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The Influence of Socio-Economic Variables on Environmental Quality in Java Island in 2023: Application of Spatial Dependency Model Regression

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Abstract
Java Island is one of the regions in Indonesia that has low environmental quality. The high population and economic activities that do not pay attention to the environment have caused environmental damage in regencies in Java Island. Environmental damage caused by pollution and waste can spread to other surrounding areas. This study aims to examine the influence of socio-economic factors on environmental pollution in Java Island using a spatial analysis approach. The data from this study use secondary data in the form of official statistical data produced by Kementerian Investasi dan Hilirisasi/BKPM, Badan Pusat Statistik (BPS) and Kementerian Lingkungan Hidup dan Kehutanan (KLHK). The analysis method used is the Spatial Error Model (SEM), which is a spatial dependence modeling involving the error component of neighboring areas as one of the variables that influences the dependent variable, the environmental quality index (EQI). The results of the analysis show that the variables of Gross Regional Domestic Product (GRDP) at Constant Prices in the industrial sector, the level of urbanization significantly reduce environmental quality in the district. Meanwhile, the Human Development Index (HDI) and other factors outside the model in neighboring areas have a positive effect on environmental quality. The results of this study are expected to be a reference for the government in implementing economic development and improving Human Resources (HR) by prioritizing sustainable development.

Keywords: Environmental Quality Index, Socio-Economic, Spatial Analysis

1. INTRODUCTION

The environment plays a crucial role in a country's development, requiring a balance between three key elements: economic growth, social inclusion, and social protection. Initiatives to enhance environmental quality are being implemented in response to the widespread degradation of forest areas and natural ecosystems (Ferronato

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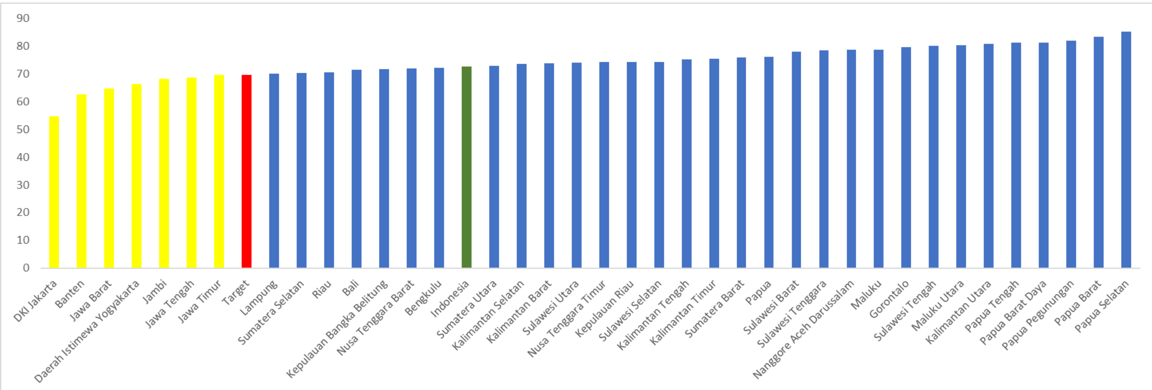
& Torretta, 2019; Shahbaz et al., 2018). In dealing with this, the issue of degradation is one of the main pillars to be achieved by 2030 in the Sustainable Development Goals (SDGs). This pillar is reflected in goals 6, 11, 12, 13, 14, and 15, which include various important elements for the sustainability of the ecosystem and the quality of human life (Elder & Olsen, 2019). To support the achievement of global development goals and plans, the Ministry of Environment and Forestry of the Republic of Indonesia has developed the Environmental Quality Index (EQI) as a performance indicator and important information material in policy-making related to environmental protection and management (BPS, 2023).

Java Island is one of the regions in Indonesia that has problems in achieving environmental quality. "Java-centric" economic development has caused various socio-economic and environmental problems in Java Island (Pujiati et al., 2023). Environmental problems include household and industrial waste disposal, ranging from liquid waste that impacts water quality, to solid and gas waste that affects air and soil quality. These various problems are reflected in the low achievement of EQI in various regions in Java Island. Based on Figure 1, the provinces in Java Island have low EQI achievements and are ranked in the bottom six. This value is below the Indonesian National EQI, which is 72.54 and the *Kementerian Lingkungan Hidup dan Kehutanan* (KLHK) Strategic Plan Targets in 2023, which is 69.48.



Source: KLHK, processed

Figure 1. EQI 34 Provinces in Indonesia in 2023

High socio-economic activities on the island of Java are thought to affect the poor quality of the environment. Industrial-based economic activities have affected the quality of the environment, such as industries that produce toxic waste and emissions that can have a damaging impact on environmental quality (Nugraha et al., 2023). In addition, the high population on the island of Java, which reaches 56.10% of Indonesia's population, can reduce environmental carrying capacity due to household waste. Pollution or waste produced in an area can spread to other areas and affect the condition of the ecosystem around the area (Häder et al., 2020). This phenomenon is known as the spatial effect explained in Tobler's First Law which explains that "Everything is related to each other, but the closest is more related than the distant" (Anselin & Li, 2020). This spatial effect explains that the impact of changes in environmental quality that are increasingly declining is not only felt in one place, but can be felt in the surrounding areas (Carmona, 2019; Gao et al., 2020).

The continuing decline in environmental quality if not addressed immediately allows for a decline in the quality of the environment which can cause losses in various aspects of human life. From a social perspective, Azam et al., (2022) will make it difficult for people to access basic resources such as clean water and fertile land. In a political context, environmental damage can exacerbate political instability by increasing resource conflicts and triggering tensions between communities or countries (Koubi, 2019; Scheffran et al., 2019). Health impacts include increased diseases such as pneumonia, Respiratory Tract Infections, Dengue Fever and diphtheria (Haryanto, 2020; K, 2024; Nii-Trebi, 2017; Rai, 2018). In an economic context, environmental damage can reduce agricultural productivity, and the productivity of communities that depend on forest products for their livelihoods (Nerfa et al., 2020; Nwokoro & Chima, 2017; Rasmussen et al., 2017). All of these impacts are interrelated, reinforcing the urgency of implementing sustainable environmental protection efforts.

There have been many studies discussing environmental quality in various countries. Chen et al., (2021a) using the spatial Durbin model method in China. Azam et al., (2022) using the panel quantile regression method in 40 countries in Asia, Ren et al., (2021) using the spatial Durbin model in China, and Ge et al., (2018) using spatial panel regression in China. However, these models have not revealed any spatial dependence, especially on environmental quality variables. Furthermore, these studies have not focused on districts in Java Island, Indonesia, which is one of the most problematic areas in terms of environmental quality in Indonesia.

With a dense population and the presence of various industries and active economic sectors, Java Island needs to pay attention to environmental quality. A study is needed to investigate socio-economic factors that influence environmental quality in Java Island in 2021. Therefore, this study aims to provide an overview of the distribution of EQI at the district level and to determine the impact of socio-economic activities on environmental quality. The results of this study are expected to be an evaluation of the government in industrialization-based economic development and community empowerment that prioritizes the concept of development following the goals of the SDGs.

2. LITERATURE REVIEW

2.1. Theoretical basis

The Enviromental Kuznets Curve (EKC) hypothesis illustrates the relationship between environmental quality and economic growth, suggesting an inverted U-shaped pattern between environmental degradation and economic progress, as shown in Figure 2 (Sarkodie & Strezov, 2019). Economic growth is represented by Gross Domestic Product (GDP) per capita and Foreign Direct Investment (FDI), while environmental degradation is indicated by rising carbon dioxide (CO_2) emissions. During the pre-industrialization phase, increasing GDP per capita and FDI of a country will increase the level of environmental degradation. This condition does not always last because in the industrialization phase there will be a turning point. Then in post-industrialization, an increase in GDP per capita and FDI will reduce the level of environmental degradation. Furthermore, the measurement of socio-economic impacts in this study adopts the Stochastic Impact of Population, Affluence, Technology (STIRPAT) model framework which can describe the influence of population factors (P), prosperity (A), and technology (T) on environmental conditions (I). Population development of an area is influenced in terms of the STRIRPAT equation contributing to understanding the various causes and

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impacts of the environment, and continues to be developed as a method to improve understanding of economic and environmental problems (Gyamfi et al., 2023). The STIRPAT model in general can be formulated as in the following equation (1):

$$I = \alpha P^b A^c T^d \quad (1)$$

The notation α is a constant, the values b, c, d describe the elasticity for population, prosperity, and technology factors respectively, and ε as the error component of the model that describes environmental conditions in an observation area.

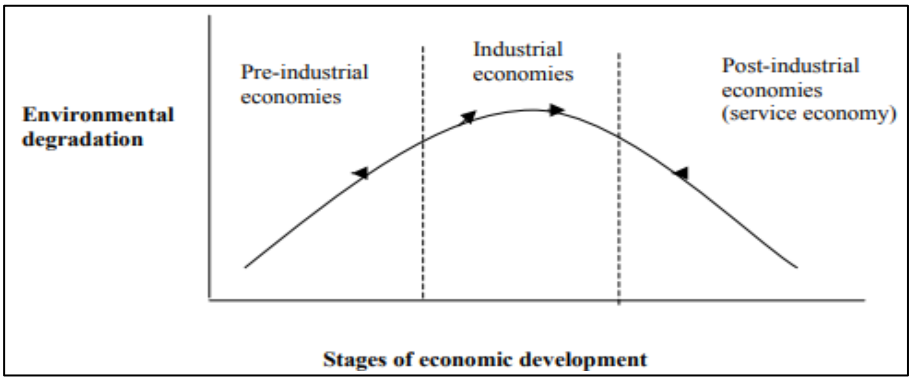

Figure 2. EQI of districts in Java Island in 2023

2.2. Environmental Quality Index (EQI)

EQI is an indicator adopted by the KLHK by combining the concept of the Environmental Performance Index (EPI) from Virginia Commonwealth University (VCU) and the EQI from the *Badan Pusat Statistik* (BPS). EQI has a value range of 1-100, higher values reflect better environmental quality (KLHK, 2010;BPS, 2023). Equation (2) shows the calculation formula for EQI at the districts level.

$$EQI_J = (0{,}376 \times WQI_J) + (0{,}405 \times AQI_j) + (0{,}219 \times LCQI_j) \quad (2)$$

Details:

j : Districts in a province, $j = 1,2, \ldots, n$
n : many districts in each province to-i
EQI_j : Environmental Quality Index of the j^{th} district/city
WQI_j : Water Quality Index (WQI) of the j^{th} district/city
AQI_j : Air Quality Index (AQI) of the j^{th} district/city
$LCQI_j$: Land Cover Quality Index (LCQI) of the j^{th} district/city

The grouping of EQI values in this study is adjusted to the provisions according to (KLHK, 2010) as in Table 1 below:

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Table 1. EQI Value Categories

Category	Range Numbers
Verry Good	$90 \leq EQI \leq 100$
Good	$70 \leq EQI \leq 90$
Moderate	$50 \leq EQI \leq 70$
Bad	$25 \leq EQI \leq 50$
Very Bad	$0 \leq EQI \leq 50$

2.2. Moran's Index

The Moran's Index is a measure used to determine the presence of spatial autocorrelation in data. A Moran's Index coefficient approaching 0 indicates no spatial autocorrelation. Conversely, a Moran Index coefficient approaching 1 or -1 indicates the presence of spatial autocorrelation. I > 0 indicates a positive autocorrelation and I < 0 indicates negative autocorrelation. The Moran's Index statistical test is carried out using the Z probability distribution approach as in Equation (3). The null hypothesis in the Moran's I test is the absence of spatial autocorrelation. The null hypothesis is rejected if |Z| > $Z_{\alpha/2}$ (Novitasari & Khikmah, 2019).

$$Z = \frac{I - \left(-\frac{1}{n-1}\right)}{\sqrt{\left(\frac{n^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^2\right)^2 - n\sum_{i=1}^{n}\left(\sum_{j=1}^{n} W_{ij}\right)^2}{(n^2-1)\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)^2}\right)}} \sim N(0,1) \quad (3)$$

Detail:

x_i : observation value $(i = 1,2, \dots, n)$
$\bar{x}$: average value of all observations
x_j : observation value $(j = 1,2, \dots, n)$
W_{ij} : spatial weighting matrix between region i and region j

2.4. Spatial Regression

Spatial regression is a development of the generally known linear regression. Spatial regression considers spatial or geographical aspects. There are 3 possible spatial regression models with a spatial dependency approach, namely Spatial Autoregressive (SAR), Spatial Error Model (SEM), and Spatial Autoregressive Moving Average (SARMA) (Ge et al., 2018). SAR is a model that shows the existence of spatial correlation in the dependent variable. SEM is a model that shows the existence of dependence between the dependent variable and a set of observed local characteristics and the error components are correlated between regions. SARMA is a combination of SAR and SEM. Multiple linear regression models and spatial regression can be written in Table 2 below (Anselin & Li, 2020; Elhorst, 2014; Ward, M. D., & Gleditsch, 2018).

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Table 3. Details of research variables

Model	Equation
Linear Model	$y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i$
Spatial Lag Model (SLM)	$y = \beta_0 + \rho W y + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i$
Spatial Error Model (SEM)	$y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \mu$ witj $\mu = \lambda W + \varepsilon_i$
Spatial Autoregressive Moving Average (SARMA) Model	$y = \beta_0 + \rho W y + \sum_{i=1}^{n} \beta_i X_i + \mu$ with $\mu = \lambda W + \varepsilon_i$

Details :

β_0	= constant	w	= weight
β_i	= regression coefficient of variable i	ρ	= spatial lag coefficient
y	= dependent variable	λ	= spatial error coefficient
x_i	= independent variable i	ε_i	= error

2.5. Data and Data Resource

The data used in this study are secondary data from official statistical publications sourced from KLHK, Kementerian Investasi dan Hilirisasi/BKPM, and BPS. The following Table 3 presents details of the variables used

Table 3. Details of research variables

Variable	Unit	Source	Referensi Pemilihan Variable
EQI	Index	KLHK	Azam et al., (2022); Chen et al., (2021b); Ge et al., (2018); Majeed & Mazhar, (2021); Permatasari et al., (2023); Pujiati et al., (2023); Brockwell et al., (2021); Ren et al., (2021)
Gross Domestic Regional Product (GDRP) at constant prices for Manufacturing Industry	Billion	BPS	Pujiati et al., (2023)
Foreign Direct Invesment (FDI)	Billion	BKPM	Azam et al., (2022); Pujiati et al., (2023)
Human Development Index (HDI)	Index	BPS	Li & Xu, (2021); Mannanal & Rajagopal, (2023); Pujiati et al., (2023)
Urbanization Level	Percent age	BPS	Fang et al., (2020); Ge et al., (2018); Liang et al., (2019); Rahman & Alam, (2021)

3. METHODS

The inferential analysis applied in this study is useful for identifying the appropriate spatial model used in modeling socio-economic variables that affect EQI in Java. In

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general, the spatial modeling carried out carries the following general equation model (Equation 4):

$$y = \beta_0 + \rho W y + \sum_{i=1}^{n} \beta_i X_i + \mu \text{ with } \mu = \lambda W + \varepsilon_i \text{ and } i = 1,2,3,4,5 \quad (4)$$

In this study, in conducting each hypothesis test, a significance level of 5 percent was used. The following are the steps taken for the inferential analysis in this study (Anselin & Li, 2020; Elhorst, 2014; Ward, M. D., & Gleditsch, 2018).

1. Perform modeling using the Ordinary Least Squares (OLS) method.
2. Identify spatial effects in the data.
3. Detect spatial autocorrelation by applying Moran's I test.
4. Test for spatial dependency.
5. Use the Lagrange Multiplier (LM) statistic for testing (LM-lag and LM-error). If LM-lag is significant, adopt the SLM or SAR. If LM-error is significant, use the SEM.
6. Develop the spatial regression equation based on the selected model.
7. Test the significance of parameters both simultaneously and partially.

4. RESULTS AND DISCUSSION

4.1. OVERVIEW OF EQI IN JAVA ISLAND IN 2023

Figure 3 presents the EQI value by districts in Java Island in 2023 with a thematic map. In the map, there are nine districts included in the "Bad" category in Java Island in 2023 with values between 25 and 50. These districts are located in the administrative cities of North Jakarta, East Jakarta, South Jakarta and Bekasi, Karawang, Bekasi City and Tangerang City which are neighboring each other. On the other hand, there are only nine districts included in the "Good" EQI category with EQI values ranging from 50 to 70. These districts are Banyuwangi, Batu City, Kuningan and Temanggung. The rest, most of the districts in Java Island, namely 100 districts, are still in the "Moderate" category with EQI values of 50 to 70. Based on this description, it can be seen that the majority of districts in Java Island have environmental quality that is at the "Moderate" level. The district with the "Bad" category are mainly found in the Jakarta area and surrounding district, while the district with the "Good" category are spread across nine locations on Java Island. Although there are many areas with fairly good quality, when viewed by looking at the EQI target set by the KHLH, there are quite a lot of areas that have not achieved the EQI target. Only eleven district or 9.24% of the Java Island area were able to achieve the EQI target of 69.48. The areas that have achieved the national EQI target include Pandeglang, Kediri City, Sampang, Gresik, Situbondo, Tulungagung, Wonosobo, Tegal City, Blora, Kuningan, Ciamis.

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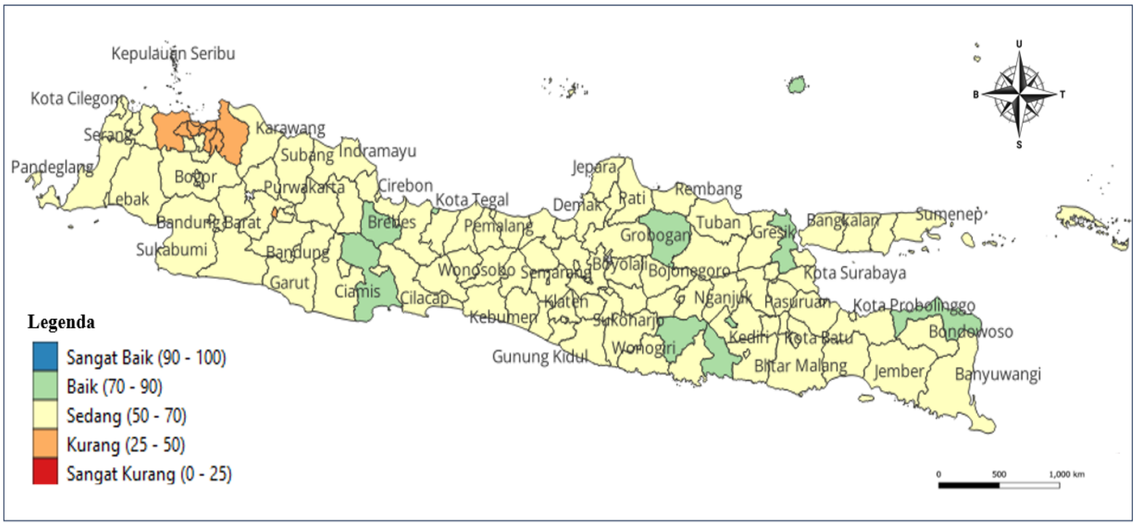

Source: KLHK, processed

Figure 3. EQI of districts in Java Island in 2023

4.1. The Influence of Socio-Economic Variables on EQI in Java Island in 2023

In accordance with the stages of spatial regression analysis. The inferential analysis process begins with forming a multiple linear regression model with OLS estimation. Furthermore, in testing the model assumptions shown in Table 4. The normality assumption test obtained the Jarque Bera test decision failed to reject H_0, meaning that the OLS model error follows a normal distribution. In the homoscedasticity test using Bruesch-Pagan, the decision failed to reject H_0 was obtained, meaning that the error variance in the model is constant or homoscedastic. Based on the results of the multicollinearity diagnosis, each variable used has a Variance Inflated Factor (VIF) value less than 10, meaning that there is no indication of multicollinearity in the model.

Table 4. OLS Estimation Results

Variable	Coefficient	*Standard error*	*p-value*
Intercept	70.260	2.529	0.000*
X_1	-0.276	0.250	0.027*
X_2	-0.463	1.221	0.080*
X_3	0.054	0.015	0.005*
X_4	-10.988	1.906	0.000*

** Significant at 5% alpha*

Table 5. Classical assumption test

Classical assumption test	Test Name	Statistic Value	*p-value*
Normality Test	Jarque-Berra	0.879	0.644
Homoskedasticity Test	Breusch-Pagan	8.816	0.065
Multicollinearity Detection using VIF			
X_1	X_2	X_3	X_4
1.275	2.450	1.765	3.012

** Significant at 5% alpha*

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Global spatial autocorrelation aims to see spatial dependence between regions based on observation values on the dependent variable. Based on the test results in Table 6 with Global Moran's I statistics, the I value is 0.210 and the $p - value$ (0.002) < 0 indicates significant positive spatial autocorrelation. This shows that the spatial pattern of EQI values is not random and there is an indication of strong spatial autocorrelation between districts in Java

Table 6. Moran's I Test

	I	*z-value*	*p-value*
Moran's I	0.210	3.745	0.002*

** Significant at 5% alpha*
Source: Processing results

The results of the LM dependency test on lag and error in Table 7 show that the p-value of LM-lag is 0.054 which is greater than the value of α which has been set at five percent, not significant. Meanwhile, the p-value of LM-Error is 0.006 which is smaller than α of five percent which results in a reject decision H_0. So the best model suitable for use in this study is SEM.

Table 7. *Lagrange multiplier diagnostics for spatial dependence*

Variable	MI/DF	Statistic Value	*p-value*
LM-lag	1	3.684	0.054
LM-Error	1	7.346	0.006*

** Significant at 5% alpha*
Source: Processing results

The SEM Equation 5 produced from Table 8 is as follows

$$y = 67.195 - 0.105X_1 - 0.542X_2 + 0.045X_3 - 8.096X_4 + 0.440\sum_{i=1}^{n}\widehat{w_{ij}}\varepsilon_{ij} \quad (5)$$

Table 8. Spatial regression estimation results - SEM

Variable	Coefficient	*Standar error*	*p-value*
Intercept	67.195	2.619	0.000*
X_1	-0.105	0.230	0.004*
X_2	-0.542	1.708	0.080*
X_3	0.045	0.022	0.037*
X_4	-8.096	1.921	0.007*
λ	0.440	0.098	0.000*

** Significant at 5% alpha*
Source: Processing results

The spatial dependency effect in this case is symbolized by lambda (λ) indicating changes in EQI caused by changes in the value of variables in the surrounding districts. Based on the results of SEM regression in 119 districts in Java, the coefficient value of

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the lambda variable that describes the occurrence of dependency between errors with a positive direction towards EQI is 0.440 and a probability value of 0.000 which is significant to the level. The results of the study indicate that changes in other variables that are not included in the model in the surrounding provinces also play a role in influencing EQI in a districts. Environmental degradation is not always fully explained by the variables in the model, because there are often external factors originating from neighboring areas. Factors outside the model can have a positive impact on environmental quality in neighboring regions through various mechanisms, such as the transfer of environmentally friendly technologies, interregional cooperation in resource management, and spillover effects from green infrastructure investments. In addition, environmental education campaigns, regional regulations, and population mobility can also encourage the spread of an environmentally friendly culture. All of these create synergies between regions that strengthen collective efforts to maintain and improve environmental quality.

Based on the analysis results in Table 8, the parameter coefficient of the GRDP at constant prices for Manufacturing Industry (X_1) of log ($^{0.105}$) is significant at the α level of ten percent, which means that every one percent increase in the GRDP at constant prices for manufacturing industry will reduce the environmental quality index of a districts in Java by 0.978 points with the assumption of other independent variables in the model. Economic growth aims to improve the standard of living of people in an area, but if economic activities do not pay attention to the environment and sustainability, it can cause environmental quality to decline. According to the EKC Theory, economic growth in the early stages tends to cause environmental degradation (Sarkodie & Strezov, 2019). This period is generally still mostly experienced by developing countries in the world. The higher the value of the industrial GDRP indicates the increasing number of economic activities in the industrial sector operating in the district/city. Industrial activities that do not pay attention to the environment from production waste that is not properly processed or the pollution produced can reduce environmental quality in a districts and can also pollute districts in neighboring areas. These results are in line with research conducted by Brockwell et al., (2021); Ge et al., (2018); Kurniawan & Managi, (2018); Salman et al., (2019) which states that economic growth can have a negative impact on environmental quality in a region.

Furthermore, in Table 8, the parameter coefficient of FDI (X_2) of -0.542 is significant at the α level of ten percent, which means that every increase in the value of FDI by one million US$ will reduce the environmental quality index of a districts in Java by 0.542 points assuming other independent variables in the model are constant. In an effort to run the wheels of the economy, investors are often given the opportunity to invest their capital in a region. Foreign investors from capitalist countries and industrial companies often look for areas with less stringent environmental regulations in order to reduce costs related to negative impacts on the environment (Liu et al., 2017; Luo et al., 2021; Zhang et al., 2020). This is in line with the results conducted by Azam et al., (2022) and Pujiati et al., (2023).

The parameter coefficient of the HDI (X_3) in Table 8 is 0.045 significant at the α level of ten percent, which means that every increase in the HDI value of one poin will reduce the environmental quality index of a districts in Java by 0.022 points assuming other independent variables in the model are constant. This result is in line with research conducted by Li & Xu (2021), Mannanal & Rajagopal (2023), and Pujiati et al., (2023).

Furthermore, Table 8 The parameter coefficient of the urbanization level (X_4) is -8.096 significant at the α level of ten percent, which means that every increase in urbanization by one percent will reduce the environmental quality of a districts in Java by 8.096 points assuming other independent variables in the model are constant. Urbanization can be interpreted as an increase in the proportion of urban population. Uncontrolled urban growth can cause loss of natural habitat through deforestation and land encroachment that converts forests into settlements and agricultural land. These results are in line with research conducted by Fang et al., (2020), Liang et al., (2019), and Rahman & Alam (2021).

5. CONCLUSION

There are variations in EQI between district in Java Island, especially the differences between the administrative cities of DKI Jakarta and the surrounding districts with EQI in other districts. There is a positive spatial dependency on the quality of the environment between districts in Java Island. The economic factors of industrial GRDP, as well as social factors of urbanization level and population density have a direct negative effect on environmental quality in a district. Meanwhile, the HDI as an indicator of human development has a positive effect on EQI.

As a suggestion, the government needs to evaluate economic activities in the industrial sector that pay less attention to environmental ethics in order to prevent waste pollution. Furthermore, it is important to build sustainable districts, where the pollution produced does not damage the environment and human health. A transmigration program is also needed so that natural resources in an area can meet the needs of life and do not exceed the environmental carrying capacity.

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