The Effect of Regional Characteristics and Relationship Among Locations In Air Pollution Using Spatial Autoregressive (SAR) and Spatial Durbin Models (SDM)

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Abstract. Bantul Regency in Special Region of Yogyakarta, which consists of 17 sub-districts, is an area that continues to grow and has increased population activities. In 2014, 16 sub-districts had been contaminated by air quality. To find out things that can affect air pollution in the area, this study conduct spatial model. This method is used as an alternative of OLS a method that does not meet assumptions when used in the case of spatial data. The reason for using spatial model is because there is an autocorrelation in air quality among sub-districts. By OLS regression model, a significant factor influencing is the number of villages according to the type of transportation infrastructure. However, this model does not pay attention to the geographical location factor and the residual assumption that normal distribution is not met. The results of spatial model is Spatial Durbin Model (SDM) have a good performance because have a small AIC than SAR. In SDM, the variables that significant effect on air pollution were population density, transportation infrastructure, lag of population density, lag of transportation infrastructure, and lag of air pollution. Sub district will have high of air pollutant if have high of population density and transportation infrastructure, also close to other sub districts which also have high population density and transportation infrastructure.

1. Introduction

The According to the Decree of the State Minister of Population and Environment No. 02 of 1988, air pollution is the inclusion of living things, substances, energy and other components into the air or changes in the air structure by human activities or natural processes so that air quality drops to a certain level which causes air to become less or unable to function properly with the allotment. Many factors cause the increasing potential of air pollution, among them can be caused by human activities such as those from factories, motorized vehicles, garbage combustion, agricultural waste and natural events such as forest fires, volcanic eruptions that emit dust, gas and hot clouds.

Bantul Regency in the Special Region of Yogyakarta (DIY), which consists of 17 sub-districts, is an area that continues to grow and has increased population activities. Population growth continues to increase, where the rate of population growth in 2000 - 2010 is 1.56%. Meanwhile, with an area of 506.85 km², the population density of Bantul Regency in 2016 was 1,940 people per km² (BPS, 2017) According to the book of Village Potential Statistics of Bantul Regency in 2011, there were 7 sub-
districts experiencing air pollution. It increased to 16 sub-districts in 2014. According to ambient air quality monitoring data in Bantul Regency from 2004 to 2015, the parameters of Total Suspended Particulate (TSP) have exceeded the required quality standard. Meanwhile, the concentration of $\text{SO}_2$ and CO in ambient air has also continued to increase from 2014 to 2016. The increase in the concentration of these substances is one of the causes of a decrease in air quality.

Many factors cause increased air pollution in Bantul Regency. To find out the dominant factors, this study conducted a statistical analysis of spatial regression. Spatial regression analysis is the development of the classical linear regression method Ordinary Least Square (OLS) based on Tobler's law which states that all things are related to one another, but something closer will have more influence than something far away. This means that there is a place or spatial influence on the data analyzed.

The OLS method does not take into account the geographic position of the data or the spatial elements in its analysis. In modeling, if the OLS method is used as an analytical tool on spatial data, it can lead to inaccurate conclusions because the assumptions of error are mutually independent and the assumption of homogeneity is not fulfilled. Likewise in the analysis of air pollution modeling. Air quality and pollution are also strongly influenced by geographic position factors. Each region has different geographic and air pollution conditions. Furthermore, air quality pollution between regions can also be interconnected. Thus, spatial regression needs to be used.

One type of spatial regression model is the Spatial Autoregressive Model (SAR). According to Anselin and Rey (2010), SAR is a model that combines OLS regression models with spatial lags on the dependent variable which means that spatial lag appears when the dependent variable observation value in a location correlates with the dependent variable observation value in the surrounding location. If the spatial effect is also found in the independent variable, Spatial Durbin Model (SDM) modeling is also performed. This model as a refinement of the SAR model, namely combining SAR models with spatial lag on independent variables (LeSage and Pace, 2009).

Some studies using this method include Bektı, (2014) use SAR to analyze spatial patterns of diarrhea and economic and environmental conditions in Bekasi, West Java, and use the SDM model on the analysis of factors affecting diarrhea in East Java. Bektı, Sutikno, and Rahayu (2013) write down the SDM model parameter estimation through Maximum Likelihood Estimation (MLE) and apply it to poverty analysis. The SAR method has also been developed for panel models, including Suryowati, et al. (2018) which use SAR random effects (SAR-RE) for analysis of the gini ratio in Papua Province. In each spatial analysis, weighting is very important for the identification of spatial autocorrelation. Suryowati, et al. (2018) have discussed several weighters that can be used.

Spatial analysis is important to use in community and environmental issues. Research of Shafie (2011) analysis of evaluation of the spatial risk factors for high incidence of dengue fever and dengue hemorrhagic fever using GIS application. Pepejal et al. (2011) also use spatial analysis tools provided by the GIS to perform environmental planning strategies for optimum solid waste landfill siting. Anselin and Lozano-Gracia (2008) analyze the spatial effects in hedonic house price models of ambient air quality. Also Liu et al. (2017) who use spatial and temporal trends analysis about the mortality burden of air pollution in China.

This study use the SAR and SDM spatial regression method to obtain factors that significantly influence air pollution in Bantul Regency, DIY, Indonesia. With this analysis it is expected to provide information on air pollution in terms of patterns and spatial factors.

2. Materials and Methods

The data used in the study are secondary data based on 2014 with 17 sub-districts in Bantul Regency (see Figure 1). Data was obtained from the Central Bureau of Statistics of Bantul Regency.
The variables used in the study consisted of the dependent variable (Y) in the form of the number of villages according to the type of environmental pollution namely air pollution. This data was obtained from the Book of Village Potential Statistics of Bantul Regency 2014. Meanwhile, the independent variables consisted of population density (X_1), transportation infrastructure (X_2), and types of landfills (X_3). Population density is defined as the population of each region (km^2). Transportation infrastructure is defined as the number of villages according to the type of land transportation infrastructure in the form of roads that are passed by vehicles. Types of landfills are defined as the number of villages by type of landfill in a hole or burned.

The analytical method used is Spatial Autoregressive regression (SAR) and Spatial Durbin Model (SDM). Spatial regression analysis is used to determine the relationship between the dependent variable and the independent variable by considering the dependencies among regions. Observations collected from a point or area in a particular region. According to Anselin (2013), LeSage and Pace (2009) the general model of spatial regression can be shown in the equation as follows:

$$y = \rho W_1 y + X \beta + u$$

$$y = (I - \rho W_1)^{-1} X \beta + (I - \rho W_1)^{-1} (I - \lambda W_2)^{-1} \varepsilon$$

where $u = \lambda W_2 + \varepsilon$; $\varepsilon \sim N(0, \sigma^2 I)$

y is vector of dependent variable. X is matrix of independent variable, $\beta$ is vector of regression coefficient parameter, $\rho$ is spatial lag coefficient parameter on dependent variable, $\lambda$ is spatial lag coefficient parameter on error, $u$ and $\varepsilon$ is vector error (n x 1), $W_1$ and $W_2$ are weighted matrix (n x n).

In Wang, et al (2013), state that adjacency relationships, distance relationships and comprehensive relationships are summarized to characterize the definitions of spatial weight matrix. According to the spatial data, type of weighting matrix can be divided into two types: point type (distance) and the neighborhood area (contiguity). On BPS, 2017 indicate that the selection function of the spatial analysis. This study uses a type of weighting Rook Contiguity. This weighting defines the area of observation determined based on the intersection of one side of the region with other neighboring regions. Determination of matrix elements is a location side by side with the location of concern given weighted $w_{ij} = 1$, while for other locations is $w_{ij} = 0$. Then weighted standardization is done.

In equation (1), if the value of $\rho \neq 0$ or $\lambda = 0$ becomes a model with the Spatial Autoregressive
Model (SAR) as in equation (2) which assumes that the autoregressive process is only on the dependent variable

\[ y = \rho W_1 y + X\beta + \varepsilon \]  
\[ y = (I - \rho W_1)^{-1} X\beta + (I - \rho W_1)^{-1} \varepsilon \sim N(0,\sigma^2I) \]  

SAR model in matrix form as in equation (3)

\[ y = \rho W_1 y + X\beta + \varepsilon \]  

with

\[
\begin{bmatrix}
  y_1 \\
  \vdots \\
  y_n
\end{bmatrix}
\] = \rho
\[
\begin{bmatrix}
  W_{11} & W_{12} & \cdots & W_{1n} \\
  W_{21} & W_{22} & \cdots & W_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  W_{n1} & W_{n2} & \cdots & W_{nn}
\end{bmatrix}
\begin{bmatrix}
  y_1 \\
  \vdots \\
  y_n
\end{bmatrix}
+ \beta_0 + Y_1 X \beta_1 + \varepsilon \\
\begin{bmatrix}
  X_{11} & \cdots & X_{1k} \\
  X_{21} & \cdots & X_{2k} \\
  \vdots & \ddots & \vdots \\
  X_{n1} & \cdots & X_{nk}
\end{bmatrix}
\begin{bmatrix}
  \beta_1 \\
  \vdots \\
  \beta_k
\end{bmatrix}
+ \varepsilon
\]  

Spatial durbin model (SDM) is a special case of SAR, namely by adding the lag effect to the independent variable so that spatial lag is added to the model. Weighting is done on independent and dependent variables. The forms of the SDM model are as follows: arselin (2013), Bakti (2013) and Wang (2013)

\[ Y = \rho W_1 Y + \beta_0 + X_1 \beta_1 + W_1 X_2 \beta_2 + \varepsilon \]  

with \( \varepsilon \sim N(0,\sigma^2I) \) and \( \beta_1 = \begin{bmatrix} \beta_{11} \\ \beta_{12} \\ \vdots \\ \beta_{1k} \end{bmatrix} \) \( \beta_2 = \begin{bmatrix} \beta_{21} \\ \beta_{22} \\ \vdots \\ \beta_{2k} \end{bmatrix} \)

Estimation parameter of Spatial Durbin Model is

\[ \hat{\beta} = (Z^T Z)^{-1} Z^T (1 - \rho W_1) Y \]  

dengan \( Z = [I \ X \ W_1 \ X] \)

To find out whether there is a spatial effect, this study uses Moran’s I test and Lagrange Multiplier. The Moran’s test is used for testing in view of spatial autocorrelation, [1], namely the assessment of the correlation between observations or locations on a geographical based variable [8]. If observations \( X_1, X_2, \ldots, X_n \) indicate interdependence of space or location, the data is said to be spatially correlated.

3. Results and Discussion

Figure 2 shows the characteristics of air pollution in 2011 and 2014. Of the 17 sub-districts in Bantul Regency in 2011, there were 7 sub-districts that had air polluted villages. Furthermore, the number of polluted villages has continued to increase until 2014, where there are 16 sub-districts that have air polluted villages. On average, there are 4 villages polluted by air (experiencing environmental pollution namely air pollution) in each sub-district.
Furthermore, Figure 3 also shows the spatial pattern of the polluted Sub district according to the number of villages with type of air pollution in Bantul Regency in 2014. The grouping of internal classes is divided into 3, namely as follows:
1) Figures 0-3 indicate sub districts that have 0-3 polluted villages which are found in Pajangan and Srandakan.
2) Figures 4-5 indicate that sub districts that have 4-5 polluted villages are found in Sedayu, Kasihan, Sewon, Piyungan, Pleret, Bantul, Pleret, Jetis, Pandak, Bamanglipuro, Pundong, Sanden and Kretek.

According to the spatial pattern, it can be seen that sub districts with many polluted villages are clustered and close together, for example Imogiri and Dlingo. Meanwhile, sub districts in the eastern region have more polluted villages compared to other regions.
according to the type of landfill in the pit or burned are located in the interval 7-8 class, which is located in Imogiri.

![Spatial pattern of Population Density](image1)

![Spatial pattern of Transportation Infrastructure](image2)

![Spatial pattern of Types of Waste Disposal](image3)

Figure 4. Spatial pattern of (a) Population Density, (b) Transportation Infrastructure, and (c) Types of Waste Disposal.

**Regression Modeling of Ordinary Least Square (OLS) Method**

Figure of the spatial pattern shows an indication of spatial influence among the sub-districts and each other. Thus, it is also necessary to prove it by testing the spatial effects in order to find out whether there is a link between sub-districts in Bantul Regency. However, before spatial modeling is carried out, it first performs regression modeling with the OLS method and tests the residual assumptions of normality, multicollinearity, heteroscedasticity, and autocorrelation. The parameter estimates of the Ordinary Least Square (OLS) method that do not involve spatial effects are presented in Table 1.

| Variable | $\beta$ | Std. Error | $t_{value}$ | P-value |
|----------|---------|------------|-------------|---------|
| Intercept | -1.0620 | 0.7795 | -1.362 | 0.1962 |
| $X_1$ | 0.0002 | 0.0003 | 0.890 | 0.3898 |
| $X_2$ | 0.8777 | 0.3409 | 2.574 | 0.0231 * |
| $X_3$ | 0.2405 | 0.3837 | 0.627 | 0.5415 |

R-Square = 0.8756

$f_{value} = 3049$ with P-value = $3.761 \times 10^{-6}$

*Note:* *) Significant at $\alpha = 5\%$
In general, the model can be interpreted that if the population density \(X_1\) in Bantul Regency increases by 10,000 people / km\(^2\), then the number of polluted villages increases by 2 villages. If the number of villages according to the type of land transportation infrastructure in the form of roads \(X_2\) increases by one type of transportation infrastructure, then the number of polluted villages will increase by 0,8777 villages. If the number of villages by type of landfill in a pit or burned \(X_3\) increases by one type of landfill in a hole or burned, the number of polluted villages will increase by 0.2405 villages.

OLS regression model has coefficient determination \((R^2)\) 0.8756 or 87.56%, which means that the three independent variables of the study can explain air pollution in Bantul Regency at 87.56%. While, the remaining 12.44% is explained by other variables outside the model. The results of the classical assumption testing in the OLS regression model were carried out by Shapiro Wilks test, Durbin Watson test, VIF value, and Breusch-Pagan test. The test results show that fulfilled assumptions are independent residuals, identical, and there is no multicollinearity. Meanwhile, residual assumptions with normal distribution are not fulfilled.

Through testing the testing of parameter significance using the t test, it was concluded that there was one significant research variable at the level of \(\alpha = 5\%\). It is number of villages according to the type of land transportation infrastructure \(X_2\). Population density \(X_1\) and the number of villages according to the type of landfill in the pit / burned \(X_2\) are not significantly influential.

**Spatial Effect Test**

Spatial effect tests were carried out with 2 tests, the Lagrange Multiplier (LM) and Moran's I test. According to the LM test in Table 2, it can be concluded that there are no spatial dependencies in lag or error. While the results of the Moran's I test in Table 3 give the conclusion that there is a significant spatial autocorrelation at \(\alpha = 5\%\) in the population density variable. It shows that there is an association with population density data in Bantul Regency. Meanwhile, the dependent and independent variables do not have spatial autocorrelation. However, based on the comparison of the values of \(E (I)\) and Moran's I, it can be seen that the value of Moran's I on is greater than \(E (I)\). This shows there is a pattern of grouping between locations on these variables.

### Table 2. Output of Lagrange Multiplier Test's t

| No | LM | Test Statistic | P-value |
|----|----|----------------|---------|
| 1  | Lagrange Multiplier lag | 0.022 | 0.882 |
| 2  | Lagrange Multiplier error | 0.004 | 0.948 |

### Table 3. Output of Moran’s I Test

| Variable | Moran’s I | E(I) | p-value |
|----------|-----------|------|---------|
| \(Y\)    | 0.0760    | -0.0625 | 0.3626  |
| \(X_1\)  | 0.2350    | -0.0625 | 0.04162 * |
| \(X_2\)  | -0.2502   | -0.0625 | 0.7958  |
| \(X_3\)  | 0.0314    | -0.0625 | 0.4948  |

**Results of Model Spatial Autoregressive (SAR)**

In this study, SAR modeling is used because in the OLS method regression assumption there is an assumption that residual normal distribution is not met. The results of the SAR model estimation are presented in Table 4. The model obtained is

\[
\hat{Y} = -1.1021 + 0.0094W_{ij}Y_j + 0.0002X_1 + 0.8781X_2 + 0.2398X_3
\]  
(6)
Table 4. Parameter Estimation of SAR Model

| Variable | Estimation | Std.error | Z_{value} | P-value |
|----------|------------|-----------|-----------|---------|
| Intercept | -1.1021 | 0.9855 | -1.1183 | 0.2634 |
| X_1 | 0.0002 | 0.0002 | 1.0224 | 0.3066 |
| X_2 | 0.8781 | 0.2984 | 2.9421 | 0.0033* |
| X_3 | 0.2398 | 0.3358 | 0.7141 | 0.4751 |
| ρ | 0.0094 | 0.1674 | 0.0651 | 0.9553 |

AIC = 46.55

Note: *) Significant at α = 5%

From the model it can be interpreted that if the population density is high, transportation infrastructure is high, and the number of types of landfills in the pit or is burned high, the number of villages polluted by air is also high. The coefficient ρ indicates the spatial lag variable in the number of polluted villages, has an estimated value of 0.0094. This value shows that neighboring sub-districts with other sub-districts that have a high number of polluted villages will have a high number of polluted villages. In the parameter significance test with α = 5%, the independent variable that gives effect is the variable number of villages according to the type of transportation infrastructure (X_2).

Results of Spatial Durbin Model (SDM)

SDM is a development of the SAR model, where there are spatial effect on dependent and independent variable. Through the Morans’I test results, it was found that there was spatial autocorrelation in the independent variables. Thus this study also performs parameter estimation of the SDM model which presented in Table 5.

Table 5. Parameter Estimation of SDM

| Parameter | Estimate | Std.error | Z_{value} | P-value |
|-----------|----------|-----------|-----------|---------|
| β_0 | 1,9903 | 1,3535 | 1,4705 | 0,1414 |
| β_{11} | 0,0004 | 0,0001 | 2,9378 | 0,0033* |
| β_{12} | 1,1694 | 0,2147 | 5,4459 | 5,154 × 10^{-8}* |
| β_{13} | -0,1721 | 0,2479 | -0,6944 | 0,4874 |
| β_{21} | -0,0021 | 0,0005 | -4,4604 | 8,179 × 10^{-6}* |
| β_{22} | 1,5129 | 0,4733 | 3,1962 | 0,0013* |
| β_{23} | -0,9838 | 0,5682 | -1,7316 | 0,0833 |
| ρ | -0,3626 | 0,2777 | -1,3057 | 0,19164 |

AIC = 34,804

Note: *) Significant at α = 5%

and the model is

\[ Y_i = -0,3626 \sum_{j=1}^{n} W_{ij} Y_j + 1,9903 + 0,0004X_{1i} + 1,1694X_{2i} - 0,1721X_{3i} - 0,0021 \sum_{j=1}^{n} W_{ij}X_{1j} + 1,5129 \sum_{j=1}^{n} W_{ij}X_{2j} - 0,9838 \sum_{j=1}^{n} W_{ij}X_{3j} \]  

(7)

Parameter estimation value β_{11}, β_{12}, β_{13} shows non spatial regression coefficient and parameter estimation value β_{21}, β_{22}, β_{23} shows spatial lag parameters on independent variables. The estimated value of the parameter ρ shows the spatial effect of the lag of the dependent variable.

The parameter estimation ρ is -0.3626 and have the negative value. It indicating that a sub district will have a number of polluted villages which are low if it is adjacent to a sub district which has a high number of polluted villages. The estimation of the parameter β_{11} is 0,0004 and β_{31} is -0,0021. The coefficient of lag population density is negative. It indicating that sub districts with low population density and be neighbor to sub districts with low population densities will have a high number of polluted villages.
The estimation of the parameter $\beta_{12}$ is 1,1694 and $\beta_{22}$ is 1,5129. The coefficient of lag parameter for the number of villages according to transportation infrastructure is positive, indicating that sub-districts that have a high number of villages according to high transportation infrastructure and be neighbor to sub districts that have a high number of villages according to transportation infrastructure will have a high number of polluted villages. It shows that some sub district that have high transportation infrastructure and be neighbor to sub districts that have a high number of villages according to transportation infrastructure will have a high number of polluted villages.

Estimated parameter $\beta_{13}$ is -0,1721 and $\beta_{23}$ is -0,9838. The lag parameter coefficient of the type of landfill in a pit or burned is of negative value, indicating that the sub districts that have small number of villages by type of landfill in a pit or burned and be neighbor to the sub district that have small number of villages according to the type of landfill will have a high polluted villages. It shows that some sub district that have high types of landfills (pit or burned) and close together (neighboring) will have a high number of polluted villages.

In the parameter significance test, variables that significantly influence air pollution are population density, transportation infrastructure, lag of population density, and lag of the transportation infrastructure. To get a model with a variable that is significantly influential, this study also build the modeling as shown in Table 6.

### Table 6. Parameter Estimation Model of SDM with the Significant Independent Variable

| Parameter | Estimation | Std. Error | Z_value | P-value |
|-----------|------------|------------|---------|---------|
| $\beta_0$ | 0,0102     | 0,7469     | 0,0137  | 0,9890  |
| $\beta_{11}$ | 0,0004 | 0,0001     | 3,8784  | 0,0001 *|
| $\beta_{12}$ | 1,0320 | 0,0642     | 16,0633 | 2,2 × 10^{-16} *|
| $\beta_{21}$ | -0,0015 | 0,0005     | -5,5194 | 3,402 × 10^{-8} *|
| $\beta_{22}$ | 1,0574 | 0,0002     | 3,3537  | 0,0007 *|
| $\rho$ | -0,6608 | 0,2577     | -2,5647 | 0,0103 *|

$\text{AIC} = 33,058$

*Note : *) Significant at $\alpha = 5\%$

and the model is

$$\hat{Y}_i = -0,6608 \sum_{j=1}^{n} W_{ij} Y_j + 0,0102 + 0,0004 X_{1i} - 0,0015 \sum_{j=1}^{n} W_{ij} X_{1j} + 1,0574 \sum_{j=1}^{n} W_{ij} X_{2j}$$  \hspace{1cm} (8)

So that it can be concluded that there is a spatial effect of lag dependent and independent variables. If a model comparison is made using the AIC value, the SDM model is preferable because it has a smaller AIC compared to OLS and SAR.

### 4. Conclusion

The incidence of air pollution in Bantul Regency has increased from 2011 to 2014. This shows that the air quality in this region is not good and need to know the factors that influence it. Through the OLS regression model, a significant factor influencing is the number of villages according to the type of transportation infrastructure. However, this model has a weakness, because it does not notice the spatial factors or geographical location. Another disadvantage is the assumption of normal distribution residuals that are not met.

Through the identification of spatial patterns it can be seen that there are spatial effects in the case of research, namely the existence of a clustered pattern on the data of the number of villages polluted by air in each sub district and there is a dependencies population density among sub districts. Thus, as an OLS alternative is the Spatial Autoregressive (SAR) regression model. The results of SAR show that if the population density is high, transportation infrastructure is high, and the number of types of landfills in the pit or is burned high, the number of villages polluted by air is also high. A sub-district will have a high number of polluted villages if it is close to other sub districts with a high number of villages polluted. However, the variable that gives a significant influence on air pollution is the variable number of villages according to the type of transportation infrastructure. Meanwhile, by SDM model, found that
the variables that significant effect on air pollution were population density, transportation infrastructure, lag of population density, lag of transportation infrastructure, and lag of air pollution. SDM have a good performance because have a small AIC than SAR.

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