Spatial Panel Data Approach on Environmental Quality in Indonesia

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Abstract. Indonesia adopted a strategic long-term development plan (2005-2025) targeting to achieve a green and everlasting Indonesia through implementing various environmental policies. One of the mandatory matters for governments is to continue environmental control by constructing Environmental Quality Indexes (EQI). This study focuses on the relationship between regional output or real Regional GDP, level of population density, and the government expenditure on environment quality on EQI in 34 provinces in Indonesia by the time period 2015 to 2019 using a spatial panel data approach. Within the context of spatial modeling, the interaction between provinces depends on their geographical location and condition. Using the geographic information system (GIS) and stata attributes, the coordinates and distances can be mapped and then defined for observation units in space via the spatial weight matrix used. From the perspective of spatial geography, this paper verifies the spatial dependence of Indonesia's Environmental Quality Index (EQI). Pesaran's CD test indicates the spatial effect on the model and SAR with random effect can be considered a better-fitting spatial panel regression model. The results of the econometric spatial panel using SAR panel with random effect analysis show that Indonesia's EQI in the provinces was dependent on the spatial. It was also found that regional GDP has a significant and negative effect on EQI and population density has a negative and significant effect on EQI. While fiscal policy on the environmental area on improving environmental quality did not pass a significance test. Thus, it is recommended to look for ways to promote green growth in the country.

1. Introduction

The concept of the SDGs was born at the UN Conference on Sustainable Development, Rio (+20), Brazil in 2012. The objective was to produce a set of universally applicable goals that balances the three dimensions of sustainable development: environmental, social, and economic. Indonesia is a significant global player both in terms of economic performance and environmental area. In the environment aspect, CO2 emissions for Indonesia were 568.3 million tonnes and emissions from Indonesia contribute 2.03% to global emissions (World Resources Institute, 2020). However, Indonesia's environmental performance index was ranked 117 of 180 countries in the world and ranked 6th out of 10 countries in Southeast Asia in 2020. Emissions in Indonesia have gotten the world's attention when the Government of Indonesia hosted the UN Climate Change Conference in Bali 2007 with the result of the Bali Road Map, a variety of decisions and programs that will reach toward a safer climate future. At the September 2009 G-20 meeting in Pittsburgh, former President Susilo Bambang Yudhoyono laid out a vision where the Indonesian government was crafting a policy that would cut emissions by 26 percent by 2020 from business as usual levels. Five years after that, in 2015, the president "Jokowi" when delivering a statement on the UN Framework Convention on Climate Change, Paris, has revision the target become 29 percent reduction in greenhouse gas emissions by 2030. However, Indonesia adopted a strategic long-term development plan (2005-2025) targeting to achieve a green and everlasting Indonesia through implementing various environmental policies.

The latest years have shown that governments from all over the world have acknowledged the importance of the environmental condition and proceeded in various ways to find solutions and apply procedures for preserving or improving the environment. As Article 45 of Law No. 32 of 2009. the regional government is given a mandate by the central government to allocate the Regional Revenue and Expenditure Budget *(APBD)* to overcome damage and improve the respective regions' environmental quality. The allocation of deconcentrated funds in the environmental sector continues to increase from year to year. However, the quality of the environment measured by the Environmental Quality Index (EQI) is relatively stagnant so, the purpose of our study is how the influence of fiscal policy, specifically the allocation of deconcentrated funds on the environment area to environmental quality conditions. [13]

Indonesia consists of 34 provinces. The interaction between provinces depends on their geographical location and condition. Nearby provinces, due to their similar geographical conditions, have similar economic activities. The western part of Indonesia is a mountain area with mining potential, the fertile central, and southern areas are dedicated to agriculture and harvest natural resources, whereas the majority of industrial activities are located in the Java islands. The eastern part of Indonesia is densely forested in origin with mining potential. Particularly in the eastern part of Indonesia, has not been well developed. Economic growth invites some consequences on externality. Strong economic growth is a catalyst for regional development. Unfortunately, the growth invites some negative consequences for the quality of the environment. In this study, we use an index derived from the environmental sustainability index, called the environmental Quality index (EQI. According to the Ministry of Environment and Forestry (2019), EQI is used to assess the performance of environmental quality improvement programs and support the process of policymaking related to environmental protection and management. This index provides a condensed description of multidimensional environmental states by aggregating several indicators (water, air, and foresty) into a single quantity. Several studies on environmental economics have explored the functional relationship between economic growth and environmental quality using Environmental Kutnetz Curve model. The environmental quality in itself naturally has a spatial pattern. Geographically, the externalities' effect is captured by the spatial pattern of the environmental impact. Within the context of spatial modeling, this indicates the nature of externalities can be determined by analyzing which factors of the surrounding locations significantly affect the environmental quality.

The objective of this study is to identify the involved growth externalities on the Indonesian environmental quality index. It can be done by estimating the coefficients of the spatial version of the IPAT function. In answering the purpose of the study, the analytical method used in econometric models uses spatial data panel analysis. The econometric model is used to analyze the impact of economic growth, population density, and fiscal policy on the environmental quality index in 34 provinces in Indonesia period time 2015-2019. Spatial panel models with time effects and fixed effects are more stable and can control heterogeneity and spatial autocorrelation than conventional panel models [8]. Using the geographic information system (GIS) and stata attributes, the coordinates and distances can be mapped and then defined for observation units in space by spatial weighting matrix.

2. Data Collection

In the 1970s, Professors Ehrlich and Commoner of Stanford established IPAT formulas for assessing environmental pressures and studied the mechanisms by which population, economic growth, and technological progress influence carbon emissions (17). The equation defines that environmental quality is the product of Population size, Affluence, and Technology ($I = P \times A \times T$). Affluence can be represented by consumption or production (growth). The data consist of the observed values of the following variables:

- EQI (Environmental quality Index), of all 34 provinces, i = 1,2, … ,34. A higher index indicates better environmental quality.
- RGDP (Regional Gross Domestic Bruto in billion rupiahs) as the measure of productivity (A).
- Population_Density (in 1000 persons/km2). Density is used instead of population size to accommodate the area of each province. It is used as a proxy for = 1,2, …, n.
- Government expenditure on the environment (allocation of deconcentrated funds each province in the environmental sector in millions rupiahs).

Data sets were collected from 34 provinces in Indonesia from 2015 to 2019. According to the description of the location in each province, we found the latitude and longitude of the site from the Internet. For the empirical exercise presented in the next section, regional gross domestic product and government expenditure on the environment is presented in a logarithmic. The analytical method used in this study is descriptive analysis with tables, graphs, Moran's I scatterplot, and thematic maps using GIS software, as well as spatial regression analysis with panel data as inferential analysis using stata software. An analysis using thematic maps was carried out to describe the pattern of the environmental quality index in Indonesia, while spatial regression analysis with panel data was carried out to determine the factors influencing the environmental quality index level in all provinces in Indonesia.

3. Model

3.1. Panel model
Pool model

$$y_{it} = \alpha + \beta x'_{it} + u_{it} \tag{1}$$

Fixed panel model

$$y_{it} = \alpha_i + \beta x'_{it} + u_{it} \tag{2}$$

Random panel model

$$y_{it} = \alpha_0 + \beta x'_{it} + w_{it} \tag{3}$$

$$w_{it} = \varepsilon_i + u_{it} \tag{4}$$

Where I denoted as the cross section of the province (i = 1, 2, . . . , 34), T represents the period (t = 2015, 2016, . . . , 2019), y_{it} as dependent variable on the i th region for the t th time period ; x_{it} as predictor variables on the i th region for the t th time period ; α as intercept term; α_i as the intercept regression model i th region ; β as slope coefficient; u_{it} as general residual term, $u_{it} \sim \mathrm{N}(0, \sigma_u^2)$; ε_i as residual term contain unit specific effect

The parameter estimation of the general model is based on the least-squares method, while parameter estimation of SAR and SEM are the maximum likelihood estimation method. Spatial autocorrelation causes linkages between regions since the value of observation in a region shall be influenced by the value of observation in the surrounding area. Meanwhile, spatial heterogeneity causes instability of correlation behavior, resulting in a variance of inconstant error, leading to differences in the function of the correlation between regions. Spatial dependence of incident duration was assessed using Global Moran’s I statistic which was first proposed by Moran and using the Pesaran test [15].

3.2. Panel data with spatial effect model

$$y_{it} = \gamma y_{i,t-1} + \lambda w_N y_{it} + \beta x'_{it} + \varepsilon_{it} \tag{5}$$

Whereas, y denoted as coefficient dependent variable ; λ as spatial autocorrelation coefficient; w_N as spatial weighting matrix NxN; y_{it} as dependent variable on the i th region for the t th time period; β as vector slope coefficient Kx1; x'_{it} as predictor variables; ε_{it} as an error component in observation units to-i and time to-t; and ρ as spatial autoregressive coefficient. [18]

3.3. SAR panel model

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \beta x'_{it} + \mu_i + \varepsilon_{it} \quad (6)$$

Whereas y_{it} denoted as dependent variable on the *i* th region for the *t* th time period; x_{it} as predictor variables on the *i* th region for the *t* th time period ; w_{ij} as the spatial weighting matrix NxN. The weight matrix is processed by a row standard, and the sum of the elements of each row is 1; α as the intercept regression model; β as slope coefficient; ρ as the spatial autoregressive coefficient; λ as spatial autocorrelation coefficient; $\mu_i$as residual term contain unit specific effect *I* th region; u_{it} denotes as spatial error auto-correlation; and ε_{it} an error component in observation units to-*i* and time to-*t*.

3.4. SEM panel model

$$y_{it} = \alpha + \beta x_{it} + u_{it} \quad (7)$$

$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad (8)$$

Whereas y_{it} denoted as dependent variable on the *i* th region for the *t* th time period; x_{it} as predictor variables on the *i* th region for the *t* th time period ; w_{ij} as the spatial weighting matrix NxN. The weight matrix is processed by a row standard, and the sum of the elements of each row is 1; α as the intercept regression model; β as slope coefficient; ρ as the spatial autoregressive coefficient; λ as spatial autocorrelation coefficient; $\mu_i$as residual term contain unit specific effect *I* th region; u_{it} denotes as spatial error auto-correlation; and ε_{it} an error component in observation units to-*i* and time to-*t*.

3.5. Spatial Weights Matrix

According to BPS (2011), the spatial weighting matrix is a measure of connectivity describing spatial processes, spatial structures, or spatial interactions. In spatial analysis, it is common to expect that close observations are more likely to be similar than those that are far apart. A spatial weight matrix needs to be constructed to reflect spatial correlation among regions. A proper spatial weight matrix is of substantial importance to get a sound spatial econometric result. To improve model credibility, we consider geographical spatial correlation among the regions. The former is constructed by the inverse distance method.

$$W_{ij}^{GS} = \begin{cases} \frac{1}{d_{ij}^{\alpha}} & i \neq j \\ 0 & i = j \end{cases} \quad (9)$$

Whereas W_{ij}^{GS} denoted as spatial weighting matrix NxN; *i* th region and *j* th region while d_{ij}^{α} as euclidean distance between regional i and j, which is calculated from each province longitudes and latitudes.

3.6. Moran's I Test

$$I = \frac{n \sum_i^n \sum_j^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{W \sum_i^n (x_j - \bar{x})^2} \quad (10)$$

Whereas, $x_i$denoted as predictor variables on the i th region; $x_j$as predictor variables on the j th region; w_{ij} as the spatial weighting matrix NxN; and $\bar{x}$ is mean value of x.

3.7. Pesaran Test

$$CD = \sqrt{\frac{2\tau}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right) \tag{11}$$

Whereas N denoted as number region of dataset; T as time period; ρ_{ij} as residual term correlation unit specific effect *i* th region and *j* th region

3.8. Hausman test

Model is divided into the fixed panel model, random panel model, spatial random effect SAR model, spatial fixed effect SAR model, spatial random effect SEM model, and spatial fixed effect SEM model, according to the Hausman test. Hausman's specification test can also be used when the model is extended to include spatial error autocorrelation or a spatially lagged dependent variable [18]. The Hausman test checks for any correlation between the error components, which is the cross-sectional random error component and the regressors in a random-effects model. Hausman test compares both random and fixed effects estimators and examines whether or not the random effects assumptions can be supported by the provided data. The Hausman test takes the form of:

$$\chi^2 = \tilde{q}'[Var(\tilde{q})]^{-1}\tilde{q} \tag{12}$$

Where $\tilde{q}$= $\hat{\beta}$ random effect model - $\hat{\beta}$ fixed effect model ; N as number region of dataset; T as time period; $\hat{\beta}$ random effect model is the estimator of $\boldsymbol{\beta}$ random effect model; and $\hat{\beta}$ fixed effect model is the estimator of $\boldsymbol{\beta}$ fixed effect model. [19]

4. Empirical Result and Analysis

Figure 1. Environmental quality index in Indonesia, 2019

Before discussing the estimation process and the significance of each factor on the environmental quality, it is important to understand the spatial pattern of the environmental quality index in this study area. The map of the observed environmental quality index of each province, from 2019 data is presented in Figure 1. The disparity of the environmental quality index shows a certain trend to spatial clustering. As displayed in Figure 1, the western provinces are aggregated in terms of their low environmental quality index intensities, these provinces are dominated by industrial areas. While eastern provinces are generally aggregated in terms of their high environmental quality index.

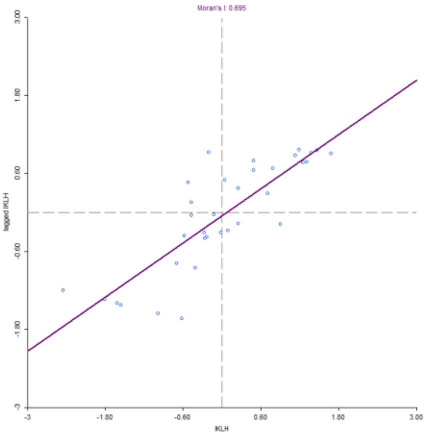

Figure 2. Moran scatterplot of environmental quality index in Indonesia, 2019

The quality of the environment in this study refers to the decree of the Ministry of Environment in which to measure the quality of the environment in an area to improve or vice versa is to use the environmental quality index (EQI). The EQI concept is built on three aspects of quality, namely water quality, air quality, and land cover quality, in this case, forest cover. We divided the classification the classification categories of EQI 2019 scores as (1) values > 75.7; (2) EQI value 67.5 < 75.7; (3) EQI value 59.3 < 67.5; (4) EQI 51.1 ≤ 59.3; and (5) EQI value < 51,1.

Table 1. Moran quadrant environmental quality index in Indonesia, 2019

Quadrant	Percentage (%)	Province
I (HH)	38	Gorontalo, Sulawesi Selatan, Kalimantan Utara, Sulawesi Barat, Maluku Utara, Kalimantan Tengah, NTT, Papua Barat, Sulawesi Tenggara, Papua, Kalimantan Timur, Maluku
II (LH)	10	Aceh, Jambi, Sulawesi Barat
III (LL)	42	Bangka Belitung, Riau, Kepulauan Riau, Selawesi Selatan, Kalimantan Barat, Bengkulu, Lampung, Jawa Tengah, NTB, Jawa Timur, DIY, Jawa Barat, Bali, Banten
IV (HL)	10	Kalimantan Selatan, Sulawesi Utara, Sumatra Utara

To further examine the clustering among provinces, we employ a Moran's I scatterplot displayed in Figure 2. In this scatterplot, the horizontal axis refers to the deviation of provincial average carbon dioxide emission intensity in 2019, whereas the vertical axis refers to the spatial lags of the deviation of the EQI. We calculate the spatial lags by using an inverse distance spatial weight matrix. The four quadrants in the scatter plot depict: the quadrant I (the star points) is the HH (high-high) clustering, which means provinces with high EQI are associated with the neighboring province with high EQI; the quadrant II (the circle points) is the LH (low-high) clustering, which means provinces with low EQI are associated with the neighboring province with high EQI; the quadrant III (the cross points) is the LL (low-low) clustering and; the quadrant IV (the square points) is the HL (high-low) clustering. The results in table 1 imply that during 2019, 38% (13 provinces) in quadrant I and 42% (14 provinces) in quadrant III demonstrate similar characteristics of positive spatial autocorrelation. On the other side, 10% (3 provinces) in quadrant II and 10% (3 provinces) in quadrant IV demonstrate negative spatial autocorrelation. Positive spatial interdependencies in EQI are indicated by the positive global Moran's I for 2019. This means that the spatial autocorrelation and dispersion of provincial EQI exist at that time. Among them, the first and third quadrants show the aggregation effect of high-valued aggregation and low-valued aggregation, which is a reflection of positive spatial correlation; the second and fourth quadrants are spatial negative correlation.

4.1. Spatial Dependence Test

Before estimating spatial panel data models, we need to test for cross-sectional dependence. The primary issue, when confronted with spatially referenced data, is to determine whether spatial dependence exists, that is, whether "nearby" cases are more correlated than distant ones. A flexible way of assessing whether dependence in the cross-section of a panel dataset is spatially related is the particularization of the Pesaran (2004) test for general cross-sectional dependence [15].

4.2. Moran's I environmental quality index 2015-2019

Table 2. Diasnostig test for spatial dependence

Year	Moran's I Test	LM Test	
	Prob	Prob. LM lag	Prob. LM error
2015	0.06760	0.04522	0.26647
2016	0.32467	0.02412	0.65610
2017	0.00740	0.00008	0.07624
2018	0.00011	0.00001	0.00542
2019	0.00192	0.00003	0.03378

The spatial autocorrelations measured through global Moran's I am shown in table 2. Positive spatial interdependencies in EQI are indicated by the positive and significant global Moran's I for each year except 2016 shows the cross-sectional dependence test reports. This indicates that Indonesia's EQI tends to cluster together. Specifically, the provinces with high EQI tend to cluster together, whereas the provinces with low EQI cluster together. We can reject that the null hypothesis errors are i.i.d (randomly distributed throughout the nation), indicating the spatial integration of EQI exports over time. All *p* values obtained by weighted spatial matrix are below ten percent except 2016, which indicates that Environmental Quality Index does have spatial dependence. Despite our findings of the spatial autocorrelation of EQI, the Moran's I test only assesses the overall pattern and trend, and Moran's I is only effective when the spatial pattern is consistent across the provinces. If some of the provinces have positive spatial autocorrelation while others have negative spatial autocorrelation, then the effects could offset one other. [16]

The paper prepared the non-spatial cross-section models and performed the corresponding moran's I test, Lagrange multiplier (LM) lag, and LM error tests. The LM (Lagrange Multiplier) test is carried out to determine the formation of a suitable spatial model to use. Based on Table 2, on the 5 percent significance test level, the LM test shows significant results in the LM lag test, or the null hypothesis of the non-spatially autocorrelated error term is rejected. While the LM error test shows insignificant results in 2015 and 2016. These results indicate that the spatial panel models are superior to the non-spatial panel. These results also seem to imply that the SAR model is a more appropriate specification than the non-spatial model as we find fairly consistent evidence across all models to reject the null hypothesis of no spatial lag. We find mixed results to reject the hypothesis for the spatially autocorrelated error term.

4.3. Pesaran test

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Pesaran's test of cross sectional independence =    16.732, Pr = 0.0000

Average absolute value of the off-diagonal elements =     0.526
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The table reports the results of testing for the absence of spatial and cross-sectional dependence in the panel data model. Pesaran's CD test tends to reject the null of cross-sectional independence, which indicates the spatial effect on the model. Finally, the estimation results were compared and analyzed by the ordinary panel data model, the spatial lag panel data model (SAR), and the spatial error panel data model (SEM).

4.4. Estimation result

Table 4. Estimation Result of Spatial Panel Data Models

Variable	OLS			SAR			SEM		
	Coefficient	Std. Error	Prob	Coefficient	Std. Error	Prob	Coefficient	Std. Error	Prob
Main									
ln_RGDP	-2.670549	1.135895	0.019	-2.032331	0.9277698	0.028	-3.48813	1.115097	0.002
Population_Density	-.0017355	0.0005357	0.001	-0.0016243	0.0004375	0.000	-0.0017123	0.0005027	0.001
Ln_Environment _Expenditure	0.5048661	0.6896473	0.464	0.8397474	0.5689484	0.140	1.092175	0.5633789	0.053
Constanta	114.6345	21.39698	0.000	47.54452	18.66338	0.011	124.158	20.89215	0.000
Spatial									
rho			0.66687091	0.7688953	0.0754645	0.000			
lambda							0.7522884	0.0785507	0.000
Variance									
lgt_theta				-0.8367354	0.1963809	0.000			
ln_phi							1.049085	0.2986578	0.000
Sigma u			6.5034738						
Sigma e			4.5965373						
sigma2_e				14.48965	1.776262	0.000	14.23346	1.754213	0.000
Model Assesment									
AIC					1041.853			1048.434	
BIC					1063.804			1070.385	
R square		0.4788			0.6023			0.4712	
N		170			170			170	
Log-likelihood					-513.9267			-517.2172	
Hausman Test		Random-effects GLS regression			SAR with random-effects			SEM with random-effects	

Equations using SAR with random-effects are as follows:

$$\widehat{EQI_{it}} = 47.54452 - 2.032331\ ^{**}LnRGDP_{it} - 0.0016243\ ^{**}\ Population\_Density_{it} + 0.8397474\ Ln\_Environment\_Expenditure_{it} + 0.7688953\ ^{**}\ wEQI_{it} \quad (11)$$

** indicates significant at 5 percent level

* indicates significant at 10 percent level

We first estimate a standard linear panel data model devoid of spatial effects. Concerning the traditional panel data models, adding the spatial autocorrelation component has improved the models immensely. The parameter estimation of the general model is based on the least-squares method, while parameter estimation of SAR and SEM are the maximum likelihood estimation method. According to the previous results, the three models, namely the ordinary panel data model, the spatial lag panel data model (SAR), and the spatial error panel data model (SEM), should be estimated with the Hausman test. According to the Hausman test results, we should judge whether the standard panel data econometric model should adopt a fixed effect or random effect.

Given the requirements to answer the research question it is imperative to analyze the effects of spatial variables on EQI. Estimation Rho 0.7688953 and significance show the dependence among provinces in the model. That means EQI in a province has an effect on another nearest province and the spatial lag in the nearest province has the same characteristics. The R2 value in the model is 0.6023. It means that RGDP, population density, and environmental deconcentration fund as the independent variable in the model can explain variations in the variable of poverty by 60 percent. The coefficient of determination R2 is usually used to measure the goodness-of-fit of models. However, it is inappropriate to use R2 to assess spatial models because the residuals of spatial models are not independent of one another. This issue can be appropriately addressed by using criteria based on likelihood estimation, such as maximum likelihood and Akaike Information Criterion (AIC) which was proposed by Akaike. In addition, AIC can serve as a comprehensive measure of model fitting and model complexity by introducing parameter numbers as a penalty term. As an alternative to AIC, Bayesian Information Criterion (BIC) combines the parameter number and the sample size into the penalty term [15]. We can see that the ACI and BIC obtained by the SAR with random effect are the lowest. The value of the AIC (1041.853), which is calculated for small samples, and BIC (1063.804) is also lower than the other models. Finding from Hausman test further, the random effect SAR is more consistent in comparison with the fixed effects SAR (prob>0.001). Consequently, the SAR with random effect can be considered a better-fitting spatial panel regression model.

4.5. Model assessment

Interpretation of the coefficient on Regional GDP is that a 1 percent increase of RGDP is associated with a -2.032331 point decrease of the EQI index (holding all else constant). The regression results also indicate that the value of the SAR panel (0.7688953) of the spatial random effect passes the significance level test of 0.1%. It can be seen that the carbon emissions from the neighboring provinces increase by 1% and the provincial carbon emissions increase by 0.7688953 %, in the case of considering, and not considering, respectively, the adjacent lag effect of the explanatory variable space. When an economy starts moving along the growth trajectory, then at the earliest stage of economic growth, the environment deteriorates rapidly due to ambient air pollution, deforestation, soil and water contamination, and several other factors. With a rise in the level of income, when the economy starts to develop at a particular level of income, environmental degradation starts to come down and environmental quality improves. This phenomenon is referred to as the Environmental Kuznets Curve (EKC) hypothesis in the literature of environmental economics, named after Simon Kuznets (1955), who described the inverted U-curve association between income inequality and economic development. The basic EKC relationship is best understood as a purely long-run concept. Estimation of the short-term dynamics may yield some interesting insights into how a country's emissions evolve, but the shape of the EKC must be found in the long-run equation. Both pollutants follow an inverted U-shaped curve with a negative coefficient of. It means environmental pollutions will increase along with the GDP growth before the turning point. This indicates that the activities of producing goods and services do not heed the principles of sustainable economic development, the activities of producing goods and services are followed by environmental degradation.

An interpretation of the population density is that a 1 percent increase will lead to a -0.0016243 point decrease in the EQI index. Population impacts environmental quality index via human production and consumption. Population density has a significant negative impact on EQI. This conclusion is consistent with the work of [20], [21], and [22]. It shows that the population density has also brought more negative impacts on the ecological environment in Indonesia. Population density is measured as the population divided by the area. Theoretically, as Indonesian population increasingly migrates to urban areas, which have greater access to modern energy technologies. However, agglomeration effects can optimize the spatial allocation of production and energy resources which could improve production and energy efficiencies. [16]. This conclusion is consistent with the work of [20], [21], and [22]. It shows that the population density has also brought more negative impacts on the ecological environment in China. A large number of people flowed into the eastern coastal areas after China issued the reform and opening policy, and efforts to protect the ecological environment in these areas should be further enhanced. [16].

dThe fiscal policy has a positive effect on EQI values, while the real GRDP has a negative effect on EQI. These results indicate that increasing the realization of deconcentrated funds can encourage an increase in the quality of the environment and vice versa with the level of regional output. Fiscal policy in this case the realization of the deconcentration fund has an insignificant effect on EQI with a positive direction. The effect is insignificant which shows that the effect of fiscal policy on EQI is still relatively small. Indonesia’s difficulties relate to a decentralized government that continues to struggle with corruption and diminished regulatory oversight, in addition to prioritizing private interests over public services, such as critical water infrastructure [13].

5. Conclution and Policy Implication

The results of the econometric analysis show that GRDP has a significant and negative effect on environmental quality, population density has a negative and significant effect, while fiscal policy (the deconcentration fund) has an insignificant and positive effect on environmental quality. In the formulation of EQI and development plans, the government must consider the effect of the influencing factors affecting the EQI in the adjacent area in the time dimension and the spatial dimension of Indonesia as a whole. Therefore, to improve the quality of the environment, local governments must be able to increase environmental-based budgets and economic development must be more environmentally friendly. The significance of the spatial effects suggests that the Indonesian government should promote the sharing and exchange of information across provinces to strengthen cross-province development. From the policy perspective, Indonesia should adopt a green policy to achieve green growth. Besides, implementation of Green GDP is needed to give value to the cost of environmental losses and therefore adjusts GDP to reflect the environmental costs. To get the required information for Green GDP accounting, monetary data together with physical data, as complementary data, is needed to reach the target of better EQI.

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