fixed Effect Model* (FEM), and *the Random Effect Model* (REM).

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4. Model Selection

Two tests will determine the best panel data regression model in model selection. The two tests are the Chow test and the Hausman test. In panel data regression, the Chow test is carried out to select a better model between CEM and FEM [7]. After the Chow test is carried out, the Hausman test can be carried out if, in the Chow test, the best model selected is the FEM model. The Hausman test is used to select a better model between REM and FEM [7].

5. Selected Panel Data Regression Testing

In regression analysis, assumption tests are significant in ensuring that the regression model meets the basic requirements to produce unbiased estimated values. These assumption tests include normality, autoregression, and heteroscedasticity tests. Normality tests are conducted to ensure that the residual distribution is normally distributed. One of the test statistics that can be used to determine whether the regression model is normally distributed is the *Kolmogorov-Smirnov test* [14]. After the residuals are normally distributed, the autocorrelation test is continued, which is used to detect whether or not there is a correlation between times in the residuals.

Autocorrelation testing is carried out to ensure that the model's residuals are not interrelated so that the estimates produced from the model are more accurate. One of the autocorrelation tests that can be used is the *Durbin-Watson test* [15]. After the autocorrelation test is fulfilled, namely, there is no autocorrelation, the next step is to carry out heteroscedasticity testing to detect whether or not there is an inequality of variance from the residuals in the regression model. In panel data regression, one of the tests that can be used is the *Breunch-Pagan test* [11]. If the residual assumption test is not fulfilled, further analysis is carried out to handle the problem using the GWPR method.

6. Geographically Weighted Panel Regression (GWPR) Model

Geographically Weighted Panel Regression (GWPR) is a model formed from a combination or development of the Geographically Weighted Regression (GWR) model using a panel data regression model [7]. This Geographically Weighted Panel Regression (GWPR) analysis aims to combine the location dimension (*cross-sectional)* and time observation to determine the effect of independent variables on dependent variables that can vary not only based on geographic location but also over time. In this study, the best panel model is the FEM model, so that the GWPR equation used is as follows:

$$y_{it} = \beta_1(u_i, v_i)x_{1it} + \beta_2(u_i, v_i)x_{2it} + \cdots + \beta_k(u_i, v_i)x_{kit} + \varepsilon_{it}$$

Where,

y_{it}	:	dependent variable at observation location *i* at the time *t*,
$\beta_k(u_i, v_i)$	:	the regression coefficient of independent variables *k* at the observation location *i*,
(u_i, v_i)	:	Coordinate the point of the geographical location of the observation location *i*
ε_{it}	:	residual of *observation i* at time *t*

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This equation is obtained from the results of the *within transformation,* which is carried out by subtracting the actual (fixed) data from the average value of *the time series* in the equation model [16].

7. GWPR Model Parameter Estimation with Kernel Weighting Function

The estimation of the GWPR model parameters is done using the kernel function. The weight value in the GWPR model is the same as the weight value in the GWR model, where this weight value has a vital role because the weight value represents the location and observation of each other or depends on the distance between observation location points. It can be done using the kernel function to determine the magnitude of the weight value for each location [17]. This model has two types of kernel functions: *fixed kernel* and *adaptive kernel. The fixed kernel* is a function with the same *bandwidth* at each observation location. *The fixed kernel* consists of *fixed Gaussian, fixed bisquare,* and *fixed exponential.* At the same time, *the adaptive kernel* is a kernel function with different *bandwidth* at each observation location [18]. *The adaptive kernel* consists of *adaptive Gaussian, adaptive bisquare,* and *adaptive exponential. Calculating the Cross Validation (CV)* value is one way to find the best *bandwidth.* The optimum *bandwidth* produces a minimum CV value [19].

8. GWPR Model Testing and Best Model Selection

The selected GWPR Model was tested using the goodness of fit and model significance tests to obtain significant parameter results [12]. The best model in the GWPR method can be selected by considering the value of the determination coefficient (R^2). The determination coefficient is a measure that describes how well a model can explain the influence of independent variables on dependent variables [20].

RESULTS AND DISCUSSION

1. Descriptive Analysis

Before modeling, a descriptive analysis of the data is first carried out. This descriptive data analysis aims to provide a general description and to know the essential characteristics of the data to be studied. This descriptive data analysis is also critical in helping to understand, analyze, and convey the information in the data. The following is a descriptive statistic of the data in Table 1.

Table 1. Descriptive Analysis of Data on Districts/Cities in Papua Province

Variables	Year	Average	Minimum	Maximum	Standard Deviation
Y	2019	57.30	30.75	80.16	11.41
	2020	57.29	31.55	79.94	11.28
	2021	57.70	32.84	80.11	11.10
	2022	58.49	34.10	80.61	10.99
	2023	59.38	35.19	81.14	10.92
X_1	2019	6.009	0.970	11.550	3.08
	2020	6.152	1.130	1.560	3.09
	2021	6.249	1.420	11.570	3.02
	2022	6.417	1.580	11.740	3.06

	2023	6.536	1.710	11.840	3.08
X_2	2019	29.22	10.35	43.65	10.02
	2020	28.21	10.03	41.76	9.61
	2021	28.38	10.16	41.66	9.73
	2022	28.20	10.10	42.03	9.58
	2023	27.61	10.01	40.01	9.43
X_3	2019	64.98	55.12	72.27	3.81
	2020	65.19	55.27	72.32	3.75
	2021	65.26	55.43	72.36	3.67
	2022	65.53	55.70	72.57	3.65
	2023	68.57	63.88	72.75	2.02
X_4	2019	10.29	3.29	15.00	2.87
	2020	10.44	3.61	15.01	2.81
	2021	10.58	3.87	15.02	2.81
	2022	10.69	4.07	15.04	2.79
	2023	10.80	4.33	15.26	2.77
X_5	2019	7102	4181	15176	2607.31
	2020	6795	3975	14763	2530.64
	2021	6820	3976	14937	2544.74
	2022	7020	4190	15189	2561.57
	2023	7346	4352	15272	2573.22
X_6	2019	64.98	55.12	72.27	3.81
	2020	65.12	55.27	72.32	3.74
	2021	65.26	55.43	72.36	3.67
	2022	65.53	55.70	72.57	3.65
	2023	65.77	55.72	72.83	3.67

Based on Table 1, the average value of the Human Development Index of the Regency/City of Papua Province in 2019-2023 tended to increase even though it had decreased in 2020. From the 2019-2023 data, the lowest Human Development Index occurred in 2019 in Nduga Regency, at 30.75%, while the highest Human Development Index occurred in 2023 in Jayapura City 81.14%. The average value of the average length of schooling (RLS) data in the Regency/City of Papua Province increased during 2019-2023. However, the average value is still around 6-7 years. From the 2019-2023 data, the smallest RLS value occurred in 2019 in Nduga Regency, while the highest RLS value occurred in 2023 in Jayapura City 11.840 years.

Furthermore, the average value of the percentage of poor people in the regencies/cities of Papua Province decreased during 2019-2023. The highest percentage of poor people occurred in 2019 in Deiyai Regency 43.65% while the lowest occurred in 2023 in Merauke Regency 10.01%. In addition, the average value for life expectancy (UHH) in the regencies/cities of Papua Province increased during 2019-2023. The highest UHH value occurred in 2023 in Mimika Regency 72.75 years while the lowest UHH value occurred in 2019 in Nduga Regency. The expected length of schooling (HLS) in the regencies/cities of Papua Province also increased during 2019-2023. The highest HLS value occurred in 2023 in Jayapura City 15.26 years, while the lowest HLS value occurred in 2019 in Nduga Regency 3.29 years.

The average value of per capita expenditure in the Regency/City of Papua Province during 2019-2023 decreased in 2020 but then increased again until 2023. The most significant per capita expenditure occurred in 2023 in Jayapura City $15{,}272{,}000$ while the most minor per capita expenditure occurred in 2020 in Nduga Regency $3{,}975{,}000$. Finally, the average life expectancy (AHH) value in the Regency/City of Papua Province during 2019-2023 increased. The most considerable AHH value occurred in 2023 in Mimika Regency, 72.83 years and the smallest AHH value occurred in 2019 in Nduga Regency, which was 55.12 years.

2. Multicollinearity Testing

The presence or absence of multicollinearity in the model can be detected using the VIF value. The following are the results of the VIF value of each variable.

Table 2. VIF values

Variabel	VIF
X_1	8.281316
X_2	3.293838
X_3	4.755180
X_4	5.268938
X_5	4.400785
X_6	4.829928

Based on Table 2, all independent variables have values $VIF < 10$, so it can be concluded that there is no multicollinearity between independent variables. So, all existing independent variables can be used for further analysis.

3. Panel Data Regression Model Selection with Chow Test and Hausman Test

Panel data regression modeling is then carried out using all independent variables. The selection of the panel data model is determined using the Chow test and the Hausman test. The following is a table of the results of the Chow test and the Hausman test.

Table 3. Results of the Chow Test and Hausman Test

Test	Count Statistics	$p - value$	Decision	Information
Chow Test	$F_{hitung} = 84.683$	2.2×10^{-16}	Reject H_0	The FEM model is better than CEM.
Hausman test	$\mathcal{X}_k^2 = 15.33$	0.01784	Reject H_0	The FEM model is better than REM.

Based on the table above, the value $p - value$ of the Chow test is less than 0.05 then H_0 reject, which means that the FEM model is better to use than the CEM model. Furthermore, the Hausman test is carried out to compare the FEM model with the REM model. The value $p - value$ of the Hausman test is less than 0.05 then H_0 reject, which means that the FEM model is better to use than the REM model. From both tests, it can be concluded that the FEM model is the best in the panel data regression model.

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4. Testing Assumptions on FEM Model Residuals

After the FEM model is selected, the next step is to test the assumptions on the residuals to determine whether the FEM model has met all the assumptions on the residuals. The following are the results of the assumption test on the residual model presented in the table below.

Table 4. Test Results on Residual Assumptions

Test	$p-value$	Decision
Normality Test	0.3606	H_0 accepted
Autocorrelation Test	0.8087	H_0 accepted
Heteroscedasticity Test	2.375×10^{-14}	H_0 rejected

Based on the table above, the results of the residual normality test carried out using the *Kolmogorov-Smirnov test* obtained a value $p-value > 0{,}05$ H_0 accepted, which means that the residuals of the FEM model are normally distributed. Likewise, the results of the autocorrelation test carried out using the *Durbin-Watson test* obtained a value of $p-value > 0{,}05$ H_0 accepted, which means that there is no autocorrelation in the residuals of the FEM model. While the heteroscedasticity test carried out using the *Breusch-Pagan test* obtained *p-value* < 0.05, H_0 rejected, which means that there is heteroscedasticity in the residuals of the FEM model.

Based on the overall results of the residual assumption test on the FEM regression model, it can be concluded that there are assumptions that are not met; namely, the residual assumption of the model is homoscedastic. The residual model is heteroscedastic, indicating a diversity of variances between observation units. This may occur because spatial aspects influence it. Therefore, further analysis is carried out to address this problem using the GWPR method.

5. GWPR Model Estimation with Kernel Weighting Function

GWPR modeling uses the FEM model obtained from the previous panel data regression. This modeling begins with estimating the parameters of the GWPR model. The first thing to do is to transform the data according to the concept of the FEM model. After the transformation, the next step is to find the kernel weighting value of the six kernel functions: *adaptive square, adaptive Gaussian, adaptive exponential, fixed square, fixed Gaussian,* and *fixed exponential. The results of this kernel weighting value are then selected based on the* optimum *bandwidth* value, as well as with the smallest *bandwidth value, which* can also be seen by using the (R^2) most significant coefficient of determination value. The following is a table of the results of the kernel function calculation.

Table 5. Results of Kernel Function

Kernel Functions	BW	R^2
Adaptive Bisquare	26	99.69%
Adaptive Gaussian	46	97.29%
Adaptive Exponential	26	98.28%
Fixed Bisquare	2.834115	98.17%
Fixed Gaussian	0.3403098	99.77%

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Fixed Exponential	0.2572253	99.88%

Based on Table 5, because the *fixed exponential kernel function* has the (R^2) most significant coefficient of determination value 99.88% and the smallest bandwidth value 0.2572253, *the fixed exponential* kernel function will then be used to form a weighting matrix to produce model parameter estimates.

By using *fixed exponential weighting,* one example of the GWPR model equation in Jayawijaya Regency is obtained as follows:

$$y_{8t} = 4.2792 \times 10^{-15} + 2.0775x_{8t1} + 0.0928x_{8t2} - 0.0167x_{8t3} + 1.7653x_{8t4} + 0.0018x_{8t5} - 0.3238x_{8t6}$$

6. GWPR Model Suitability Testing

The suitability test of this model is conducted to determine whether there is a significant difference between the panel regression model and the GWPR model. The results of the suitability test of this model are as follows:

Table 6. Results of GWPR Model Suitability Testing

$p-value$	Decision
2.686198×10^{-8}	Reject H_0

With the significance level, $\alpha = 5\%$ the value obtained from $p - value < 0,05$ the reject H_0 means a significant difference exists between the panel regression model and the GWPR model on the HDI data in the Regency/City of Papua Province.

7. Best Model Selection

Model evaluation is done to see which model is the best among the models used. In this study, model evaluation is done by comparing the coefficient of determination values (R^2). The model with R^2 the most significant value is the best. The following are the results R^2 of the panel data model and the GWPR model.

Table 7. Selection of the Best Model

Model	R^2
GWPR	99.88%
FEM	96.49%

Based on Table 7, (R^2) the most considerable determination coefficient value is obtained from the GWPR model 99.88%. This means that the GWPR model is better than the FEM model in modeling the Human Development Index in the Regency/City of Papua Province in 2019-2023.

8. Significance of Model Parameters

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The GWPR model parameter significance test was conducted to determine which independent variables significantly influence the HDI. The model parameter significance test was conducted using a significance level of $\alpha = 5\%$. An independent variable is significant to the HDI if $p - value$ the test result is less than α . From the parameter significance test analysis results, nine groups of regencies/cities were obtained based on independent variables that significantly influence the HDI. The nine groups are included in the grouping map image, which is colored according to their respective groups. The following are groups of regencies/cities based on independent variables that have a significant influence on the HDI:

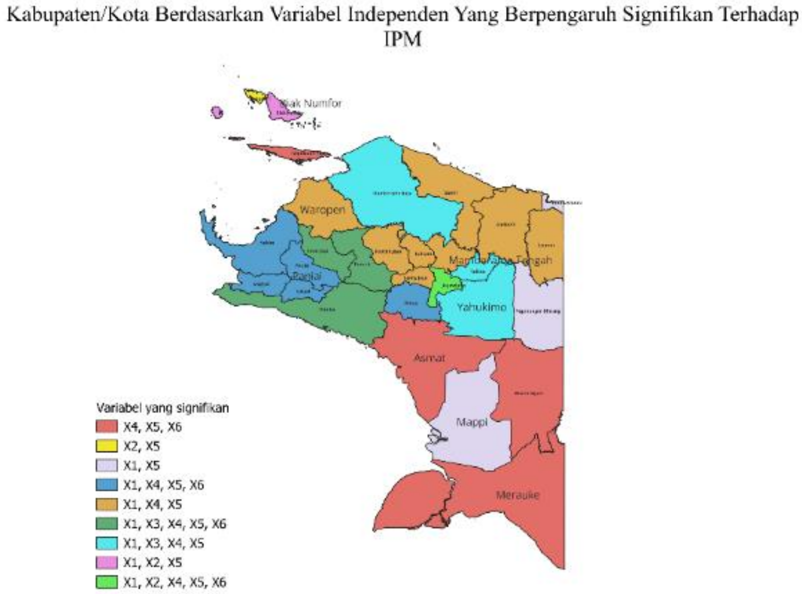

Figure 1Map of District/City Grouping Based on Independent Variables that Have a Significant Influence on HDI

Table 8. Grouping of Districts/Cities Based on Independent Variables that Have a Significant Influence on the Human Development Index

Regency/City	Significantly Influential Variables
Asmat, Boven Digoel, Yapen Islands, Merauke	X_4, X_5, X_6
Biak Numfor	X_1, X_2, X_5
Deiyai, Dogiyai, Nabire, Nduga, Paniai	X_1, X_4, X_5, X_6
Intan Jaya, Mimika, Puncak	X_1, X_3, X_4, X_5, X_6
Jayapura, Keerom, Lanny Jaya, Central Memberamo, Puncak Jaya, Sarmi, Tolikara, Waropen	X_1, X_4, X_5
Jayawijaya	X_1, X_2, X_4, X_5, X_6
Jayapura City, Mappi, Star Mountains	X_1, X_5
Greater Memberamo, Yahukimo, Yalimo	X_1, X_3, X_4, X_5
Supiori	X_2, X_5

Based on Figure 1 and Table 8, it can be seen that the per capita expenditure variable has a significant effect on the value of the HDI in all regencies/cities. The RLS variable has a significant effect on seven groups of regencies/cities, but RLS does not have a significant effect on regencies/cities with details of regencies, namely Asmat, Boven Digoel, Yapen Islands, Merauke, and Supiori. The UHH variable only significantly affects two groups of regencies/cities with details of regencies, namely Intan Jaya, Mimika, Puncak, Memberamo Raya, Yahukimo, and Yalimo.

The percentage of poor population variable significantly affects three groups of regencies/cities with details of the regencies, namely Biak Numfor, Jayawijaya, and Supiori. The HLS variable significantly affects six groups of regencies/cities but does not significantly affect the regencies/cities, namely Biak Numfor, Jayapura City, Mappi, Pegunungan Bintang, and Supiori. The AHH variable has a significant effect on four groups of regencies/cities with details of the regencies, namely Asmat, Boven Digoel, Yapen Islands, Merauke, Deiyai, Dogiyai Regency, Nabire, Nduga, Paniai, Intan Jaya, Mimika, Puncak, and Jayawijaya. The results of this grouping are only based on the RLS variables, percentage of poor population, UHH, HLS, per capita expenditure, and AHH, which significantly affect the HDI value in Papua Province. Other variables that have a significant effect on different HDIs can be produced. The results of this grouping are also only based on a period of five years. If the period differs, it can also produce variables that significantly affect different HDIs.

CONCLUSION

Based on the discussion, it was found that by using panel data regression, the best model that can be formed is the FEM model, but the FEM model that was formed did not meet the homoscedasticity assumption, so further modeling was carried out using GWPR. In this study, the best kernel weighting function obtained in GWPR modeling was *fixed exponential*. The GWPR model obtained had a determination coefficient (R^2) of 99.88%. From the GWPR model, nine groups of regencies/cities were obtained based on independent variables that significantly influence the HDI. The per capita expenditure variable significantly influences the value of the HDI in all regencies/cities in Papua Province. This study did not discuss what factors most influence the HDI value; it only looked at the factors that significantly influence the HDI so that further research could be carried out on analyzing the factors that most influence the HDI.

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