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Provincial Real Economic Growth in Indonesia: Investigating Key Factors Through Spatial Analysis

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Abstract

This study addresses the need to understand provincial real economic growth, as measured by gross regional domestic product (GRDP), by conducting a spatial analysis. The study focuses on the influential factors of physical investment, working labor force, social infrastructure relative to the head-count index of poverty, and human development index (HDI). Data from 34 provinces spanning eight years (2015-2022) were examined using geographically weighted panel regression with a fixed effect of provincial units and adaptive bisquare kernel function as spatial weights. The study identifies distinct spatial patterns in the variable impact on provincial real economic growth, forming groups based on influential factors. Physical investment and HDI significantly drive growth in most provinces. The working labor force strongly impacts Papua Island's growth. Intriguingly, social infrastructure relative to the head-count index of poverty link to economic growth emerges in the central and eastern regions of Indonesia (Kalimantan, Sulawesi, Maluku, and Papua), highlighting its role in poverty reduction and inclusive growth. The findings highlight the importance of region-specific policies to optimize the potential of these variables and promote balanced economic growth across the province.



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1. Introduction

The economic landscape of Indonesia is marked by diverse regional disparities, with provinces experiencing varying economic growth and development levels [1]. These disparities can be attributed to a multitude of factors, including differences and changes in natural resources, infrastructure, government policies, socio-economic and cultural conditions, demography, and other internal and external influences that impact economic growth at the provincial level [2–7]. As a result, the economic growth trajectory can vary between both provinces and over time [8, 9]. As economic growth is multifaceted and influenced by a complex interplay of

factors, conducting a comprehensive spatial analysis is essential [10]. Such an analysis allows us to account for the spatial heterogeneity and interactions among various determinants of economic growth across provinces [10]. By employing spatial analysis techniques, policymakers can gain valuable insights into the spatial patterns and dynamics of economic growth, facilitating evidence-based decision-making for sustainable development [11].

Data at the regional level cannot be said to be independent of each other between regions because there are similarities between neighboring regions [8, 12]. Ignoring the influence or spatial dependence on the dependent (response) or independent (explanatory)

variable is similar to not including one or more relevant independent variables in the model [13]. Spatial distance is an important factor in reducing regional socio-economic disparities [14, 15]. The spatial factors are important in understanding regional disparities, especially given the complexity of regional economic growth patterns [15].

Spatial effects between regions can be in the form of spatial dependence and spatial diversity [16]. Spatial dependencies occur due to the linkage of events in one region to other events in different areas. Spatial diversity occurs due to differences in the effect of the independent variables on the dependent variable between regions. Spatial diversity can be in the form of structural instability (non-stationary) and heteroscedasticity [17]. Non-stationary is related to structural parameters (regression coefficients) that differ between regions, while heterogeneity is related to the range of errors that vary between regions. One model of spatial diversity is geographic weighted regression (GWR). The development of GWR on panel data is known as geographic weighted panel regression (GWPR) which combines GWR modeling with panel regression models.

In previous research, infrastructure, foreign investment, human capital, globalization, and physical investment (Gross Fixed Capital Formation/GFCF) affect GDP per capita [18]. The HDI can affect the GDP per capita [19]. In both long-term and short-term, export and GFCF have positive impact on GRDP showing that the increase in export and/or GFCF will increase GRDP, which will result in economic growth [20]. GRDP is influenced by investment (GFCF) and Original Local Government Revenue (OLGR) [21]. GRDP is influenced by the number of the working force and OLGR [17]. The number of workers, OLGR, human development index (HDI), and minimum wages have varied effects on GRDP at the regency/city level [22]. Another study shows the opportunity to achieve higher economic growth through a productive labor force by increasing government spending on the health and education sectors [23]. Physical infrastructure (roads and bridges, irrigation, as well as airports and ports) and social infrastructure (health and education) affect GDP [3].

Based on previous research, this study uses four independent variables, namely GFCF, the number of working labor force, the number of social infrastructure relative to head-count index of poverty, and HDI. By incorporating these four independent variables into the GWPR model, it is expected to provide an overview of the effect of these independent variables on GRDP and a more comprehensive understanding of economic growth and regional development at the provincial level. The

division of the number of social facilities by regional poverty indicator is intended so that research can provide insight into how social facility factors influence economic growth by taking into account regional poverty conditions. By analyzing the interplay of these factors across provinces, we seek to shed light on the dynamics of economic growth and identify the drivers that contribute to regional disparities.

In this research, we aim to examine the diverse determinants influencing provincial real economic growth, measured by gross regional domestic product (GRDP), in Indonesia through spatial analysis of GWPR. Understanding the underlying determinants that drive these disparities is of paramount importance for policymakers seeking to bolster economic performance and reduce provincial disparities, thereby fostering inclusive growth across the provinces [1, 24]. By recognizing each province's unique challenges and opportunities, policymakers can develop context-specific policies and allocate resources more efficiently to address the diverse needs of different regions. Our study provides policymakers with the insights they need to navigate the intricate world of regional economic growth to support a path of more inclusive growth that brings prosperity to all provinces. Essentially, our work not only breaks down and explains the factors that lead to economic differences between regions but also helps policymakers work towards balanced and fair development.

2. Materials and Methods

2.1. Data

This research utilizes panel data obtained from Statistics Indonesia (BPS), comprising cross-section of 34 provincial units in Indonesia and spanning time series of eight years from 2015 to 2022. The panel data is structured as balanced, short, and fixed. It is balanced, as there are no missing values, and data is available for each unit and time. The data is considered short, as the number of time series observations is less than the number of cross-sectional units. Additionally, the panel data is fixed, as the same set of cross-sectional units is observed consistently over the entire period.

The dataset consists of one dependent variable, GRDP, denoted as Y , and four independent variables, X_1 to X_4 . Detailed descriptions of these variables are provided in Table 1. GRDP was chosen as the dependent variable because GRDP information can provide an overview of the size of economic activity in a province, while the rate of economic growth illustrates changes in the percentage of GRDP from time to time.

Table 1. Research variables

Label	Variable	Description	Unit	Transformation
Y	GRDP	Nominal of Gross Regional Domestic Product (GRDP) at Constant Prices with 2010 base year.	Million rupiah	natural logarithm
X ₁	GFCF	Nominal of Gross Fixed Capital Formation (GFCF) as physical investment. GFCF reflects the physical investment that plays a role in the development of economic sectors.	Million rupiah	natural logarithm
X ₂	WLF	Number of Working Labor Force (WLF) in August. WLF shows the productive potential of the region from the level of labor participation in economic activity.	People	natural logarithm
X ₃	SI-HCI	Number of Social Infrastructure (SI) relative to the head-count index of poverty (HCI). SI are the health and education facilities. Health facilities can support increased quality of life and productivity, while educational facilities can create a skilled, knowledge-based labor force.	Unit	natural logarithm
X ₄	HDI	Human Development Index (HDI). HDI provides an overview of the quality of human development achievements based on three dimensions, which are health, knowledge, and a decent standard of living.	Percent	natural logarithm

2.2. Method

The research was conducted in R using various R packages, mainly the GWPR.light [25] and rgdal [26]. This research follows the given procedures:

- 1). Prepare and align panel data and spatial data. This research merges the data panel with the spatial data attached to ESRI shapefile format.
- 2). Perform data exploration to get the general overview of the data.
- 3). Check multicollinearity using variance inflation factor (VIF). The formula to calculate the VIF for the *k*-th independent variable is presented by equation 1:

$$VIF = (1 - R_k^2)^{-1} \tag{1}$$

where R_k^2 is the coefficient of determination (R-squared) for the regression model where the *k*-th independent variable is regressed on all the other independent variables in the model.

- 4). Perform panel regression model as follows:
 - a. Specify the data with pooled model or common effect model (CEM). CEM assumes that the relationships between the variables are constant across all cross-sectional units and time series. The form of CEM is presented by equation 2:

$$\ln(Y_{ij}) = \alpha + \beta_1 \ln(X_{1ij}) + \beta_2 \ln(X_{2ij}) + \beta_3 \ln(X_{3ij}) + \beta_4 \ln(X_{4ij}) + \varepsilon_{ij} \tag{2}$$

which *i* is cross-sectional unit of province with $n=34$; *j* is time series of year with 2015 as $j=1$ so on until 2022 as $j=t=8$; Y_{ij} is GRDP for *i*-th province and *j*-th year; X_{1ij} is GFCF for *i*-th province and *j*-th year; X_{2ij} is WLF for *i*-th province and *j*-th year; X_{3ij} is SI-HCI for *i*-th province and *j*-th year; X_{4ij} is HDI for *i*-th province and *j*-th year; α is the intercept; $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameters for independent

variables, and ε_{ij} as error term for *i*-th province and *j*-th year.

$$\ln(Y_{ij}) = \alpha + \beta_1 \ln(X_{1ij}) + \beta_2 \ln(X_{2ij}) + \beta_3 \ln(X_{3ij}) + \beta_4 \ln(X_{4ij}) + \varepsilon_{ij} \tag{3}$$

which *i* is cross-sectional unit of province with $n=34$; *j* is time series of year with 2015 as $j=1$ so on until 2022 as $j=t=8$; Y_{ij} is GRDP for *i*-th province and *j*-th year; X_{1ij} is GFCF for *i*-th province and *j*-th year; X_{2ij} is WLF for *i*-th province and *j*-th year; X_{3ij} is SI-HCI for *i*-th province and *j*-th year; X_{4ij} is HDI for *i*-th province and *j*-th year; α is the intercept; $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameters of independent variables; and ε_{ij} as error term for *i*-th province and *j*-th year.

- b. Perform Lagrange Multiplier Breusch–Pagan (LM-BP) test to test the presence of cross-sectional unit of province or time effects on the residuals of CEM [15, 16]. If the LM-BP test for two-way and one-way effects resulted in insignificant p-values, then the appropriate model is CEM and continues to step (6).
- c. Specify the data with fixed effect model (FEM) and the random effect model (REM) along with the significant one-way or two-way error components. FEM allows for individual-specific intercepts, capturing unit-specific time-invariant characteristics that may cause heterogeneity across units. Meanwhile, REM assumes that the individual-specific intercepts are random variables with certain distributional assumptions. The equation forms of FEM/REM unit, time, and unit and time are presented by equation 3, 4, and 5, respectively:

$$\ln(Y_{ij}) = \alpha + \mu_i + \beta_1 \ln(X_{1ij}) + \beta_2 \ln(X_{2ij}) + \beta_3 \ln(X_{3ij}) + \beta_4 \ln(X_{4ij}) + \varepsilon_{ij} \tag{4}$$

$$\ln(Y_{ij}) = \alpha + \lambda_j + \beta_1 \ln(X_{1ij}) + \beta_2 \ln(X_{2ij}) + \beta_3 \ln(X_{3ij}) + \beta_4 \ln(X_{4ij}) + \varepsilon_{ij} \quad (5)$$

$$\ln(Y_{ij}) = \alpha + \mu_i + \lambda_j + \beta_1 \ln(X_{1ij}) + \beta_2 \ln(X_{2ij}) + \beta_3 \ln(X_{3ij}) + \beta_4 \ln(X_{4ij}) + \varepsilon_{ij} \quad (6)$$

which i is cross-sectional unit of province with $n=34$; j is time series of year with 2015 as $j=1$ so on until 2022 as $j=t=8$; Y_{ij} is GRDP for i -th province and j -th year; X_{1ij} is GFCF for i -th province and j -th year; X_{2ij} is WLF for i -th province and j -th year; X_{3ij} is SI-HCI for i -th province and j -th year; X_{4ij} is HDI for i -th province and j -th year; α is the intercept; $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameters for independent variables; μ_i is the effect of cross-sectional unit for i -th province, fixed for FEM and random for REM; λ_j is the effect of time series for j -th year, fixed for FEM and random for REM; and ε_{ij} as error term for i -th province and j -th year.

- d. Chow test is used to test the significance parameter between CEM and FEM [27, 28]. If there is not enough evidence to reject the null hypothesis then the appropriate model is CEM and continue to step (6).
- e. Hausman test to test whether the model is REM or FEM [27, 28].
- f. Check the assumption of uncorrelated and normality of the errors of panel regression model. Handle data if the assumption is violated.
- g. Breusch-Pagan (BP) test is used to test the variance homogeneity of the errors of panel regression model [16]. If there is not enough evidence to reject the null hypothesis then the appropriate model is panel regression model, whether CEM, FEM, or REM. Continue to step 7).

5). Perform spatial panel regression model with GWPR. The GWPR with CEM is the same as GWR. The GWPR with fixed effect is called as GWPR FEM followed by the significant effect, i.e., GWPR FEM unit, GWPR FEM time, or GWPR FEM unit and time. The same rule applied to GWPR REM. The procedure to perform spatial panel regression model with GWPR as follows:

- a. Calculate the Euclidean distance between the location of i -th unit and j -th unit with equation 7:

$$d_{ij} = \left[(u_i - u_j)^2 + (v_i - v_j)^2 \right]^{1/2} \quad (7)$$

which (u_i, v_i) is the coordinate of i -th unit and (u_j, v_j) is the coordinate of j -th unit

- b. Select the best kernel function with the optimum adaptive bandwidth based on the smallest cross-validation (CV) criterion. This research considered five adaptive kernel functions presented by equation 8 to 12, respectively [25], [29]:

- Bisquare

$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i} \right)^2 \right]^2 & \text{for } d_{ij} \leq h_i \\ 0 & \text{for } d_{ij} > h_i \end{cases} \quad (8)$$

- Gaussian

$$w_j(u_i, v_i) = \exp \left[-\frac{1}{2} \left(\frac{d_{ij}}{h_i} \right)^2 \right] \quad (9)$$

- Exponential

$$w_j(u_i, v_i) = \exp \left(-\left(\frac{d_{ij}}{h_i} \right) \right) \quad (10)$$

- Tricube

$$w_j(u_i, v_i) = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h_i} \right)^3 \right]^3 & \text{for } d_{ij} \leq h_i \\ 0 & \text{for } d_{ij} > h_i \end{cases} \quad (11)$$

- Boxcar

$$w_j(u_i, v_i) = \begin{cases} 1 & \text{for } d_{ij} \leq h_i \\ 0 & \text{for } d_{ij} > h_i \end{cases} \quad (12)$$

which $w_j(u_i, v_i)$ is the weight w_{ij} at location (u_i, v_i) , d_{ij} is the distance between i -th location and j -th location, and h_i is the bandwidth for i -th location.

- c. Create a spatial weight matrix with selected adaptive kernel function.
- d. Perform the GWPR model. The equation form of GWPR CEM (GWR) is presented in equation 13, while GWPR FEM/REM unit, time, and unit and time are presented by equation 14, 15, and 16, respectively.

$$\ln(Y_{ij}) = \alpha_i + \beta_{1i} \ln(X_{1ij}) + \beta_{2i} \ln(X_{2ij}) + \beta_{3i} \ln(X_{3ij}) + \beta_{4i} \ln(X_{4ij}) + \varepsilon_{ij} \quad (13)$$

$$\ln(Y_{ij}) = \alpha_i + \mu_i + \beta_{1i} \ln(X_{1ij}) + \beta_{2i} \ln(X_{2ij}) + \beta_{3i} \ln(X_{3ij}) + \beta_{4i} \ln(X_{4ij}) + \varepsilon_{ij} \quad (14)$$

$$\ln(Y_{ij}) = \alpha_i + \lambda_j + \beta_{1i} \ln(X_{1ij}) + \beta_{2i} \ln(X_{2ij}) + \beta_{3i} \ln(X_{3ij}) + \beta_{4i} \ln(X_{4ij}) + \varepsilon_{ij} \quad (15)$$

$$\ln(Y_{ij}) = \alpha_i + \mu_i + \lambda_j + \beta_{1i} \ln(X_{1ij}) + \beta_{2i} \ln(X_{2ij}) + \beta_{3i} \ln(X_{3ij}) + \beta_{4i} \ln(X_{4ij}) + \varepsilon_{ij} \quad (16)$$

which i is cross-sectional unit of province with $n=34$; j is time series of year with 2015 as $j=1$ so on until 2022 as $j=t=8$; Y_{ij} is GRDP for i -th province and j -th year; X_{1ij} is GFCF for i -th province and j -th year; X_{2ij} is WLF for i -th province and j -th year; X_{3ij} is SI-HCI for i -th province and j -th year; X_{4ij} is HDI for i -th province and j -th year; α_i is the intercept

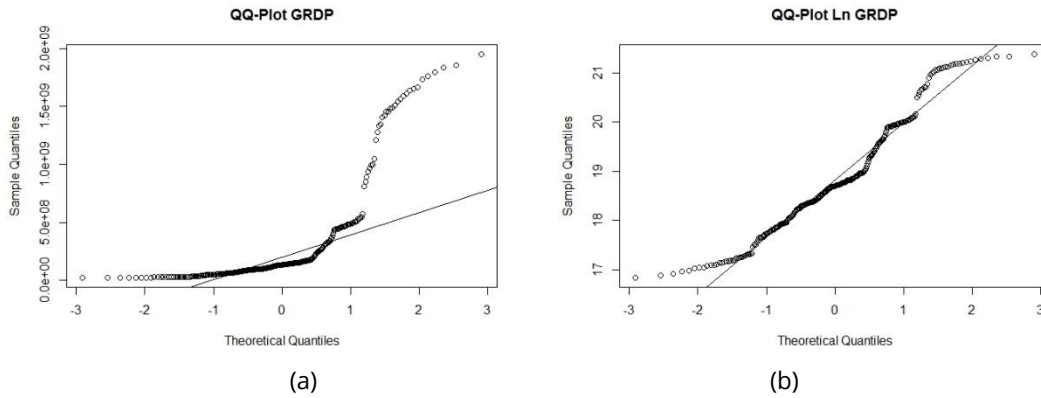


Figure 1. QQ-plot of GRDP (a) original scale and (b) transformed by natural logarithm.

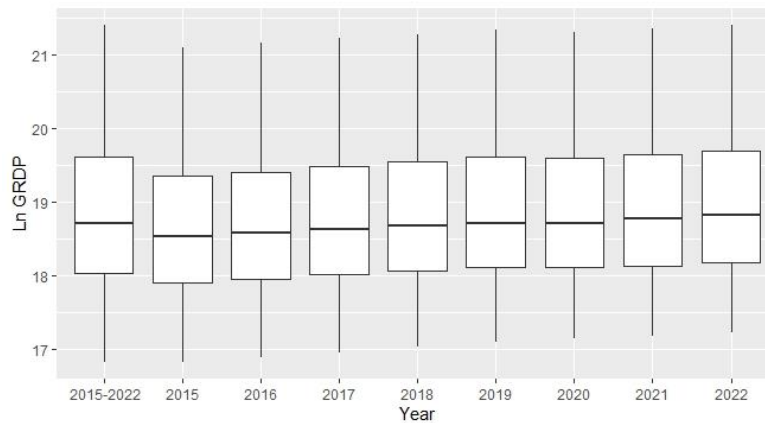


Figure 2. Boxplot of Ln GRDP over time and all over time.

for i -th province; $\beta_{1i}, \beta_{2i}, \beta_{3i}, \beta_{4i}$ are the parameters of independent variables for i -th province; μ_i is the effect of cross-sectional unit for i -th province, fixed for FEM and random for REM; λ_j is the effect of time series for j -th year, fixed for FEM and random for REM; and ε_{ij} as error term for i -th province and j -th year.

- 6). Select the best model between panel regression model and spatial panel regression model using the goodness fit of criteria: the smallest Akaike's Information Criterion (AIC), the highest coefficient of determination (R^2), and the smallest residual sum of squares (RSS). The equations related to AIC, R^2 , and RSS are presented by equation 17, 18, and 19, respectively.

$$AIC = 2k - 2\ln(L) \tag{17}$$

$$R^2 = 1 - \frac{\sum_{i=1}^n \sum_{t=1}^T (y_{it} - \hat{y}_{it})^2}{\sum_{i=1}^n \sum_{t=1}^T (y_{it} - \bar{y}_{it})^2} \tag{18}$$

$$RSS = \sum_{i=1}^n \sum_{t=1}^T w_{it} (y_{it} - \hat{y}_{it})^2 \tag{19}$$

- 7). Perform partial test of parameter model with the T-Student test.
- 8). Interpret the model.

3. Results and Discussion

3.1. Data Exploration

In this section, we delve into the exploration of the panel data utilized in our research to gain valuable insights into the distribution and characteristics of the variables. As the dependent variable, GRDP, displayed a non-normal distribution, we opted to address this issue by performing a natural logarithmic transformation on the dependent variable. Figure 1 illustrates the transformation, showcasing how the data distribution of GRDP became relatively normal after the application of the natural logarithm. We also applied the natural logarithmic transformation to all independent variables.

Figure 2 presents the boxplot of GRDP, revealing an upward trend in the median value over the years. Moreover, there are no outliers in the GRDP data for both individual years and the entire period from 2015 to 2022. To provide a comprehensive overview of the research variables, we present their statistics in Table 2.

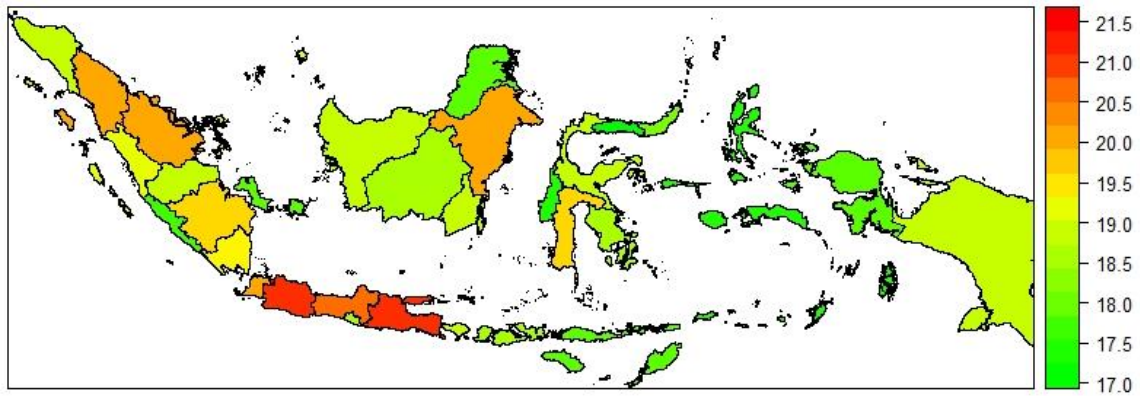


Figure 3. Spatial distribution of provincial GRDP, 2022.

Table 2. Variables summary

Statistics	Y	X ₁	X ₂	X ₃	X ₄
Number of observation	272	272	272	272	272
Min	16.830	15.571	12.495	4.165	4.047
Q1	18.038	17.046	13.836	5.651	4.228
Median	18.703	17.516	14.533	6.296	4.256
Mean	18.842	17.687	14.527	6.323	4.253
Q3	19.611	18.539	15.122	6.982	4.279
Max	21.393	20.432	16.970	8.665	4.402
SD	1.142	1.144	1.021	0.999	0.059
Skewness	0.485	0.405	0.528	0.132	-0.269
Kurtosis	2.564	2.614	3.091	2.537	4.326

Table 3. Correlation coefficient and VIF

Variable	Correlation Coefficient with Y	P-value of correlation test	VIF
X ₁	0.980	0.000	1.897
X ₂	0.872	0.000	4.629
X ₃	0.827	0.000	2.158
X ₄	0.442	0.000	5.782

Thematic maps are invaluable tools for detecting spatial autocorrelation or spatial effects, indicating whether regions tend to cluster, spread, or show randomness. In Figure 3, we showcase the thematic map of GRDP values across provinces in 2022. The color intensity on the map represents high to low GRDP values, with red indicating higher values, yellow for medium values, and green for lower values. The thematic map reveals a tendency for GRDP values to cluster, indicating similarity in economic growth characteristics among provinces located closely or in neighboring regions. Furthermore, the maps suggest that economic growth performance is higher in Western Indonesia compared to Central and Eastern Indonesia.

We assess the linear relationships between the dependent variable, GRDP, and each independent variable, utilizing the Pearson correlation coefficient. A correlation coefficient value near |1| indicates a strong

linear relationship, while a correlation coefficient of 0 signifies no linear relationship between the variables. The direction of the linear relationship is determined by the coefficient's sign, which can be positive or negative.

The results of the correlation test, performed with the T-Student test, reveal that each correlation coefficient produces a p-value below the significance level of 0.05, providing evidence to support the presence of a linear correlation between the variables at a 95 percent confidence level. Table 3 presents the magnitude and direction of the linear correlations, with values ranging from 0.442 to a high of 0.980, all positively correlated. This indicates that as GRDP increases, there is a linear association with a higher value of each independent variable, and conversely, as GRDP decreases, it shows a linear association with a lower value of each independent variable.

As we investigate models with multiple independent variables, it becomes crucial to examine the potential issue of multicollinearity. An examination using the variance inflation factor (VIF) reveals that the effect of multicollinearity is not substantial, as the VIF values do not surpass ten [30]. This suggests that the impact of multicollinearity on our models is relatively minimal and does not compromise the validity of the results.

3.2. Selection of Panel Regression Model

In this section, the selection of the appropriate panel regression model was conducted through statistical tests, including the Lagrange Multiplier Breusch Pagan (LM-BP) test, Chow test, and Hausman test, all performed at a 95 percent confidence level (significant level of 0.05 or 5 percent). The results of the three tests are presented in Table 4.

The LM-BP test was employed to determine the presence of fixed or random effects, either one or two ways, arising from unit provinces and/or the period of years in the panel data. The results of the LM-BP test indicated

Table 4. LM-BP, Chow, and Hausman test results.

Test	Degree of Freedom		Statistics Value	P-value
	1	2		
LM-BP test				
Unit and time effects	2		779.584	0.000*
Unit effect	1		775.809	0.000*
Time effect	1		3.775	0.052
Chow test	165	102	211.958	0.000*
Hausman test	4		17.282	0.002*

Note: *Significant at 95 percent confidence level.

Table 5. The parameter estimates of FEM unit.

Term	Estimate	SE	T-statistic	P-value
β_1	0.330	0.023	14.176	0.000*
β_2	0.071	0.078	0.919	0.359
β_3	0.019	0.041	0.466	0.642
β_4	3.217	0.342	9.416	0.000*

Note: *Significant at 95 percent confidence level.

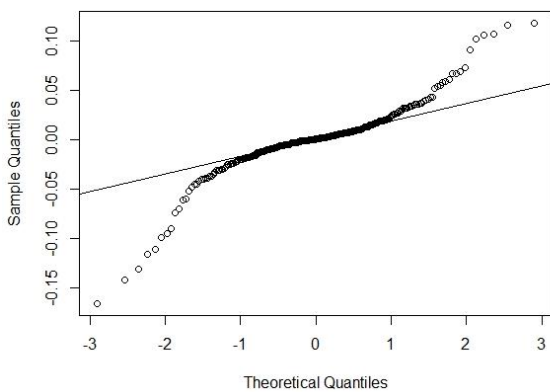


Figure 4. QQ-plot of residuals of FEM unit

significant evidence of a two-way effect of unit provinces and year periods at a 95 percent confidence level. However, the one-way effect test yielded only significant provincial unit effects, leading to the conclusion that there is a one-way effect from provincial units to panel data with a 95 percent confidence level.

Based on the results of these LM-BP tests, the panel regression model was performed with one-way effects from provincial units, specifically using FEM and REM units. The Chow test results, which are significant, suggest that the FEM unit is more suitable than the CEM. Additionally, the Hausman test was conducted between FEM units and REM units, and the results indicated that the FEM unit is more appropriate than the REM unit. Consequently, the final panel regression model for our analysis is the FEM unit. Table 5 presents the parameter estimates of the FEM unit, indicating that out of the four independent variables, only GFCF (X_2) and HDI (X_4) demonstrated statistical significance in their influence on GRDP at a 95 percent confidence level. However, it is noteworthy that all the coefficients for the independent variables were positive, suggesting a positive relationship

with GRDP, even for the non-significant independent variables.

The estimates for the fixed effect of units are not presented in this section, it is intriguing to observe that they all exhibit negative values. This finding implies that despite the individual significance of GFCF (X_2) and HDI (X_4) in driving real economic growth, there are additional factors within the provincial units that exert a negative influence on GRDP.

3.3. Check the Assumption of Panel Regression Model

For the panel regression model, the assumption of uncorrelated errors can be considered fulfilled since the observed data comes from independently conducted surveys. To visually assess the normality assumptions of the errors, a QQ-plot of the residuals is used and presented in Figure 4. The scattering of points on the plot relatively follows the diagonal line, indicating that the residuals are relatively normally distributed even there is a slight deviation in the tails.

To proceed from the panel regression model to the spatial panel spatial regression model using GWPR, we conduct the Breusch-Pagan (BP) test to identify spatial diversity. The BP test results show the chi-squared statistic (and p-value) of 56.732 (0.000), in which significant p-value provides sufficient evidence to state that there is spatial diversity. This indicates that the variety of provincial units is not homogeneous, allowing us to apply local modeling for each province using the GWPR FEM units.

3.4. Adaptive Kernel Function and Bandwidth

The weighting matrix is constructed by first selecting the optimal adaptive bandwidth through a kernel function,

Table 6. CV value of bandwidth and kernel function.

Kernel	Bandwidth	CV
Bisquare	15	0.0003
Gaussian	15	0.0008
Exponential	15	0.0006
Tricube	15	0.0004
Boxcar	15	0.0010

Table 7. Summary of regression coefficient and coefficient of determination.

Statistics	Intercept	$\hat{\beta}_{1i}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$	$\hat{\beta}_{4i}$	R ²
Number of observations	34	34	34	34	34	34
Min	-6,33	-0,009	-0,209	-0,144	-0,154	0,8270
Q1	-4,078	0,138	-0,116	-0,069	2,559	0,8689
Median	-3,216	0,303	-0,079	-0,042	3,571	0,8888
Mean	-2,535	0,322	-0,034	0,086	3,698	0,9053
Q3	-1,63	0,473	-0,012	0,263	5,321	0,9570
Max	5,051	0,703	0,507	0,466	5,839	0,9633
SD	2,52	0,202	0,154	0,195	1,737	0,0461

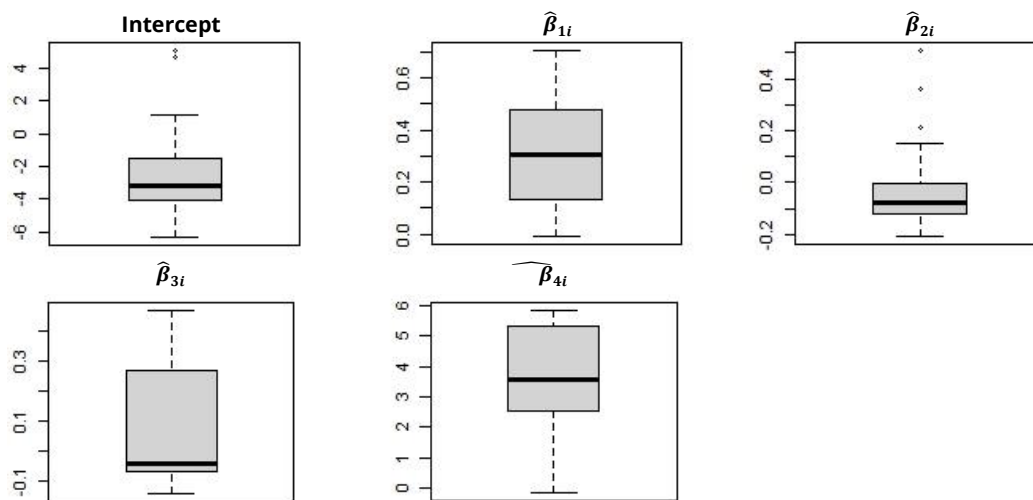


Figure 5. Boxplot of regression coefficient of GWPR FEM unit.

determined based on the FEM units with the smallest cross-validation (CV) value. Table 6 presents the CV value of adaptive bandwidth and kernel functions. The utilization of adaptive bandwidth ensures that the weight assigned to each data point varies spatially, capturing the spatial heterogeneity and spatial interactions that influence the real economic growth in different regions across the provinces in Indonesia.

The resulting bandwidth, obtained with the smallest CV value (0.0003), is an adaptive bandwidth of size 15, utilizing a bisquare kernel function. The optimal bandwidth of 15 indicates that approximately 15 nearest data observation points have a significant influence on the observed data at a specific location. Importantly, due to its adaptive nature, each location can have a distinct bandwidth, enabling a more localized and context-specific analysis.

3.5. GWPR FEM Unit

Table 7 presents the summary of the regression coefficient and coefficient of determination of GWPR FEM unit. Meanwhile, Figure 5 presents the boxplot of the regression coefficient. The results of the GWPR FEM unit regression reveal a mix of positive and negative regression coefficients, with none of them being exactly zero, although some are presented as 0.000 due to rounding. Notably, there are outliers in the intercept and the regression coefficient for WLF (X_2), which have higher values compared to other coefficients. These outliers are prominent in provinces like Papua, Papua Barat, and Nusa Tenggara Timur. Table 7 shows the coefficient of determination (R-squared) for the GWPR FEM unit ranges from 0.8270 to 0.9633, indicating that approximately 82.70% to 96.33% of the variability in the dependent variable (GRDP) can be explained by the independent variables in the model.

Table 8. Group of provinces based on the significant independent variable.

Group	Sig. IV	Number of province	Code and name of province
1	X_4	4	15. Jambi; 16. Sumatera Selatan; 17. Bengkulu; 19. Kepulauan Bangka Belitung.
2	$X_1 + X_2$	1	94. Papua.
3	$X_1 + X_4$	17	11. Aceh; 12. Sumatera Utara; 13. Sumatera Barat; 14. Riau; 18. Lampung; 21. Kepulauan Riau; 31. DKI Jakarta; 32. Jawa Barat; 33. Jawa Tengah; 34. DI Yogyakarta; 35. Jawa Timur; 36. Banten; 51. Bali; 52. Nusa Tenggara Barat; 53. Nusa Tenggara Timur; 73. Sulawesi Selatan; 74. Sulawesi Tenggara.
4	$X_3 + X_4$	2	61. Kalimantan Barat; 62. Kalimantan Tengah.
5	$X_1 + X_2 + X_3$	1	91. Papua Barat.
6	$X_1 + X_3 + X_4$	9	63. Kalimantan Selatan; 64. Kalimantan Timur; 65. Kalimantan Utara; 71. Sulawesi Utara; 72. Sulawesi Tengah; 75. Gorontalo; 76. Sulawesi Barat; 81. Maluku; 82. Maluku Utara.

Table 9. Comparison of model criteria.

Model	R ^{2*}	RSS	AIC
FEM unit	0,858	0,328	-1.024,046
GWPR FEM unit	0,999	0,191	-1.952,435

Note: * The panel model uses *adjusted* R², while the spatial panel uses *global* R².

Examining the magnitude and significance of the regression coefficients for each province, we observe the formation of six distinct groups based on the combination of independent variables that significantly influence GRDP (see Table 8). Group one consists of provinces affected by the independent variable HDI (X_4), while group two is influenced by GFCF (X_1) and WLF (X_2).

Group three comprises provinces impacted by GFCF (X_1) and HDI (X_4). Group four includes provinces influenced by SI-HCI (X_3) and HDI (X_4). Group five is characterized by GFCF (X_1), WLF (X_2), and SI-HCI (X_3). Lastly, group six comprises provinces affected by GFCF (X_1), SI-HCI (X_3), and HDI (X_4). Even when an independent variable does not have a significant effect on GRDP in a province, it is retained in the model as it still contributes to the estimation of GRDP.

3.6. Best Model

To ensure the robustness of this study, the selection of the best model involves a comparison of various criteria, including Akaike's Information Criterion (AIC), coefficient of determination (R-squared), and residual sum of squares (RSS). The model that fulfills the smallest AIC value, the highest coefficient of determination, and the smallest RSS is considered the best model. The evaluation results for each criterion are presented in Table 9.

Upon thorough evaluation using the established criteria, it becomes evident that the GWPR FEM unit model emerges as the best model. The GWPR FEM unit model attains the smallest AIC value, indicating its superior goodness of fit and better explanatory power. Moreover,

it achieves the highest coefficient, implying that it can explain a greater proportion of the variance in the dependent variable (GRDP). Additionally, the GWPR FEM unit model yields the smallest RSS, reflecting its ability to accurately predict GRDP as the model's predictions are closer to the observed values.

Consequently, considering the compelling findings and the consistency with the best model criteria, the GWPR FEM unit model is indisputably the best-fitted model. This model's success underscores the significance of integrating spatial diversity analysis and adopting the adaptive bandwidth approach, which significantly enhances our understanding of the spatial patterns and dynamics of provincial economic growth in Indonesia.

4. Conclusions

In conclusion, the spatial analysis of provincial real economic growth in Indonesia using GWPR FEM unit revealed six groups of provinces based on significant independent variables. The independent variables impacting the provincial real economic growth (GRDP) include physical investment (GFCF), working labor force (WLF), social infrastructure relative to the head-count index of poverty (SI-HCI), and human development index (HDI).

The findings revealed the significance of physical investment and human development index as major drivers of economic growth in most provinces. Moreover, the working labor force played a crucial role in promoting economic growth in provinces on Papua Island. The research also identified an intriguing relationship between social infrastructure relative to the head-count index of poverty and real economic growth in provinces in the central and eastern regions of Indonesia, including provinces on the islands of Kalimantan, Sulawesi, Maluku, and Papua.

These findings highlight the heterogeneity of factors driving economic growth across different provinces and

emphasize the importance of context-specific policies for regional development. Policymakers can leverage these insights to tailor targeted interventions and optimize resource allocation to foster inclusive and sustainable economic growth across Indonesia.

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