Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 10, Number 1, 2026
DOI: 10.30829/zero.v10i1.28152
Page: 328 - 340

Spatial Analysis of Indonesia's 2019 Provincial Voter Turnout Using Geographically Weighted Regression

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Article Info

Article history:

Accepted 22 April 2026

Keywords:

Geographically Weighted Regression;
Indonesia General Elections;
Political Participation;
Spatial Heterogeneity.

ABSTRACT

This study analyzes spatial heterogeneity in voter behavior using the Geographically Weighted Regression (GWR) model, estimated via GWR 4.0 software to ensure reproducibility. Using 2019 provincial-level data, we compare an OLS model against GWR to evaluate the mean voter turnout across Indonesia's concurrent elections. The GWR model significantly improved estimation performance, evidenced by a reduction in AICc from -140.960 to -146.581 and an increase in Adjusted R^2 from 36.48% globally to a local range of 65.30%–82.60%. Statistical testing via F-statistic yielded a p-value of 0.0633, significant at the 10% level acceptable given the sample size (n=34). Findings reveal significant spatial non-stationarity: the Gini ratio shows a pervasive positive mobilization effect, while education and infrastructure display region-specific impacts, with infrastructure accessibility strongly influencing turnout in eastern Indonesia. These results underscore the mathematical necessity of incorporating geographic variance into predictive electoral models to capture localized socio-political dynamics.

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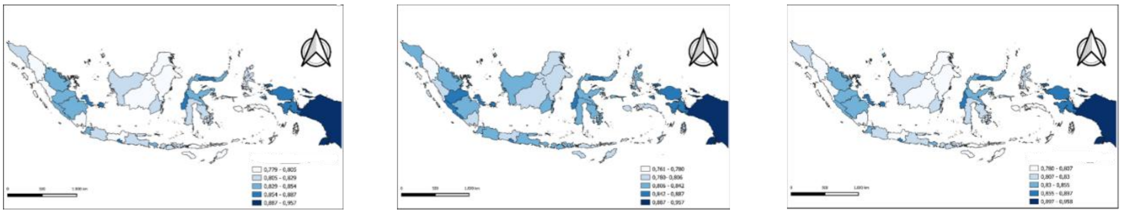
1. INTRODUCTION

Electoral participation is a fundamental metric of democratic health, yet its spatial distribution is rarely uniform, particularly in highly decentralized and geographically fragmented nations. In 2019, Indonesia conducted a massive logistical operation by holding its first simultaneous general elections, yielding a high aggregate national turnout of approximately 81.9%. Since the Reformasi era began in 1998, Indonesia has transitioned from authoritarian rule to a vibrant, albeit complex, electoral democracy. This 2019 milestone was not merely a bureaucratic feat but a stress test for the nation's democratic consolidation, showcasing a dedication to political transparency through the concurrent Presidential (Pilpres) and Legislative (Pileg) elections.

However, evaluating this phenomenon strictly through a national aggregate is analytically deceptive. It obscures a 'mosaic' of political behaviors that vary wildly across the archipelago's 34 provinces from industrialized urban centers to the remote highlands of Papua. Understanding these regional discrepancies is critical, as elections are the fundamental component reflecting public participation in governance [1], [2]. Since electoral outcomes shape policy direction [3], addressing persistent disengagement in specific regions is essential to prevent weak political representation and ensure long-term democratic stability.



DPD DPR Presidential

Figure 1. Spatial Distribution of Voter Turnout in the 2019 Indonesian General Election (Data source: General Election Commission (KPU), processed by the author)

The participation distribution map in Figure 1 illustrates this spatial disparity. While the national average is high, provincial turnout ranges from 78% in North Sumatera to a peak of 96% in Papua. This striking disparity suggests that the influence of socio-economic factors is spatially heterogeneous. For instance, based on 2019 Statistics Indonesia (BPS) data, the exceptionally high turnout in Papua coincides with a higher proportion of damaged national roads, which may trigger unique community-based mobilization patterns in remote areas. Conversely, the lower turnout in North Sumatra is observed alongside a higher Gini ratio, highlighting how economic inequality potentially dampens voter engagement in the western region differently than in the east. This visible geographic variation confirms that global assumptions are inadequate. While reflecting local culture, such phenomena underscore that space is not merely a backdrop for elections but an active factor that structures political engagement [4]. Consequently, viewing voter turnout through a spatial lens allows researchers to better understand how geographic location and regional disparities influence participation [5]–[7].

Historically, quantitative analyses of Indonesian elections have relied on aspatial global models, such as multinomial logistic regression and ordinary least squares (OLS) [8]. These models operate under the strict assumption of spatial stationarity, positing that the relationship between explanatory variables such as education, income, and infrastructure remains constant across all locations. When spatial non-stationarity is present in a dataset, global estimators calculate an "average" coefficient that may not accurately represent the true dynamics in any single geographic region. These methodological limitations can lead to biased statistical inferences, elevated residual errors, and ultimately, suboptimal policy recommendations. Despite this, much of the existing literature continues to emphasize demographic variables like inequality [9], [10], income [11], and education [12], [13] while paying limited attention to how these effects shift across different geographic coordinates [4], [14], [15].

Despite the limitations of global models, much of the existing literature continues to emphasize demographic variables while paying limited attention to how these effects shift across geographic coordinates. While a few localized studies have begun to apply spatial techniques—such as spatial autocorrelation in South Tangerang [16] or municipal-level clustering using Moran's I [17]—these efforts remain geographically isolated and largely descriptive. Furthermore, although Geographically Weighted Regression (GWR) has been successfully utilized to analyze socio-economic issues like poverty in Indonesia [18], its application within the political sphere remains significantly constrained [5], [19], [20]. Consequently, there is a pressing need to transition toward spatial modeling frameworks that explicitly accommodate geographic variance. By generating localized parameter estimates, GWR offers a robust solution to map exactly how statistical associations shift across space. Currently, there is a distinct lack of research that examines national-level electoral involvement while accounting for the extreme socio-economic and infrastructural fragmentation inherent in the Indonesian archipelago.

This study addresses the methodological gap in modeling Indonesian electoral participation by shifting the analytical focus away from broad political narratives and global averages, focusing instead on the strict statistical measurement of local spatial variations. The specific research objectives of this study are defined as follows:

a. To quantitatively test whether the empirical determinants of voter turnout in the 2019 elections exhibit statistically significant spatial heterogeneity across the 34 provinces.
b. To mathematically measure and map the spatially varying, localized effects of senior secondary education, economic inequality (Gini ratio), infrastructural deficits, and rurality on electoral turnout using a GWR framework.

c. To rigorously compare the predictive performance and goodness-of-fit of the localized GWR model against a traditional global OLS model, utilizing standard information-theoretic diagnostic criteria, including the Adjusted R^2 and the Corrected Akaike Information Criterion (AICc).

By grounding the analysis in applied spatial statistics, this research provides a replicable diagnostic and modeling workflow that demonstrates the efficacy of GWR in environments where global assumptions of homoskedasticity and spatial stationarity systematically fail.

2. RESEARCH METHOD

This study delineates the systematic approach employed to investigate the factors influencing provincial voter turnout in Indonesia. The methodological framework transitions from defining the variables to establishing a global regression baseline, followed by the application of spatial analysis to mathematically model regional non-stationarity.

2.1 Data and Variable

The dependent variable (Y) in this study is explicitly defined as the arithmetic average of the voter turnout percentages across three concurrent national elections held on April 17, 2019: the Presidential election, the House of Representatives (DPR), and the Regional Representative Council (DPD). According to the correlation test (Figure 2), there is a highly significant and robust relationship (at the 10% significance level) between voter turnout in a province across the three elections in 2019. Therefore, if the level of public participation in a province is high during one election, it can be observed that the level of voter turnout in the same province will also be high in another election. This finding also indicates that the level of public involvement in national elections can be estimated by taking the average of public involvement in the three different types of elections. The mathematical justification for averaging these three turnout rates—rather than modeling them independently—is rooted in their extreme collinearity; preliminary Pearson correlation analysis revealed coefficients exceeding 0.90 ($p < 0.01$) among the three elections. The variable is maintained in its native percentage format to preserve the interpretability of the linear coefficients.

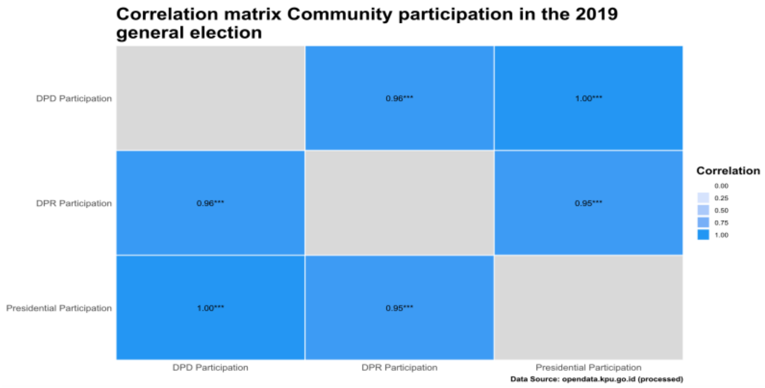


Figure 2. Correlation of Percentage of Voter Turnout in the Election of DPD, DPR, and President in 2019 (Data source: General Election Commission (KPU), processed by the author)

The empirical foundation of this study is built upon a cross-sectional, provincial-level dataset for the year 2019, covering all 34 administrative provinces of Indonesia. All data were sourced from official governmental publications, primarily BPS-Statistics Indonesia and the General Election Commission (KPU).

The independent variables incorporated into the modeling process are consistently defined as follows:

a. Senior Secondary Education (X1): The percentage of the population that has completed at least senior secondary education.
b. Gini Ratio (X2): A standard continuous index measuring the inequality of household expenditure distribution.
c. Damaged Road Proportion (X3): The ratio of the length of national roads classified as "damaged" or "severely damaged" relative to the total length of national roads.
d. Rural Ratio (X4): The percentage of administrative villages classified as rural relative to the total number of administrative villages and urban wards.

The dataset is complete, with absolutely no missing values across any of the variables for the 34 provinces, negating the need for data imputation techniques. The descriptive statistics of the variables used in this study are summarized in Table 1.

Table 1. Descriptive Statistics of the 2019 Provincial Dataset (n=34)

Variable	Unit	Mean	Standard Deviation	Minimum	Maximum
Dependent: Average Turnout (Y)	%	83	0.04	78	96
X1: Senior Secondary Education	%	39.45	8.47	27.44	63.31
X2: Gini Ratio	Index	0.35	0.04	0.27	0.43
X3: Damaged Road Proportion	%	7	0.06	0.00	29
X4: Rural Ratio	%	79	0.14	17	97

Data sourced from BPS-Statistics Indonesia and KPU

Global Regression Model and Diagnostics

Prior to spatial modeling, the analysis begins with the formulation of a global Ordinary Least Squares (OLS) regression model, mathematically defined as:

$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i \quad ; \qquad i = 1,2,\dots,n \tag{1}$$

where Yi is the average turnout for province i, $\boldsymbol{\beta}_0$ is the intercept, $\boldsymbol{\beta}_1$ represents the global coefficients for the independent variables (X_{ik}), p is the number of predictors, and ε_i is the random error term.

To empirically justify the transition from a global model to a spatial model, spatial diagnostocs are conducted. The Breusch-Pagan (BP) test is utilized to assesses heteroscedasticity, where a rejection of constant variance indicates that the error variance fluctuates significantly across different geographical regions. Furthermore, spatial autocorrelation is evaluated using Moran's I to determine if residual errors are spatially clustered.

Geographically Weighted Regression (GWR)

Analysis in this study employs Geographically Weighted Regression (GWR) to address spatial non-stationarity, which global models like Ordinary Least Squares (OLS) fail to capture. The GWR model is formulated as follows [21]:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p-1} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad ; \qquad i = 1,2,\dots,n \tag{2}$$

where (u_i, v_i) represents the geographic coordinates (longitude and latitude) of the i-th observation point, and $\beta_k(u_i, v_i)$ denotes the local regression coefficient for each independent variable at location i. To ensure full reproducibility of the results, the GWR estimation and spatial weight calculations were conducted using the GWR 4.0 software.

Weight Matrix and Distance Calculation

The parameter estimation for each province i relies on a spatial weighting matrix, W(u_i, v_i), which gives more influence to geographically closer observations. Because the spatial coordinates are based on the Earth's surface (latitude/longitude), the **Great-circle distance** formula is strictly utilized to calculate the distance dij between province i and province j, rather than a simple straight-line Euclidean distance.

The spatial weight matrix is computed using a **Bisquare Kernel function** [21]:

1. Fixed Gaussian Kernel

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right) \tag{3}$$

2. Fixed Bisquare Kernel

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2, \text{if } d_{ij} < b$$
$$= 0, if\ d_{ij} \geq b \tag{4}$$

3. Adaptive Gaussian Kernel

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right), \text{if } j \text{ is the nearest neighbor of } i$$
$$= 0, otherwise \tag{5}$$

4. Adaptive Bisquare Kernel

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2, \text{if } j \text{ is the nearest neighbor of } i \\ = 0, \text{if } d_{ij} \geq b \tag{6}$$

where d_{ij} is the distance between the i-th observation and the j-th observation and b is the bandwidth.

Bandwidth Selection and Model Optimization:
The optimal bandwidth b is iteratively identified using the Golden Section Search method. The objective function optimized during this search is the Corrected Akaike Information Criterion (AICc). The use of AICc is critical and highly justified for this study; it incorporates a strict penalty for the number of estimated parameters, which prevents model overfitting when dealing with a small sample size (n = 34 provinces).

Parameter Estimation and Local Significance Testing:
The local coefficients are estimated using the weighted least squares equation:

$$\widehat{\boldsymbol{\beta}}_i = (\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{W}_i\boldsymbol{y} \tag{7}$$

$\boldsymbol{X}$ is a matrix of independent variables of size $n \times (k+1)$ with the first column being 1 for the intercept term, $\boldsymbol{y}$ is a vector of dependent variables of size $n \times 1$, $\widehat{\boldsymbol{\beta}}_i = \left(\hat{\beta}_{0i}, \hat{\beta}_{1i}, \cdots, \hat{\beta}_{ki}\right)^T$ in the form of a vector of local coefficients of the GWR model, and $\boldsymbol{W}_i$ is a diagonal matrix showing the weights for each location at the i-th observation calculated through a kernel function.
To evaluate whether a specific variable significantly affects turnout in a particular province i, a local significance test is conducted using a pseudo t-statistic:

$$\boldsymbol{t_j(u_i, v_i)} = \frac{\boldsymbol{\beta_j\,\widehat{(u_i,v_i)}}}{\boldsymbol{SE(\,\beta_j\,\widehat{(u_i,v_i)})}} \tag{8}$$

where $\beta_j\,\widehat{(\boldsymbol{u_i}, \boldsymbol{v_i})}$ is the standard error for the j-th variable on the i-th observation obtained from the following formula:

$$var(\,\beta\widehat{(u_i, v_i)}) = CC^T\sigma \tag{9}$$

And

$$C = (X^TW(u_i, v_i)X)^{-1}X^TW(u_i, v_i) \tag{10}$$

test statistic $t_j(u_i, v_i)$ will be t-distributed with degree of freedom equal to effective number degree of freedom residual, that is δ_1.
To address the spatial reach of each predictor, this study reports the proportion of regions where local coefficients are significant at both α= 0.05 and α= 0.10 levels, rather than assuming uniform significance. This approach provides quantitative depth to the GWR analysis.

GWR Improvement ANOVA Testing
The goodness of fit test can be conducted on the GWR model or the local model formed. This test compares whether the local model is better than the global model. The test is conducted with the following procedure [21].
Hypothesis:

$H_0 : \beta_j(u_i, v_i) = \beta_j$ for each $i.j$ with $i \in \{1,2,\cdots,n\}\, j \in \{1,2,\cdots,k\}$
(All local parameters at each location are equal to their global parameters)
$H_1 : \beta_j(u_i, v_i) \neq \beta_j$ for any $i.j$ with $i \in \{1,2,\cdots,n\}\, j \in \{1,2,\cdots,k\}$
(There is at least one local parameter at a location that is not equal to the global parameter)

Test Statistic:
The transition from OLS to GWR is evaluated using the F-statistic. Given the sample size of n=34, a significance threshold of α= 0.10 is applied to the F-test to account for the specific constraints of the dataset while maintaining statistical rigor. This adjustment is necessary to avoid misinterpretation of model improvement in a relatively small spatial sample. The test statistic used is similar to the restricted test, which compares the average difference in residuals between the global model and the local model. The test statistic is formulated as follows [21].

$$F_{stat} = \frac{\frac{RSS_{OLS} - RSS_{GWR}}{v}}{\frac{RSS_{GWR}}{\delta_1}} \tag{11}$$

With:
RSS_{OLS} and RSS_{GWR} are the residual sum of squares of the OLS model and GWR model, respectively.
v is the difference between the residual free degree of the OLS model and the free degree of the GWR model, namely $v = (n-k) - \delta_1$ with $\delta_1 = (n - 2tr(S) + tr(S^TS))$.

The test statistic F_{stat} will be F-distributed with numerator degree of freedom v and denominator degree of freedom δ_1.
Decision:
If $F_{stat} > F_{(v,\delta_1)}(\alpha)$ obtained, the decision is to reject H_0. Thus, there is at least one local parameter at a location that is not equal to the global parameter. Therefore, the GWR model significantly improves the global regression model.

Determination of Best Model

To determine the best model to use, the next step is to compare several indicators from each model (including comparison with linear regression models with the OLS method). The evaluated indicators include AIC, $AICc$, BIC, CV, R^2, and R^2_{adj}. The optimal model will be chosen based on the criteria of having the lowest AIC, AICc, and CV values, as well as the highest R^2 and R^2_{adj}. The R^2 value quantifies the proportion of variability in the dependent variable that can be accounted for by the independent variables employed in the modeling process.

Methodological Limitations

While the applied modeling framework provides a robust approach for detecting spatial non-stationarity, two specific methodological limitations must be explicitly acknowledged. First, the sample size is constrained to the macro-level administrative divisions of Indonesia (n = 34 provinces). While the use of AICc mitigates the risk of overfitting in small samples [22], this constrained sample size inherently limits broader statistical generalization. Second, utilizing provincial-level spatial aggregation carries the risk of the modifiable areal unit problem (MAUP) [23], [24]. This macro-level aggregation may conceal significant intra-provincial heterogeneity and local socio-political dynamics, potentially introducing spatial aggregation bias. Future studies could build upon this framework by utilizing district or municipal-level disaggregation.

3. RESULT AND ANALYSIS

3.1. Global Model (OLS) Baseline and Diagnostics

The empirical analysis began with the estimation of a global OLS model to establish a quantitative baseline. As shown in Table 2, on a unified national scale, only the Gini Ratio and the Proportion of Damaged Roads exert a statistically significant influence on average voter turnout at the 5% and 1% levels, respectively.

Table 2. Global Regression (OLS) Estimation Results

Variable	Coefficient	Standard Error	t-statistic	p-value
Constant	0.8531	0.1383	6.1686	0.0000***
Senior Secondary Education (X1)	-0.0017	0.0011	-1.5943	0.1217
Gini Ratio (X2)	0.3146	0.1383	2.2747	0.0305**
Proportion Length of Damaged Road (X3)	0.1493	0.0515	2.8954	0.0071***
Rural Ratio (X4)	0.0235	0.0375	0.6285	0.5345
$R^2{}_{adj}$	36.48%	n_{obs}	34	
AIC	-140.960	BIC	-131.802	

(** significant at 5%, *** significant at 1%)

The OLS model assumes spatial stationarity. However, the Koenker (BP) test yielded a significant result, indicating **heteroscedasticity** and the presence of spatial heterogeneity across the Indonesian archipelago, which justifies the transition to a Geographically Weighted Regression (GWR) model.

3.2. Local Model (GWR) and Improvement Testing

Based on the optimization process, the GWR model with a fixed bisquare kernel function was selected for bandwidth optimization (36.184), as it provides a robust local fitting mechanism for the distributed data points across the 34 provinces (AIC = -146.581, AICc = -140.650, BIC = -134.207).

Table 3. Search for Optimum Kernel and Bandwidth

Kernel	Bandwidth	AIC	AICc	BIC
Fixed Bisquare	36.184	-146.581	-140.650	-134.207
Fixed Gaussian	23.056	-144.445	-140.184	-133.815
Adaptive Bisquare	24.000	-145.679	-122.122	-123.798
Adaptive Gaussian	24.000	-144.435	-139.254	-132.799

To confirm the significance of this spatial model, an ANOVA test was conducted. As shown in Table 4, the GWR Improvement test yields an F-statistic of 2.7083 (p-value = 0.0633). This indicates that the localized GWR model is significantly different from, and superior to, the global OLS model at the 10% significance level.

Table 4. GWR Improvement Testing

Source	Sum Square	Degree of Freedom	Mean Square	F-statistic	P-value
Global Residual	0.022	29.000			
GWR Improvement	0.005	3.161	0.002	2.7083	0.0633*
GWR Residuals	0.017	25.839	0.001		

* Significant at alpha=10%

The superiority of the GWR model is further supported by a reduction in the AICc value and a substantial improvement in the Adjusted R^2. Figure 3 illustrates the local Adjusted R^2 values for each province, demonstrating that the spatial model effectively captures regional variations in voter turnout that the global model missed.

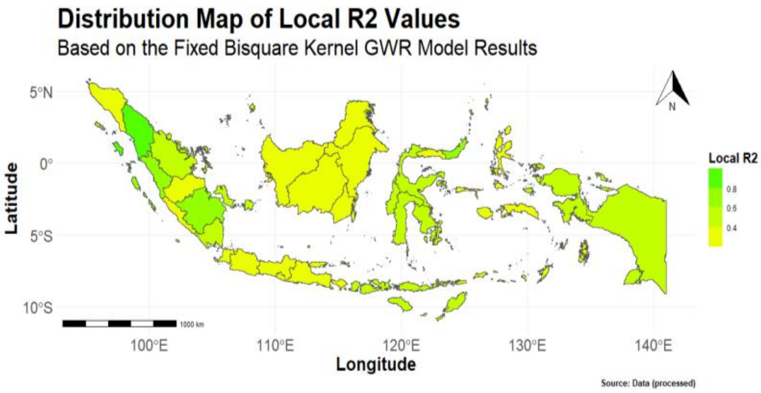


Figure 3. Distribution Map of Local R^2_{adj} GWR Model Results

3.3. Analysis of Local Coefficients and Spatial Patterns

The fundamental advantage of Geographically Weighted Regression (GWR) over global estimators lies in its capacity to disaggregate national trends into location-specific parameters. Table 5 presents the descriptive statistical summary of the localized coefficients extracted from the GWR model across the 34 provincial spatial units. The wide intervals between the minimum and maximum values for each predictor explicitly confirm the presence of spatial non-stationarity.

Table 5. Summary of GWR Local Coefficients

Variable / Parameter	Minimum	Median	Maximum
Intercept	0.35065	0.58849	1.60336
Senior Secondary Education (X_1)	-0.01021	-0.00103	0.00934
Gini Ratio (X_2)	0.34878	0.47542	0.59028
Damaged Road Proportion (X_3)	0.09735	0.16617	0.25377
Rural Ratio (X_4)	-1.49740	0.04080	0.44158

Table 5 presents the descriptive statistical summary of the localized coefficients extracted from the Geographically Weighted Regression (GWR) model across the 34 provincial spatial units. The most critical finding in this summary is the profound magnitude of variance between the minimum and maximum values for each predictor, which definitively confirms the presence of spatial non-stationarity.

Unlike the global OLS model that assumes a uniform, constant relationship across the entire nation, the GWR coefficients demonstrate that the independent variables frequently change directions shifting from negative to positive impacts depending on the geographic location:

a. Senior Secondary Education (X_1) The local coefficients range from a minimum of -0.01021 to a maximum of 0.00934. This interval, traversing zero, empirically proves that higher educational attainment acts as a deterrent to voting in certain regions (indicated by the negative extreme) while serving as a catalyst for participation in others (indicated by the positive extreme).
b. Gini Ratio (X_2) Unlike variables that traverse zero, the impact of economic inequality remains consistently positive across the archipelago, ranging from a minimum of 0.34878 to a maximum of 0.59028, with a median of 0.47542. This indicates that across all spatial clusters, economic inequality acts as a driving force for voter mobilization, though the intensity of this effect varies by region.

c. Damaged Road Proportion (X_3) Ranging from 0.09735 to 0.25377, the infrastructural deficit variable also exhibits spatial heterogeneity but maintains a strictly positive influence across all regions. The median of 0.16617 suggests a general trend where poor roads increase turnout, likely through protest votes or demands for development.

d. Rural Ratio (X_4) This variable demonstrates extreme fluctuation, ranging from a highly suppressive -1.49740 to a positive 0.44158, with a median of 0.04080. This illustrates that the urban-rural divide operates under entirely different political mechanics depending on the specific province, suppressing participation in some areas while boosting it in others.

Fundamentally, the descriptive statistics in Table 5 validate the methodological transition to GWR. The spatial variance, specifically the fact that the effects of socio-economic variables fluctuate significantly in magnitude, and in some cases (such as education and rural ratio) exert diametrically opposed effects in different provinces, mathematically renders any "one-size-fits-all" national electoral policy assumption obsolete.

3.3.1. Spatial Distribution of Education Impacts

Figure 4 illustrates the spatial distribution of the GWR coefficients for the Senior Secondary Education variable. The results reveal a distinct "East-West" dichotomy. In Eastern Indonesia (particularly in Papua and parts of Sulawesi), the coefficients are predominantly positive, suggesting that the higher educational attainment directly correlates with increased voter turnout. Conversely, in Western Indonesia (specifically across Java and Sumatera), the relationship is largely negative or statiscally insignificant.

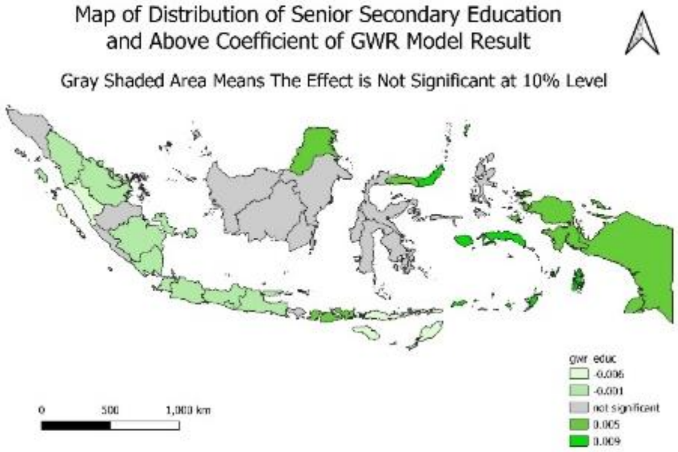


Figure 4. Map of Distribution of Senior Secondary Education and Above Coefficient of GWR Model Result (Data source: BPS, KPU; processed by the author)

3.3.2. Spatial Distribution of Economic Inequality Impacts

Figure 5 visualizes the GWR results for the Gini ratio. Unlike education, the influence of economic inequality on voter turnout is remarkably consistent across the archipelago. The map is predominantly characterized by positive coefficients, indicating that in almost all significant regions, higher levels of economic disparity correlate with higher rates of electoral participation.

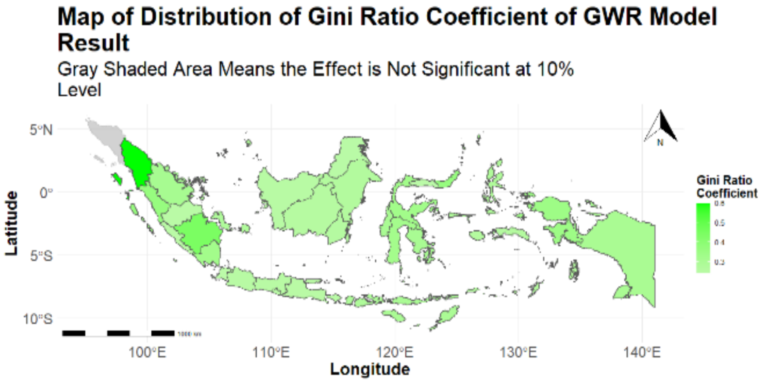


Figure 5. Map of Distribution of Gini Ratio Coefficient of GWR Model Result (Data source: BPS, KPU; processed by the author)

3.3.3. Spatial Distribution of Infrastructure Impacts

Figure 6 maps the coefficients for the proportion of damaged roads, revealing a Center-Periphery dichotomy. In Outer Java (Sumatera, Sulawesi, Bali, Nusa Tenggara, and Papua), the coefficients are predominantly positive, meaning that severe infrastructure deficits correlate with higher voter turnout. In contrast, in Java the country's political and economic center the relationship is markedly different and largely insignificant.

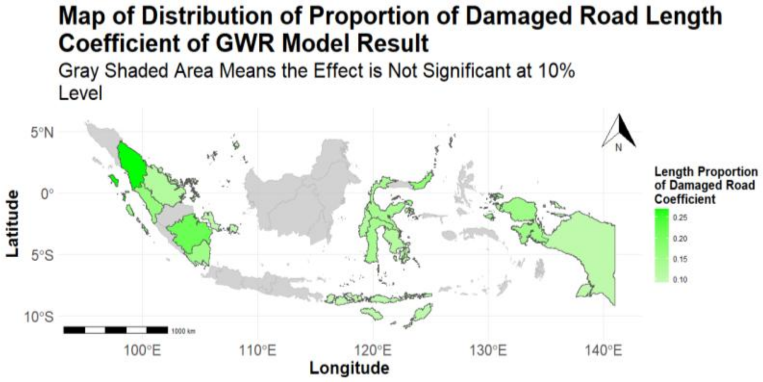


Figure 6. Map of Distribution of Length Proportion of Damaged Road Coefficient of GWR Model Result (Data source: BPS, KPU; processed by the author)

3.3.4 Spatial Anomalies: The Case of Aceh

Figure 7 displays the combination of significant variables influencing voter turnout in each province. Notably, Aceh emerges as a striking spatial outlier. It is the only province where none of the predictor variables (Education, Inequality, or Infrastructure) show a statistically significant correlation with voter turnout, indicating a complete decoupling from the national structural trends.

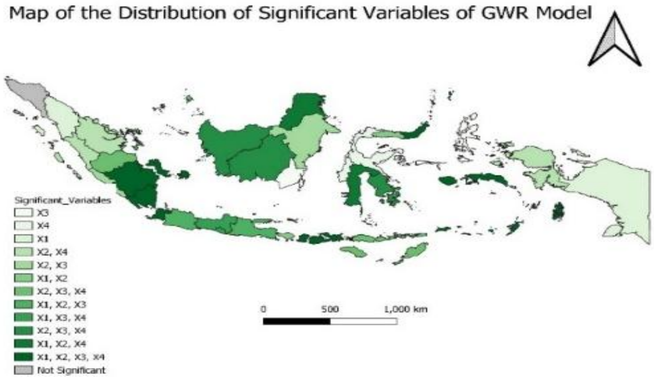


Figure 7. Map of the Distribution of Significant Variables of GWR Model (Data source: BPS, KPU; processed by the author)

3.4 Discussion

The application of Geographically Weighted Regression (GWR) in this study provides empirical evidence that the determinants of voter turnout in Indonesia are fundamentally non-stationary. By mapping these localized effects, several underlying theoretical and socio-political dynamics emerge, explaining why standard global models fail to capture the reality of Indonesian electoral behavior.

3.4.1 The Bifurcated Impact of Education and the *Noken* System

The spatial distribution of the education coefficient reveals a stark "East-West" dichotomy. In Western Indonesia (such as Java and Sumatera), higher educational attainment is associated with lower or stagnant voter turnout. This aligns with a critical offshoot of Modernization Theory [25], which suggests that highly educated urban voters tend to develop critical political attitudes, leading to skepticism, lower party identification, and occasionally, political apathy or conscious abstention (golput) [12], [26], [27].

Conversely, in Eastern Indonesia, particularly in Papua, electoral participation remains exceptionally high regardless of individual educational attainment. This anomaly can be explained by the institutionalization of local cultural practices, specifically the noken system [28]. Recognized by the Constitutional Court for specific districts in Papua, the noken system allows for collective voting where tribal leaders (Big Men) cast votes on behalf of their entire community [29]. Consequently, high turnout in these eastern regions is not necessarily a reflection of individual civic engagement driven by education, but rather a product of communal mobilization and traditional consensus.

3.4.2 Economic Inequality as a Catalyst for Patronage

Unlike education, the Gini ratio demonstrates a pervasive, nationwide positive correlation with voter turnout. From a theoretical standpoint, this consistency supports the Relative Power Theory [30] and the mechanics of clientelism. In regions characterized by stark economic disparity, the economically marginalized population becomes highly susceptible to transactional politics.

Political elites and brokers exploit these inequalities by deploying patronage networks, vote-buying (money politics), and the distribution of club goods to mobilize the lower-income electorate [[6], [7], [10]. Therefore, the high turnout in highly unequal provinces does not necessarily indicate a healthy democracy; rather, it highlights how economic vulnerability can be weaponized as a highly effective mobilization tool during simultaneous elections [9].

3.4.3 Center-Periphery Dynamics and "Asphalt Politics"

The structural impact of infrastructure, measured by the proportion of damaged national roads, perfectly illustrates the center-periphery divide in Indonesian political economy. In the "Outer Islands" (Sumatera, Sulawesi, and parts of Eastern Indonesia), severe infrastructure deficits strongly correlate with higher voter turnout. This phenomenon can be interpreted through the lens of "Asphalt Politics." [31]. In these marginalized regions, infrastructure is a matter of economic survival. Voters are highly motivated to participate in elections to support candidates who promise tangible developmental deliverables or to cast protest votes against the incumbent’s neglect.

In contrast, in Java the country’s political and economic center where infrastructure is relatively mature and interconnected the condition of roads ceases to be a significant mobilizing factor, rendering the variable statistically insignificant in the GWR spatial mapping [32].

3.4.4 The Spatial Anomaly of Aceh: Identity over Economics

The GWR analysis successfully identified Aceh as a profound spatial outlier a "political silo" structurally decoupled from national electoral logic. In Aceh, none of the standard developmental metrics (education, inequality, or infrastructure) significantly influenced voter turnout.

This anomaly is rooted in Aceh’s unique institutional arrangement of asymmetric decentralization (Otonomi Khusus) and a distinct local party system (Partai Lokal) born from the post-conflict Helsinki Agreement [33]. Within this ecosystem, voter mobilization in 2019 was driven by entrenched post-conflict patronage networks and intense religious identity [34]. As a province with strong oppositional tendencies against the central government's secular-nationalist coalition, the electorate’s behavior was dictated by ideological resistance and the defense of Islamic values. Consequently, tangible material incentives failed to translate into votes, demonstrating that in Aceh, the politics of identity and historical grievance completely overshadow the politics of economic utility.

3.4.5 Policy Implications for Electoral Governance

The empirical evidence of spatial non-stationarity in voter behavior carries significant implications for electoral management in Indonesia. The shift from a global to a localized analytical framework suggests that the General Elections Commission (KPU) should transition from a "one-size-fits-all" approach to a more geographically targeted strategy.

3.4.5.1 Region-Specific Voter Education Strategies

The bifurcated impact of education where it negatively correlates with turnout in Western Indonesia but shows different dynamics in the East suggests that voter education must be tailored to regional socio-political contexts. In highly educated urban centers (e.g., Java), campaigns should focus on mitigating political skepticism and "rational apathy" among middle-class voters. Conversely, in regions influenced by collective voting cultures like the *noken* system in Papua, policy focus should shift toward strengthening individual voting rights and secret ballot awareness while respecting local traditions.

3.4.5.2 Infrastructure as a Catalyst for Participation

The strong correlation between road quality and turnout in peripheral regions (Outer Java) indicates that infrastructure is not merely a logistical concern but a psychological determinant for voters. For rural and remote electorates, the provision of accessible transportation to polling stations (TPS) can significantly lower the physical barriers to voting. Policymakers should recognize that in developing regions, electoral participation is often a "protest vote" or a demand for better developmental deliverables.

3.4.5.3 Addressing Spatial Outliers (The Aceh Context)

The identification of Aceh as a profound spatial outlier suggests that standard developmental metrics (education, inequality, infrastructure) are insufficient to explain participation in post-conflict or ideologically distinct regions. For such areas, the electoral commission must employ localized sociocultural and religious-based communication strategies that resonate with the regional identity and historical grievances, rather than relying on national economic narratives.

3.4.5.4 Data-Driven Resource Allocation

By utilizing the GWR framework, electoral commissions can optimize the allocation of socialization budgets. Resources should be prioritized in provinces with low Local R^2 values, as these areas indicate the presence of unmapped external factors or "hidden" local dynamics that require deeper qualitative intervention and more intensive monitoring to ensure democratic participation.

4 CONCLUSION

This study conclusively demonstrates that the empirical determinants of voter turnout in Indonesia's 2019 elections exhibit statistically significant spatial heterogeneity. By transitioning from a global Ordinary Least Squares (OLS) baseline to Geographically Weighted Regression (GWR) framework, this research mathematically captures the spatial non-stationarity inherent in the archipelagic dataset. The global OLS model, which assumes spatial constancy, systematically failed to account for regional variations, leading to biased parameter estimation and elevated residual errors.

In contrast, the localized GWR model optimized using a fixed bisquare kernel and great-circle distances significantly outperformed the global baseline. This methodological superiority is quantitatively evidenced by a substantial reduction in the Corrected Akaike Information Criterion (AICc) and a marked improvement in explanatory power, where local Adjusted R^2 values drastically exceeded the global average. The GWR framework successfully isolated the localized effects of education, inequality, and infrastructure, providing precise, location-specific coefficients that a global estimator would otherwise obscure or render insignificant.

This study demonstrates that the GWR workflow provides a robust framework for handling spatially fragmented datasets, which are common in applied mathematics and public policy research. By providing local rather than just global estimates, this methodology allows researchers to uncover hidden spatial patterns that global models might overlook. The practical value of this approach extends beyond electoral studies to any field requiring precise spatial analysis, such as urban planning, public health, and regional economic policy.

These findings underscore the mathematical necessity of incorporating spatial variance into predictive regression models when analyzing highly fragmented geographic areas. The demonstrated GWR workflow provides a robust mathematical foundation for modeling other spatially dependent socio-economic phenomena. For future spatial modeling, researchers are encouraged to build upon this framework by incorporating spatio-temporal dimensions, such as Geographically and Temporally Weighted Regression (GTWR), to capture parameter shifts over multiple election cycles. Furthermore, subsequent spatial analyses should utilize more granular, municipal-level data to mitigate the modifiable areal unit problem (MAUP) and further refine the precision of localized parameter estimations.

ACKNOWLEDGEMENT

We would like to express our deepest gratitude to all those who contributed to the completion of this journal article. We are especially grateful to Politeknik Statistika STIS and Badan Pusat Statistik for providing generous resources and unwavering support necessary for this study. We also extend our heartfelt thanks to UIN Sumatera Utara Medan for the invaluable opportunity to present the results of this research on political participation in Indonesia from a spatial analysis perspective. Finally, we acknowledge the anonymous reviewers for their thoughtful and constructive comments, which significantly helped refine the manuscript.

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