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ESTIMATING THE CONCENTRATION OF NO_2 WITH THE COKRIGING METHOD IN THE CAPITAL CITY OF JAKARTA

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ABSTRACT

The increase in transportation activities is the leading cause of the emergence of the air pollution risk, which harms public health, especially in big cities. Nitrogen dioxide (NO_2) gas is one of the critical factors explaining air pollution. NO_2 contributes to particle pollution and acid deposits and is a precursor of ozone, the leading cause of photochemical smog. Meanwhile, Sulfur dioxide (SO_2) is another substance that is a source of pollutants and can cause acid rain and aerosolized sulfate particle pollution. Therefore, it is necessary to estimate the concentration of pollutants, especially NO_2. One method that can be used in this estimation is Cokriging, which considers secondary variables to record primary variables. Based on the results obtained, the Cokriging analysis shows that the estimation of NO_2 content in the five predicted areas, namely Tanjung Priok, Johar Baru, Gelora Bung Karno, Pancoran, Halim Perdanakusuma, has a quality standard value below 80 μppm (quality standard value set by the BMKG). In summary, the research unveils variations in SO2 and NO2 levels across distinct regions in Jakarta, with Monas recording the highest SO2 levels (10 μppm), while Grogol exhibits the lowest NO2 levels (16 μppm). The average SO2 level among all surveyed areas is 5.875 μppm, while NO2 averages 17.375 μppm. These findings emphasize the pressing need to implement measures aimed at preserving air quality within the limits established by government standards. Additionally, Cokriging estimates reveal that the content of NO2 in Tanjung Priok, a coastal area, significantly deviates from estimations in other Jakarta areas and ranks as the highest among the locations studied, with GBK displaying the lowest content.

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1. INTRODUCTION

Air quality is deteriorating globally at an alarming rate due to increasing industrialization and urbanization. In particular, nitrogen dioxide (NO_2) concentrations are increasing significantly due to anthropogenic activities [1], with most of the NO_2 generated by road vehicles and industrial activities [2]. The increase in transportation activities is the leading cause of air pollution risks that negatively affect public health, especially in big cities. Both indoor and outdoor air pollution can cause various diseases in humans and can even lead to death [3]. Based on satellite data, air pollution is mainly concentrated in the Java region, especially in the Jakarta metropolitan area and some parts of Sumatra. In DKI Jakarta, it is estimated that the average resident could lose 5.5 years of life expectancy if air pollution levels like in 2019 continue throughout their lifetime. In some areas, the reduction in life expectancy is even more severe, reaching more than six years [4]. Nitrogen dioxide gas (NO_2) is one of the important contributing factors to air pollution. NO_2 contributes to particle pollution and acid deposits and is a precursor to ozone, the leading cause of photochemical haze [5]. Meanwhile, Sulfur Dioxide (SO_2) is another substance that is a source of pollutants and can cause acid rain and aerosol sulfate particle pollution. Increased concentrations of substances such as SO_2 and NO_2 can endanger the population's health and are evidenced by the high mortality rate in some developing countries due to poor air conditions [6].

Jakarta has been known as a polluted city with a high air pollution index [7]. The capital city of Jakarta is the center of the economy in Indonesia, with many residents and industries. However, industry presence also brings negative impacts because some produce emissions and pollution directly released into the air [8]. The parameters used in calculating the ISPU following KEP-45/MENLH/10/1997 are particulates with a size of 10 μm (PM_{10}), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3) in the form of oxidants, and nitrogen dioxide ($NO_{2)}$ [9]. The Meteorology, Climatology, and Geophysics Agency (BMKG) established eleven air quality monitoring locations in Jakarta [10]. However, it is not enough to measure air quality at these locations because it is essential for the community and government to know the air conditions in the area where they live. It is closely related to the branch of statistics, namely *Geostatistics* [11]. Therefore, it is necessary to estimate the concentration of pollutants, especially NO_2. One method that can be used in this estimation is Cokriging, which considers secondary variables to predict primary variables. The cokriging method can produce more accurate predictions compared to the regular kriging method and this method can be used to handle situations where the spatial structure of the observed variables changes over time or space. In this study, the variable SO_2 becomes a secondary variable considered to predict the primary variable NO_2 in five administrative areas in DKI Jakarta, namely Tanjung Priok, Johar Baru, Gelora Bung Karno, Pancoran, and Halim Perdanakusuma. From this research, it is hoped that it can be an illustration for the community regarding the description of the level of air pollution in the region so that it can be material for consideration and monitoring in the level of air pollution through NO_2 levels in the five regions in DKI Jakarta.

2. RESEARCH METHODS

2.1 Data

The data used in this study are quantitative data consisting of content NO_2 in μppm and SO_2 gas content in the DKI Jakarta area. This research data comes from publications on the Meteorology Climatology and Geophysics Agency *website* for air quality content in February 2023. Measurement of NO_2 levels was carried out with the passive *gas* method using *passive sampler* equipment in eight locations, namely Ancol, Bandengan (Delta), Bivak, Grogol, Kemayoran, Kementen, TMII, and Monas. Sample analysis was conducted at the BMKG air quality laboratory using a *spectrophotometer*. Meanwhile, the measurement of SO_2 gas in the exact location using an *ion chromatography* device.

2.2 Research Variables

The variables used in this study consisted of primary and secondary variables, with the primary variable being the content of NO_2 and the second being SO_2 content as shown in Table 1. The estimation areas taken in this study include Tanjung Priok, Johar Baru, Gelora Bung Karno, Pancoran, and Halim Perdanakusuma.

Table 1. Definition of Research Variables

No	Variables	Definition
1	Primary variable	Content of NO_2 in eight areas in DKI Jakarta (Ancol, Bandengan (Delta), Bivak, Grogol, Kemayoran, Kementen, TMII, and Monas)
2	Secondary variables	SO_2 content in eight areas in DKI Jakarta (Ancol, Bandengan (Delta), Bivak, Grogol, Kemayoran, Kementen, TMII, and Monas)
3	Variable distance	*Longitude* and *latitude* coordinates of each region

2.3 Variogram and Semivariogram

Variogram is a statistical tool essential for spatial data estimation. This is because if two spatial values are located close to each other, they are relatively more similar compared to two spatial values that are far apart. The variogram is formulated as follows

$$\boldsymbol{2\gamma(h) = E[Z(s) - Z(s+h)]^2} \tag{1}$$

To perform estimation on spatial data, a tool is employed to depict, model, and calculate the spatial correlation between random variables $\boldsymbol{Z(s)}$ and $\boldsymbol{Z(s+h)}$. This tool is known as a semivariogram. The magnitude of the semivariogram is half of the variogram value [12] .

2.3 Covariance Function

The covariance of the *random* variables X and Y *is* defined as follows [13]:

$$Cov(X,Y) = E[(X-\mu_X)(Y-\mu_Y)] \tag{2}$$

with $E(X) = \mu_X$ and $E(Y) = \mu_Y$

Some properties of covariance are as follows:

1. $Cov(X \pm Y, Z) = Cov(X,Z) \pm Cov(Y,Z)$
2. If $X = Y$ then $Cov(X,Y) = Cov(XX) = Var(X)$
3. $Cov(X,Y) = 0 \quad X,$ and Y *independent*
4. $Cov(aX, bY) = ab\ Cov(X,Y)$

2.4 Experimental Covariance

The experimental auto-covariance can be expressed as follows [13]:

$$C(h) = \frac{1}{N}\sum_{i=1}^{N}[U_i - \bar{U}][U_{i+h} - \bar{U}] \tag{3}$$

While the experimental cross-covariance can be expressed as follows [13]:

$$C_{12}(h) = \frac{1}{N}\sum_{i=1}^{N}[U_i - \bar{U}][V_{i+h} - \bar{V}] \tag{4}$$

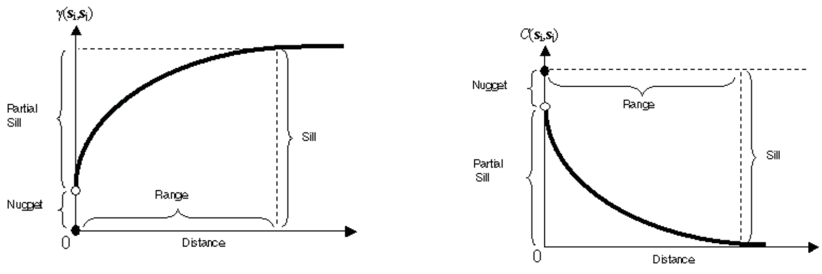
Where:

N : Number of distinct pairs separated by distance h
U_i : Observed value of the first regional variable at location i
U_{i+h} : Observed value of the first regional variable at location $i+h$
$\bar{U}$: Average of the first regional variable
V_{i+h} : Observed value of the second regional variable at location $i+h$
$\boldsymbol{\bar{V}}$: Average of the second regional variable

2.6 Theoretical covariance

The theoretical covariance model that can be used is the *spherical* covariance model [13]:

$$C(h) = \begin{cases} (P+Q) & ,0 = h \\ (P+Q)\left(1 - \frac{3h}{2r} + \frac{h^3}{2r^3}\right) & ,0 < h \le r \\ 0 & ,h < r \end{cases} \quad (5)$$



(a) **(b)**

Figure 1. Illustration and Relation of Nugget Effect, Sill, and Range (a) Variogram (b) Covariance

where P *(nugget effect)* is the approximation of *auto covariance* and *cross-covariance* values at a distance around zero; Q (*sill*) is the maximum value reached by *auto covariance* and *cross-covariance*; r (*range*) is the distance when covariance reaches its maximum value; *h* is the distance between locations; $P \geq 0, Q \geq 0$ and $r > 0$.

2.7 Cokriging

One type of Spatial method is *Cokriging. Cokriging* is a Spatial interpolation method that uses two variables, namely primary and secondary variables, in the process [14]. Cokriging is an extension of auto-kriging because it considers the additional correlated information in the auxiliary variables. It appears more complex because the additional variables increase the complexity of the notation. [15]. Cokriging uses the correlation between smooth and course model data to improve prediction accuracy, unlike other Kriging variants [16]. *Cokriging* must fulfil the assumptions of dependency and *heterogeneity*. Secondary variables are correlated with primary variables and contain essential information about primary variables. If the correlation value between these variables is high, the *Cokriging* results are promising. The *Cokriging* interpolation method is a linear combination of primary and secondary variables [13].

$$\hat{u}_0 = \sum_{i=1}^{n} a_i u_i + \sum_{j=1}^{m} b_j v_j \; ; \sum_{i=1}^{n} a_i = 1; \sum_{j=1}^{m} b_j = 0 \quad (6)$$

where $\hat{u}_0$ is the estimated value of **z** at location 0 (approximate location); $u_1. \dots .\, u_n$ is the primary variable data at the nearest location; $v_1. \dots .\, v_m$ is the data of secondary variables at the nearest location; and $a_1. \dots .\, a_n$ and $b_1. \dots .\, b_m$ are the weights of *Cokriging* that must be determined.

$$R = \hat{u}_0 - u_0 = \sum_{i=1}^{n} a_i u_i + \sum_{j=1}^{m} b_j v_j - u_0 \quad (7)$$

with $u_1. \dots .\, u_n$ is a random variable that represents *u* at the *n* closest locations sampled, and $v_1. \dots .\, v_m$ is a random variable that represents *v* at the *m* closest locations sampled. The Cokriging system can be obtained by summing up each equation. i.e., n + m +2 = 0. and then rearranging each part.

$$\sum_{i=1}^{n} a_i cov\{u_i u_j\} + \sum_{i=1}^{m} b_j cov\{v_i v_j\} + \mu_1 = cov\{u_0 . u_j\}; j = 1. \dots . n \quad (8)$$

$$\sum_{i=1}^{n} a_i cov\{u_i u_j\} + \sum_{i=1}^{m} b_j cov\{v_i v_j\} + \mu_2 = cov\{u_0 . u_j\}; j = 1. \dots . n \tag{9}$$

Therefore, in matrix form, it becomes as follows.

$$\boldsymbol{C} = \begin{bmatrix} cov\{u_1u_1\} & \dots & cov\{u_1u_n\} & cov\{u_1v_1\} & \dots & cov\{u_1v_m\} & 1 & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ cov\{u_nu_1\} & \dots & cov\{u_nu_n\} & cov\{u_nv_1\} & \dots & cov\{u_nu_m\} & 1 & 0 \\ cov\{v_1u_1\} & \dots & cov\{v_1u_n\} & cov\{v_1v_1\} & \dots & cov\{v_1v_m\} & 0 & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ cov\{v_mu_1\} & \dots & cov\{v_mu_n\} & cov\{v_mv_1\} & \dots & cov\{v_mv_m\} & 0 & 1 \\ 1 & \dots & 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & \dots & 0 & 1 & \dots & 1 & 0 & 0 \end{bmatrix}$$

where $\boldsymbol{C}$ is the *covariance* matrix of primary and secondary variables between observed locations, the following equation calculates the value of the *spherical* covariance model.

$$C(h) = \begin{cases} P + Q & ; 0 = h \\ (P+Q)\left\{1 - 1.5\left(\frac{h}{r}\right) - 0.5\left(\frac{h}{r}\right)^3\right\} & ; 0 \le h \le r \\ 0 & ; h > r \end{cases} \tag{10}$$

where P is the approximation of auto covariance with cross-covariance at a distance around 0, $\boldsymbol{Q}$ (sill) is the maximum value reached by auto covariance, and cross coefficient where the *sill* value is equal to the variance of the data. At the same time, r *(range)* is the distance when the covariance reaches the maximum value.

$$\boldsymbol{D} = \begin{bmatrix} cov\{u_0u_1\} \\ \vdots \\ cov\{u_0u_n\} \\ cov\{u_0v_1\} \\ \vdots \\ cov\{u_0v_m\} \\ 1 \\ 0 \end{bmatrix}$$

$\boldsymbol{D}$ is the variation vector between the observation and the estimated location u_0. The vector containing weights for primary and secondary variables and the *Lagrange* multiplier is denoted by $\boldsymbol{w}$. The estimator for $\boldsymbol{w}$ is

$$\boldsymbol{w} = \boldsymbol{C}^{-1}\boldsymbol{D}$$

$$\boldsymbol{w} = \begin{bmatrix} a_1 \\ \vdots \\ a_n \\ d \vdots \\ b_m \\ \mu_1 \\ \mu_2 \end{bmatrix}$$

2.8 Research Analysis Steps

The stages of analysis in this study can be carried out as follows:

1. Providing variable value data NO_2 U_i at the latitude and longitude coordinates of the observation location $z_i = (x_i, y_i)$ for $i = 1.2. \dots 8$ and the value of the variable SO_2 V_j at the observation location $w_j = (x_j, y_j)$ for $i = 1,2, \dots 8$ and the coordinates of the estimation location $z_0 = (x_0, y_0)$ for five sub-districts.
2. Forming a distance matrix between observation locations by calculating the Euclidean distance. The distance between the *i-th* location located at the coordinates of *latitude* and *longitude* (x_i, y_i) to the *j-th*

location located at the coordinates of *latitude* and *longitude* (x_j, y_j) obtained using the following equation

$$h_{ij} = \sqrt{\left((x_i - x_j)^2 - (y_i - y_j)^2\right)}$$

3. Calculating the distance between the estimation location located at the *latitude* and *longitude* coordinates (x_0, y_0) with each observation location at the coordinates of *latitude* and *longitude* (x_i, y_i) obtained by the following equation

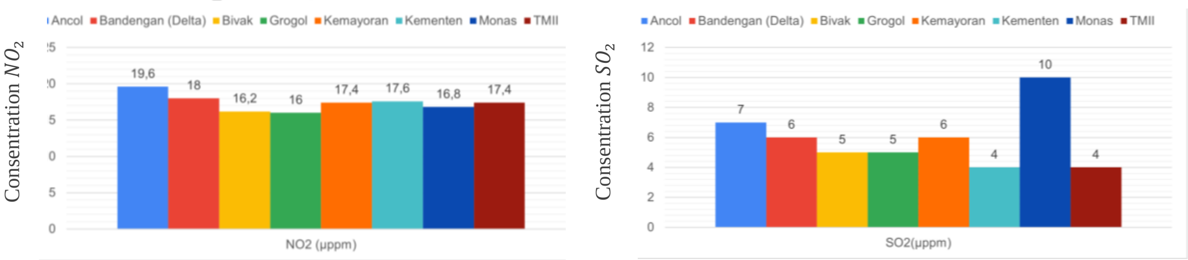
$$h_{i0} = \sqrt{((x_i - x_0)^2 - (y_i - y_0)^2)}$$

4. Calculating experimental auto covariance and cross-covariance with **Equation (3)** and **Equation (4)**.
5. Plotting the distance between locations (h) against the experimental covariance
6. Determining the values of P, Q, and r from the plot in step 5
7. Calculating the value of the spherical covariance model $C(h)$ that fits in **Equation (5)**
8. Forming matrices $\boldsymbol{C}$ and $\boldsymbol{D}$
9. Calculating the inverse of matrix $\boldsymbol{C}$
10. Finding the weight value by forming a matrix $\boldsymbol{w} = \boldsymbol{C}^{-1}\boldsymbol{D}$
11. Calculating the expected value of variables at the location z_0. which is $\widehat{U}_0$ in **Equation (6)**

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics of NO_2 and SO_2 Concentration Data

The data used in this study comes from the monitoring results of eight observation locations in the DKI Jakarta area, namely, Ancol, Bandengan (Delta), Bivak, Grogol, Kemayoran. Kementen, TMII, and Monas. presented in **Figure 2**.



(a) (b)

Figure 2. Histogram of Concentration Data (a) NO_2 (b) SO_2

Based on **Figure 2** (a), it can be seen that the amount of NO_2 levels in the DKI Jakarta area has the highest levels at the Ancol observation location of 19.6 μppm and the lowest NO_2 levels at the Grogol observation location of 16 μppm, Bandengan (Delta) by 18 μppm. Bivak by 16.2 μppm, Kemayoran and TMII by 17.4 μppm, Kementen by 17.6 μppm, and Monas by 16.8 μppm. The average observation result of NO_2 in February 2023 was 17.375 μppm. Based on **Figure 1**(b), the highest levels of SO_2 are in the Monas observation location at 10 μppm and the lowest levels of SO_2 in the Kementen and TMII areas at 4 μppm. Meanwhile, other locations each produced SO_2 levels of 7 μppm for Ancol, Bandengan (Delta), and Kemayoran at 6 μppm, Bivak and Grogol at 5 μppm. The observation of NO_2 in February 2023 has an average of 5.875 μppm. The elevated levels of NO2 at Ancol may be attributed to the area's heavy traffic, particularly during peak hours. NO2 is a byproduct of vehicular emissions, and congested traffic conditions can lead to increased NO_2 emissions. Additionally, the use of high levels of fossil fuels in a specific area can contribute to higher NO2 and SO_2 emissions. Therefore, it's crucial to consider both traffic patterns and fuel usage as factors affecting air quality in these areas.

3.2 Correlation Between Research Variables

The primary variable in this study is NO_2 content. while SO_2 content is a secondary variable. Correlation testing between the two variables was conducted. The results of the correlation testing between the two research variables can be seen in **Table 2** below:

Table 2. Results of Correlation Testing of Research Variables

***Pearson* Correlation Value**	**Description**
0.764	Mutually correlated

Table 2 shows that the two variables are moderately correlated. Thus, this result supports using the Cokriging method in estimating the NO_2 variable by using information from the SO_2 variable as a secondary variable.

3.3 Estimation of NO_2 Content with Cokriging Method

The first step taken to estimate the NO_2 content was to calculate the distance from one location to other observation locations using **Equation (2)**. Furthermore, the distance between each observation location and the location to be estimated was calculated using **Equation (3)**. The next step was to calculate the value of *experimental auto covariance* and *experimental cross-covariance* following **Equation (4)**. After obtaining the *experimental auto covariance* value, the next step was determining the *spherical auto covariance*. Estimating the values of P. Q. and r is required to get it. The values of P, Q, and r for *spherical auto covariance are* determined from the distance *plot* against *experimental auto covariance*. **Figure 3** below presents a plot of distance against the *experimental auto covariance* value of the first variable (NO_2):

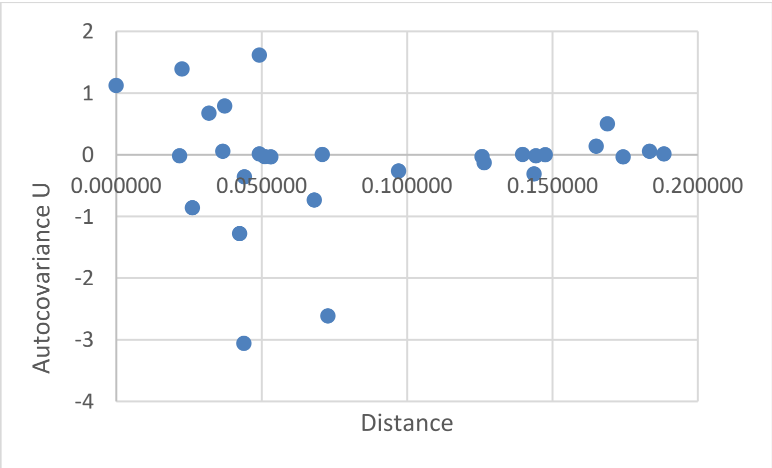


Figure 3. The plot of Distance Between Observations against Autocovariance of NO_2

Figure 3 illustrates the relationship between the distance between observation locations and the experimental autocovariance value for the first variable, NO_2. This plot is a critical component in the process of estimating NO_2 content. The obtained values, P = 1.124375, Q = 1.615625, and r = 0.049216 play a key role in calculating the spherical autocovariance for NO2. P indicates the range over which spatial dependence is significant, suggesting that NO_2 concentrations exhibit significant spatial dependence up to approximately 1.124375 units. Q, on the other hand, signifies that spatial dependence becomes negligible at a distance about of 1.615625 units. The value of r (0.049216) indicates a relatively weak spatial dependence of NO_2 concentrations between observation locations. In summary, **Figure 2** and the derived P, Q, and r values provide valuable insights into the spatial autocorrelation structure of NO_2 concentrations, aiding in the estimation and modelling of NO_2 content across various locations. These findings are essential for environmental and geospatial analysis, contributing to a better understanding of spatial patterns and variabilities in air quality data. Meanwhile, the distance plot against the *experimental auto covariance* between the second variable is as follows:

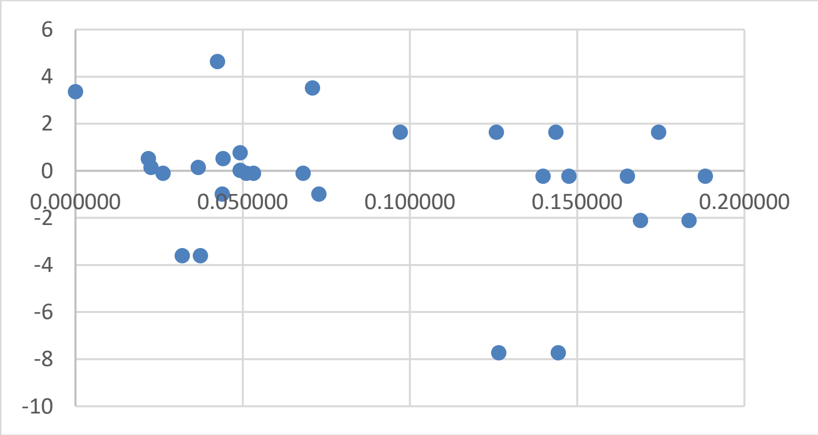


Figure 4. **The plot of Distance Between Observations against SO_2 *Autocovariance***

Based on **Figure 4.** the values of P = 3.359375, Q = 4.640625, and r = 0.042419 are obtained to calculate *spherical auto covariance* between SO_2 variables. The distance plot against the *experimental cross-covariance* between the first and second variables is as follows:

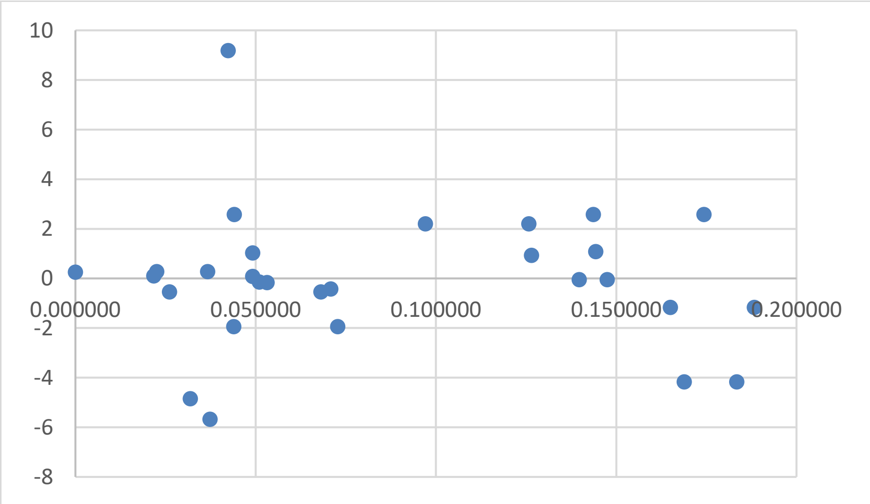


Figure 5. **Plot of Distance Between Observations against Plot of Distance Against *Experimental Cross Covariance***

Based on **Figure 5** the value of P = 0.246875, Q = 9.178125, and r = 0.042419 for the calculation of *spherical cross-covariance* between the first variable and the second variable.

Thus, the *spherical auto covariance* value of the first variable (NO_2) is formulated as follows:

$$C_U(h) = \begin{cases} (1.124375 + 1.615625)\left(1 - \dfrac{1.5h}{0.049216} + \dfrac{h^3}{2(0.049216)^3}\right). 0 \le h \le 0.049216 \\ 0 \qquad .h > 0.049216 \end{cases}$$

The spherical auto covariance value of the second variable *variance* (SO_2) is formulated as follows:

$$C_V(h) = \begin{cases} (3.359375 + 4.640625)\left(1 - \dfrac{1.5h}{0.042419} + \dfrac{h^3}{2(0.042419)^3}\right), 0 \le h \le 0.042419 \\ 0 \qquad .h > 0.042419 \end{cases}$$

The *spherical cross-covariance* value between the two variables can be formulated as follows:

$$C_{UV}(h) = \begin{cases} (0.246875 + 9.178125)\left(1 - \dfrac{1.5h}{0.042419} + \dfrac{h^3}{2(0.04219)^3}\right). 0 \le h \le 0.042419 \\ 0 \qquad .h > 0.042419 \end{cases}$$

After obtaining the value of spherical auto covariance and spherical cross-covariance between variables at each point, a ***C*** matrix can be formed and calculate the *auto covariance* between variables at the alleged location and eight measurement locations. NO_2 is based on the formula $C_u(h)$, and SO_2 is based on the formula $C_{uv}(h)$, forming the D matrix.

$$\boldsymbol{D} = \begin{bmatrix} 0 & -1.3610 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -2.3280 & 0 & 1.3695 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.8348 & -0.4506 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -0.07893 & 0 & -2.3311 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & -7.9718 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3.8925 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1.6648 & -3.8883 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -2.2549 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Then, forming the weight vector $\boldsymbol{w}$ is calculated by performing matrix multiplication between matrix $\boldsymbol{C}$ and matrix $\boldsymbol{D}$. The following is the result of the calculation of the vector $\boldsymbol{w}$

$$\boldsymbol{w} = \boldsymbol{C}^{-1}\boldsymbol{D} = \begin{bmatrix} 0.968751 & -2.560142 & 1.854088 & 1.446223 & 1.446223 \\ -0.736345 & 2.322799 & -1.713368 & -1.190790 & -1.190790 \\ 0.313206 & 0.429461 & 0.311315 & -0.025840 & -0.025840 \\ -0.266935 & 1.128471 & -0.245786 & -0.069545 & -0.069545 \\ 0.738410 & -1.773275 & 0.808804 & 0.734191 & 0.734191 \\ -0.269718 & 1.202161 & -0.874616 & -0.549028 & -0.549028 \\ 0.522350 & -0.961637 & 1.734180 & 1.203817 & 1.203817 \\ -0.269718 & 1.202161 & -0.874616 & -0.549028 & -0.549028 \\ -0.675405 & 2.196399 & -1.747631 & -1.121612 & -1.121612 \\ 0.801227 & -2.205924 & 1.803056 & 1.201233 & 1.201233 \\ -0.317436 & -0.024504 & 0.145434 & 0.102002 & 0.102002 \\ 0.423565 & -0.763215 & 0.490228 & 0.344580 & 0.344580 \\ -0.415391 & 1.459932 & -0.943814 & -0.743888 & -0.743888 \\ 0.305568 & -1.013295 & 0.861451 & 0.507422 & 0.507422 \\ -0.427698 & 1.363904 & -1.470174 & -0.797158 & -0.797158 \\ 0.305568 & -1.013295 & 0.861451 & 0.507422 & 0.507422 \\ -2.140953 & 6.256386 & -5.722728 & -3.278111 & -3.278111 \\ 0.097548 & -3.224008 & 1.351649 & 1.115219 & 1.115219 \end{bmatrix}$$

After obtaining the weight vector $\boldsymbol{w}$, the estimated NO_2 content is calculated based on the **Equation (5)**. The estimation results can be seen in **Table 3**.

Table 3. Estimation Results in All Estimation Areas

No.	Location	NO_2	Longitude	Latitude
1	Tanjung Priok	24.362481	106.866517	-6.138280
2	Johar Baru	15.005356	106.856188	-6.183054
3	GBK	7.496268	106.803089	-6.215420
4	Pancoran	12.376980	106.842976	-6.255484
5	Halim Perdanakusuma	12.376980	106.886493	-6.246114

Based on the estimation results in **Table 3** above, the following results are obtained:

1. Tanjung Priok

   The estimation results from the Cokriging method show that the NO_2 content in Tanjung Priok is 24.362481 μppm, which is still below the quality standard value set by BMKG of 80 μppm. It shows that the environmental conditions in the area around Tanjung Priok are very dense. Tanjung Priok is located in the North Jakarta Administrative City, Indonesia, known as Indonesia's principal port and one of the busiest ports in Asia. In addition, Tanjung Priok is also the center of industry and trade in North Jakarta, with ports, docks, warehouses, logistics facilities, and processing industries in the vicinity. With such a dense environment, the air quality in Tanjung Priok is likely to be poor.

2. Johar Baru

   The estimation results from the Cokriging method show that the NO_2 content in Johar Baru is 15.005356 μppm, which is still below the quality standard value set by BMKG of 80 μppm. Johar Baru is located in Central Jakarta and is one of the most densely populated urban villages. Although this location is in a strategic area of downtown Jakarta, there are critical, slum, and crowded dwellings. Therefore, it is crucial to analyze NO_2 levels to evaluate air quality in such a densely populated area. With the estimated results that are still below the quality standard, it can be seen that the air quality in Johar Baru is still within the limits allowed by the standards set by BMKG.

3. Gelora Bung Karno (GBK)

   Estimation results from the Cokriging method show that the NO_2 content in Gelora Bung Karno (GBK) is 7.496268 μppm. Gelora Bung Karno is the largest sports complex in Indonesia and one of the largest in Southeast Asia. The complex is often used for various activities and events that attract many people. However, piles of garbage in the GBK area have become a topic of conversation because after the event, there is a build-up of garbage. It can affect environmental conditions and air quality around GBK. Meanwhile, the estimation results show that the NO_2 content at GBK is within the allowed limits. Although it still needs attention to waste and environmental issues, the air quality in the GBK area seems to be well maintained based on the estimation results.

4. Pancoran

   The estimation results from the Cokriging method show that the NO_2 content in Pancoran is 12.376980 μppm. Pancoran is one of the areas in South Jakarta, Indonesia, located in the Southern part of Jakarta city center. The area is known for its high population density, with various settlements ranging from densely populated settlements to residential complexes. Traffic congestion is also one of the challenges in this area. Under such conditions, the estimated results of the Cokriging method indicate the presence of relatively high NO_2 content in Pancoran. It suggests the possibility of poor air quality in the area, which could impact the health and environment around Pancoran.

5. Halim Perdanakusuma.

   The estimation results from the Cokriging method show that the NO_2 content in Halim Perdanakusuma is 12.376980 (μppm). Halim Perdanakusuma is an area located in East Jakarta. The area is known to be very congested with vehicular traffic due to its proximity to Halim Perdanakusuma Airport. The traffic density causes high pollution from vehicle fumes in the vicinity. It indicates that the air quality in the area may be affected by high vehicle pollution levels.

4. CONCLUSIONS

The following are conclusions from the results of the analysis and discussion of the research that has been done:

1. After measuring SO_2 and NO_2 levels in several areas around Jakarta, it was found that there are differences in the amount of SO_2 and NO_2 levels in each area. The area with the highest SO_2 levels is Monas with 10 μppm, while the areas with the lowest SO_2 levels are Kementen and TMII with 4 μppm. Meanwhile, Ancol had the highest NO_2 levels at 19.6 μppm and Grogol had the lowest NO_2 levels at 16 μppm. The average SO_2 level in all measured areas was 5.875 μppm, while the average NO_2 level was

17.375 µppm. It can be concluded that there is a need for efforts to maintain air quality in these areas to stay within the quality standard limits set by the government.

2. Based on the estimation results using the Cokriging method. the estimated content in Tanjung Priok was 24.362481. Johar Baru was 15.005356, Gelora Bung Karno (GBK) was 7.496268, Pancoran was 12.376980, and Halim Perdanakusuma was 12.376980. From these results, it can be concluded that the content in Tanjung Priok, which is a coastal area, has a difference from the estimation results in other Jakarta areas, and is the highest compared to other areas measured. At the same time, the lowest content is in GBK.

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