

ESTIMATION OF RESISTANCE OF MINE RESULTS USING ORDINARY INDICATOR KRIGING

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ABSTRACT

Kriging is a geostatistical analysis of the data used to estimate the value that represents a no sample point based sample point in the surrounding by considering the spatial correlation in the data. Kriging is an interpolation method that generates unbiased predictions or estimations and has a minimum error. Indicator kriging is an estimation method that does not require the assumption of normality of data and can also be used to treat data that have a significant outlier. The indicator kriging that based on the principle of ordinary kriging also called ordinary indicator kriging. In this case study conducted Morowali estimated iron content in Central Sulawesi using ordinary indicator kriging method. The data used in the form of data coordinate point and iron content. The results obtained are presented probability value locations that fall within the zone of potential and non potential with the value the error variance. Based on the analysis to obtain a plot depicting the location of the entry in the zones of potential iron mine on the abscissa coordinate (7150–7210), the ordinate (54180–54540), and the depth ranges (440–500) meters and also the coordinates of the abscissa (7710–8130), the ordinate (54800–54960), and depths ranging from (327–342) meters.

Keywords: indicator kriging, ordinary indicator kriging, iron, potential

A. INTRODUCTION

Geostatistics is a statistical method used to process geological data and spatial information. The purpose of geostatistical analysis is to predict a part of a set that is spatially scattered from the measurement results so that it can be interpolated on the data. Daniel Krige, a South African mining engineer in his master's thesis "A Statistical Approach to Some Mine Valuations and Allied Problems", at the University of Witwaterstand South Africa in 1951, introduced one of the assessment methods used to handle variables that varied in value with changes in location or place. which is often called the nationalized variable. The estimation method used to deal with nationalized variables is called the kriging method. In its development, there are several kriging methods developed for geostatistical data. One method of developing kriging that can be used is kriging indicator. The kriging indicator does not require data normality assumptions and can also be used to overcome data that have significant outliers. In the kriging indicator, continuous data will be codified based on a predetermined threshold value [2]. Indicator kriging which is run based on the principle of ordinary kriging is called the ordinary indicator kriging. The output of the ordinary kriging indicator is an estimated value at a predetermined threshold. On this basis in this study, ordinary indicator kriging will be used as a method to determine how much the chances of an observation location has a content that has the potential to produce the desired production. In this paper, the objective to be achieved

is to know the steps for estimating the content of mining products using the ordinary indicator kriging method and its application in estimating iron content in Morowali, Central Sulawesi using the ordinary indicator kriging method so that it can know the location included in the potential zone category or non potential iron mine.

B. DISCUSSION

1. Spatial Data

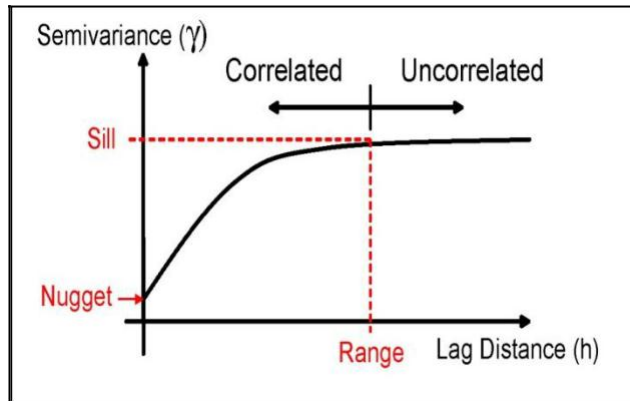
Spatial data is a type of data obtained from measurement results that contain information about locations and measurements. This data is presented in the geographical position of an object, related to its location, shape and relationship with other objects, using points, lines and extents. Spatial data can be either discrete or continuous data and can also have regular or irregular spatial locations. Spatial data is said to have a regular location if between locations that are close to one another have an irregular position with equal distance, while it is said to be irregular if between locations that are close to one another have irregular positions with different distances. Based on the type of data, there are 3 basic types of spatial data, namely geostatistical data, area data (lattice data), and point patterns [1]

2. Experimental Semivariogram

Semivariogram is the basic device of geostatistics for visualization, modeling and exploitation of spatial autocorrelation of nationalized variables. Experimental semivariogram is a semivariogram obtained from the observed data or measured data. Semivariogram can be used to measure spatial correlation in the form of variance in observations at locations and distance locations. The experimental semivariogram estimate at h distance is as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(s_i + h) - Z(s_i)]^2$$

The experimental semivariogram plot image is as follows:



3. Theoretical Semivariogram

In the analysis of geostatistical data, the matching process between an experimental semivariogram and a theoretical semivariogram is called structural analysis. In addition, structural analysis can also be done by means of comparison of the mean square error (MSE) of each semivariogram theoretical. There are several theoretical semivariogram models that are known and are usually used as a comparison of experimental semivariograms

1. Spherical Model

The semivariogram is formulated as follows:

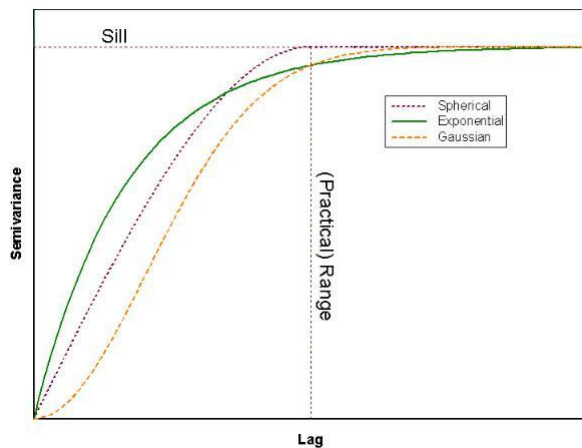
2. Exponential Model

In the exponential model an increase in semivariogram is very steep and reaches the sill value asymptotically, formulated as follows:

3. Gaussian model

The Gauss model is a quadratic form of exponential so that it produces a parabolic form at close range. The Gauss model is formulated as follows:

Here are the three theoretical semivariogram models:



4. Ordinary Kriging Indicator

Kriging is an analysis of geostatistical data which is used to estimate the value representing a point that is not sampled based on the sample points surrounding it by considering the spatial correlation in the data. Kriging is an interpolation method that produces unbiased predictions or estimates and has a minimum error. This estimation method uses a semivariogram that represents spatial differences and values between all pairs of data samples. The semivariogram also shows the weights used in interpolation.

The kriging $Z(s)$ estimator is defined as follows:

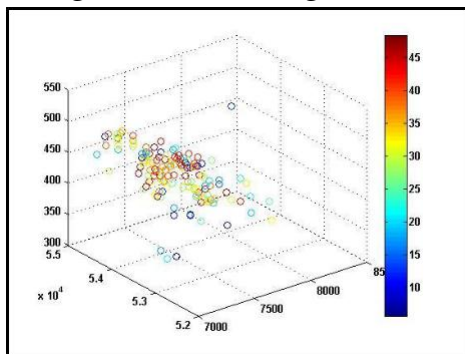
$$\hat{Z}(s) = \frac{\sum_{i=1}^n w_i Z(s_i)}{\sum_{i=1}^n w_i}$$

Many methods can be used in the kriging method but based on the assumptions of the mean used it can be divided into three namely Simple Kriging, Ordinary Kriging, and Universal Kriging. Simple Kriging assumed that the mean was constant and known. Ordinary Kriging assumes that the mean is constant and unknown, while Universal Kriging assumes that the mean is not constant and changes according to location. In its development, the three methods become the basis for developing kriging methods such as: Probability Kriging, Disjunctive Kriging, Cokriging, Bayesian Kriging and Indicator Kriging. The kriging indicator is an estimation method in the mining industry and has even been used by environmental experts to map disaster-prone areas. Kriging indicators do not require the assumption of data normality and can also be used to overcome data that have significant outliers. Estimation using the kriging indicator is that the value of the sampled data will be

codified into an indicator value based on a predetermined threshold value. Values that exceed a predetermined limit value are coded 0, whereas for values that are below the threshold are coded. Ordinary kriging indicator is kriging indicator which is run based on the principle of ordinary kriging to get the weight value that will be used to calculate the value. The resulting value will range between 0 and a maximum of 1 or a value of $0 \leq \leq 1$. This value represents the probability a location to have a content less than or equal to the threshold is a location that is categorized as a non-potential zone.

Assuming Stationarity

Data Testing is said to be stationary if the plot does not contain a certain trend. This can be seen by the randomness of the color of the content in the plot or not forming a certain color gradation.



From the picture above shows the colors contained in the plot are random or do not form a particular color gradation. So it can be concluded that the stationary assumptions are met.

Data Codification

In estimation using kriging indicator, the original data value will be codified into the indicator value based on a predetermined threshold value. The original value that exceeds the predetermined limit value is coded 0, while for values that are below the threshold is given code 1. In this case study, a threshold of 30% will be used. The determination of this standard implies that the company will benefit if mining iron with more than 30% so that new data will be formed as follows:

| No | X | Y | D | Fe | Ind |
|----|---------|----------|--------|-------|-----|
| 1 | 7554.88 | 52778.56 | 384.81 | 6.43 | 1 |
| 2 | 7770.63 | 52779.94 | 392.61 | 19.20 | 1 |
| 3 | 7963.03 | 52811.81 | 368.05 | 31.90 | 0 |
| 4 | 7408.63 | 52990.31 | 392.56 | 25.33 | 1 |
| 5 | 7191.16 | 53008.44 | 347.37 | 5.74 | 1 |
| 6 | 8020.16 | 53016.19 | 387.73 | 25.50 | 1 |
| 7 | 7827.59 | 53046.13 | 426.56 | 32.55 | 0 |
| 8 | 7191.50 | 53216.38 | 336.24 | 21.50 | 1 |
| 9 | 7767.38 | 53222.75 | 396.46 | 31.06 | 0 |
| 10 | 7571.38 | 53229.38 | 439.03 | 20.56 | 1 |

Table 1. Codification of Iron Content Data

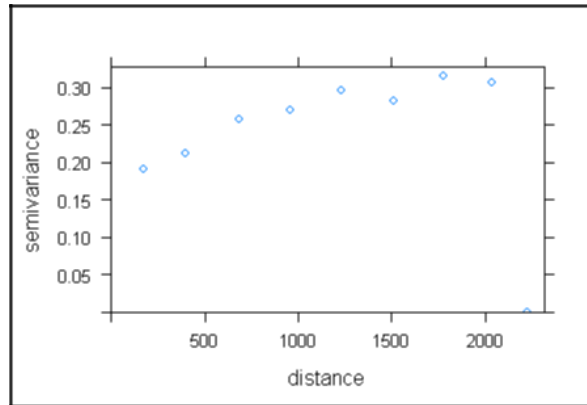
Structural Analysis

This analysis is a process of matching experimental semivariogram with theoretical semivariogram. The initial step to calculate this experimental semivariogram is to make data pairs by combining 2 data from n data. In this case study there are 144 data so that $C(144,2) = 10296$ data pairs are obtained. Based on the experimental semivariogram estimates and run with the R program the following results are obtained:

| Kelas | Pasangan | Jarak (m) | Semivariogram |
|-------|----------|-----------|---------------|
| 1 | 2224 | 174.349 | 0.191 |
| 2 | 2648 | 400.256 | 0.212 |
| 3 | 1680 | 683.308 | 0.257 |
| 4 | 1252 | 958.642 | 0.270 |
| 5 | 917 | 1232.373 | 0.296 |
| 6 | 766 | 1509.040 | 0.282 |
| 7 | 553 | 1779.263 | 0.315 |
| 8 | 253 | 2036.688 | 0.306 |
| 9 | 3 | 2228.123 | 0.000 |

Table 2. Experimental Iron Semivariogram

From the table above it can be seen that the most data pairs are in the second class with an average distance of 400,256 meters, which is as many as 2648 data pairs with a semivariogram value of 0.212. From the analysis, the value of the sill (variance of the iron data that has been codified) is 0.242 and the range value of 687.5 is obtained from the middle value of the distance in the class whose semivariogram is close to the sill value. The experimental semivariogram plot is as follows:



After the sill and range values are obtained, then structural analysis will be carried out, namely the matching process between the experimental semivariogram and the theoretical semivariogram which has the shape of the curve closest to the experimental semivariogram. The fourth plot of the iron semivariogram model consisting of experimental models, spherical models. The result of structural analysis is that the theoretical semivariogram which is suitable for the iron content is a spherical model semivariogram. This can be seen in the picture that shows the model that approaches the experimental model, namely the spherical model. To be more convincing, a comparison of MSE values from each theoretical semivariogram was used and the model with the smallest MSE compared to the other two theoretical semivariogram models was chosen so that the chosen spherical model with MSE was 0.009.

| limit class | np | Jarak | Eks per | Sph | Eks pon | Gauss | error Sph ^2 | error Ekspn ^2 | error Gauss ^2 |
|------------------|------|----------|------------|-------|------------|-------|--------------------|----------------------|----------------------|
| 0 – < 275 | 2224 | 174.349 | 0.191 | 0.092 | 0.054 | 0.096 | 0.010 | 0.019 | 0.009 |
| 275 – < 550 | 2648 | 400.256 | 0.212 | 0.205 | 0.107 | 0.166 | 0.000 | 0.011 | 0.002 |
| 550 – < 825 | 1680 | 683.308 | 0.257 | 0.242 | 0.152 | 0.209 | 0.000 | 0.011 | 0.002 |
| 825 – < 1100 | 1252 | 958.642 | 0.270 | 0.242 | 0.182 | 0.227 | 0.001 | 0.008 | 0.002 |
| 1100 – < 1375 | 917 | 1232.373 | 0.296 | 0.242 | 0.202 | 0.235 | 0.003 | 0.009 | 0.004 |
| 1375 – < 1650 | 766 | 1509.040 | 0.282 | 0.242 | 0.215 | 0.239 | 0.002 | 0.004 | 0.002 |
| 1650 – < 1925 | 553 | 1779.263 | 0.315 | 0.242 | 0.224 | 0.241 | 0.005 | 0.008 | 0.006 |
| 1925 – < 2200 | 253 | 2036.688 | 0.306 | 0.242 | 0.229 | 0.241 | 0.004 | 0.006 | 0.004 |
| 2200 – < 2475 | 3 | 2228.123 | 0.000 | 0.242 | 0.233 | 0.242 | 0.059 | 0.054 | 0.058 |
| Mean | | | | | | | 0.009 | 0.014 | 0.010 |

Estimated Iron Content

After obtaining a theoretical semivariogram that matches the data, the semivariogram will be used to estimate iron. In this study estimates were made for 500 locations. Based on the formula and run with the R program, we get the estimated

iron content in Morowali, Central Sulawesi. Examples of estimation results are as follows:

| No | X | Y | D | | Error | information |
|----|------|-------|-----|--------|--------|---------------|
| 1 | 7030 | 54200 | 440 | 0.5561 | 0.0818 | Non Potensial |
| 2 | 7030 | 54220 | 442 | 0.5351 | 0.0866 | Non Potensial |
| 3 | 7030 | 54240 | 444 | 0.5202 | 0.0905 | Non Potensial |
| 4 | 7030 | 54260 | 446 | 0.5103 | 0.0936 | Non Potensial |
| 5 | 7030 | 54280 | 448 | 0.5038 | 0.0962 | Non Potensial |
| 6 | 7030 | 54300 | 450 | 0.4990 | 0.0984 | Potensial |
| 7 | 7030 | 54320 | 452 | 0.4941 | 0.1004 | Potensial |
| 8 | 7030 | 54340 | 454 | 0.4873 | 0.1022 | Potensial |
| 9 | 7030 | 54360 | 456 | 0.4776 | 0.1037 | Potensial |
| 10 | 7030 | 54380 | 458 | 0.4643 | 0.1048 | Potensial |

Example of Iron Content Estimation Results

The interpretation of the above table for example the estimation at the location (7030, 54200, 440) to have an iron content of less than 30% is equal to 0.5561 meaning this location can be said to be a non-potential zone for an iron mine because the opportunity value for having an iron content is less than equal 30% relatively large, ie more than 50%. Whereas at the location (7030, 54380, 458) it can be said as a potential zone of iron mines because the opportunity value to have an iron content of less than equal to 30% is relatively small at 0.4643. From the estimation table a plot of the estimated iron content will be made based on the coordinates of its location. The plot results will show the location of the estimated points and also the color gradation according to the depth level of the estimated iron content results.

C. CONCLUSION

One method of ordinary indicator kriging is one of the methods of kriging which functions to predict or estimate the mine content in the mining industry. This method can be applied to data that does not require normality assumptions and can also be used to overcome data that have significant outliers. The results of the experimental semivariogram calculation obtained a sill value of 0.242 and a range value of 687.5. While the structural analysis obtained a theoretical semivariogram suitable for the iron content is the spherical model semivariogram. The final results of estimation of iron content in Morowali, Central Sulawesi using ordinary indicator

kriging is in the form of plots that describe locations that fall into the potential zone of iron mines, namely the abscissa coordinates (7150–7210), ordinate (54180-54540), with depths ranging between (440 -500) meters and at abscissa coordinates (7710–8130), ordinate (54800-54960), with depths ranging from (327–342) meters.

D. REFERENCES

1. Cressie, N.A.C. 1993. Statistics For Spatial Data. John Wiley and Sons, Inc. New York
2. Kim, Y.C. 1988. Advanced Geostatistics For Highly Skewed Data. Department of Mining and Geological Engineering. Arizona University.
3. Bohling, G. 2005. Introduction to Geostatistics and Variogram Analysis. (<http://people.ku.edu/~gbohling/cpe940/Kriging>, accessed May 20, 2012).
4. Bohling, G. 2005. Kriging. (<http://people.ku.edu/~gbohling/cpe940/Kriging>, accessed May 16, 2012)
5. Lloyd, C.D and Atkinson, P.M. 2001. Assessing Uncertainty in Estimates with Ordinary and Kriging Indicator. The Queen's University of Belfast's School of Geography. Northern Ireland, UK.