Jurnal Varian
Vol. 8, No. 3, October 2025, pp 333–346
e-ISSN: 2581-2017

Spatio-Temporal Using Geographically Weighted Panel Regression for Modeling Environmental Quality Index

Zakiyah Mar'ah, Ruliana, Nurul Azurah Fikriani, Nur Ikhwana
Universitas Negeri Makassar, Makassar, Indonesia

Article Info

Article history:

Received : 07-29-2025
Revised : 10-22-2025
Accepted : 10-25-2025

Keywords:

Environmental Quality Index;
Geographically Weighted Regression;
Geographically Weighted Panel Regression;
Spatio-Temporal.

ABSTRACT

The Environmental Quality Index (EQI) represents a numerical measure used to assess Indonesia's environmental conditions and is published annually by the Ministry of Environment and Forestry. In 2019, the EQI was recorded at 66.55, reflecting a decline of 5.12 points from 71.67 in 2018. This study aimed to analyze EQI across 34 Indonesian provinces during the 2018–2022 period using the Geographically Weighted Panel Regression (GWPR) approach. Data were obtained from the official Statistics Indonesia website. The purpose of employing GWPR was to capture both spatial and temporal variations in the factors influencing EQI, recognizing that environmental dynamics differ by region. Model selection tests for panel data indicated that the Fixed Effects Model (FEM) was the most appropriate specification. Therefore, GWPR was applied in combination with FEM to improve estimation accuracy. The results showed that the significant determinants of EQI varied across provinces, highlighting the heterogeneous nature of environmental challenges. The GWPR with Fixed Effect Model achieved a global R^2 of 84.38%, a substantial improvement compared to the 42.52% R^2 from the conventional global Fixed Effect panel regression. This finding confirmed that GWPR provided stronger explanatory power by incorporating local variations into the analysis. The study concluded that adopting GWPR is essential for more precise modeling of environmental quality. Furthermore, the results highlighted the importance of region-specific environmental policies tailored to each province's unique conditions in Indonesia.

Accredited by Kemenristekdikti, Decree No: 200/M/KPT/2020
DOI: https://doi.org/10.30812/varian.v8i3.5416

Corresponding Author:

Ruliana,
Department of Statistics, Universitas Negeri Makassar,
Email: ruliana.t@unm.ac.id

How to Cite:
Mar'ah. Z., Ruliana, R., Fikriani, N. A., Ikhwana, N. (2025). Spatio-Temporal Using Geographically Weighted Panel Regression for Modeling Environmental Quality Index. *Jurnal Varian*, *8*(3), 333–346.

A. INTRODUCTION

interdependence wherein each influences the other. While nature often affects human beings passively, human activities actively shape the environment, frequently leading to its degradation or improvement. A well-maintained environment contributes to human well-being and supports sustainable development, whereas environmental decline can significantly impact public health, economic productivity, and overall quality of life (Ansari et al., 2021; Saini et al., 2020).

Indonesia, as an archipelagic nation rich in natural resources, possesses tremendous ecological diversity that supports economic growth and social development. However, improper environmental management, including unsustainable land use, air and water pollution, and deforestation, has led to a decline in environmental quality in many regions (Khan et al., 2021). To monitor environmental performance, the Indonesian Ministry of Environment and Forestry (KLHK) annually reports the Environmental Quality Index (EQI), which integrates three main components: the Air Quality Index (AQI), the Water Quality Index (WQI), and the Land Cover Quality Index (LCQI) (KLHK, 2019).

Various studies have examined EQI in different contexts. For example, Listyaningrum et al. (2022) analyzed EQI in a metropolitan university setting, and Fakher (2019) evaluated the environmental quality from 1996 to 2016. While these studies provide important insights, most rely solely on cross-sectional or temporal data and do not explicitly incorporate spatial and temporal heterogeneity in their modeling.

Given the spatially diverse nature panel of environmental phenomena and the importance of tracking changes over time, statistical models that account for both geographical variation and temporal dynamics are essential. Regression analysis serves as a fundamental statistical method for identifying the relationship between predictor variables and a response variable. More specifically, panel data regression combines cross-sectional and time-series observations, allowing for richer inferences. However, standard panel models often assume homogeneity across spatial units, which may not be realistic in a geographically and ecologically diverse country like Indonesia. To address this limitation, the Geographically Weighted Panel Regression (GWPR) model has been developed, integrating the spatial flexibility of Geographically Weighted Regression (GWR) with the longitudinal strength of panel data structures (Musella et al., 2023). This model is particularly suitable when the influence of predictor variables varies across locations and time, capturing spatial heterogeneity more effectively.

Previous applications of GWPR include a study by Bruna & Yu (2016), who applied GWPR with fixed effects in regional economic development analysis in Europe. In the Indonesian context, Mar'ah & Sifriyani (2023) implemented the GWPR approach to model COVID-19 case distributions across provinces. Inspired by these developments, the current study applies the GWPR model to Environmental Quality Index (EQI) data in Indonesia from 2018 to 2022, aiming to identify province-specific determinants of environmental quality and how they vary both spatially and temporally. This research is important because it addresses the methodological gap in previous EQI studies that overlooked spatial-temporal heterogeneity, provides more precise insights into the localized drivers of environmental quality, and generates evidence-based knowledge to support region-specific environmental policies. By integrating spatial and temporal dynamics, this study not only advances statistical modeling in environmental research but also strengthens the scientific basis for sustainable development strategies in Indonesia. By incorporating spatial and temporal perspectives, this research not only enriches the field of environmental studies but also provides a stronger foundation for sustainable development initiatives in Indonesia. The insights obtained are expected to deliver tangible benefits to communities and ecosystems by enabling policymakers to implement more precise, context-specific strategies. With improved knowledge of region-specific environmental challenges, authorities can allocate resources more effectively, prioritize vulnerable areas, and design interventions that directly enhance public health, economic security, and social welfare. For citizens, this can foster cleaner living environments, improved access to safe water, and greater resilience against ecological risks. For nature, better environmental management contributes to biodiversity conservation, ecosystem restoration, and the reduction of climate-related threats. Ultimately, the study supports both the protection of Indonesia's natural wealth and the advancement of human well-being across generations.

B. RESEARCH METHOD

The data used in this research are secondary data obtained from the official website of Statistics Indonesia (2022), the publication Indonesian Environmental Statistics in Figures for 2022, and the Ministry of Environment and Forestry's Statistical Information System (KLHK, 2019). This study uses a balanced panel dataset that combines annual data from 2018 to 2022 and data from 34 provinces in Indonesia, yielding 170 total observations. Variables used are the environmental quality index (Y), air quality index (X1), water quality index (X2), land cover quality index (X3), human development index (X4), percentage of households that have adequate sanitation (X5), number of poverty (X6), and population density (X7). The flowchart of the analysis stage is shown in Figure 1, with the stages in analyzing the data carried out in this research as follows:

1. Exploring the environmental quality index
2. Determining the panel regression model ("The Error Component Model").
   a. Chow test is a statistical test used to determine the best model between the Fixed Effect Model (FEM) and the Common Effect Model (CEM) to estimate panel data.
   b. The Hausman test is a statistical test used to determine the best model between the Fixed Effect Model (FEM) and the Random Effect Model (REM) to estimate panel data.

3. Testing the normality of the residuals from the panel data regression model using the Kolmogorov-Smirnov test.
4. Testing the multicollinearity by calculating the VIF (Variance Inflation Factor) value of each predictor.
5. Testing the heteroscedasticity of panel data using the Breusch-Pagan test.
6. Transforming panel data using the within estimator (Giesselmann & Schmidt-Catran, 2019) because the best panel regression model is FEM. The within estimator is shown in Equation (1).

$$\hat{y}_i = y_i - \bar{y}_i \tag{1}$$

   where $\hat{y}_i$ is the result of the transformation at the i-th location, y_i is the observed value at the i-th location, and $\bar{y}_i$ is the average observed value at the i-th location.
7. Selecting the best kernel based on the smallest Cross Validation (CV) value. There are two types of kernels used in this research. Gaussian Kernel shown in Equation (2).

$$w_j\left(u_i, v_i\right) = \exp\left\{-\frac{1}{2}\left(\frac{d_{ij}}{b_i}\right)^2\right\} \tag{2}$$

   Bisquare Kernel shown in Equation (3).

$$w_{ij} = \begin{Bmatrix} \left(1-\left(\frac{d_{ij}}{b_i}\right)^2\right)^2, & for\ d_{ij} \leq b \\ 0, & for\ d_{ij} > b \end{Bmatrix} \tag{3}$$

   Which, w_{ij} is the weight of the i-th location and the j-th location, b_i is the bandwidth of the i-th location, and d_{ij} is the Euclidean distance of the i-th location and the j-th location (Harianto et al., 2021).
8. Performing Geographically Weighted Panel Regression (GWPR) modeling on panel data with the best kernel weighting. The general GWPR model is shown in Equation (4) (Mar'ah & Sifriyani, 2023).

$$y_{it} = \beta_0\left(u_{it}, v_{it}\right) + \sum_{k=1}^{p} \beta_k\left(u_{it}, v_{it}\right) x_{itk} + \varepsilon_{it} \tag{4}$$

   Where $i = 1, 2, 3, \ldots, N$ (observation location), $t = 1, 2, 3, \ldots, T$ (observation time), $k = 1, 2, 3, \ldots, p$ (predictor variable), y_{it} is the response variable value at the i-th observation and t-th time, (u_{it}, v_{it}) is the coordinate point of the i-th observation location and t-th time, $\beta_0\left(u_{it}, v_{it}\right)$ is the intercept from the i-th observation and time t, x_{itk} is the value of the k-th predictor variable at the i-th observation and t-th time, and ε_{it} is the residual at the i-th observation location and t-th time t.

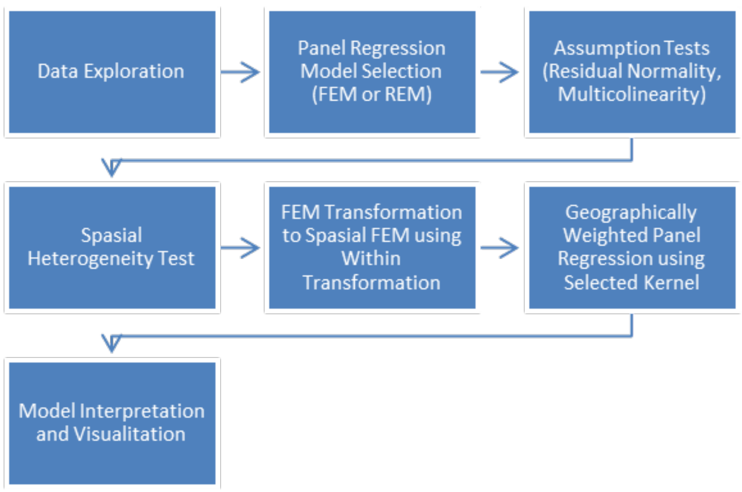

Figure 1. The stages of data analysis

C. RESULT AND DISCUSSION

1. Data Exploration

To enhance comprehension of spatial and temporal variations in environmental conditions across Indonesia, Figure 2 illustrates changes in the Environmental Quality Index (EQI) from 2018 to 2022. The figure emphasizes both regional disparities and evolving trends in environmental performance. Examination of the lowest and highest EQI values offers insight into provinces facing considerable environmental pressures and those demonstrating marked improvements.

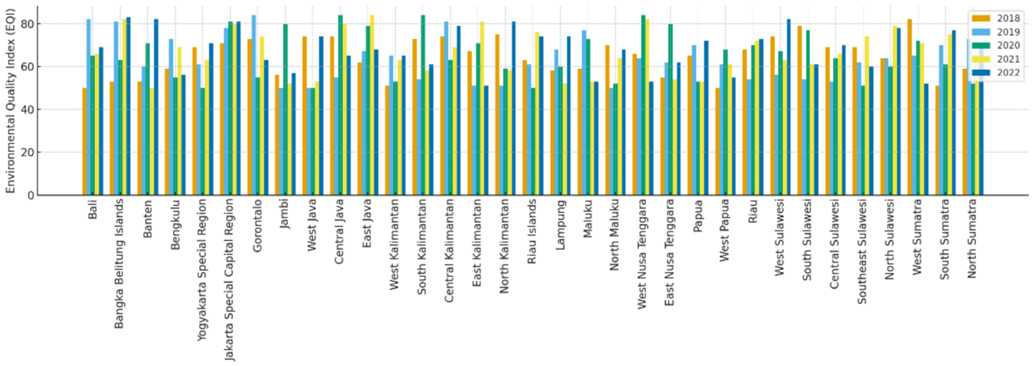

Figure 2. Distribution of the environmental quality index in Indonesia in 2018-2022

Figure 2 shows that the distribution of the Environmental Quality Index (EQI) in Indonesia from 2018 to 2022 varied significantly across provinces. At the lower end, the lowest EQI value was recorded in the Jakarta Special Capital Region in 2018 at 39.06%, reflecting the environmental pressures of rapid urbanization and population density. In the following years, Jakarta experienced a gradual increase, although the progress slowed, with only a 0.22% increase between 2021 and 2022. Meanwhile, several provinces demonstrated relatively stable EQI levels, generally ranging from 60% to 75%, indicating moderate environmental quality that did not change significantly over the five years.

On the other hand, the highest EQI was observed in West Papua in 2022, at 84.22%, suggesting that provinces with lower industrial activity and richer natural resources tend to maintain higher environmental quality. The year 2020 marked a noticeable decline in several provinces, indicating a temporary setback in environmental conditions, followed by a partial recovery in subsequent years. Overall, the five-year trend highlighted regional disparities: urban and industrialized provinces struggled to improve environmental quality, while less populous and resource-rich provinces maintained higher EQI scores. This pattern highlighted the need for targeted, localized environmental management strategies across Indonesia.

2. Selection of Panel Data Regression Model

a. Chow Test

The null hypothesis (H_0) states that the model used is the Common Effect Model (CEM), while the alternative hypothesis (H_1) states that the more appropriate model is the Fixed Effect Model (FEM). Chow test produced an F value of 3.329 and a p-value of 6.056×10^{-7}, which is smaller than the significance level of 0.05, indicating that the null hypothesis—stating that the Common Effect Model (CEM) is more appropriate—was rejected. This statistical outcome suggested a significant individual effect across the cross-sectional units in the panel data, and therefore, the Fixed Effect Model (FEM) provided a better fit. In other words, FEM was better at capturing heterogeneity among entities, making it the preferred model for further analysis (see Table 1).

Table 1. Chow Test

F	df1	df2	p-value
3.329	33	129	6.056 x 10-7

b. Hausman Test

The null hypothesis (H_0) states that the model used is the Random Effect Model (REM), while the alternative hypothesis (H^1) states that the more appropriate model is the Fixed Effect Model (FEM). Hausman test produced a chi-squared value of 91.393 and a p-value of 2.2×10^{-12}, which is smaller than the significance level of 0.05. This result indicated that the null hypothesis—stating that the Random Effects Model (REM) is consistent and efficient—was rejected. Consequently, the Fixed Effects Model (FEM) was preferred, as it provided more reliable estimates by accounting for potential correlation between the regressors and the individual-specific effects. Therefore, FEM was considered the more appropriate model for this analysis (see Table 2).

Table 2. Hausman Test

X^2	df	p-value
91.393	7	2.2 x 10-12

3. Normality Test of Residuals

Based on the results of the Kolmogorov-Smirnov normality test, the D value is 0.049 and the p-value is 0.40, which is greater than the significance level of 0.05. This indicates that we failed to reject the null hypothesis of normality, suggesting that the residuals were normally distributed. The normality of residuals is an important assumption in regression analysis, as it ensures the validity of statistical inference, including hypothesis testing and confidence interval estimation.

4. Multicollinearity Test

Before proceeding with the regression analysis, it is essential to examine multicollinearity among the predictor variables, as high intercorrelation can distort coefficient estimates and reduce the model's reliability. Table 3 shows the results of the multicollinearity test using the Variance Inflation Factor (VIF).

Table 3. Hausman Test

Variable	X1	X2	X3	X4	X5	X6	X7
VIF	3.507	1.325	1.817	2.89	2.249	1.447	2.603

The test results for all predictor variables showed Variance Inflation Factors (VIFs) less than 10. This means there was no multicollinearity, or, in other words, no strong linear relationships among the predictor variables. A VIF below the commonly accepted threshold of 10 suggests that the variance of the estimated regression coefficients is not inflated by multicollinearity. This ensures that the model's estimates are stable and interpretable, and that each predictor contributes uniquely to explaining the variation in the dependent variable.

5. Heteroscedasticity Test

The heteroscedasticity test shows that the Breusch Pagan value is 57.644 and the p-value is 4.451×10^{-10}, which is smaller than the significance level of 0.05; therefore, it is indicated that there was heteroscedasticity in the data distribution or the homoscedasticity assumption in the panel data regression was not fulfilled. The presence of heteroscedasticity indicated spatial heterogeneity in the data; hence, a Geographically Weighted Panel Regression model was applied.

6. Geographically Weighted Panel Regression (GWPR) Model

The Geographically and Temporally Weighted Regression (GWPR) model integrates the principles of Geographically Weighted Regression and panel data regression. Before parameter estimation, data transformation is conducted using the within estimator method, as the Fixed Effects Model was previously identified as the most suitable. This transformation involves deducting each variable's value by its average over time for a given unit. To determine the appropriate kernel, Euclidean distance was employed to measure spatial proximity between provinces.

Table 4. Kernel Selection

Kernel	CV
Adaptive Gaussian	277.945
Adaptive Bisquare	291.043

The optimal bandwidth was selected as the one that yielded the lowest Cross-Validation (CV) score. For the weighting scheme, either the Adaptive Gaussian or the Adaptive Bisquare functions were considered. Based on the CV results summarized in Table 4, the Adaptive Gaussian kernel demonstrated the lowest CV value and was therefore utilized for spatial weighting in the model. As the Adaptive Gaussian kernel was selected, the bandwidth for each location is shown in Table 5.

DOI: https://doi.org/10.30812/varian.v8i3.5416

Table 5. Bandwidth in Each Location

Province	Bandwidth	Province	Bandwidth
Bali	19.327	Riau Island	23.145
Bangka Belitung Islands	23.709	Lampung	24.773
Banten	24.288	Maluku	29.451
Bengkulu	27.800	North Maluku	27.107
DI Yogyakarta	20.256	Aceh	34.325
DKI Jakarta	23.489	West Nusa Tenggara	20.817
Gorontalo	21.694	East Nusa Tenggara	21.770
West Papua	32.380	Papua	37.447
Jambi	27.762	Riau	28.656
West Java	22.804	West Sulawesi Barat	29.451
Central Java	20.384	South Sulawesi	26.231
East Jawa	19.736	Central Sulawesi	20.657
West Kalimantan	18.903	Southeast Sulawesi	21.644
South Kalimantan	17.976	North Sulawesi	23.215
Central Kalimantan	17.813	West Sumatera	29.451
North Kalimantan	17.017	South Sumatera	26.231
East Kalimantan	17.017	North Sumatera	31.065

The adaptive Gaussian kernel produced different bandwidths across provinces, as shown in Table 5. This variation reflects the kernel's ability to adapt locally to the spatial distribution of data points. Unlike fixed-bandwidth methods, the adaptive approach allows the kernel to use narrower bandwidths in densely populated areas and wider ones in sparsely populated regions. This flexibility enhances the accuracy of geographically weighted panel regression by capturing local spatial heterogeneity more effectively, ensuring that the model reflects region-specific relationships between variables.

Adaptive means each province has a different weight. Each bandwidth and distance obtained was substituted into Equation (2). These weights were used to estimate the GWPR model's parameters. GWPR is a point-approach model; therefore, the number of models formed equals the number of observation locations. There were 34 provinces in Indonesia, hence 34 models were formed. The GWPR model included parameters that significantly influenced the response variable, EQI. For example, the model for South Sulawesi Province included the significant parameters shown in Table 6.

Table 6. Significance Test of GWPR Model Parameters for South Sulawesi

Variable	Parameter Estimate	Standard Error	t-value	p-value
Intercept	-0.0901	0.8577	-0.1050	0.917
X1	0.3933	0.1396	2.8168	0.008
X2	0.0828	0.1079	0.7672	0.449
X3	0.2433	0.0647	3.7607	0.001
X4	0.0675	0.2994	0.2254	0.823
X5	0.2306	0.0585	3.9396	0.000
X6	0.0003	0.0004	0.7637	0.451
X7	-0.0005	0.0002	-1.9539	0.059

The predictor variable is said to significantly influence the response variable when the p-value is smaller than the significance level of 0.1. Table 6 shows that in South Sulawesi Province, there were four predictor variables that significantly influenced EQI they were the air quality index (X1), the land cover quality index (X3), the percentage of households that have adequate sanitation (X5), and the population density (X7). Therefore, the GWPR model for South Sulawesi Province is shown in Equation (5).

$$\widehat{Y_{sulsel}} = 0.3933X_1 + 0.2433X_3 + 0.2306X_5 - 0.0005X_7 \tag{5}$$

Equation 5 states that if the air quality index increases by 1 unit, the EQI in Sulawesi Selatan will increase by 0.3933%. If the land cover quality index increases by one unit, then EQI will increase by 0.2433%. If the percentage of of households with adequate sanitation increases by 1 unit, then EQI will increase by 0.2306%. And if the population density increases by one unit, then EQI will decrease by 0.0005%. The coefficient of determination for the GWPR model in Sulawesi Selatan is 0.82, indicating that the predictor variables explain 82% of the Environmental Quality Index, with the remaining 18% explained by other factors not included in the research.

The GWPR model in each province was different; therefore, the predictor variables that significantly influenced EQI also vary. Figures 3 to 9 show the predictor variables that had a significant effect in each province in Indonesia.

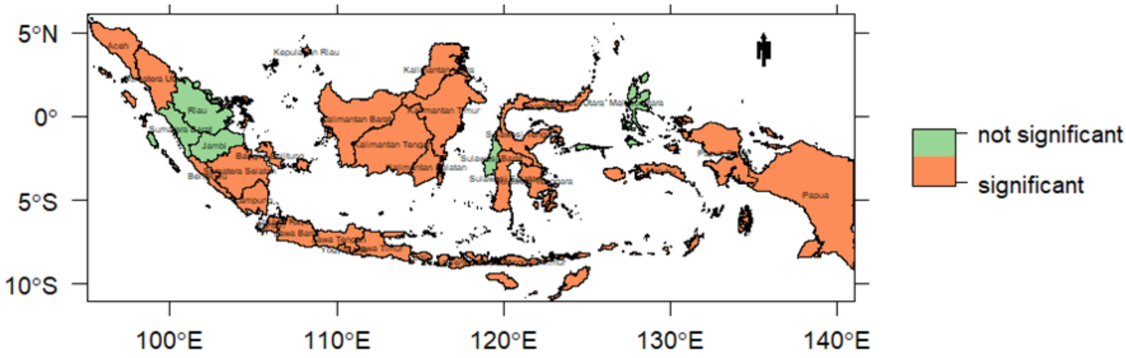

Figure 3. Map of Indonesian provinces showing air quality index as a significant factor in EQI

Figure 3 illustrates the distribution of Indonesian provinces according to the significance of air quality in influencing environmental quality. Provinces shaded in orange were identified as areas where air quality had a significant impact on the Environmental Quality Index (EQI). In contrast, provinces shaded in green represented areas where air quality had no significant effect. The map showed that the majority of provinces across Sumatra, Java, Kalimantan, Sulawesi, Papua, and other regions fell into the orange category. This indicated that air pollution and poor air quality played a crucial role in shaping environmental conditions across most of the country.

Furthermore, only a limited number of provinces were shaded green, suggesting that their environmental quality was shaped more by other factors such as water quality, land use, or natural resource management. The dominance of orange provinces highlighted that air pollution control had been a pressing challenge across Indonesia. These findings emphasized the need for targeted policies to address air quality problems, particularly in urbanized and industrialized provinces where emissions were higher. At the same time, provinces with non-significant results could serve as models for identifying alternative environmental drivers beyond air quality that sustain ecological balance.

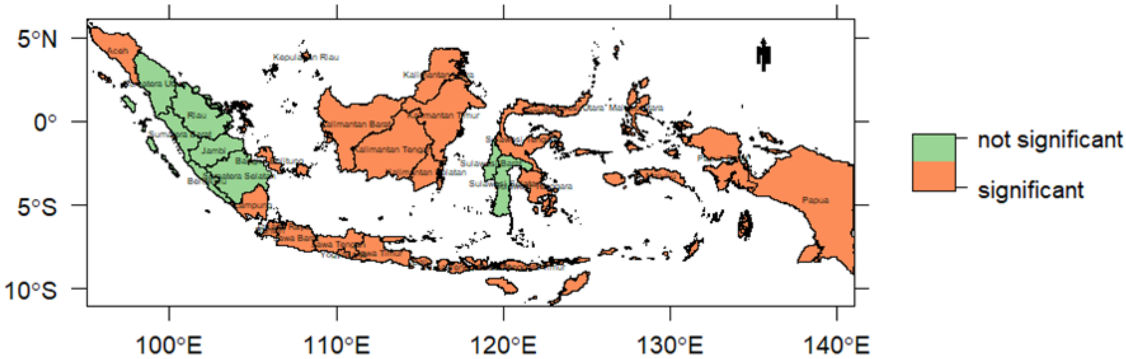

Figure 4. Map of Indonesian provinces showing water quality index as a significant factor in EQI

Figure 4 illustrates the spatial variation of the influence of water quality on the Environmental Quality Index (EQI) across Indonesian provinces. Provinces highlighted in orange were found to have a statistically significant relationship, indicating that water quality strongly shaped environmental outcomes in those areas. In contrast, provinces shaded in green showed no significant effect, suggesting that other environmental factors might have played a more dominant role in determining overall quality. The results emphasized that water quality did not have a uniform effect and that its influence varied substantially across regions.

This spatial patterning suggested that water management needed to be context-specific rather than generalized at the national level. Provinces with significant impacts required stronger interventions to maintain and improve water quality and ensure sustainable environmental conditions. Meanwhile, provinces where water quality was not significant likely relied on other indicators, such as air quality, land cover, or waste management, to achieve environmental outcomes. These findings highlighted the need for tailored policy responses and resource allocation that account for regional disparities in environmental determinants.

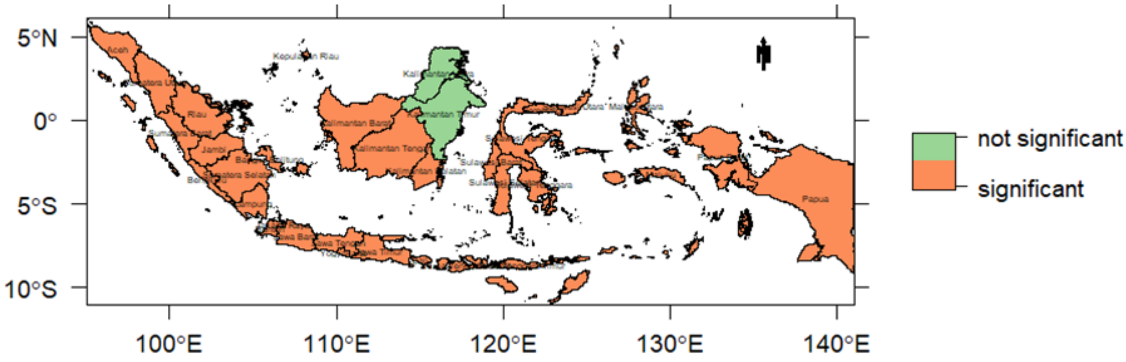

Figure 5. Map of Indonesian provinces showing water quality index as a significant factor in EQI

Figure 5 illustrates the spatial distribution of the effect of land cover quality on the Environmental Quality Index (EQI) across Indonesian provinces. Provinces shaded in orange were found to exert a significant influence, indicating that land cover strongly shapes environmental quality across most regions. In contrast, provinces highlighted in green showed no significant effect, suggesting that in those areas other environmental components, such as water or air quality, might have played a more dominant role. The overall pattern revealed that the majority of Indonesia, particularly Java, Sumatra, Sulawesi, Papua, and large parts of Kalimantan, experienced a substantial impact of land cover on environmental conditions.

This finding suggested that land cover acted as a major determinant of environmental quality nationwide. Since most provinces were significantly affected, efforts in environmental management and sustainability planning needed to prioritize land-use and land-cover changes, such as deforestation control, urban expansion, and agricultural practices. Only a few provinces in northern Borneo did not show significance, suggesting that more localized factors are at play. Thus, the results highlighted the critical importance of monitoring land cover dynamics as part of environmental policy strategies across Indonesia.

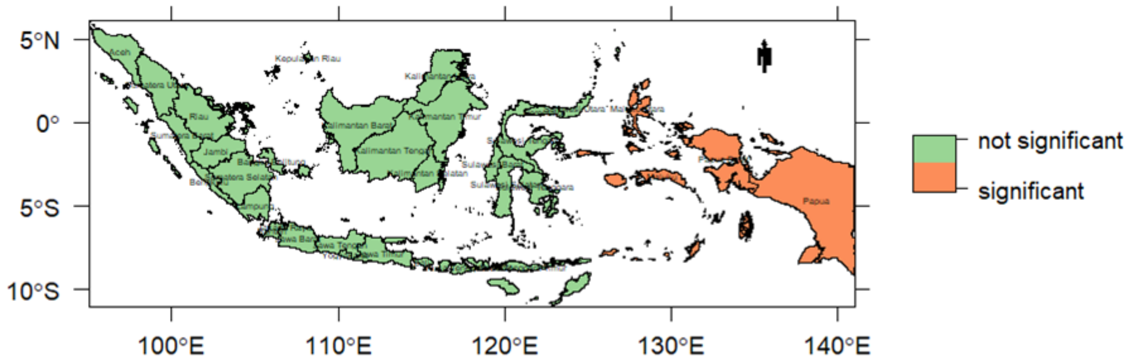

Figure 6. Map of Indonesian provinces showing human development index as a significant factor in EQI

Figure 6 illustrates the spatial distribution of provinces in Indonesia, where the Human Development Index (HDI) significantly affected the Environmental Quality Index (EQI). Provinces shaded in orange, primarily located in eastern Indonesia, such as Papua and Maluku, were found to experience a strong influence from HDI on environmental quality. Conversely, provinces shaded in green, which were mainly concentrated in the western part of Indonesia, including Sumatra, Java, and parts of Kalimantan, showed no significant impact from HDI. This pattern indicated that disparities in human development were not equally linked to environmental outcomes across the country.

The results suggested that HDI played a more critical role in shaping environmental quality in eastern regions than in western regions. In areas with lower HDI, such as Papua, improvements in education, health, and economic opportunities likely had a stronger impact on environmental conditions. Meanwhile, in the more developed western provinces, other factors, such as land cover, air quality, and water quality, might have dominated environmental dynamics. This highlighted the importance of region-specific strategies, where policies in eastern Indonesia needed to integrate human development initiatives with environmental management to ensure balanced and sustainable progress.

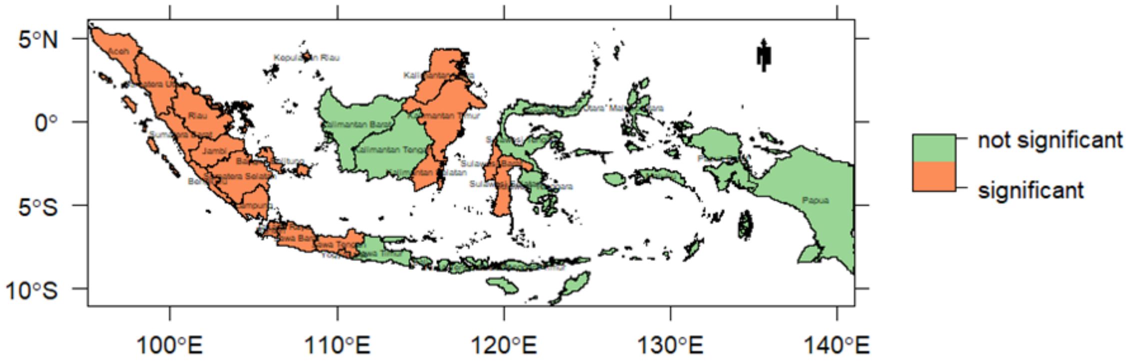

Figure 7. Map of Indonesian provinces showing the percentage households that have adequate sanitation as a significant factor in EQI

Figure 7 illustrates the distribution of provinces in Indonesia, showing that the percentage of households with adequate sanitation significantly affects the Environmental Quality Index (EQI). Provinces shaded in orange were identified as areas where sanitation coverage exerted a strong influence on environmental quality, while provinces shaded in green were those where sanitation did not have a statistically significant effect. The spatial distribution of these provinces was scattered across the archipelago, with significant provinces spread between western, central, and eastern Indonesia. This pattern suggested that the impact of sanitation was not concentrated in one specific region but varied depending on local conditions.

The findings indicated that adequate sanitation coverage played a critical yet uneven role in shaping environmental quality across Indonesia. In provinces with significant sanitation improvements, access to proper sanitation facilities likely reduced pollution levels and contributed to healthier environmental conditions. Meanwhile, in provinces where sanitation was not significant, other factors such as land cover, water quality, or socio-economic variables might have overshadowed its effect. This highlighted the importance of adopting localized policies and programs that accounted for regional differences in how sanitation influenced environmental quality, rather than applying a uniform national approach.

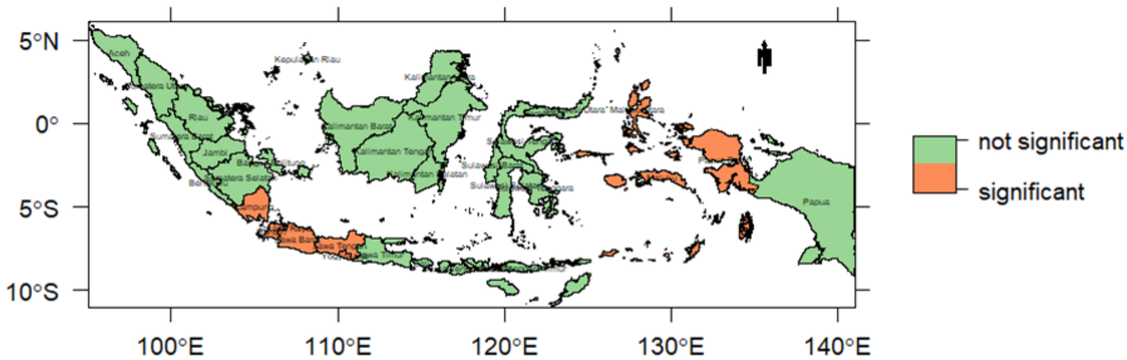

Figure 8. Map of Indonesian provinces showing the number of people in poverty as a significant factor in EQI

Figure 8 illustrates the distribution of Indonesian provinces where poverty was identified as a significant factor influencing environmental quality. The map showed provinces in orange where poverty had a strong and statistically significant impact, while provinces in green were categorized as not significant. These findings highlighted that the effect of poverty on environmental quality was not uniform across the country. Instead, certain provinces were more vulnerable to the adverse consequences of poverty, indicating that local socio-economic conditions played an important role in shaping environmental outcomes.

The significant provinces appeared scattered rather than concentrated in one geographic cluster, suggesting that poverty's influence varied by region. Some provinces in eastern Indonesia, as well as parts of Java and Sumatra, showed stronger links between poverty and deterioration in environmental quality. In contrast, many other provinces showed no significant relationship, implying that other factors might have played a larger role in determining environmental quality in those areas. This pattern suggested that the relationship between poverty and environmental quality was region-specific and context-dependent, underscoring the need for tailored policy approaches to address poverty's environmental implications across Indonesia.

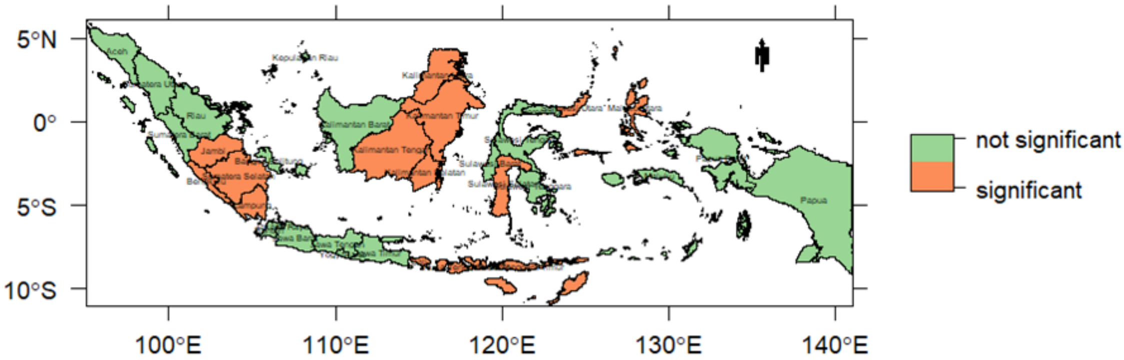

Figure 9. Map of Indonesian provinces showing the population density as a significant factor in EQI

Figure 9 illustrates the provinces in Indonesia where population density was identified as a significant factor influencing environmental quality. Provinces highlighted in orange, such as those in Sumatra, Java, Kalimantan, Sulawesi, and parts of Papua, showed a strong, significant relationship between population density and environmental conditions. These results suggested that areas with higher population densities tended to experience stronger environmental pressures, likely due to increased demand for land, natural resources, and infrastructure. In contrast, provinces colored green did not show a significant relationship, indicating that population density alone did not necessarily lead to deteriorating environmental quality across all regions.

The distribution of significant provinces was not confined to a single island or region but spread across multiple parts of Indonesia. This pattern indicated that the impact of population density was highly context-dependent, varying with local economic structures, land-use practices, and environmental management policies. While densely populated areas such as Java faced more evident challenges, some less populated regions also showed significant influence, suggesting that even moderate increases in population density could strain environmental systems under certain conditions. These findings emphasized that the role of population density in shaping environmental quality was complex and region-specific, requiring policies that considered both demographic pressures and local environmental capacities.

Recognizing that environmental challenges vary across regions, it is essential to pinpoint the specific factors driving EQI locally. This localized approach acknowledges that no single variable uniformly affects all provinces; instead, each region may face distinct environmental pressures—such as poor sanitation, limited access to clean water, or high levels of air pollution—that shape its Environmental Quality Index (EQI). To capture this diversity, the subsequent table presents the influential variables for each province, based on statistical analysis. Table 7 identifies the variables that significantly influence EQI at the 10% significance level, highlighting which environmental indicators—such as household sanitation, the human development index, or air quality—play a critical role in determining environmental quality across different parts of Indonesia. This information was crucial for designing targeted interventions and region-specific environmental policies.

Table 7. Significant Variables in Each Province

No	Province	Significant Variables
1	Lampung	X1, X2, X3, X5, X6, X7
2	Banten, DI Yogyakarta, DKI Jakarta, West Java, Central Java	X1, X2, X3, X5, X6
3	West Papua, Maluku	X1, X2, X3, X4, X6
4	South Kalimantan, Central Kalimantan	X1, X2, X3, X5, X7
5	North Maluku	X2, X3, X4, X6, X7
6	Bali, West Nusa Tenggara, East Nusa Tenggara, North Sulawesi	X1, X2, X3, X7
7	Bangka Belitung Island, Riau Island, Aceh	X1, X2, X3, X5
8	North Kalimantan, East Kalimantan	X1, X2, X5, X7
9	Bengkulu, South Sulawesi, South Sumatera	X1, X3, X5, X7
10	Papua	X1, X2, X3, X4
11	Gorontalo, East Java, West Kalimantan, Central Sulawesi, Southeast Sulawesi	X1, X2, X3
12	North Sumatera	X1, X3, X5
13	Jambi	X2, X5, X7
14	Riau, West Sulawesi	X3, X4
15	West Sumatera	X3, X5

Vol. 8, No. 3, October 2025, pp 333–346
DOI: https://doi.org/10.30812/varian.v8i3.5416

As shown in Table 7, in Lampung, all variables except the human development index (X4) significantly influenced the environmental quality index. Meanwhile, in Riau and West Sulawesi, only the land cover quality index (X3) and the human development index (X4) significantly influenced the environmental quality index. Therefore, it was shown that each province had different characteristics according to the significant variables. Furthermore, the global R2 value for the GWPR model (84.38%) is greater than that for the global FEM panel regression model (42.52%), indicating that GWPR was the best model for modeling EQI in Indonesia.

This research applied the Geographically Weighted Panel Regression (GWPR) model to thoroughly investigate spatial and temporal disparities in the Environmental Quality Index (EQI) across Indonesia's 34 provinces during 2018–2022. The study yielded several significant insights from both methodological and empirical standpoints. Methodologically, results from the Chow and Hausman tests suggested that the Fixed Effect Model (FEM) was the most suitable specification for the panel data, effectively accounting for unobserved provincial heterogeneity. Further diagnostic evaluations showed that the residuals were normally distributed, and multicollinearity was not a major issue, as indicated by Variance Inflation Factor (VIF) values below 10 for all predictors. Nonetheless, the Breusch-Pagan test identified heteroscedasticity in the data, thereby justifying the use of a model with spatially varying coefficients, such as GWPR.

The GWPR model, enhanced with adaptive Gaussian kernel weighting, provided substantial improvements in model fit. The global R^2 value increased from 42.52% in the conventional FEM model to 84.38% in the GWPR model, suggesting that incorporating spatial and temporal dimensions significantly enhanced the model's explanatory power. This result reinforced the need to account for spatial heterogeneity when analyzing environmental quality, which is inherently influenced by geographic, social, and ecological factors.

At the substantive level, the study uncovered substantial variation in the factors influencing EQI across provinces. For example, in South Sulawesi, four predictors were statistically significant: the air quality index (X1), land cover quality index (X3), percentage of households with adequate sanitation (X5), and population density (X7). The positive coefficients for X1, X3, and X5 highlighted the roles of clean air, sustainable land use, and access to sanitation in promoting environmental quality. In contrast, the negative association with population density indicated potential environmental degradation in densely populated regions. In contrast, provinces such as Riau and West Sulawesi showed significance only for land cover quality (X3) and the human development index (X4), suggesting that improvements in vegetation coverage and socioeconomic well-being may be more critical drivers of EQI in those regions. Meanwhile, Lampung province demonstrated the greatest influence, with six of seven variables significantly associated with EQI, indicating the multifactorial nature of environmental quality in that region. The findings of this study, which reveal province-specific variations in the determinants of environmental quality, aligned closely with previous empirical research in Indonesia that also underscores the multifactorial and spatially heterogeneous nature of the Environmental Quality Index (EQI). For instance, studies by Mannanal & Rajagopal (2023) and Kusumadewi & Kristanto (2025) highlighted the significant roles of population density, sanitation access, and human development in shaping environmental outcomes—factors that also emerged as key predictors in provinces such as Sulawesi Selatan, Riau, and Lampung in this research. Moreover, the consistent identification of negative environmental impacts associated with high population density and positive contributions from socioeconomic indicators reinforced the need for localized modeling approaches, such as GWPR, to capture regional disparities and inform place-based environmental policies.

These findings underscore the context-dependent nature of environmental determinants, underscoring the need for localized models to inform targeted policy interventions. The maps in Figures 3 to 9 visually depict the geographic variability in each factor's significance, offering valuable insights for region-specific policy planning.

Furthermore, the GWPR model's localized coefficients showed that the same predictor may exert different magnitudes and directions of influence across provinces. This spatial non-stationarity was a key strength of the GWPR framework, making it a powerful tool for modeling complex environmental phenomena.

Overall, the analysis demonstrated that EQI was not only a function of environmental indicators (e.g., air, water, and land cover) but also strongly intertwined with human development and socioeconomic factors. These insights are vital for national and regional policymakers aiming to enhance environmental sustainability, particularly in provinces with declining EQI trends or rapid urbanization pressures.

D. CONCLUSION AND SUGGESTION

Spatio-Temporal is an approach used to analyze data that has an effect at a location and time. One of the methods in spatio-temporal is Geographically Weighted Panel Regression (GWPR). For the case study on the Environmental Quality Index (EQI) in

Indonesia, the best model was GWPR with Fixed Effect Model, as the GWPR FEM model had a higher R2 value than the global FEM model. GWPR FEM produced 34 different models in each province in Indonesia. Each province in Indonesia has different characteristics, as shown in Table VII, which indicates that each province has different significant variables. For example, in Province Sulawesi Selatan, the significant variables for EQI are the air quality index (X1), the land cover quality index (X3), the percentage of households with adequate sanitation (X5), and the population density (X7). Meanwhile, in Province Riau and Province Sulawesi Barat, only land cover quality index (X3) and human development index (X4) significantly influence EQI. These differences in characteristics can serve as a reference for the government and society in overcoming environmental problems, based on the factors identified in the research.

Future studies could further enhance the analysis of the Environmental Quality Index (EQI) by exploring several directions. First, incorporating additional explanatory variables—such as climate indicators, industrial activity, or regional policy interventions—could provide a more comprehensive understanding of the factors influencing EQI. Second, future research may apply advanced spatio-temporal models that account for spatial spillover effects, such as Spatial Durbin Panel Models (SDPM) or dynamic panel frameworks, to capture interactions between neighboring provinces over time. Moreover, since this study used provincial-level data, future investigations may benefit from using more granular spatial units (e.g., districts or cities) to uncover localized patterns and heterogeneity in environmental quality. Lastly, integrating qualitative assessments, such as policy analysis or stakeholder interviews, can complement the quantitative results and offer deeper insights into the socio-political dynamics that affect environmental outcomes across regions.

ACKNOWLEDGEMENT

The authors would like to express their deepest gratitude to all those who have contributed to the completion of this research. Our thanks also go to the Department of Matehmatics at the State University of Makassar for providing resources and facilities that greatly assisted in conductingthis research. We thank the author's family and our colleagues for their assistance in reviewing this article.

DECLARATIONS

AUTHOR CONTIBUTION

All authors contributed to the writing of this article.

FUNDING STATEMENT

This study was conducted without any financial support.

COMPETING INTEREST

The author declares that there is no conflict of interest in publishing this article.

REFERENCES

Ansari, N. A., Agus, C., & Nunoo, E. K. (2021, October 15). Earth, Forests and Biodiversity. In *SDG15 - Life on Land: Towards Effective Biodiversity Management*. Emerald Publishing Limited. https://www.emerald.com/books/monograph/10768/chapter/80380424/Foundations-of-SDG15-LIFE-on-Land-Earth-Forests

Badan Pusat Statistik Indonesia. (2022). *Statistik Lingkungan Hidup Indonesia 2022*. BPS. https://www.bps.go.id/id/publication/2022/11/30/eb06d1c8e37285cac10c3086/statistik-lingkungan-hidup-indonesia-2022.html

Bruna, F., & Yu, D. (2016). Geographically weighted panel regression and development accounting for European Regions. *Proceedings of the 6th Seminar Jean Paelinck in Spatial Econometrics*, 1–20.

The Error Component Model. (2018, October 22). In Y. Croissant & G. Millo (Eds.), *Panel Data Econometrics with R* (1st ed., pp. 23–51). Wiley. https://doi.org/10.1002/9781119504641.ch2

Fakher, H.-A. (2019). Investigating the determinant factors of environmental quality (based on ecological carbon footprint index). *Environmental Science and Pollution Research*, *26*(10), 10276–10291. https://doi.org/10.1007/s11356-019-04452-3

Giesselmann, M., & Schmidt-Catran, A. W. (2019). Getting the Within Estimator of Cross-Level Interactions in Multilevel Models with Pooled Cross-Sections: Why Country Dummies (Sometimes) Do Not Do the Job. *Sociological Methodology*, *49*(1), 190–219. https://doi.org/10.1177/0081175018809150

Harianto, Nugroho, W. H., & Sumarminingsih, E. (2021). Geographically and Temporally Weighted Regression Model with Gaussian Kernel Weighted Function and Bisquare Kernel Weighted Function. *IOP Conference Series: Materials Science and Engineering*, *1115*(1), 012063. https://doi.org/10.1088/1757-899X/1115/1/012063

Khan, I., Hou, F., Le, H. P., & Ali, S. A. (2021). Do natural resources, urbanization, and value-adding manufacturing affect environmental quality? Evidence from the top ten manufacturing countries. *Resources Policy*, *72*, 102109. https://doi.org/10.1016/j.resourpol.2021.102109

KLHK. (2019). *Indeks Kualitas Lingkungan Hidup 2019*. Direktorat Jenderal Pengendalian Pencemaran dan Kerusakan Lingkungan. https://ppkl.menlhk.go.id/website/filebox/1032/210927135903BUKU%20STATISTIK%20PPKL%20TAHUN%202019.pdf

Kusumadewi, D. A., & Kristanto, B. Y. (2025). Analysis of Factors Affecting the Environmental Quality Index (EQI) and Its Implications for Sustainable Development. *Journal of Sustainability, Society, and Eco-Welfare*, *2*(2), 124–140. https://doi.org/10.61511/jssew.v2i2.2025.1452

Listyaningrum, N., Dewanti, T., Wahyudi, T. P., Josiana, G. R., Latifah, Ariefin, R. F., & Suprayogi, S. (2022). Study of the Environmental Quality Index in an Urban Campus Area. *IOP Conference Series: Earth and Environmental Science*, *1039*(1), 012065. https://doi.org/10.1088/1755-1315/1039/1/012065

Mannanal, M. S., & Rajagopal, N. (2023). Healthcare Expenditure and Human Development Index as Determinants of Environmental Quality: A Panel Study on Selected Asian Countries. *Millennial Asia*, 09763996231199642. https://doi.org/10.1177/09763996231199642

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

Musella, G., Castellano, R., & Bruno, E. (2023). Evaluating the spatial heterogeneity of innovation drivers: A comparison between GWR and GWPR. *METRON*, *81*(3), 343–365. https://doi.org/10.1007/s40300-023-00249-0

Saini, J., Dutta, M., & Marques, G. (2020). A comprehensive review on indoor air quality monitoring systems for enhanced public health. *Sustainable Environment Research*, *30*(1), 6. https://doi.org/10.1186/s42834-020-0047-y

[This page intentionally left blank.]