

Spatial Analysis of Gross Enrollment Ratio in Higher Education Using the Geographically Weighted Regression Approach

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ABSTRAK

Penelitian ini menganalisis faktor-faktor yang memengaruhi Angka Partisipasi Kasar Perguruan Tinggi (APK-PT) di Indonesia dengan menekankan perbedaan regional yang tidak dapat ditangkap secara memadai oleh model *Ordinary Least Squares* (OLS) maupun data panel yang bersifat global. Analisis menggunakan data sekunder tahun 2023 dari Badan Pusat Statistik (BPS) dan Kementerian Pendidikan, meliputi Produk Domestik Regional Bruto (PDRB), pendanaan pendidikan, rasio dosen–mahasiswa, jumlah mahasiswa, pengeluaran per kapita, jumlah penduduk, serta indeks kedalaman kemiskinan. Untuk menangkap heterogenitas spasial dalam hubungan tersebut, penelitian ini menerapkan *Geographically Weighted Regression* (GWR) dengan fungsi pembobot kernel Gaussian. Hasil penelitian menunjukkan bahwa model GWR mampu menjelaskan 50.57% variasi APK-PT, mencerminkan peningkatan kinerja model setelah variasi spasial antarwilayah dimasukkan dan memberikan kecocokan model yang lebih baik dibandingkan regresi OLS. Pengaruh variabel penjelas terhadap APK-PT terbukti berbeda antarprovinsi, sehingga wilayah dapat dikelompokkan ke dalam lima kelompok berdasarkan kombinasi faktor signifikan, terutama jumlah mahasiswa, pengeluaran per kapita, dan indeks kedalaman kemiskinan. Temuan ini mengindikasikan bahwa perancangan kebijakan pendidikan tinggi perlu disesuaikan secara spesifik untuk setiap kelompok wilayah guna meningkatkan APK-PT dan mengurangi ketimpangan antarprovinsi.

Kata kunci: Angka Partisipasi Kasar Perguruan Tinggi; Analisis Spasial; Geographically Weighted Regression

ABSTRACT

This study analyzes the factors influencing the Gross Enrollment Rate of Higher Education (GER-HE) in Indonesia by emphasizing regional differences that cannot be adequately captured by global Ordinary Least Squares (OLS) or panel data models. The analysis is based on secondary data for 2023 obtained from Badan Pusat Statistik (BPS) and the Ministry of Education, including Gross Regional Domestic Product (GRDP), education funding, lecturer–student ratio, number of students, per capita expenditure, total population, and the poverty depth index. To capture spatial heterogeneity in these relationships, the study applies Geographically Weighted Regression (GWR) with a Gaussian kernel weighting function. The results indicate that the GWR model explains 50.57% of the variation in GER-HE, reflecting improved model performance after accounting for spatial variation across regions and providing a better fit than the OLS regression. The effects of explanatory variables on GER-HE vary across provinces, allowing regions to be classified into five groups based on combinations of statistically significant factors, particularly the number of students, per capita expenditure, and the poverty depth index. These findings suggest that higher education policies should be tailored to the specific characteristics of each regional group to enhance GER-HE and reduce interprovincial disparities.

Keywords: Gross Enrollment Ratio Higher Education; Spatial Analysis; Geographically Weighted Regression.

INTRODUCTION

The Gross Enrollment Ratio for Higher Education (GER-HE) represents the proportion of individuals enrolled in tertiary education (regardless of age) compared to the total population within the official higher education age range of 19 to 23 years. Based on data from Badan Pusat Statistik (BPS), Indonesia's GER for higher education in 2024 was around 32% [1], indicating that only about one third of the eligible population pursued studies at the tertiary level. This relatively low participation rate poses a challenge to achieving Sustainable Development Goal (SDG) 4.3, which emphasizes equitable access to quality education [2]. Although GER provides an overall picture of higher education participation, a more comprehensive analysis is necessary to identify and understand the underlying factors that influence this rate.

Empirical studies indicate that GER-HE is shaped by a combination of government, household, and regional factors, with substantial variation across regions. From the government side, higher education participation is influenced by the share of central government expenditure on higher education relative to GRDP [3] and the availability of education funding schemes [4], [5]. At the institutional level, the lecturer–student ratio has also been shown to affect GER-HE [3], [6]. Household economic capacity, commonly proxied by per capita expenditure, plays an important role in shaping access to higher education [6], [7]. In addition, regional characteristics such as population size [3] and poverty levels [6] further contribute to disparities in GER-HE across provinces.

The determinants of the GER-HE vary considerably across regions and may change over time. Panel data regression is commonly employed to analyze such variation by combining cross-sectional and temporal dimensions [8]. Recent empirical evidence from 2024 indicates that regional or individual effects play a dominant role in explaining GER-HE. In contrast, time effects are statistically insignificant [7], suggesting that GER-HE dynamics are primarily spatial. However, conventional panel regression models impose spatially constant coefficients, which may yield biased or inefficient estimates when spatial heterogeneity is present.

To overcome this limitation, this study adopts Geographically Weighted Regression (GWR) to explicitly capture spatial heterogeneity and non-stationarity in the determinants of GER-HE [9], [10]. GWR allows the relationships between explanatory variables and GER-HE to vary across provinces, thereby revealing localized patterns that cannot be identified using global or panel data approaches [11]. Spatial weighting is implemented using a Gaussian kernel with a fixed bandwidth to ensure consistent estimation of local parameters across locations [12]. The main objectives of this study are to identify region-specific determinants of GER-HE and to examine how their effects vary spatially across provinces. The expected policy contribution is to provide spatially explicit evidence that can support more targeted and region-sensitive higher education policies aimed at increasing participation and reducing regional disparities in GER-HE.

METHOD

Data

Data used in this study are cross-sectional and limited to the year 2023, which represents the most recent data available at the time of the analysis, including GER-HE [13], Gross Regional Domestic Product (GRDP) [14], the student–lecturer ratio [15], number of students [15], per capita expenditure [16], total population [17] and the poverty depth index [18] for each province. In

addition, education funding data were sourced from the regional education balance sheet published by the Ministry of Education and Culture [19]. A summary of the variables is provided in Table 1.

Table 1. Research Variables

Variable	Description	Unit
Y	Gross Enrollment Rate of Higher Education (GER-HE)	%
X_1	Gross Regional Domestic Product (GRDP)	Billion Rupiah
X_2	Education Funding (EF)	Billion Rupiah
X_3	Lecturer-Student Rasio (LSR)	Lecturers/Students
X_4	Number of Students (NS)	Individuals
X_5	Per Capita Expenditure (PCE)	Thousand Rupiah/Person
X_6	Total Population (TP)	Thousand People
X_7	Poverty Depth Indeks (PDI)	%

The analysis covers 34 provinces, while Southwest Papua, South Papua, Central Papua, and the Papuan Pegunungan are excluded due to incomplete data availability. These provinces are newly established administrative regions, and several key indicators were not yet consistently reported for 2023. Although this exclusion may lead to a minor underrepresentation of eastern Indonesia, it is unlikely to substantially bias the overall spatial analysis, as the remaining provinces still capture the dominant national variation in higher education participation.

Analysis Methods

Spatial Dependency

Spatial dependency refers to the existence of a correlative relationship between a variable and itself based on spatial proximity, whether in the form of distance, time, or region. When values from adjacent locations show similarities and form a clustered pattern, this reflects the existence of positive spatial dependency. Conversely, if adjacent locations have strikingly different and scattered values, then this indicates the existence of negative spatial dependency. Spatial dependency can be measured using Moran's I statistic. The following is Moran's I formula [20].

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \tag{1}$$

Moran's I test is used to identify the presence or absence of global spatial dependency in continuous data. Spatial dependency testing is performed with the following hypotheses: $H_0: I = 0$ (no spatial dependency between locations) and $H_1: I \neq 0$ (there is spatial dependency between locations). The hypothesis is evaluated using the following statistical test:

$$Z(I) = \frac{I - E(I)}{\sqrt{Var I}} \sim N(0,1) \tag{2}$$

Spatial Heterogeneity

Spatial heterogeneity testing can be performed in various ways, one of which is the Breusch-Pagan (BP) test, which has the following hypotheses [21]: $H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_n^2 = \sigma$ (no

spatial heterogeneity) and H_1 : here is at least one i where $\sigma_i^2 \neq \sigma$ (there is spatial heterogeneity). The BP test statistic is defined as [22]:

$$BP = \frac{1}{2} \mathbf{f}' \mathbf{Z} (\mathbf{Z}' \mathbf{Z})^{-1} \mathbf{Z}' \mathbf{f} \sim \chi^2_{(k-1)} \quad (3)$$

Geographically Weighted Regression Model

Spatial regression is a methodological extension of linear regression, classified as a point-element model [23]. Geographically Weighted Regression (GWR) is a method used in spatial regression analysis. In the GWR model, the relationship between the response variable Y and the explanatory variables X_1, X_2, \dots, X_K at the i th location is formulated as follows.

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \quad (4)$$

In the GWR model, coefficient estimation is performed using Weighted Least Squares (WLS), a least squares approach that assigns location specific weights to each observation. These weights are represented by a diagonal weighting matrix, whose diagonal elements are defined by a weighting function based on the spatial location of the observations. The weighting matrix enables the estimation of local parameters that vary across space.

The spatial weight matrix employed in this study is constructed using a k-nearest neighbors (KNN) approach with $k = 4$ and a fixed bandwidth, and is row-standardized to ensure that the total weight assigned to each observation is equal. In the GW model, spatial weights are generated through a kernel function, such that observations located closer to a given location receive greater influence in the parameter estimation process than those located farther away [22].

The specification of spatial weighting is a key component of the GWR model, as it determines how strongly nearby locations influence local parameter estimates. Spatial weights are defined through the chosen kernel function [9]. In this study, spatial weights are generated using a Gaussian kernel function, which assigns smoothly decreasing influence with increasing distance. This kernel is well suited for provincial-level data, as it produces stable coefficient estimates and supports the modeling of gradual spatial variation across 34 provinces. The Gaussian kernel function is defined as follows.

$$W_j(u_i, v_i) = \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{h}\right)^2\right) \quad (5)$$

where h is the bandwidth and d_{ij} is the distance between the i -th location and the j -th location based on the coordinate points $(u_i - v_i)$ and $(u_j - v_j)$.

The determination of an optimal bandwidth is conducted using a cross validation (CV) procedure [24]. The optimal bandwidth is selected as the value that minimizes the CV criterion. In this context $\hat{y}_{\neq i}$ represents the fitted value from the GWR model estimated without the i -th observation. The bandwidth corresponding to the lowest CV value is selected as the optimal bandwidth [9].

RESULT AND DISCUSSION
Descriptive Analysis

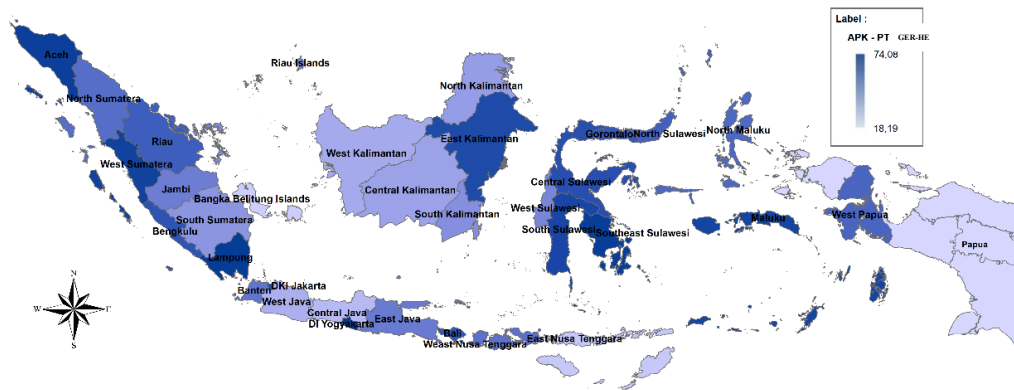


Figure 1. Distribution Map of GER-HE in Indonesia in 2023

Figure 1 illustrates the spatial distribution of GER-HE across Indonesian provinces in 2023, with values ranging from 18.19 to 74.08 percent. Higher GER-HE levels are concentrated in Java and several provinces in Sumatra, Kalimantan, and Sulawesi, indicating relatively better access to higher education and stronger regional capacity. In contrast, lower participation rates are more common in eastern Indonesia, particularly in Papua and parts of Maluku and Nusa Tenggara, reflecting disparities in educational infrastructure and regional development.

Spatial Dependence and Heterogeneity Test

Spatial dependence was assessed using Moran’s Index (I), while spatial heterogeneity was evaluated using the Breusch–Pagan (BP) test. The results are summarized in Table 2.

Table 2. Spatial Dependence and Heterogeneity Test

Test	P value	Decision
Moran’s I	0.7472	Fail to Reject H ₀
Breusch-Pagan	0.1091	Fail to Reject H ₀

Table 2 indicates that Moran’s I ($p = 0.7472$) and the Breusch–Pagan test ($p = 0.1091$) are not statistically significant at the 5% level, suggesting the absence of global spatial dependence and spatial heterogeneity. Nevertheless, the GWR model is subsequently employed to explore potential local variations in the relationships between variables that may not be captured by global diagnostic tests, thereby providing additional insight into spatially varying processes [25].

Geographically Weighted Regression Model

The initial steps taken to obtain the Geographically Weighted Regression model are determining the latitude and longitude coordinates of each location, calculating the Euclidean distance, and determining the optimum bandwidth value based on the Cross Validation (CV)

criteria using Gaussian kernel weighting, are presented in Table 3. The optimum bandwidth value obtained is 1257.169 with a CV score of 22558.43.

Table 3. Optimal Bandwidth dan CV Score Using Gaussian Kernel

Iteration	Bandwidth	CV Score
10	1257.169	22558.43

Although parameter estimates are obtained for all provinces using the GWR model, Table 4 presents results for five representative provinces as an example.

Table 4. Parameter Estimates by Province for the GWR Model

Province	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$	$\hat{\beta}_7$
Aceh	27.8492	-4.73E-07	9.77E-05	-	-3.32E-06	0.00111	-	6.81133
East Java	7.91854	3.904E-06	-	-	-4.46E-06	0.00326	-	5.14754
Banten	7.78327	3.139E-06	-0.0003	-394.822	-7.59E-06	0.00332	0.00014	6.72207
South Sulawesi	16.1831	2.842E-06	-	-	8.358E-06	-	-	-
Papua	15.3737	1.001E-06	-	70.15986	06	0.00175	0.00041	2.43496
		05	0.00051	598.1535	05	-0.0004	0.00129	0.21642

The GWR model explains 50.57% of the variability in the GER-HE variable ($R^2 = 0.5057$). By comparison, the OLS regression model shows considerably lower explanatory power ($R^2 = 0.1532$), indicating a better model fit for the GWR approach.

The GWR model is the most appropriate model to describe the distribution of GER-HE in Indonesia. The following GWR models are obtained differently in each province; for example, the GWR models for Banten, East Java, and Papua are shown in equations (8), (9), and (10) below.

$$\hat{Y}_{\text{Banten}} = 7.78327 + 0.000003139X_1 - 0.0003X_2 - 394.822X_3 - 0.00000759X_4 + 0.00332X_5 - 0.00014X_6 + 6.72207X_7 \quad (8)$$

$$\hat{Y}_{\text{East Java}} = 7.91854 + 0.000003904X_1 - 0.00036X_2 - 335.0339X_3 - 0.00000446X_4 + 0.00326X_5 - 0.00019X_6 + 5.14754X_7 \quad (9)$$

$$\hat{Y}_{\text{Papua}} = 15.3737 + 0.00001001X_1 - 0.00051X_2 + 598.1535X_3 + 0.00004106X_4 - 0.0004X_5 - 0.00129X_6 + 0.21642X_7 \quad (10)$$

Table 5. GWR Model Goodness of Fit Test

	DF	Sum of Squares	Mean Square	F-statistic	Decision
GWR Improvement	5.3532	1215.0	226.975		
GWR Residuals	20.6468	1703.9	82.527	2.7503	Reject H_0

At the 5% significance level, the F-statistic value ($F = 2.7503$) exceeds the critical value ($F = 2.7109$). Therefore, the null hypothesis is rejected, indicating a statistically significant difference between the OLS regression model and the GWR model. This result confirms that the GWR model provides a better fit to the data.

Table 6. Parameter Estimates by Province for the GWR Model

Provinsi	$T_{value}\beta_0$	$T_{value}\beta_1$	$T_{value}\beta_2$	$T_{value}\beta_3$	$T_{value}\beta_4$	$T_{value}\beta_5$	$T_{value}\beta_6$	$T_{value}\beta_7$
Aceh	1.16941	-0.04469	0.19967	-0.95765	-0.25895	0.7466	-0.6638	1.92562
East Java	0.39802	0.41625	-0.81621	-1.29697	-0.39988	2.60089	-0.55228	2.31102
Banten	0.38015	0.343	-0.68628	-1.47652	-0.66147	2.55062	-0.3963	2.63755
South Sulawesi	0.79957	0.28895	-0.52303	-0.26315	0.731161	1.4421	-1.18802	1.23558
Papua	0.49908	0.70247	-0.6723	1.55233	2.663437	-0.2477	-2.59857	0.08181

Table 6 presents the results of the t-test for parameter significance in the GWR model for five selected provinces. The results indicate that variables X_5 in East Java, variables X_5 and X_7 in Banten, and variables X_4 and X_6 in Papua are statistically significant, as the absolute values of the calculated t-statistics exceed the critical t-value (2.4231).

Table 7. Comparison of OLS and GWR Regression Model

Model	AIC	R^2
OLS	265.8771	0.1532
GWR	241.0096	0.5057

Table 7 indicates that the GWR model outperforms the OLS model, as evidenced by a lower AIC value and a higher coefficient of determination (R^2), suggesting that the GWR model provides a more effective representation of the data.

Grouping of Provinces Based on Significant Variables

The classification presented in Table 8 integrates the significant parameters identified across regions (Table 6), highlighting spatial variations in the influence of explanatory variables among provinces.

Table 8. Significant Variables for Each Province

Group	Significant Variable(s)	Province
1	X_4, X_6	West Papua, Papua
2	X_5	East Java, Bali
3	X_7	Jambi, South Sumatra, Bengkulu, Lampung, Bangka Belitung Islands
4	X_5, X_7	DKI Jakarta, West Java, Central Java, DI Yogyakarta, Banten
5	No significant variable	Aceh, North Sumatra, West Sumatra, Riau, Riau Islands, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku



Figure 2. GER-HE Distribution Map in Each Province Based on Significant Variables

Figure 2 illustrates the spatial clustering of Indonesian provinces based on locally significant determinants of GER-HE, revealing pronounced regional heterogeneity. Papua and West Papua are mainly influenced by demographic characteristics, while provinces in Java and Bali are dominated by household economic capacity. Several provinces in central Sumatra are associated with poverty conditions, whereas much of Kalimantan, Sulawesi, and Maluku show no dominant significant factors, suggesting the influence of institutional or local policy conditions. These spatial patterns are consistent with human capital theory and education demand theory, which conceptualize higher education participation as an investment decision shaped by economic capacity, demographic conditions, and social constraints. Household economic capacity, proxied by per capita expenditure, reduces financial barriers to enrollment [26], [27], demographic factors affect participation through demand side pressures and labor market competition [28], and poverty related indicators reflect structural deprivation that limits affordability and academic preparedness [29].

The spatial variation in these relationships supports the relevance of spatially adaptive analytical approaches.

CONCLUSION

This study shows that the GWR model provides a useful extension to global modeling approaches for analyzing the GER-HE in Indonesia, particularly for examining local variation in parameter estimates across provinces. Although global diagnostic tests do not indicate statistically significant spatial dependence or overall spatial heterogeneity, the GWR results reveal meaningful spatial variation in coefficient estimates, suggesting that the relationships between explanatory variables and GER-HE are not entirely uniform across space. Based on locally significant parameters, the 34 provinces are classified into five groups: provinces influenced by (1) X_4 and X_6 , (2) X_5 , (3) X_7 , (4) X_5 and X_7 , and (5) provinces with no statistically significant predictors. These findings indicate that, even in the absence of global spatial effects, local differences in the strength and relevance of covariates remain present. From a policy perspective, the results support the consideration of region specific interventions rather than uniform national policies. The analysis is limited by its cross sectional design and the restricted set of explanatory variables. Future research could build on this analysis by incorporating spatial panel data and employing advanced techniques such as multiscale GWR (MGWR) to further evaluate the stability and scale sensitivity of local parameter estimates.

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