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Hypotheses

Mapping of Mn and Pb as Effect of Landfill Pollutant based on Ordinary Kriging Interpolation

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Abstract: Spatial interpolation is an important method, getting information about pollutan from landfill location in groundwater quality mapping. Ordinary kriging is used to predict the unknown values in some locations, based on the autocorrelations among the nearby locations. In this research, ordinary kriging interpolation was used to divine the chemical characteristic of Manganese (Mn) and Lead (Pb), then 22 samples, around the Integrated Waste Management (TPST) Bantar Gebang, were taken for the purpose. In conclusion, there is an autocorrelation spatial among those locations. In addition, the Gaussian variogram model gives a better result than the Exponential model and the higher of Mn and Pb is in the southeast of TPST Bantar Gebang. This location has the high chance to be an affected pollution area.

Keywords: Spatial Interpolation, Ordinary Kriging, Landfill Pollutant

Introduction

Spatial analysis is a statistical analysis method used to analyze data which the influence of location is noticed. The first law of geography was explained by Tobler. He said that everything is interconnected, but the closest was the most influential (Anselin and Rey, 2010). This law is the basic assessment method of spatial problems. The important one is spatial autocorrelation. It used to get the pattern of the relationship or correlation among the closest locations. The problem is the missing data at a location. Spatial interpolation is the famous method to overcome this problem.

Fischer and Getis (2009) explained that spatial interpolation is a simple method, predicting unknown values in some locations, based on values that had been known at nearby locations. Moreover, this method examined geographic variance factors and linkages among those locations. There are some different types of spatial interpolation methods, such us ordinary kriging, cokriging, Inverse Distance Weighted (IDW) and Radial Basis Function (RBF). Bekti (2012) had used ordinary kriging to interpolate data on poverty in East Java. Furthermore, Irwansyah *et al*. (2013) had used ordinary kriging to interpolate Peak Ground Acceleration (PGA) in earthquakes vulnerable zoned area in Aceh.

Spatial interpolation is one of the most significant method in groundwater quality mapping. The map provides a lot of information about the pattern of water quality distribution in a location, such as locations of the poor quality water and the relationship pattern among those locations. The mapping gives a rule to determine the groundwater quality and its spread. Taghizadeh-Mehrjardi *et al*. (2013) defined that there are two steps on the groundwater quality mapping, i.e., sampling technique (where the location is taken) and prediction (data interpolating on a grid is used to obtain a smooth mapping). Thus, the second step required an appropriate spatial interpolation method.

D'agostino *et al*. (1998) conducted a study of the spatial and temporal variability of groundwater nitrite by kriging and cokriging. The main result was cokriging as the best method, because it was more accurate than kriging. Istok and Cooper (1988) stated that kriging was more precise in Lead (Pb) estimation. Nazari Zade *et al*. (2006) had done research on the quality of groundwater in plain Balarood Plain, Khuzestan province. They had conclution that the spherical model of the ordinary kriging was better than the experimental variogram in interpolating EC, C-l and SO_4^{2-}.

This research maps the water quality by utilizing spatial interpolation around the landfill. The water

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quality in Jabodetabek is at risk of exposure to waste pollution. The main chemical characteristics of water quality to note are Manganese (Mn) and Lead (Pb). Meanwhile, the interpolating method used is ordinary kriging. The result provides a map of water quality information due to pollution from waste disposal, especially around the Integrated Waste Management (TPST) Bantar Gebang, Bekasi.

Methodology

The sample is taken from previous research by Bekti *et al*. (2016), as in Fig. 1. Water samples from 22 wells on a radius of 1 km from landfill Bantar Gebang (TPST) was collected on May- August 2015. The wells are used by residents to meet their daily needs, i.e., drinking, bathing and cooking. All of those were located at latitudes between 6°21'25,139" S and 6°20'26,840" S and also longitudes between 106°59'15,759" E and 107°0'17,136" E. Sample locations were indicated by dots in Fig. 1. Furthermore, it were analyzed in the laboratory of University of Padjadjaran, Bandung. The water quality analysis is based on the Regulation of the Ministry of Health no. 492/Men Kes/IV/2010 about the requirements of drinking water quality. The standard quality of Mn is 0.4 mg L^{-1} and Pb is 0.01 mg L^{-1}.

Spatial analysis consists of spatial dependency (autocorrelation) of Moran's I and ordinary kriging interpolation. Moran's I test performs the autocorrelation between observations and locations. The null hypothesis of Moran's I test is no autocorrelation, while the statistics test is:

$$Z_{test} = \frac{I - I_o}{\sqrt{\mathrm{var}(I)}} \quad (1)$$

where, var (I) is the variance and E (I) is the expected value of Moran's I. The null hypothesis is rejected if $Z_{test} > Z_{\alpha/2}$ and there is a spatial autocorrelation.

Ordinary Kriging is geostatistics method which is used to predict data in a certain location. Consider that a random variable Z has been measured at sampling points or locations, x_i with i is location i = 1, 2, 3,…, n. It uses to predict or estimate the value at a point x_0 (Davis and Ierapetritou, 2007). The data point, $Z(x_i)$, is obtained from latitute and longitude coordinate in i-th location. The prediction of is $\hat{Z}(x_0)$:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (2)$$

where:

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (3)$$

$$\lambda = C^{-1} D \quad (4)$$

The value of λ_i is calculated from Equation 4. C is covariance matrix among data point (x_i) and D is the covariance vector between data point (x_i) and target estimation (x_o).

Fig. 1. Sample points location

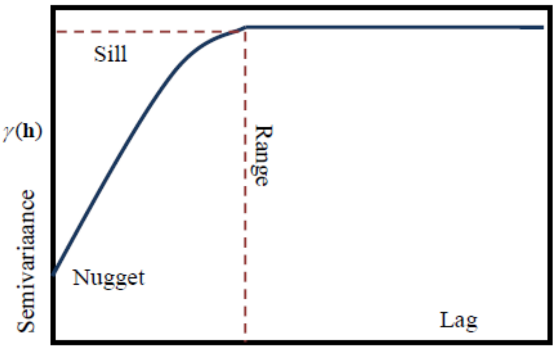

Fig. 2. General Semivariogram

The covariance matrix, *C*, can be estimated from variogram model, such as Gaussian, Spherical, Pentaspherical, Exponential and Stable Exponential Model. In these models, there are some parameters, namely nugget, sill and range. Range is the distance where the model flattens firstly. Sill is the value that semivariogram model attains at the range. Nugget is the value at which the semivariogram intercepts the y-axis. It measures error or spatial sources of variation at smaller distance than sampling interval. These parameters can be performed by empirical semivariogram in Fig. 2. Semivariogram plots the semivariance versus lag. It is more often represented as a graph that shows the variance in measure with distance between all pairs of sample locations. It also indicates the spatial correlation from some observations, measured at sample locations. The empirical semivariance can be calculated by Equation 5 (Fischer and Getis, 2009):

$$\hat{\gamma}(h)=\frac{1}{2n(h)}\sum_{\alpha=1}^{n(h)}\left[z\left(x_i+h\right)-z\left(x_i\right)\right]^2 \quad (5)$$

where, $z(x_i)$ and $z(x_i + h)$ are the actual values of Z at location (x_i) and (x_i + h) respectively and $n(h)$ is the number of paired comparisons at lag h.

Results and Discussion

Figure 3 shows the exploration of chemical characteristic of Manganese (Mn) and Lead (Pb) around TPST Bantar Gebang. TPST location is indicated by blue dot. The average of Mn concentration is 0.9218 mg L^{-1} and average of Pb concentration is 0.0108 mg L^{-1}. There are 14 samples with high Mn which are higher than the standard quality (0.4 mg L^{-1}). These sample locations are partly at the southeast area of TPST and the others are at the northern (Fig. 3). There are 7 samples of Pb which are higher than the standard quality (0.01 mg L^{-1}). Just like the Mn locations, these samples are at southeast and northern area of TPST. As a result, Mn at locations with a distance less than 500 m from TPST is higher than Mn with a distance more than 500 m of TPST.

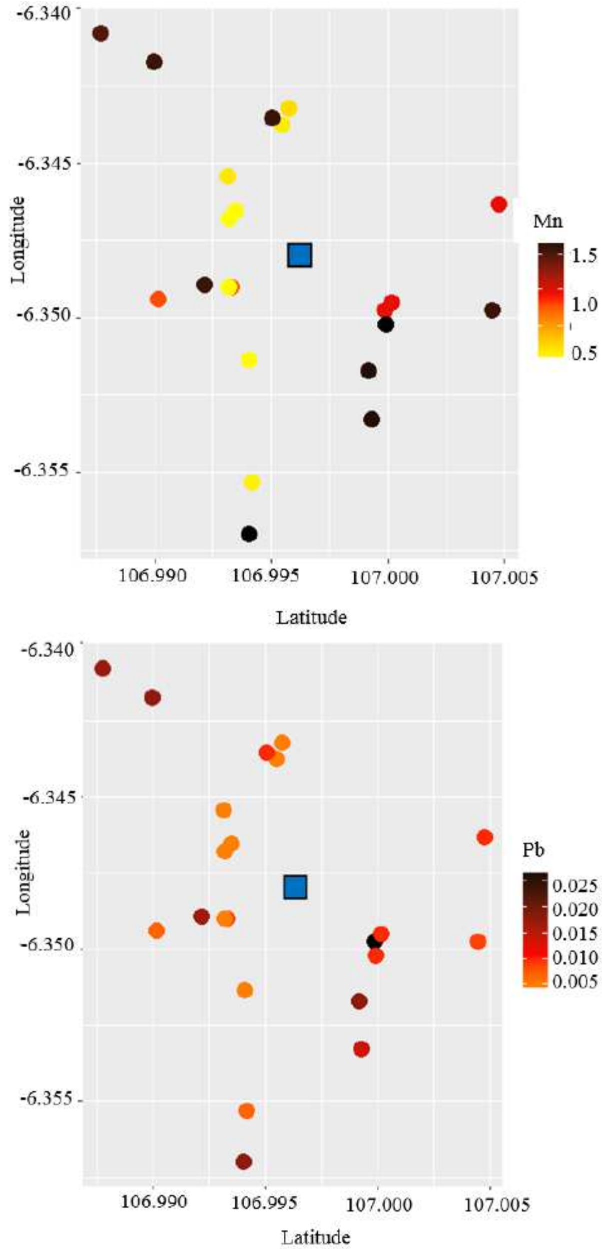

Fig. 3. The Pattern of Mn and Pb

Autocorrelation Test by Moran's I

The detection of spatial autocorrelation is very important to show the water quality relathionship in some locations. It can be performed by Moran's I. This test aims to determine the spatial dependency or autocorrelation between Mn and Pb compound (inorganic compounds of groundwater) among 22 samples. The type of weighting used is standardizing matrix. The location with a distance of 0° to 0,005° is noted as 1. This distance is calculated by Euclidean distance. Hypotheses used are:

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Ho: I = 0 (no dependencies among inorganic compounds)
H1: I ≠ 0 (dependencies among inorganic compounds)

Table 1 shows the Moran's I coefficients and the Pvalues of Mn and Pb at 5% of significant rate (α = 5%). Mn and Pb have a same value of Pvalue (0.02), which are less than α. Therefore, there are dependencies of Mn and Pb among 22 samples. The Mn concentration in a certain location is affected by Mn in the other location. Locations which are close together tend to have the same characteristic of Mn. This conclusion appropriates with the pattern in Fig. 3, showing that some samples at southeast area of TPST have the same level of Mn and its level is higher than the other locations. Moran's I coefficient of Mn is 0.251. There is a positive autocorrelation among samples. It means that samples having the same level of Mn are in adjacent area (yellow colors in Fig. 3). It also applies on inorganic compound of Pb.

Spatial Interpolation by Ordinary Kriging

The first Ordinary kriging processes are both of the construction of empirical semivariance (Equation 5) and semivariogram (Fig. 2). It determines the characteristics of spatial correlation among samples, sill, range and nugget. After that, semivariogram model will be created. Semivariograms of Mn and Pb use the Gaussian and Exponential model and they are interpreted on Fig. 4. The value of sill, range and nugget of Mn's Gaussian variogram are 0.49, 0.001 and 0.4 respectively. It shows that the semivariance attains at the range of 0.001. The value, which the semivariogram intercepts the y-axis, is 0.4. Meanwhile, the value of sill, range and nugget of Pb's Gaussian variogram are 0.000017, 0.01 and 0.00007 respectively the points in the variogram show that there are 15 groups of data and their spatial autocorrelation. For example, in Gaussian variogram of Mn, there are 15 groups of data which are close together and every single group has some observations.

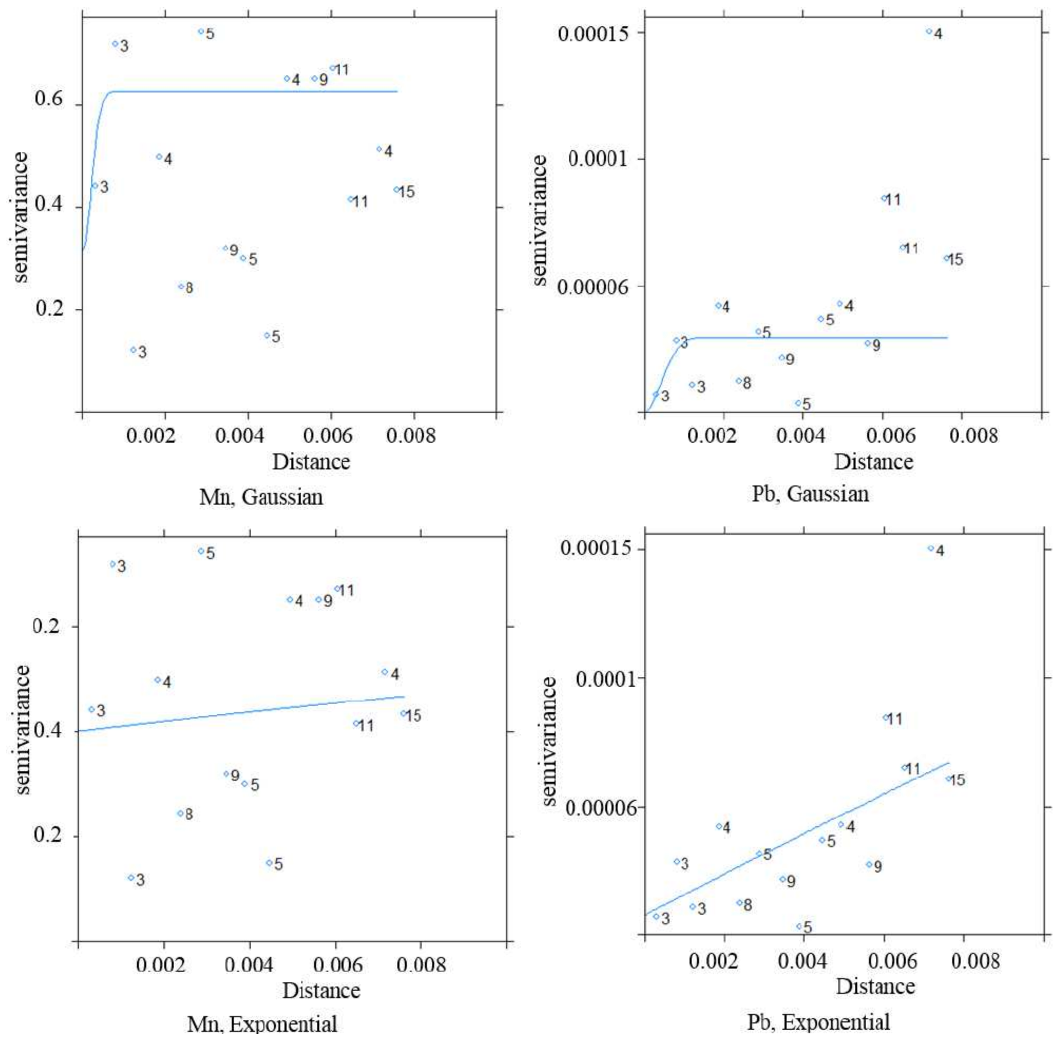

Fig. 4. Variogram of Mn and Pb

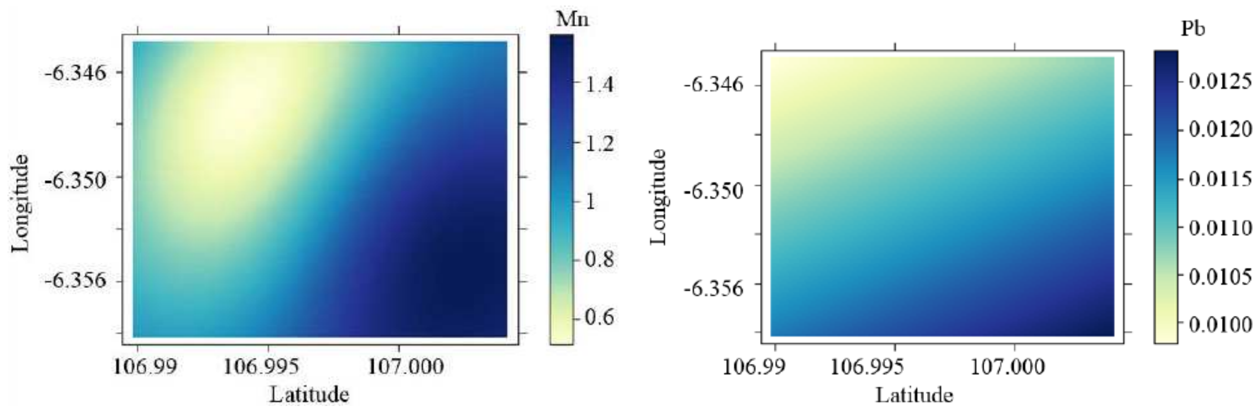

Fig. 5. Interpolation of Mn and Pb

Table 1. Moran's I test of inorganic compounds

Inorganic compound	Moran's I	P-value
Mn	0.251	0.02
Pb	0.268	0.02

Table 2. The parameter estimate of Variogram models and SSE Interpolation

Inorganic compound	Sill	Range	Nugget	SSE
Gaussian:				
Mn	0.490000	0.001	0.40000	0.550000
Pb	0.000017	0.010	0.00007	0.000279
Exponential:				
Mn	0.21000	0.020	0.40000	1.068000
Pb	0.00004	0.003	0.00002	0.001041

In next step, the Gaussian and Exponential model are used to interpolate the data of Mn and Pb, then calculates the Sum Square Error (SSE). Table 2 gives the information about the comparison of SSE of these models. The lowest value of SSE indicates the best model, so the interpolation of Gaussian model gives the best result. The SSE value of Mn and Pb in Gaussian model are 0.550 and 0.000279 respectively.

Besides that, interpolation based on Gaussian model is used to predict Mn and Pb in other locations. It shows in Fig. 5. The interpolation applies to a certain location in latitudes 6.345 S and 6.356 S and longitudes 106.99 E and 107.004 E. As a result, the compound of Mn and Pb are approximately 0.6-1.4 and 0.01-0.0125 mg L^{-1} respectively. The most compound of Mn is in the southeast and the least is in northwest area of TPST Bantar Gebang. It is accordance with the exploration in Fig. 3. The number of Pb is also high in southeast area. It shows that location has the high chance to be an affected pollution area. These results are in accordance with the result of the research from Rosid *et al*. (2011) that claimed that the groundwater flew beneath the surface, carrying leachate and trending south to north in the Bantar Gebang landfill. The water flew from the southeast to the northwest. The geoelectric method measurement of Self-Potential (SP) has been done at the southeast and southern regions of Bantar Gebang.

Conclusion

The water quality mapping in the waste disposal area, particularly around the Integrated Waste Management (TPST) Bantar Gebang in Bekasi, is important to provide information about the water quality due to the pollution. There are some mathematical and statistical methods used. Ordinary Kriging can be applied to predict groundwater quality and maps the results. The method gives the prediction based on autocorrelation among the nearby locations. The autocorrelation is calculated from semivariance that performs the autocorrelations among locations.

Based on Moran's I test of Manganese (Mn) and Lead (Pb), it can be concluded that there is a spatial autocorrelation among locations. It shows that the compound of Mn and Pb in a certain location is affected by the other location. For example, the area with high compound of Mn (or Pb) are among the areas with the high compound of Mn (or Pb). Otherwise, the area with low compound of Mn (or Pb) are among the areas with the low compound of Mn (or Pb). This analysis shows that the best interpolation method is ordinary kriging.

The ordinary kriging is started by select the model of variogram. The gaussian model gives the better result than the exponential model. The values of sill, range and nugget in Gaussian model of Mn are 0.49, 0.001 and 0.4, also Pb are 0.000017, 0.01 and 0.00007. The interpolation result shows that the most number of Mn and Pb is in the southeast area of TPST Bantar Gebang.

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Author's Contributions

Rokhana Dwi Bekti: Design the study, collecting data, working on statistical data analysis and writing the manuscript.

Kris Suryowati: Working on mathematical data analysis and editing the manuscript.

Heruna Tanty: Working on laboratory analysis and chemical data analysis and editing the manuscript.

Ethics

This article is original work and not under consideration for publication either in any other journal. All authors approved this article. No ethical issue in anticipated now and after the publication.

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