The Correlation of SDG 1 and 8 and Spatial Effect of Human Development Index in Central Java

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Abstract. Human Development Index (HDI) is the approach to measure socio-economics since 1990. Furthermore, integrating socio-economics with the environment brings the development of Sustainability Development Goals (SDGs). The relations between human development and sustainable development are complementary to build a better society. However, by 2020, the growth of HDI in Indonesia starts slowing down during Covid-19 to only 0.03% from the previous year. Central Java is one of the provinces that can still manage the HDI growth higher than Indonesia. This study aims to find the SDG 1 and 8 factors that affect HDI in Central Java with the spatial econometrics method to analyze the spatial dependency in variables. The variables of SDG 1 and 8 in this study are Ln Poverty Line, Ln GDRP per capita, unemployment, and poverty rate. This study shows that the SDG 1 and 8 variables have significant results and implicates spatial effects through Spatial Lag in the HDI of Central Java. The implication of this study is to encourage collaborative action in strengthening the implementation of SDGs and improving the HDI of the regions and cities in Central Java.

1. Introduction

Region development is not always about economic growth but also about the individual that lives in the city. According to Amartya Sen [1], economic growth is only focused on the circulation of goods and services without looking at the human condition in the region. Therefore, in the 1990s United Nation of Development Program (UNDP) was pioneered by economist Mahbub Ul Haq, succeeding in the Human Development Index (HDI) to measure human welfare [2]. Since 1990s, UNDP has led the assessment of human development and publishes every country’s human development report annually. The concept of human development measures human development to assess the socio-economics of people concerning equity, efficiency, participation and sustainability [3][4]. According to Amartya Sen, Human Development is a tool to measure the individual’s ability to be more independent in their way [4]. The HDI indicators, according to UNDP [5], are longevity (life expectancy at birth), knowledge (literacy rate and average years of study levels), and decent living standards (income per capita). However, in 2010, UNDP updated the HDI indicators in knowledge indicators, replacing literacy to mean years of schooling and changing the aggregation index into geometric mean. The newest HDI indicators are still applied now.
Human development provides the measurement for basic human needs such as health, education, and livelihood through economics. However, the rise of the economy will destroy the environment if there is no limitation. According to the study [6], the idea of integrating economic and environment leads to what today called Sustainable Development Goals (SDGs). SDGs have 17 goals with three main pillars; (i) economic, (ii) social, and (iii) environmental. The relationship between HDI and SDGs also elaborates that human development is advocates sustainability, and without sustainability, human development will have no progress[7]. The HDI focuses on maintaining an individual’s quality to have a decent life-with a better economy. This is explained by the study [7] that says human development and sustainable development share a fundamental view to empower people, focusing on capabilities, ability, and capacity.

The HDI measurements strongly relate to SDG 1, no poverty, and SDG 8, decent work, and economic growth. SDG 1 focuses to end extreme poverty that people measure live under poverty line 1.9 USD per day by 2030 in goal 1-1 and to reduce the number of people who live under the poverty line in goal 1-2 [8]. Moreover, SDG 8 focus on-sustaining the per capita economic growth in goal 8-1. SDG 8 also promotes decent work and economic growth by decreasing the unemployment rate and providing more job opportunities in goal 8-5 [8].

Research on human development is increasing mainly in analyzing the correlation between HDI and related to the SDG 1 about poverty and SDG 8 about employment. In the first study [2], the HDI has a significant relationship between Gross Domestic Regional Product per capita (GRDP per capita) in 33 provinces in Indonesia. The positive relationship with HDI and GRDP is due to public consumption being influenced by income, which is a component of the HDI. In Riau Province, the variables that affect the increase in HDI are the percentage of poverty and the percentage of GDRP [9]. Poverty has a negative significance which means that the HDI rate will increase if the percentage of poverty decreases. The increase in the economy has a positive significance, which means that the HDI will increase if the percentage of economic improvement increases.

The research about HDI in Central Kalimantan [10] also explains HDI and poverty have a negative effect. Another research [11] shows that in 2017, HDI in Indonesia negatively correlated to poverty and unemployment. The negative correlation between HDI and poverty was also proved in the West Seram Regency, Maluku Province, in 2018, where the other variable, such as dependency ratio, is positive [12]. Several studies’ negative effect of poverty and unemployment means the increasing number of poverties will drop the HDI. The study [13] explains that it is tough to reduce poverty because the poverty line keeps moving up. If the income of the poor people does not increase, they cannot pass the poverty line and also challenging to increase the HDI.

Moreover, the HDI of one region can affect another region that can be identified with spatial econometrics to show the pattern and clusterization. Spatial econometrics is a development concept from traditional econometrics concerned with examining the spatial dependence and spatial heterogeneity between the observations area [14]. LeSage [15] also elaborates that spatial econometrics is a technique designed to analyze the dependencies among geographical proximity observations. The dependency is caused by hierarchical spatial relationships, spatial spillovers, and other types of spatial interactivity [14]. The Spatial Lag and Spatial Error Model (SEM) are the common models for finding dependency in spatial econometrics. According to LeSage [14], the concept of a spatial lag relates to the set of associated areas with a particular location. In other words, spatial lag examines the dependency of variables from one area to another. On the other hand, spatial error is a model that analyzes the dependency of error values in associated areas [16]. To find the exact model requires running diagnostic with weight matrix of the areas and the dependent variables with $\alpha < 5\%$.

The study to find the correlation of HDI with the spatial econometrics approach was conducted in 2019. The study [17] analyzes the spatial effect of HDI in regencies and cities all over Indonesia with socio-demographic variables, including the percentage of households with proper sanitation, the poverty rate, the open unemployment rate, and the dependency ratio. The study finds that the spatial regression with the spatial lag model has robust result to a robust result in analyzing the dependency of HDI than classic regression. Regions and cities with a similar level of HDI form clusters where regions and cities
with high-high relations tend to be in Java Island, Sumatra Island, Borneo Island, and Celebes Island. Meanwhile, the low-low relations of Indonesia’s regions and cities tend to form clusters in Nusa Tenggara Island and Papua Island. According to the study, all variables working together can increase HDI in regions and cities in Indonesia up to 81 percent [17].

The HDI measurement model is internalized by Indonesia under the name *Indeks Pembangunan Manusia* (IPM). The HDI has been managed by the Central Statistics Agency (BPS) since 1996 and has been updated every three years, and since 2004, it has been updated annually. BPS Indonesia explains that HDI perceives how individuals can obtain development outcomes in income, health, and education. In Indonesia, the HDI reached 71.94 in 2020, with the lowest HDI is 60.44 in Papua and the highest is 80.77 in DKI Jakarta [18].

In Indonesia, SDGs is being localized under the name *Tujuan Pembangunan Berkelanjutan* (TPB). According to the TPB report [19], 2.7 percent of Indonesians live under extreme poverty with a minimum poverty line of 1.9 USD per day. In addition, people living under the national poverty line is 9.22 percent in 2019, decreasing by 0.6 percent from 2018. The TPB also reports that the GDP per capita in 2019 increased to 59.1 million Rupiah from 56 million Rupiah. This improvement brings Indonesia from a low-income country to an upper-income country. Unemployment also decreased to 5.28 percent in 2019, with 2.51 million new job opportunities [20].

Unfortunately, the pandemic strikes since 2020 slowing down the HDI of Indonesia with only 0.03% of growth in 2020 as the pandemic strikes and leads the disparities of the regions and cities more visible than in previous years [18]. Furthermore, the GDP of Indonesia will start to fall to 2.07 percent in 2020 [21]. Until now, the data of TPB Indonesia in amidst the pandemics is also not available yet. The government is struggling to stop the falling of HDI and GDP in Indonesia. However, one province that can still maintain to increase the number of HDI and decrease the disparity is Central Java. In 2020, the HDI growth surpassing the HDI of Indonesia with a 0.20% growth rate from 2019. The HDI of Central Java increased to 71.87 in 2020 from 71.67 in 2019. From the TPB report in 2019, Central Java has 10.58 percent people live under the poverty line from 11.19 in 2018 [22]. The success in 2019 also finds in-increasing of GDRP per capita in Central Java up to 6.71 percent from 2018 [22]. This study analyzed the correlation of SDGs through Poverty Line, GDRP per capita, Poverty rate, and unemployment with HDI in Central Java in 2020. The spatial effect will examine the relationship with the spatial econometrics approach to find the best spatial regression model.

2. Method

2.1. Data source and variables

The data for this study is gathered from The National Statistics Bureau. The HDI of Central Java consists of 35 Provinces and Cities such as (Table 1):
Table 1. List of Regencies and Cities in Central Java.

| No | Regencies/Cities      | No | Regencies/Cities      |
|----|-----------------------|----|-----------------------|
| 1  | Cilacap Regency       | 19 | Kudus Regency         |
| 2  | Banyumas Regency      | 20 | Jepara Regency        |
| 3  | Purbalingga Regency   | 21 | Demak Regency         |
| 4  | Banjarnegara Regency  | 22 | Semarang Regency      |
| 5  | Kebumen Regency       | 23 | Temanggung Regency    |
| 6  | Purworejo Regency     | 24 | Kendal Regency        |
| 7  | Wonosobo Regency      | 25 | Batang Regency        |
| 8  | Magelang Regency      | 26 | Pekalongan Regency    |
| 9  | Boyolali Regency      | 27 | Pemalang Regency      |
| 10 | Klaten Regency        | 28 | Tegal Regency         |
| 11 | Sukoharjo Regency     | 29 | Brebes Regency        |
| 12 | Wonogiri Regency      | 30 | Magelang City         |
| 13 | Karanganyar           | 31 | Surakarta City        |
| 14 | Sragen Regency        | 32 | Salatiga City         |
| 15 | Grobogan Regency      | 33 | Semarang City         |
| 16 | Blora Regency         | 34 | Pekalongan City       |
| 17 | Rembang Regency       | 35 | Tegal City            |
| 18 | Pati Regency          |    |                       |

This study consists of one dependent variable and four independent variables with following details (Table 2):

Table 2. List of Variables.

| No | Variable                                           | Explanation               | Code     |
|----|----------------------------------------------------|---------------------------|----------|
| 1  | Human Development Index                            | Y (dependent)             | HDI      |
| 2  | Poverty Line (rupiah)                              | X1 (independent)          | LnPovLine|
| 3  | Gross Regional Domestic Products per Capita (rupiah)| X2 (independent)          | LnGDRPCap|
| 4  | Unemployment (percentage)                          | X3 (independent)          | Unemployment|
| 5  | Poverty Rate (percentage)                          | X4 (independent)          | Pov_Percent|

In this study, the Poverty Line and GRDP per capita are simplified to Log natural (ln) to simplify the analysis. The application used is GeoDa with classical regression tools, Queen Contiguity, Moran’s I, and Spatial Regression.

2.2. Data Analysis Procedures

2.2.1. Classic regression
The method required to see the relationship between the dependent and independent variables used as a determinant of the advanced spatial model is through Ordinary Least Square. The variable terms that can be used are R-squared 0.5 < x < 0.1 and = 10%. Classical regression has a mathematical Equation 1

\[ HDI = f(\ln\text{PovLine}, \ln\text{GDRP}, \text{Unemployment}, \text{Poverty Percent}) \]  

2.2.2. Moran’s I
Moran’s I is used to see the dependency within locations. According to Chotib (2019), the Moran’s I test will explain as the following Equation 2:

\[ Z = \frac{1-E(I)}{\sqrt{V(I)}} \]  

4
where:
Z: Moran’s I
I: vector residual
E(I): expected value of Moran’s I
V: variances
With hypothesis
H0 : I = 0, no dependency within locations
H0 : I ≠ 0, there is a dependency within locations
H0 will be rejected if |Z| > Za/2

2.2.3. Queen Contiguity
According to LeSage [15]. Queen Contiguity is a weighting matrix for spatial proximity by looking at the intersection of each location’s sides and angles that have similarities and vertices. The Queen Contiguity value is defined to be wij = 1. The formula of Queen Contiguity is shown in the Equation 3 below:

\[ W_{1} \text{ or } W_{2} = (W11 \text{ } W12 \text{ } \ldots \text{ } W1n \text{ } W21 \text{ } W22 \text{ } \ldots \text{ } W2n \text{ } Wn1 \text{ } Wn2 \text{ } \ldots \text{ } Wnn) \]  

(3)

2.2.4. Spatial Regression
According to the study [23], the Spatial Error Model and Spatial Lag Model are used to see the correlation among locations. To find the exact model, the first step to analyze is the OLS from classic regression. In addition, check the probability of LM from the OLS test that rejects H0 (23). If the LM error and LM Lag do not reject H0, find the most robust model with the highest score.

3. Results and discussion
3.1. Data Explorations
The analysis using the classic regression model shows that the human development index can be affected by several factors. Table 3 shows that HDI is affected positively by Poverty Line and GDP per capita. On the other hand, HDI is affected negatively by the unemployment and poverty percentage. The result shows that this the correlation is robust with R² = 0.770597 and all of the probability value is below 0.1 as the significance for the data.

| Variable      | Coefficient | Std.Error | p-value |
|---------------|-------------|-----------|---------|
| Constant      | -146.02*    | 49.6031b  | 0.00395*** |
| LnPovLine     | 11.9957     | 3.92735   | 0.00470**  |
| LnGDRPCap     | 4.17328     | 1.09984   | 0.00067*** |
| Unemployment  | -0.517288   | 0.263417  | 0.05888*   |
| Pov_Percent   | -0.338432   | 0.145355  | 0.02682**  |
| R²            | 0.770597    |           |          |

* This value indicates the number to multiply the values of predictors.
* This value indicates the estimate number from mean.
* This value indicates the significance to hypothesis at * p≤0.1; ** p≤0.05; *** p≤0.01

This study model equation as the following Equation 4

\[ HDI_i = -146.02 + 11.9957x_{1i} + 4.917328x_{2i} - 0.517288x_{3i} - 0.338432x_{4i} \]  

(4)

Where:
This empirical result shows that the average HDI rate in Central Java will drop to -146.02 percent if the other factors are rejected. The table shows that the correlation of the Poverty Line has a positive impact and HDI in Central Java with a p-value of 0.00395. According to the Central Statistical Bureau of Indonesia, the poverty line is a method to set the standard of poverty by calculating minimum expenditure for basic needs. People who live under the Poverty Line based on the expenditure of the city are considered poor. From the table, it means that 1% the Poverty Line will increase the HDI by 11.99%. The higher standard of Poverty Line will represent a higher cost to fulfill basic needs. It can be interpreted as a higher Poverty Line will increase the HDI as the people have higher standard for daily basics.

HDI in Central Java also has a positive correlation with GDRP per capita with a p-value of 0.00470. It means that every 1% increasing in GDRP will affect the improvement of HDI by 4.17%. The positive effect of GDRP per capita that improves HDI is also in favor of the previous research[2][9][24]. The correlation between GDRP per capita and HDI can be considered as the higher income of the people in regions and cities in Central Java will increase their access to improve their skills, and have better access to education, food and health.

The unemployment rate in Central Java has a negative correlation with HDI, with a p-value of 0.058. Every 1% of decreasing will affect the improvement of HDI by 0.5%. A similar study also finds that there is a negative correlation between HDI and unemployment [11][12][24]. This means that the unemployment rate drops, the quality of life will improve, significantly affecting the HDI. The improvement of quality and job opportunities for people in Central Java will help to boost the HDI. This also happens for the percentage of poverty rate in Central Java that has a negative correlation with HDI. It means that if the rate of HDI can be increased by suppressing the poverty rate.

The map (Figure 1) shows a pattern of clustering in HDI among the cities and municipalities in Central Java. It means that regencies/cities with high HDI are likely to be surrounded by other regencies and cities with high HDI are categorized into ten categories (based on color) with the lowest threshold
of 66.11 to 67.45, and the highest threshold 82.21 to 83.14. The pattern formed in the southeastern with regions that have the highest HDI are Salatiga, Semarang (City), and Surakarta with 83.14, 83.05, and 82.21, respectively. On the contrary, the region with low HDI more scatter with the lowest HDI 66.11 is Brebes Regency. Other regencies with a low HDI are Pemalang Regency and Banjarnegara Regency, with 66.32 and 67.45, respectfully.

Regions and cities in Central Java with High HDI potentially have high development and various services and become the center of primary services as in-Christaller’s theory [17]. The services will impact the growth of accessibility and economics from primary to secondary economic activities. This growth finally improving not only the central region but also the surrounding with efficiency in education, health, and socio-economics activity.

3.2. Spatial Econometrics Models

Using spatial identification and dependency tests are ways to know which proper spatial econometric model to the study.

Table 4. Output table for Spatial Econometric of HDI

| TEST                        | MI/DF | VALUE   | PROB     |
|-----------------------------|-------|---------|----------|
| Moran’s I (error)           | 1a    | 3.4401b | 0.00058**|
| Lagrange Multiplier (lag)   | 1     | 8.4663  | 0.00362**|
| Robust LM (lag)             | 1     | 2.3639  | 0.12417  |
| Lagrange Multiplier (error) | 1     | 7.3921  | 0.00655* |
| Robust LM (error)           | 1     | 1.2898  | 0.25609  |
| Lagrange Multiplier (SARMA) | 2     | 9.7561  | 0.00761* |

a This number indicates the degree of freedom.  
b This value indicates robustness of the test.  
c This value indicates the significancy of the test at * p≤0.1; ** p≤0.05; *** p≤0.01.

The result from Table 4 shows that Moran’s I test has a significant and positive result. It means that the HDI in a region is influenced by the value of the variable from its region and the spatial lag from other regions that are close and have the same characteristics. The table also shows that Lagrange Multiplier (Lag) and Lagrange Multiplier (Error)/SEM are significant. However, the solid probabilities for both models are different, and it shows that Robust LM (lag) is more significant than Robust LM (error). The use of Spatial Lag shows the spatial dependency of HDI in Central Java regions and cities by the error.

As Lagrange Multiplier (Lag) is more robust than Lagrange Multiplier (Error)/SEM, now we test the variables to HDI of regions and cities in Central Java (Table 5)

Table 5. Output table for Lagrange Multiplier (lag)

| Variable     | Coefficient | p-value     | p-value       |
|--------------|-------------|-------------|---------------|
| W_HDI        | 0.402281a   | 0.00024b*** | 0.00004*     |
| CONSTANT     | -175.042    | 0.00000***  | 0.00001***   |
| LnPovLine    | 12.2272     | 0.00011***  | 0.00011***   |
| LnGDRPCap    | 3.89659     | 0.00001***  | 0.00001***   |
| Unemployment | -0.350761   | 0.10468     |               |
| Pov_Percent  | -0.264755   | 0.02752**   |               |
| R2           | 0.830769    |             |               |

a This value indicates the number to multiply the values of predictors  
b This value indicates the significancy to hypothesis at * p≤0.1; ** p≤0.05; *** p≤0.01

This study model equation as Equation 5

\[ HDII = -175.042 + 12.2272x_1 + 3.89659x_2 - 0.338432x_4 \]  

(5)
Where:

HDI\textsubscript{i}: HDI of the regions and cities in Central Java
X\textsubscript{1i}: Ln Poverty Line of the regions and cities in Central Java
X\textsubscript{2i}: Ln GDRP per Capita of the regions and cities in Central Java
X\textsubscript{3i}: Unemployment rate of the regions and cities in Central Java
X\textsubscript{4i}: Poverty rate of the regions and cities in Central Java

Comparing to the Classic Regression (Table 3), the spatial lag model (Table 5) has different results, such as the R\textsuperscript{2} value with Classic regression and Spatial Lag are 77.05\% and 83.06\% respectively. This means that the spatial model is more accurate than classic regression and can determine the relationship between HDI and other variables. However, one variable that is unemployment has no significance with HDI in this model. The Spatial lag model interprets the mean of independent variables that surround one region or city increasing by 1. It will add or reduce the coefficient in the variables. For example, if the poverty line increases by 1, the HDI of regions and cities in Central Java will add to 13.0972. On the other hand, if the poverty rate adds by 1, the HDI of regions and cities in Central Java will decrease to 0.486829.

This correlation among regions and cities in Central Java also can be observed from the Moran’s scatterplot and LISA’s value as shown below:

![Moran's I Scatterplot of HDI in Central Java](image)

**Figure 2.** Moran’s I Scatterplot of HDI in Central Java

Source: Researcher’s Analysis, 2021

Information:
The quadrant shows the clusters of regions and cities in Central Java with details:

I. Quadrant I: regions and cities with high-high HDI relations.
II. Quadrant II: regions and cities with low-high HDI relations.
III. Quadrant III: regions and cities with low-low HDI relations.
IV. Quadrant IV: regions and cities with high-low HDI relations.

Table 6 and Figure 2 show that regions and cities in Central Java tend to cluster in Cluster III. It means low HDI regions and cities have a neighbor with low HDI dominates Central Java. It means that a region with low HDI impacts another area. On the other hand, only nine or 35.71\% percent of regions and cities are categorized as cluster I which means regions and cities with high HDI tend to have high HDI neighbors. This relationship among regions and cities shows that a region with high HDI positively affects the surrounding area. The minor cluster with fewer regions and cities is Cluster IV, with five
regions with a high HDI with low HDI neighbors. There are six Regions and cities with low-high connections, meaning the regions and cities with low HDI have high HDI neighbors. Those relationships mean that some regions and cities have no impact on each other.

Table 6. Clusters HDI of Regions and Cities in Central Java

| Types            | Regions/Cities | Percentages |
|------------------|----------------|-------------|
| Cluster I (High-high) | 9             | 35.71       |
| Cluster II (Low-High)   | 6             | 24          |
| Cluster III (Low-Low)   | 15            | 42.85       |
| Cluster IV (High-Low)   | 5             | 14.28       |
| Total             | 35            | 100         |

The correlation of the regions from the Table 6 will be shown as a spatial in the following map (Figure 3).

Figure 3. Map of Related HDI Clusters in Central Java

Source: Researcher’s Analysis, 2021

Information:
- a. Blue color represents cluster of regions/cities with Low-Low HDI relation.
- b. Red color represents cluster of regions/cities with High-High HDI relation.
- c. Pink: color represents cluster of regions/cities with High-Low HDI relation.
- d. Grey: color represents cluster of regions/cities with no HDI relation.

The clusters of HDI (Figure 3) are divided into four categories: not significant, high-high, low-low, low-high and high-low. There are 25 cities and regions in Central Java with no robust correlation of the HDI. The map shows that the relationship of Low HDI regions and cities tend to be at the west of Central Java. These regions and cities are Tegal Regency, Purbalinga Regency, Banyumas Regency, Pekalongan Regency, and Banjarnegara Regency. The relationship of High HDI regions (Figure 3 in red) is clustering at the southeastern of Central Java, such as Boyolali Regency, Karanganyar Regency, and Sukoharjo Regency. Meanwhile, Tegal City has and a high-low correlation of the HDI with Tegal Regency. From this map, it can be inferred that there are still disparities caused by uneven development in Central Java. This results in line with research in China that there are spatial impacts of the economic growth in surrounding regions because of the agglomeration and spillover effects [25]. The study [17]
also found spatial effects in HDI in regions and cities all over Indonesia and found a connection of spillover effects.

According to Myrdal [17], the spillover effects are divided into two categories (i) backwash spillover and (ii) spread effects. Backwash spillover is the condition where the development in one area harms the surrounding. On the other hand, the spread effect is the positive for the neighbors from the developing areas. It can be inferred that the HDI disparities of these regions and cities in Central Java are caused by the strong backwash and weak spread effect. The continuation of these spatial economic impacts will delay the improvement of SDGs and the increase of HDI in Central Java.

4. Conclusion
Following the findings, SDGs 1 and 8 will help the improvement of HDI in Central Java. By having the results of spatial effect in the HDI, there should be a collaborative inter-regional program from all regions to enhance the HDI and SDGs in Central Java. The governments can work together for an even distribution of HDI and SDGs towards collaborative regional development in Central Java as follows:

1. Collaboration for every region in Central Java to build a program that can provide the transfer of knowledge and skills from high HDI areas to low HDI areas to increase the economic productivity of the people.
2. Develop the program focusing on innovation in the economic and education sector to improve the economy in low HDI areas according to the economic base in the region.
3. Develop the collaborative framework and policy to assessing the spillover effects in Central Java.

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