**Bulletin of Applied Mathematics and Mathematics Education**
Vol. 6, No. 1, April 2026, pp. 11-26
e-ISSN: 2776-1029 p-ISSN: 2776-1002 DOI: 10.12928/bamme.v6i1.16002

APPLIED MATHEMATICS

# Geographically weighted panel regression using Haversine distance for mapping sustainable development goals

**Mohamad Hidayat Hala** [1], **Hasan S. Panigoro** [1], **Amanda Adityaningrum** [1,*]

[1] Universitas Negeri Gorontalo, Jl. Jend. Sudirman No.6, Dulalowo Tim., Kec. Kota Tengah, Kota Gorontalo, Gorontalo 96128 Indonesia
*Corresponding author

## Abstract

The Sustainable Development Goals (SDGs) vary widely across Asian countries, indicating that the factors driving SDGs achievement may vary by location. Global models may miss these local variations, so this study used Geographically Weighted Panel Regression (GWR Panel), a method that estimates separate regression coefficients for each geographical location. The GWR Panel in this study was used to capture spatially varying SDGs determinants across 46 Asian countries from 2015 to 2024. This study also compares four Adaptive Kernel functions (Gaussian, Exponential, Bisquare, Tricube) with Haversine distances, as kernel choice directly affects which neighboring countries influence each local coefficient estimate, where applying the incorrect kernel to spatially heterogeneous data can lead to biased local estimates. The best kernel was selected using Cross-Validation (CV). The Adaptive Exponential Kernel produced the lowest CV value (81.686), compared to Adaptive Gaussian (83.128), Bisquare (84.485), and Tricube (85.095), confirming it as the most accurate kernel for this data. The results identified 16 distinct country groups, demonstrating that SDGs determinants vary across Asia. Education, gender, economic growth, infrastructure, environment, institutions, and partnerships are universally important. Meanwhile, water, health, hunger, and climate show the greatest regional variation. SDGs policies should be adjusted to local contexts.

**Keywords**: adaptive kernel, geographically weighted panel regression, GWR, Haversine distance, SDGs

**How to cite**: Hala, M. H., Panigoro, H. S., & Adityaningrum, A. (2026). Geographically weighted panel regression using Haversine distance for mapping sustainable development goals. *Bulletin of Applied Mathematics and Mathematics Education, 6*(1), 11-26. https://doi.org/10.12928/bamme.v6i1.16002

**Article history**: Received 16/03/2026, Accepted 25/05/2026, Published 04/06/2026

**Correspondence address**: Universitas Negeri Gorontalo, Jl. Jend. Sudirman No.6, Dulalowo Tim., Kec. Kota Tengah, Kota Gorontalo, Gorontalo 96128 Indonesia. E-mail: amanda@ung.ac.id

## INTRODUCTION

The Sustainable Development Goals (SDGs) are 17 global goals with 169 targets set by the United Nations to guide progress toward sustainable development by 2030 (United Nations Department of Economic and Social Affairs, 2024). SDGs achievement is important because a country's failure to meet its targets hinders human development, increases social and economic inequality, and worsens environmental conditions (Filho et al., 2020).

The SDGs Index Report shows unequal performance across regions in achieving the SDGs. For example, developed countries that are members of the Organization for Economic Co-operation and Development (OECD) rank highest with an average score of 79.16, followed by Eastern Europe at 73.14 and Asia at 67.65. In contrast, North Africa scores 66.28, Oceania scores 63.25, and Sub-Saharan Africa ranks lowest at 55.46 (Sachs et al., 2025).

This condition shows structural challenges, such as regional gaps, gaps in industrial development, and high environmental risk (Çelik et al., 2025). Previous research by Bhatia (2025) identified performance gaps across Asian subregions, where East Asia struggles with environmental issues, South Asia faces slow progress in Zero Hunger, Central Asia lags in Gender Equality, and Southeast Asia and West Asia encounter challenges in Sustainable Cities and Communities, and in Peace, Justice, Strong Insitutions. In addition, prior research by Monica (2025) showed that score differences across regions reflect different levels of SDGs achievement, and it shows structural gaps in each Country's development model. Therefore, this condition shows the need for an analysis that considers local differences to better understand the key factors affecting SDGs achievement.

Previous research on the determinants of SDGs achievement mainly uses global models. For example, Asadikia et al. (2022) applied the Gradient Boosting Machine and found that only some SDGs indicators significantly affect the overall score. Other research used factor analysis and multivariate regression on the SDGs Index 2023 and showed that the 17 indicators differ in their relevance. Although these studies identify differences in indicator importance, they still estimate a single average effect across all regions. This approach ignores spatial heterogeneity, in which the impact of an indicator varies across locations due to economic, social, cultural, and geographic differences. Ignoring spatial variation can violate the homoscedasticity assumption in classical regression and lead to biased estimates (Pratama et al., 2021; Wati & Utami, 2020). Thus, spatial analysis is needed to capture variations in effects at the local level.

Geographically Weighted Regression (GWR) is a spatial regression method in which regression parameters are estimated locally at each observation point (Wati & Utami, 2020). Research by Faricha et al. (2025) concluded that GWR produced an $R^2$ of 97.72%, which is higher than that of Ordinary Least Squares (92.32%). This result shows that considering regional differences can improve model accuracy.

GWR Panel is another GWR development that combines GWR with panel data. It combines the advantages of panel data in controlling for individual and time differences with GWR's ability to capture spatial differences (Mudjiningsih et al., 2023). By controlling for individual fixed effects that capture local conditions, panel data increases degrees of freedom and reduces bias from omitted variables (Hussein & Tawfiq, 2021; Nabilla et al., 2023).

GWR and GWR Panel implementation require specifying a weighting function and a distance metric, as spatial weights are used in the local regression model to give higher importance to observations closer to the target location (Fotheringham et al., 2002). Previous research by Martha et al. (2021) has applied three adaptive kernel weight functions (Gaussian, Exponential, and Bisquare) in the GWR Panel. Arum and Alfian (2022) compared the Fixed Gaussian Kernel with the Adaptive Gaussian Kernel by using Euclidean distance in the GWR Panel method. Results showed that the Adaptive Gaussian Kernel achieved the best performance, as indicated by the smallest Cross-Validation (CV) value. Another research by Nasri et al. (2023) used the Adaptive Tricube Kernel weight function. For most of these studies, the GWR Panel method used Euclidean distance. However, no research has compared the four Adaptive Kernel functions (Gaussian, Exponential, Bisquare, and Tricube) simultaneously. Additionally, previous research used Euclidean distance in the GWR Panel, which assumes that the Earth's surface is flat, whilst Miftahuddin et al. (2020) and Nabilla (2023) found that Haversine distances do provide slightly higher accuracy for geographic coordinates.

Spatial analysis results may be affected by the difference between these two distance calculations. As the Euclidean distance is based on the Pythagorean theorem, it assumes a flat Earth and therefore ignores Earth's curvature. In contrast, the Haversine distance, which uses the Haversine formula, calculates the great-circle distance between two points on a sphere using latitude and longitude, making it more suitable for geographical data (Herwanto et al., 2024; Miftahuddin et al., 2020; Veness, 2011). This aligns with Nabila's (2023) research, which found that the Haversine distance is more accurate than the Euclidean distance for geographical coordinates. Moreover, Faricha et al. (2025) showed that GWR based on Haversine distance has a high determination coefficient, indicating the model performs very well. This means that accounting for Earth's curvature in distance calculations may improve the reliability of spatial analysis results.

Based on the explanation above, SDGs patterns within Asia vary across subregions due to its large geographical area. The Euclidean distance does not account for Earth's curvature at this scale, leading to inaccurate distance calculations. Additionally, kernel choice determines which neighboring countries are given more weight in each local estimation. An incorrect distance or kernel can result in biased local estimates of SDGs factors when used with data with uneven spatial patterns. Therefore, this study fills a gap by comparing four Adaptive Kernel functions with the Haversine distance in the GWR Panel for SDGs analysis in Asia, where both distance accuracy and kernel selection directly affect the reliability of local estimates.

## RESEARCH METHOD

### Data

Data for this research were collected from the Sustainable Development Report (Sachs et al., 2025), which covers 46 Asian countries from 2015 to 2024. Panel data were used in this research, resulting in 460 observations and a balanced panel, as all 46 countries have complete data across all 10 years. In the research, saturated sampling (total sampling) was used, so the number of samples equaled the number of populations (Syapitri et al., 2021).

The dependent variable ($Y$) is the SDGs score, while the independent variables ($X$) consist of all SDGs indicators without variables of No Poverty, Reduced Inequalities, and Life Below Water. Poverty is excluded due to limited availability and inconsistent quality across countries and years (Yurevna, 2025). Meanwhile, for Reduced Inequalities, previous research by Silvia and Nastasi (2022) noted that data for the indicator are unavailable in several countries, primarily because inequality in Asia is largely internal, leading to incomplete national reporting across nations. Similarly, the Life Below Water indicator is excluded because some Asian countries lack marine territories or aquatic areas, making it difficult to consistently measure marine-related indicators across countries (Arora et al., 2023).

Thus, the independent variables used included Zero Hunger ($X_1$), Good Health and Well-being ($X_2$), Quality Education ($X_3$), Gender Equality ($X_4$), Clean Water and Sanitation ($X_5$), Affordable and Clean Energy ($X_6$), Decent Work and Economic Growth ($X_7$), Industry, Innovation and Infrastructure ($X_8$), Sustainable Cities and Communities ($X_9$), Responsible Consumption and Production ($X_{10}$), Climate Action ($X_{11}$), Life on Land ($X_{12}$), Peace, Justice and Strong Institutions ($X_{13}$), and Partnerships for the Goals ($X_{14}$).

The spatial distances were calculated using the coordinates of each Country's capital city. The map of Asia was taken from Natural Earth (2025).

### Geographically weighted panel regression (GWR Panel)

The GWR Panel combines Fixed Effects Model (FEM) for panel data regression with Geographically Weighted Regression (GWR). This analysis considers both spatial and temporal factors and requires the addition of a weighting function for each research location (Mar’ah & Sifriyani, 2023; Sifriyani et al., 2024; Warsito et al., 2018). In FEM, each location $i$ has an individual intercept $\beta_{0i}^{*}$ that captures time-invariant unobserved characteristics, with the coefficient $\beta_k$ assumed to be constant across all locations. FEM is written in Eq. (1) (Hsiao, 2014).

$$y_{it} = \beta_{0i}^{*} + \sum_{k=1}^{K} \beta_k x_{kit} + \varepsilon_{it} \tag{1}$$

GWR Panel extends the FEM in two ways (Warsito et al., 2018; Yu et al., 2021, Yu et al., 2023). First, the globally constant coefficient $\beta_k$ is replaced by a spatially varying coefficient $\beta_k(u_i, v_i)$

that varies across geographic locations. Second, the unit-specific intercept $\beta_{0i}^{*}$ is replaced with a spatially varying intercept $\beta_0(u_i, v_i)$. The intercept $\beta_{0i}^{*}$ in the FEM has no spatial structure and only says that each unit has its own intercept. On the other hand, the intercept $\beta_0(u_i, v_i)$ in GWR Panel varies across geographic space based on distance weighting. The GWR Panel model is given in Eq. (2) (Warsito et al., 2018; Yu et al., 2021; Yu et al., 2023),

$$y_{it} = \beta_0(u_i, v_i) + \sum_{k=1}^{K} \beta_k\,(u_i, v_i)x_{kit} + \varepsilon_{it} \tag{2}$$

where $y_{it}$ is the dependent variable at location *i* and time *t*; $x_{kit}$ is the independent variable *k* at location *i* and time *t*; $\beta_0(u_i, v_i)$ is the intercept at location *i*; $\beta_k(u_i, v_i)$ is the regression coefficient for variable *k* at location *i*; $(u_i, v_i)$ are the coordinates of geographic location *i* (latitude and longitude); $\varepsilon_{it}$is the error term at location *i* and time *t*; and *K* is the total number of independent variables. The regression coefficient $\beta_0(u_i, v_i)$ and $\beta_k(u_i, v_i)$ vary across geographic locations but are constant over time (Warsito et al., 2018; Yu et al., 2021; Yu et al., 2023).

The parameters in Eq. (2) are estimated through a two-stage process (Caraka & Yasin, 2017; Hsiao, 2014; Warsito et al., 2018). The first stage is applying the within-transformation to eliminate $\beta_{0i}^{*}$from the model. This used three steps. First, modify the original Eq. (1) at each time point *t*, which is written in Eq. (3).

$$y_{it} = \beta_{0i}^{*} + \sum_{k=1}^{K} \beta_k\,(u_i, v_i)x_{kit} + \varepsilon_{it} \tag{3}$$

Second, define the time-average of the dependent and independent variables for each location *i* across all *T* periods ( $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$and $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$). Compute the time-average version of Eq. (1) by averaging across $t = 1, \dots, T$, thus, it is written as in Eq. (4).

$$\overline{y}_i = \beta_{0i}^{*} + \sum_{k=1}^{K} \beta_k\,(u_i, v_i)\overline{x}_{ki} + \varepsilon_i \tag{4}$$

Third, subtract Eq. (4) from the Eq. (3), so $\beta_{0i}^{*}$ appears on both sides $(\beta_{0i}^{*} - \beta_{0i}^{*})$, resulting in the demeaned model (without $\beta_{0i}^{*}$, as it canceled) in Eq. (5) (Warsito et al., 2018; Yu et al., 2021, 2023).

$$(y_{it} - \bar{y}_i) = \sum_{k=1}^{K} \beta_k(u_i, v_i)(x_{kit} - \bar{x}_{ki}) + (\varepsilon_{it} - \overline{\varepsilon}_i) \tag{5}$$

The within-transformation removes all time-invariant individual fixed effects from the model (Hsiao, 2014). The second stage is to apply the Weighted Least Squares (WLS) estimator to the demeaned model in Eq.(5), where each location *i* is given spatially weighted observations based on its geographic location. The estimator is provided in Eq. (6) (Caraka & Yasin, 2017; Warsito et al., 2018; Yu et al., 2021; Yu et al., 2023)

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i)X)^{-1} X^T W(u_i, v_i)y \tag{6}$$

where $W(u_i, v_i)$ is the diagonal weighting matrix for location $(u_i, v_i)$, and *X* and *y* represent the demeaned independent $(x_{kit} - \bar{x}_{ki})$ and dependent $(y_{it} - \overline{y}_i)$ variables. The spatially varying intercept $\beta_0(u_i, v_i)$ is then calculated from the estimated slope coefficients, as shown in Eq. (7) (Hsiao, 2014; Warsito et al., 2018).

$$\hat{\beta}_0(u_i, v_i) = \bar{y}_i - \sum_{k=1}^{K} \hat{\beta}_k(u_i, v_i)\,\overline{x}_{ki} \tag{7}$$

*Haversine distance*
The Haversine distance, which is the shortest distance between two points on a sphere, is calculated by using spherical trigonometry based on Earth's curvature (Herwanto et al., 2024). By using the latitude and longitude coordinates of the two points, the Haversine formula determines the shortest path along Earth's surface. The calculation is shown in Eq. (8) (Veness, 2011).

$$d = \left(2 \times atan2\left(\sqrt{a}, \sqrt{1-a}\right)\right) \times \sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos(\varphi_1) \times \cos(\varphi_2) \times \sin^2(\frac{\Delta\lambda}{2}) \tag{8}$$

where *d* is the distance between two points on the Earth's surface; *R* is Earth's radius (mean = 6371 km); *c* is the central angle between two points calculated using the atan2 function; $\varphi$ is the latitude coordinate; $\lambda$is the longitude coordinate; also,$\Delta\varphi$ and $\Delta\lambda$are the difference in latitude (lat2-lat1) and in longitude (lon2-lon1).

*Weighting function*
The weighting function is important in the GWR Panel model, where the diagonal weighting matrix elements $W_{ij}$are calculated from the Haversine distance $(d_{ij})$ and the specified bandwidth $(b_i)$ (Nabilla et al., 2023). Bandwidth can be specified as a fixed distance (fixed bandwidth) or as a fixed number of nearest neighbors (adaptive bandwidth) (Fotheringham et al., 2002). An adaptive bandwidth kernel is one whose bandwidth is expressed as a function of the number of neighbors, thereby adjusting to the point density but not to the coefficient surface curve, which would be required to optimize coefficient surface estimation if an approach aimed to locally adapt the kernel (Geniaux, 2026). The optimal bandwidth is mostly determined using the Cross-Validation (CV) method, as shown in Eq. (9) (Fotheringham et al., 2002),

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2 \tag{9}$$

The bandwidth that produces the smallest CV value is selected as the optimal bandwidth (Yu et al., 2021; Yu et al., 2023). The Adaptive Kernel weighting function adjusts based on the number of observation points in an area. In regions with many points, the bandwidth is reduced for better accuracy, while in regions with fewer points, the bandwidth is increased to match the sparser data. This approach ultimately leads to more reliable parameter estimates (Taek et al., 2023).

Commonly used Adaptive Kernel weighting functions include Gaussian, Exponential, Bisquare, and Tricube, represented by Eq. (10), Eq. (11), Eq. (12), and Eq. (13), respectively (Candra Dewi et al., 2025; Fotheringham et al., 2002; Leung et al., 2000; McMillen, 2001).

*Gaussian*

$$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b_i}\right)^2\right] \tag{10}$$

*Exponential*

$$w_{ij} = exp\left(-\frac{d_{ij}}{b_i}\right) \tag{11}$$

*Bisquare*

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b_i}\right)^2\right]^2, & \text{if } d_{ij} < b_i \\ 0, & \text{if } d_{ij} \geq b_i \end{cases} \tag{12}$$

*Tricube*

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b_i}\right)^3\right]^3, & \text{if } d_{ij} < b_i \\ 0, & \text{if } d_{ij} \geq b_i \end{cases} \tag{13}$$

### Step analysis

This research consisted of the following steps for analysis: (1) Conduct descriptive analysis; (2) Perform multicollinearity test among the independent variables; (3) Estimate panel data regression models: CEM (Common Effect Model), FEM (Fixed Effect Model), and REM (Random Effect Model); (4) Perform Chow test and Hausman test to select the best panel data model; (5) Check residual assumption (normality, spatial heterogeneity and autocorrelation) for the selected model; (6) Estimate the GWR Panel model using four Adaptive kernel functions with Haversine distance; (7) Conduct goodness-of-fit test and significance test for the GWR Panel model; (7) Compare the performance between the global panel model and the GWR Panel model; and (8) Draw conclusion based on the analysis results. Analyses were performed in R Studio, and maps for visualization were created in QGIS.

## RESULTS AND DISCUSSION

### Descriptive statistics

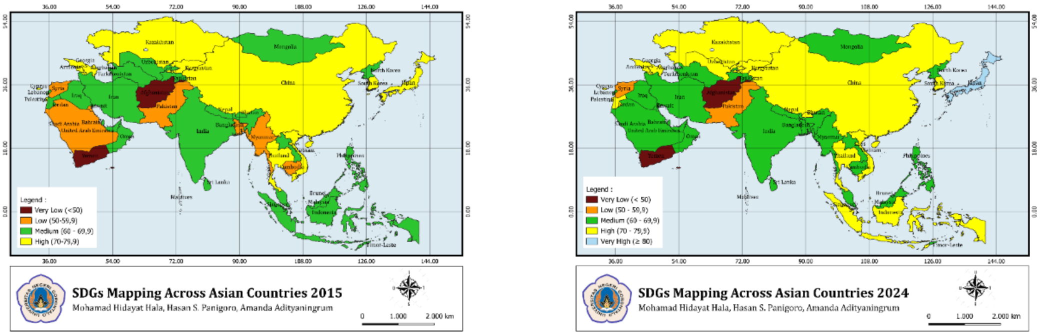
Table 1 presents descriptive statistics on SDG scores for 46 Asian countries from 2015 to 2024. Overall, sustainable development has improved across the Asian region over the past decade. During the observation period, the average SDG score increased from 64.7 in 2015 to 68.0 in 2024. Between 2015 and 2024, the minimum score ranged from 42.8 to 47.7, while the maximum score increased from 79.3 to 80.7.

**Table 1.** Descriptive analysis

| Year | N | Mean | Minimum | Maximum |
|---|---|---|---|---|
| 2015 | 46 | 64.7 | 42.8 | 79.3 |
| 2016 | 46 | 65.1 | 44.3 | 79.3 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 2023 | 46 | 67.5 | 46.2 | 80.2 |
| 2024 | 46 | 68.0 | 47.7 | 80.7 |

Figure 1 illustrates the spatial distribution of SDG scores in Asia for 2015 and 2024. The classification uses five categories: very low (<50), low (50–59.9), medium (60–69.9), high (70–79.9), and very high (≥80).

SDG achievement across Asia has shown a positive trend, although significant disparities remain, particularly in conflict-affected regions. It is therefore justified to apply GWR approaches to understand the local determinants of SDG performance because of this observed spatial heterogeneity.



(a) (b)

**Figure 1.** Visualization of SDG Score in Asia: (a) 2015, and (b) 2024.

### Multicollinearity test

All independent variables were tested for multicollinearity using the Variance Inflation Factor (VIF) test statistic (Gujarati, 2022). The results are presented in **Table 2**.

**Table 2.** Multicollinearity Test

| Variables | $VIF$ |
|---|---|
| $X_1$ and $X_2$ | 1.607 |
| $X_1$ and $X_3$ | 1.891 |
| $X_1$ and $X_4$ | 1.579 |
| $X_1$ and $X_5$ | 1.361 |
| ⋮ | ⋮ |
| $X_{14}$ and $X_{10}$ | 1.001 |
| $X_{14}$ and $X_{11}$ | 1.002 |
| $X_{14}$ and $X_{12}$ | 1.069 |
| $X_{14}$ and $X_{13}$ | 1.122 |

Table 2 shows that all VIF values are below 10. When the VIF is below 10, all the independent variables are not highly collinear (Kusumawardani et al., 2021). As a result, the analysis indicates that multicollinearity is absent among the independent variables for the 46 Asian countries from 2015 to 2024.

### Estimate of panel data regression

There are three main approaches to estimating panel data models: CEM, FEM, and REM. The Chow and Hausman tests were conducted to determine which of these three approaches was most suitable (Gujarati, 2022). In the Chow test, CEM and FEM are compared, while in the Hausman test, FEM and REM are compared (Puspitaningtyas, 2025).

Based on the Chow test, FEM was found to be more appropriate than CEM, with an F-statistic of 89.819 and a p-value of 0.001 ($p\text{-value} < \alpha = 0.05$). Additionally, the Hausman test resulted in a coefficient of 27.678 ($p = 0.015 < \alpha = 0.05$), indicating that FEM is more consistent than REM. Consequently, a FEM was chosen for this research.

### Residual assumption

Following the selection of FEM as the appropriate model, residual assumption tests were conducted. According to the Kolmogorov-Smirnov normality test, the D-statistic was 0.043, and the p-value was 0.348. This indicates that the residuals are normally distributed ($p\text{-value} > \alpha = 0.05$) (Gujarati, 2022).

However, the Breusch-Pagan test detected heteroscedasticity (BP = 179.84, p < 0.001). Heteroscedasticity (p-value < $\alpha$ = 0.05) indicates that the model does not meet the classical assumption (Arum & Alfian, 2022; Puspitaningtyas, 2025).

Additionally, based on Moran's I test, the residual does not exhibit spatial dependence with a p-value greater than $\alpha$ = 0.05 (p-value = 0.952, Moran's I = -0.048). According to Moran's I statistic, spatial autocorrelation is measured by values ranging from -1 to 1, where z-scores and p-values indicate statistical significance. When the p-value is greater than α, this indicates that the spatial dependence is not present in the residual (Comber et al., 2023; He et al., 2020). Following Geniaux & Martinetti (2018), spatial heterogeneity alone shows sufficient justification for the GWR Panel application when spatial dependence is not significant. Cai et al. (2014) also reported Moran's I as descriptive rather than as a gatekeeping test for GWR specification, consistent with the model selection framework described. Consequently, it appears that a spatial approach, such as GWR Panel, is required to accommodate regional variances.

### Estimate of GWR panel

Based on the Hausman test, the within-transformation was then applied to each variable. Table 3 displays the demeaned values for Afghanistan as an example. The values of $(y_{it} - \bar{y}_i)$ and $(x_{kit} - \bar{x}_{ki})$ in Eq. (5) referring to each observation are expressed as a deviation from its country-specific time-average, eliminating the time-invariant individual fixed effect $\beta_{0i}^*$ prior to WLS estimation in Eq. (6).

The GWR panel estimation used a weight function based on the Haversine distance as stated in Eq. (8), along with four Adaptive Kernel functions in Eq. (10), Eq. (11), Eq. (12), and Eq. (13). Table 4 compares the CV values of these kernels.

**Table 3.** Within-Transformation for Afghanistan

| Year | *Y* | X1 | X2 | X3 | ⋯ | X12 | X13 | X14 |
|---|---|---|---|---|---|---|---|---|
| 2015 | -3.177 | 0.983 | -2.655 | -8.788 | ⋯ | -16.118 | 2.003 | -5.255 |
| 2016 | -1.721 | -0.439 | -1.222 | -8.788 | ⋯ | -11.742 | 2.974 | -2.320 |
| 2017 | -0.918 | -1.731 | 0.102 | -7.463 | ⋯ | -6.120 | 2.833 | -1.108 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ | ⋮ | ⋮ |
| 2022 | 0.477 | -0.312 | 0.626 | 11.533 | ⋯ | 9.280 | -2.934 | 1.620 |
| 2023 | 0.200 | -0.312 | 1.722 | 11.533 | ⋯ | 9.280 | -3.745 | 1.123 |
| 2024 | 3.102 | -0.312 | 1.722 | 11.533 | ⋯ | 9.280 | -4.106 | 1.123 |

Based on Table 4, the adaptive exponential kernel has the lowest CV value, making it the optimal choice for GWR Panel modeling of SDG data in Asia. This kernel was then used in the next estimation step.

**Table 4.** Comparison of CV Values of Adaptive Kernel

| Adaptive Kernel | CV |
|---|---|
| Gaussian | 83.128 |
| Exponential | 81.686 |
| Bisquare | 84.485 |
| Tricube | 85.095 |

Next, parameter estimation in the GWR Panel model was conducted using WLS estimation in Eq. (6), with adaptive exponential kernel in Eq. (11) as the weighting function. This results in local parameters that differ by location. Due to these differences, each Country has a different regression coefficient value. Table 5 presents the example of estimation results for two countries, Afghanistan and Yemen.

As shown in Table 5, the intercept values approach zero ($-4.54 \times 10^{-16}$ for Afghanistan and $6.99 \times 10^{-16}$ for Yemen), consistent with the two-stage estimation described in Eq. (3), Eq. (4), and Eq. (5).

**Table 5.** GWR panel coefficients for Afghanistan and Yemen

| Afghanistan | | | | Yemen | | | |
|---|---|---|---|---|---|---|---|
| Intercept | $-4.54 \times 10^{-16}$ | | | Intercept | $6.99 \times 10^{-16}$ | | |
| $\beta_1$ | 0.066 | $\beta_8$ | 0.096 | $\beta_1$ | 0.048 | $\beta_8$ | 0.118 |
| $\beta_2$ | 0.100 | $\beta_9$ | 0.061 | $\beta_2$ | 0.034 | $\beta_9$ | 0.064 |
| $\beta_3$ | 0.056 | $\beta_{10}$ | 0.088 | $\beta_3$ | 0.069 | $\beta_{10}$ | 0.122 |
| $\beta_4$ | 0.081 | $\beta_{11}$ | 0.052 | $\beta_4$ | 0.043 | $\beta_{11}$ | 0.022 |
| $\beta_5$ | 0.042 | $\beta_{12}$ | 0.043 | $\beta_5$ | 0.004 | $\beta_{12}$ | 0.088 |
| $\beta_6$ | 0.073 | $\beta_{13}$ | 0.063 | $\beta_6$ | 0.093 | $\beta_{13}$ | 0.092 |
| $\beta_7$ | 0.095 | $\beta_{14}$ | 0.066 | $\beta_7$ | 0.071 | $\beta_{14}$ | 0.075 |

Furthermore, all regression coefficients for the independent variables are positive in both countries, suggesting that increases in SDG indicators are generally associated with higher SDG scores, though the effect's significance varies across countries. These findings align with previous research about a multi-country study by Dvulit et al. (2024), which found strong but variable links between social, ecological, and economic factors and SDG progress. Similarly, Del-Aguila-Arcentales et al. (2023) demonstrated that innovation positively influences SDG achievement, with effects differing across national contexts.

### Model suitability test

Next, a model suitability (goodness-of-fit) test was conducted to determine whether the GWR Panel model differs significantly from the FEM model (Maharadja et al., 2021). The test is conducted using F statistics, as outlined in Eq. (14) (Caraka & Yasin, 2017),

$$F = \frac{JKG_{(H_0)}/dk_1}{JKG_{(H_1)}/dk_2} \tag{14}$$

where $JKG_{(H_0)}$ is the sum of squared errors from the GWR Panel model; $JKG_{(H_1)}$is the sum of squared errors from the FEM model; and $dk_1$ and $dk_2$ are the degrees of freedom for the GWR Panel and FEM models, respectively. The null hypothesis (that the GWR Panel model is not significantly different from the FEM model) is rejected if the calculated F-statistic exceeds the critical F-value or if the p-value is less than the significance level $\alpha$ (Marsono, 2025). Table 6 presents the results of the model suitability test.

**Table 6.** Model suitability test result

| F-test | P-value |
|---|---|
| 0.791 | 0.000 |

As presented in Table 6, the p-value is 0.000, which is less than the significance level α (0.05). Consequently, the $H_0$is rejected. This indicates a significant difference between the GWR Panel and the FEM models. Thus, it is evident that the GWR Panel model provides a superior fit for the SDGs data in Asia.

### Parameter significance test

The next step is to test its parameters to determine which variables exhibit significant effects at each location (Sartika, 2021; Wati et al., 2023). In the GWR Panel model, parameter significance testing is performed partially for each geographic unit in order to identify which independent variables have a significant local effect on the dependent variable. This test is conducted using t-statistics, where for each location $i$, the local t-statistic for parameter $\beta_k(u_i, v_i)$ is outlined in Eq. (15) (Mentari et al., 2026; Sifriyani et al., 2024; Yu, 2010).

$$t = \frac{\hat{\beta}_k(u_i, v_i)}{SE\left(\hat{\beta}_k(u_i, v_i)\right)} \tag{15}$$

The null hypothesis (which states that $\beta_k(u_i, v_i) = 0$) is rejected if $|t| > t_{table}$ or $p - value < \alpha$ (Sifriyani et al., 2024). As part of GWR-based estimation, this partial testing procedure is a standard component, consistent with the exploratory objective of the GWR Panel, which aims to map the variation in relationships between independent and dependent variables across geographical space (Brunsdon et al., 1999; Caraka, 2017; Yu, 2010). Table 7 presents the results of the parameter significance test for two countries, Afghanistan and Yemen, as examples.

**Table 7.** Parameter significance test for Afghanistan and Yemen

| Afghanistan | | | | Yemen | | | |
|---|---|---|---|---|---|---|---|
| Variable | p-value | Variable | p-value | Variable | p-value | **Variable** | **p-value** |
| $X_1$ | 0.002 | $X_8$ | 0.000 | $X_1$ | 0.032 | $X_8$ | 0.000 |
| $X_2$ | 0.000 | $X_9$ | 0.002 | $X_2$ | 0.202 | $X_9$ | 0.005 |
| $X_3$ | 0.000 | $X_{10}$ | 0.000 | $X_3$ | 0.000 | $X_{10}$ | 0.000 |
| $X_4$ | 0.000 | $X_{11}$ | 0.011 | $X_4$ | 0.001 | $X_{11}$ | 0.407 |
| $X_5$ | 0.012 | $X_{12}$ | 0.001 | $X_5$ | 0.818 | $X_{12}$ | 0.000 |
| $X_6$ | 0.000 | $X_{13}$ | 0.000 | $X_6$ | 0.000 | $X_{13}$ | 0.000 |
| $X_7$ | 0.000 | $X_{14}$ | 0.000 | $X_7$ | 0.010 | $X_{14}$ | 0.000 |

Based on Table 7, all independent variables in Afghanistan have p-values less than 0.05. This means that all SDG indicators have a significant impact on the Country's SDG score. In Yemen, variables included Good Health and Well-being, Clean Water and Sanitation, and Climate Action have p-values larger than 0.05. Therefore, these three variables do not have a significant effect on the SDG score in Yemen.

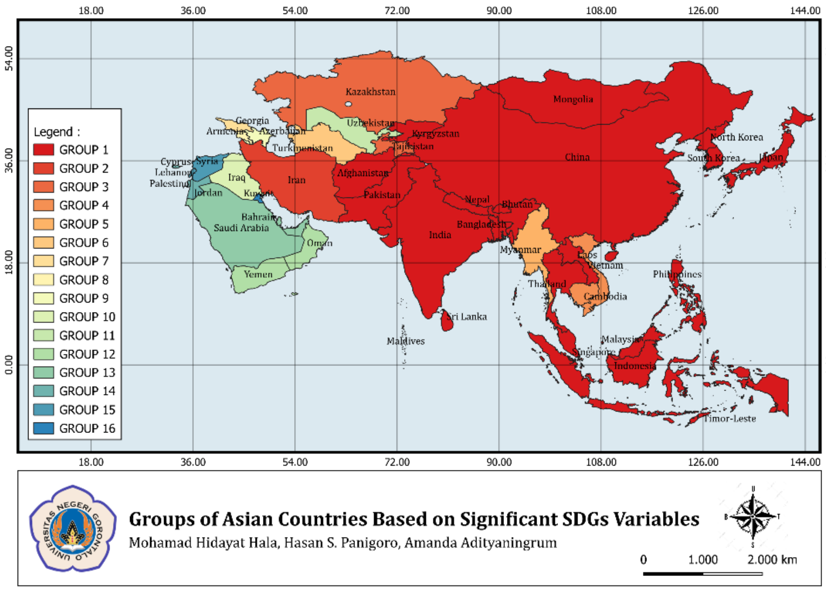


**Figure 2.** Map of 16 groups of Asian countries based on significant SDG indicator patterns.

The parameter significance test was conducted across 46 Asian countries, identifying different groups of countries with different combinations of significant variables (based on their p-values, as shown in Table 7 for two countries as examples). The complete grouping results are presented in Table 8.

As shown in Table 7, the 16 groups identified in the analysis show that countries depend on different combinations of SDG indicators. This finding supports the idea that sustainable development pathways differ across the region.

As presented in Table 7, in most countries, several variables are statistically significant. In each group, Quality Education ($X_3$), Gender Equality ($X_4$), Decent Work and Economic Growth ($X_7$), Industry Innovation and Infrastructure ($X_8$), Life on Land ($X_{12}$), Peace, Justice, and Strong Institutions ($X_{13}$), and Partnerships for the Goals ($X_{14}$) are significantly important. These aspects of the SDGs are universally important across Asia, regardless of income level or geographic location, and should remain a priority for policymakers.

The map of 16 groups based on significant patterns in SDG indicators (see Table 7) is shown in Figure 2. As illustrated in Figure 2, Group 1 is the largest, with 22 countries, and all 14 variables are significant when tested individually (significance parameter test). The group includes all countries in South Asia (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka), all countries in East Asia (China, Japan, North Korea, South Korea, Mongolia), as well as most countries in Southeast Asia (Brunei, Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand, Timor-Leste).

**Table 8.** Group country based on significant SDG variables

| No | Significant Variables | Countries |
|---|---|---|
| 1. | All independent variables | Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, China, India, Indonesia, Japan, North Korea, South Korea, Kyrgyzstan, Laos, Malaysia, Maldives, Mongolia, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Timor-Leste |
| 2. | $X_1, X_2, X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Iran |
| 3. | $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}$ | Kazakhstan, Tajikistan |
| 4. | $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{14}$ | Cambodia, Vietnam |
| 5. | $X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Myanmar |
| 6. | $X_1, X_2, X_3, X_4, X_6, X_7, X_8, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Turkmenistan |
| 7. | $X_1, X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Georgia |
| 8. | $X_1, X_3, X_4, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Armenia |
| 9. | $X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Azerbaijan |
| 10. | $X_3, X_4, X_5, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$ | Iraq |
| 11. | $X_1, X_2, X_3, X_4, X_6, X_7, X_8, X_{10}, X_{12}, X_{13}, X_{14}$ | Uzbekistan |
| 12. | $X_1, X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}$ | Oman, Yemen |
| 13. | $X_3, X_4, X_6, X_7, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}$ | Bahrain, Qatar, Saudi Arabia, UAE |
| 14. | $X_1, X_3, X_4, X_7, X_8, X_9, X_{12}, X_{13}, X_{14}$ | Cyprus, Jordan, Palestine |
| 15. | $X_1, X_3, X_4, X_7, X_8, X_{11}, X_{12}, X_{13}, X_{14}$ | Lebanon, Syria |
| 16. | $X_3, X_4, X_7, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}$ | Kuwait |

Essentially, all variables contribute to explaining SDG achievements. So, policies in these countries may need to consider multiple areas of development rather than focusing primarily on one or two priorities.

In the remaining 15 groups, one or more variables are not significant. Information from these groups can be used to identify which areas of development may be less relevant or face barriers in particular countries. For example, the most frequently missing variable is Clean Water and Sanitation ($X_5$), which is statistically insignificant in many West Asian and Central Asian countries.

As well, the variables for Zero Hunger ($X_1$) and Good Health and Well-being ($X_2$) are often not significant, particularly in West and Central Asia. Further, several countries in these areas (West and Central Asia) also show insignificant results in Climate Action ($X_{11}$). This pattern indicates the need to address these crucial issues to develop more effective strategies.

### Model performance comparison

The Akaike Information Criterion (AICc) was used to compare the model performance. The lowest AICc value was considered the most suitable for the available data, which indicates that the model achieves a better balance between model fit and complexity (Afifah et al., 2025; Lutfiani et al., 2019).

The analysis found that the AICc value for panel data regression using FEM is 558.300, whereas the GWR Panel produces a value of 487.912. The GWR Panel model is therefore the most appropriate choice for this analysis as it balances good fit with a reasonable level of complexity.

## CONCLUSION

This study applied the GWR Panel to examine the determinants of SDG achievement across 46 Asian countries from 2015 to 2024. The analysis compared four Adaptive Kernel functions using the Haversine distance and identified the Adaptive Exponential Kernel as the best-performing kernel, with a CV score of 81.686, compared to Adaptive Gaussian (83.128), Bisquare (84.485), and Tricube (85.095). This kernel selection results in geographically appropriate neighbor weighting for each country, reducing the risk of biased estimates in spatially heterogeneous SDGs data.

The results confirm significant spatial heterogeneity in how SDG indicators affect aggregate scores across Asia. Based on statistically significant patterns in the variables, 16 distinct country groups were identified.

Several key findings emerge from this analysis. First, a large group of 22 countries across South Asia, East Asia, and most of Southeast Asia shows that all 14 SDG indicators are statistically significant. In these countries, every indicator contributes to explaining SDG achievement. Second, Quality Education ($X_3$), Gender Equality ($X_4$), Decent Work and Economic Growth ($X_7$), Industry Innovation and Infrastructure ($X_8$), Life on Land ($X_{12}$), Peace, Justice, and Strong Institutions ($X_{13}$), and Partnerships for the Goals ($X_{14}$) are significant in almost all countries. Third, Clean Water and Sanitation ($X_5$) is the most frequently missing variable, particularly across West Asia and Central Asia. Good Health and Well-being ($X_2$) and Zero Hunger ($X_1$) are also commonly not significant in West Asia and parts of Central Asia. Climate Action ($X_{11}$) shows no significant effect in several Central Asian and West Asian countries, suggesting that climate policies may not yet be effectively integrated into national development strategies in these regions.

Considering spatial heterogeneity, GWR Panel analysis offers a more detailed explanation of sustainable development drivers than global models (FEM) can provide. For example, FEM would estimate one coefficient for Clean Water and Sanitation ($X_5$) across all 46 countries, masking its non-significance in West and Central Asia. Given the diversity of patterns identified using the GWR panel, one-size-fits-all approaches are not appropriate. Designing development strategies should consider which SDG indicators are likely to have the greatest impact on their specific national contexts. Based on these findings, local conditions must be considered when implementing SDGs to be effective. Future research could apply GWR Panel methods to sub-national data for more detailed analysis and examine longer time periods.

Future research may also include indicators such as No Poverty, Reduced Inequalities, and Life Below Water as data availability improves, since excluding variables that could be spatially correlated with the included indicators may introduce omitted-variable bias in the estimation of local coefficients.

## ACKNOWLEDGEMENT

Not available.

## DECLARATION

### Author contribution

All authors contribute in the research and/or writing the paper, and approved the final manuscript.

| | |
|---|---|
| *Mohamad Hidayat Hala* | Conceptualizing the research idea, leading the investigation, and setting up the methodology. |
| *Hasan S. Panigoro* | Assisting the investigation, reviewing the validity of the methodology, analyzing the data, and writing the original draft. |
| *Amanda Adityaningrum* | Assisting the investigation, reviewing the paper, enriching the data analysis, and translating the paper into English. |

### Funding

This research did not receive any funding.

### Conflict of interest

All authors declare that they have no competing interests.

### Ethics declaration

We as authors acknowledge that this work has been written based on ethical research that conforms with the regulations of our institutions and that we have obtained the permission from the relevant institutes when collecting data. We support the Bulletin of Applied Mathematics and Mathematics Education (BAMME) in maintaining the high standards of personal conduct, practicing honesty in all our professional practices and endeavors.

### The use of artificial intelligence

We do not use any generative AI tools to write any part of this paper.

### Additional information

Not available.

## REFERENCES

Afifah, P. N., Permata, S. A., & Saputra, W. A. (2025). Evaluasi model regresi GWR dan NBR untuk analisis kriminalitas di Banten: Tantangan sampel terbatas. *Teorema: Teori dan Riset Matematika*, *10*(2), 167. https://doi.org/10.25157/teorema.v10i2.19317

Arora, N. K., Mishra, I., & Arora, P. (2023). SDG 14: Life below water-viable oceans necessary for a sustainable planet. *Environmental Sustainability*, *6*(4), 433–439. https://doi.org/10.1007/s42398-023-00299-0

Arum, P. R., & Alfian, S. (2022). Pemodelan pertumbuhan ekonomi di Jawa Barat menggunakan metode geographically weighted panel regression. *J Statistika: Jurnal Ilmiah Teori dan Aplikasi Statistika*, *15*(2), 219–227. https://doi.org/10.36456/jstat.vol15.no2.a5506

Asadikia, A., Rajabifard, A., & Kalantari, M. (2022). Region-income-based prioritisation of sustainable development goals by gradient boosting machine. *Sustainability Science*, *17*(5), 1939–1957. https://doi.org/10.1007/s11625-022-01120-3

Bhatia, M. (2025). Appraising the progress of Asian nations towards achieving sustainable development goals. *Pune International Centre Research Programme*. https://pure.jgu.edu.in/id/eprint/9261/1/AED%202025.pdf

Brunsdon, C., Fotheringham, A. S., & Charlton, M. (1999). Some notes on parametric significance tests for geographically weighted regression. *Journal of Regional Science*, *39*(3), 497–524.

https://doi.org/10.1111/0022-4146.00146

Cai, R., Yu, D., & Oppenheimer, M. (2014). Estimating the spatially varying responses of corn yields to weather variations using geographically weighted panel regression. *Journal of Agricultural and Resource Economics*, *39*(2), 230–252. http://www.jstor.org/stable/44131327

Dewi, N. L. A. C., Hayati, M. N., & Fauziyah, M. (2025). Pemodelan GWR menggunakan fungsi pembobot adaptive box-car pada angka kesakitan DBD di pulau Kalimantan tahun 2023. *VARIANSI: Journal of Statistics and Its Application on Teaching and Research*, *7*(01), 55–65. https://doi.org/10.35580/variansiunm355

Caraka, R. E. (2017). Pengantar Spasial Data Panel. In *Spatial Data Panel* (pp. 1–58). Wade Group.

Caraka, R. E., & Yasin, H. (2017). Geographically Weighted Regression (GWR). In *Mobius*. SAGE Publications, Inc.

Çelik, S., Öztürk, Ö. F., Akkucuk, U., & Şaşmaz, M. Ü. (2025). Global sustainability performance and regional disparities: A machine learning approach based on the 2025 SDG index. *Sustainability*, *17*(16), 7411. https://doi.org/10.3390/su17167411

Comber, A., Brunsdon, C., Charlton, M., Dong, G., Harris, R., Lu, B., Lü, Y., Murakami, D., Nakaya, T., Wang, Y., & Harris, P. (2023). A route map for successful applications of geographically weighted regression. *Geographical Analysis*, *55*(1), 155–178. https://doi.org/10.1111/gean.12316

Del-Aguila-Arcentales, S., Alvarez-Risco, A., & Yáñez, J. A. (2023). Innovation and its effects on compliance with Sustainable Development Goals and competitiveness in European Union countries. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(3), 100127. https://doi.org/10.1016/j.joitmc.2023.100127

Dvulit, Z., Maznyk, L., Horbal, N., Brych, L., Skrzypek-Ahmed, S., Szymoniuk, B., & Dluhopolska, T. (2024). Modeling the integrated influence of social, ecological, and economic components on achieving sustainable development goals: A cross-country analysis. *Sustainability*, *16*(22), 9946. https://doi.org/10.3390/su16229946

Faricha, F. A. R., Widodo, E., & Oktia Putri, A. (2025). Analisis demand kebutuhan alat panen agroindustri di sumatra dengan pendekatan geographically weighted regression: Egrek Digital Merah Putih. *Matrik : Jurnal Manajemen dan Teknik Industri Produksi*, *26*(1), 69–76. https://doi.org/10.30587/matrik.v26i1.10191

Filho, W. L., Wolf, F., Salvia, A. L., Beynaghi, A., Shulla, K., Kovaleva, M., & Vasconcelos, C. R. P. (2020). Heading towards an unsustainable world: some of the implications of not achieving the SDGs. *Discover Sustainability*, *1*(1), 2. https://doi.org/10.1007/s43621-020-00002-x

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley. https://books.google.co.id/books?id=GFjFX-3dH68C

Geniaux, G. (2026). Top-down scale approaches for multiscale GWR with locally adaptive bandwidths. *Journal of Geographical Systems*. https://doi.org/10.1007/s10109-025-00481-4

Geniaux, G., & Martinetti, D. (2018). A new method for dealing simultaneously with spatial autocorrelation and spatial heterogeneity in regression models. *Regional Science and Urban Economics*, *72*, 74–85. https://doi.org/10.1016/j.regsciurbeco.2017.04.001

Gujarati, D. N. (2022). *Basic Econometrics*. Prentice Hall.

He, X., Mai, X., & Shen, G. (2020). Poverty and physical geographic factors: An empirical analysis of Sichuan Province using the GWR model. *Sustainability*, *13*(1), 100. https://doi.org/https://doi.org/10.3390/su13010100

Herwanto, R., Susanto, F., Dwi, R., Prayoga, M. H., Marta Dinata, R., & Wamiliana, W. (2024). Haversine geo-spasial data android model untuk optimasi rute kebersihan lingkungan terdekat. *Jurnal Pepadun*, *5*(1), 83–92. https://doi.org/10.23960/pepadun.v5i1.201

Hsiao, C. (2014). *Analysis of Panel Data*. Cambridge University Press. https://books.google.co.id/books?id=7LIkBQAAQBAJ

Hussein, M. S., & Tawfiq, A. F. (2021). Suggested method for treatment of outliers in panel data. *Turkish Online Journal of Qualitative Inquiry*, *12*(9), 6548–6553.

Kusumawardani, R., Astuti, S. P., & R, Z. D. (2021). *Ekonometrika Suatu Pengantar*. Gerbang Media Aksara.

Leung, Y., Mei, C.-L., & Zhang, W.-X. (2000). Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A: Economy and Space*, *32*(1), 9–32. https://doi.org/10.1068/a3162

Lutfiani, N., Sugiman, & Mariani, S. (2019). Pemodelan Geographically Weighted Regression (GWR) dengan fungsi pembobot Kernel Gaussian dan Bi-square. *UNNES Journal of Mathematics*, *8*(1), 82–91.

Maharadja, A. N., Maulana, I., & Dermawan, B. A. (2021). Penerapan metode regresi linear berganda untuk prediksi kerugian negara berdasarkan kasus tindak pidana korupsi. *Journal of Applied Informatics and Computing*, *5*(1), 95–102. https://doi.org/10.30871/jaic.v5i1.3184

Mar'ah, Z., & Sifriyani, S. (2023). Geographically Weighted Panel Regression (GWPR) for Covid-19 case in Indonesia. *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, *17*(2), 0879–0886. https://doi.org/10.30598/barekengvol17iss2pp0879-0886

Marsono, M. (2025). Faktor-faktor yang mempengaruhi deforestasi Indonesia dengan menggunakan geographically weighted regression. *Reliability: Journal of Industrial Statistics*, *1*(1), 33–44.

Martha, S., Yundari, Y., Rizki, S. W., & Tamtama, R. (2021). Penerapan Metode Geographically Weighted Panel Regression (GWPR) Pada Kasus Kemiskinan di Indonesia. *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, *15*(2), 241–248. https://doi.org/10.30598/barekengvol15iss2pp241-248

McMillen, D. P. (2001). *One hundred fifty years of land values in Chicago: A nonparametric approach*. SSRN.

Mentari, N., Ampa, A. T., Ihwal, M., Ruslan, R., Yahya, I., & Arisona, D. C. (2026). Pemodelan Geographically Weighted Regression (GWR) pada Indeks Pembangunan Manusia di Pulau Papua. *Journal of Biology, Chemistry, Mathematics and Physics Education*, *3*(1), 1–12. https://doi.org/10.61761/biochamp.3.1.1-12

Miftahuddin, Y., Umaroh, S., & Karim, F. R. (2020). Perbandingan metode perhitungan jarak Euclidean, Haversine, dan Manhattan dalam penentuan posisi karyawan. *Jurnal Tekno Insentif*, *14*(2), 69–77. https://doi.org/10.36787/jti.v14i2.270

Monica. (2025). Regional disparities and international spillover in achieving the sustainable development goals (SDGs) across the globe. *Discover Sustainability*, *6*(1), 993.

Mudjiningsih, L. A. S., Prihanta, W., & Safitri, F. (2023). Upaya peningkatan hasil belajar bahasa indonesia materi kosakata baru melalui model pembelajaran PBL dengan games tournaments pada Kelas 2 SDN Junrejo 2 Batu. *Pendas: Jurnal Ilmiah Pendidikan Dasar*, *8*(1), 4760–4773. https://doi.org/10.23969/jp.v8i1.8441

Nabilla, V. H., Indonesia, Dony Permana, & Fadhilah Fitri. (2023). Comparison of Haversine and Euclidean Distance Formula for Calculating Distance Between Regencies in West Sumatra. *UNP Journal of Statistics and Data Science*, *1*(3), 120–125. https://doi.org/10.24036/ujsds/vol1-iss3/39

Nasri, R., Gusriani, N., & Anggriani, N. (2023). Geographically weighted panel regression (GWPR) model for poverty data in West Java province 2019-2021. *Jurnal Diferensial*, *5*(2), 106–116. https://doi.org/10.35508/jd.v5i2.12213

Natural Earth. (2025). *Admin 0 – Countries (1:10m Cultural Vectors)*. https://naturalearthdata.com/

Pratama, A., Suyitno, S., & Purnamasari, I. (2021). Pemodelan persentase penduduk miskin di Provinsi Kalimantan Timur menggunakan model Geographically Weighted Panel Regression. *Jurnal MSA (Matematika dan Statistika Serta Aplikasinya )*, *9*(2). https://doi.org/10.24252/msa.v9i2.21021

Puspitaningtyas, A. (2025). Model firm value pada perusahaan sektor teknologi yang terdaftar di Bursa Efek Indonesia periode 2018-2023. *JISOSEPOL: Jurnal Ilmu Sosial Ekonomi dan Politik*, *3*(2), 475–486. https://doi.org/10.61787/rdv2dr16

Sachs, J. D., Lafortune, G., Fuller, G., & Guilherme, I. (2025). *Financing Sustainable Development to 2030 and Mid-Century. Sustainable Development Report 2025.* Dublin University Press. https://www.tara.tcd.ie/items/da339e6f-bd95-4f35-9058-258627e836fd

Sartika, E. (2021). Pemodelan tingkat pengangguran di Jawa Barat dengan analisis Geographically Weighted Regression (GWR). *Sigma-Mu*, *12*(2), 30–43. https://doi.org/10.35313/sigmamu.v12i2.2583

Sifriyani, Budiantara, I. N., Mardianto, M. F. F., & Asnita. (2024). Determination of the best geographic weighted function and estimation of spatio temporal model – Geographically weighted panel regression using weighted least square. *MethodsX*, *12*, 102605. https://doi.org/10.1016/j.mex.2024.102605

Silvia, A., & Nastasi, S. (2022). *Inequality and social security in the Asia-Pacific region*. United Nations Development Programme. https://www.undp.org/publications/inequality-and-social-security-asia-pacific-region

Syapitri, H., Amila, & Aritonang, J. (2021). *Buku Ajar Metodologi Penelitian Kesehatan*. Ahlimedia Book. https://books.google.co.id/books?id=7_5LEAAAQBAJ

Taek, Y., Bekti, R. D., & Suryowati, K. (2023). Penerapan model geograpgically weighted regression (GWR) menggunakan fungsi pembobot adaptive Kernel Gaussian dan adaptive Kernel Bisquare pada tingkat pengangguran terbuka di Pulau Papua. *Jurnal Statistika Industri dan Komputasi*, *8*(2), 84–101. https://doi.org/10.34151/statistika.v8i2.4459

United Nations Department of Economic and Social Affairs. (2024). *The Sustainable Development Goals Report 2024*. United Nations. https://doi.org/10.18356/9789213589755

Veness. (2011). Calculate distance, bearing and more between latitude/longitude points. *Movable Type Scripts.* Information Design & Management, Welsh Prose.

Warsito, B., Yasin, H., Ispriyanti, D., & Hakim, A. R. (2018). The step construction of geographically weighted panel regression in air polluter standard index (APSI) data. *E3S Web of Conferences*, *73*, 12006. https://doi.org/10.1051/e3sconf/20187312006

Wati, D. C., Lina, I. R., & Anggraeni, A. S. (2023). Analisis Geographically Weighted Panel Regression di bidang Infrastruktur, sosial, kesehatan, kependudukan, dan pendidikan terhadap produk domestik regional bruto di Nusa Tenggara Timur. *ESTIMASI: Journal of Statistics and Its Application*, 230–244.

Wati, D. C., & Utami, H. (2020). Model Geographically Weighted Panel Regression (GWPR) dengan Fungsi Kernel Fixed Gaussian pada Indeks Pembangunan Manusia di Jawa Timur. *Jurnal Matematika Thales*, *2*(1). https://doi.org/10.22146/jmt.49230

Yu, D. (2010). Exploring spatiotemporally varying regressed relationships: The geographically weighted panel regression analysis. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *38*.

Yu, D., Zhang, Y., Meng, J., Wang, X., He, L., Jia, M., Ouyang, J., Han, Y., Zhang, G., & Lu, Y. (2023). Seeing the forest and the trees: Holistic view of social distancing on the spread of COVID-19 in China. *Applied Geography*, *154*, 102941. https://doi.org/10.1016/j.apgeog.2023.102941

Yu, D., Zhang, Y., Wu, X., Li, D., & Li, G. (2021). The varying effects of accessing high-speed rail system on China’s county development: A geographically weighted panel regression analysis. *Land Use Policy*, *100*, 104935. https://doi.org/10.1016/j.landusepol.2020.104935

Yurevna, R. Z. (2025). Achieving SDG 1 in Central Asia: A comprehensive approach to ending poverty. *European Journal of Economics and Management Sciences*, *4*, 3–8. https://doi.org/10.29013/EJEMS-24-4-3-8