Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/130305

Prediction of Spread Shear Strength of Rock with Ordinary Point Kriging Method using GStat-R

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Received: 13 Jan. 2019 , Revised: 12 Feb. 2019 , Accepted: 23 Feb. 2019
Published online: 1 May 2019

Abstract: In this study, we used the Ordinary Point Kriging for predicting the spread of shear strength of rock at a site in an unobserved location. Based on the nature of rocks, the rock quality index is measured by rock shear strength with less strong rock properties which has a weaker of the strength of rocks to support the load and become a weak field. The calculation of the spread of the shear strength of rock can be made using GStat-R program in R software to get accurate results. In the calculation of prediction using the kriging method, we can use *gstat* library, *sp* library, *Rcmdr* library and several algorithms in GStat-R and apply them to the data to get a prediction of shear strength index of deployment at an unobserved location.

Keywords: Spatial Data, Shear Strength of Rock, Semivariogram, Ordinary Kriging, GStat-R

1 Introduction

Geostatistics is an interdisciplinary science that merges the sciences at mining, geology, mathematics, and statistics [1]. The variogram as a basic tools in Geostatistics is used to quantify the spatial correlation between observations [2]. The data used in a geostatistical is spatial data including data of observation value based on location. Inside, there is a geostatistical prediction process for predicting mineral reserves, this prediction can be done through kriging process. Kriging was named from D.G. Krige, a mining engineer from South Africa, who first developed the technique of moving averages to estimate the gold content to eliminate the effect of regression. G. Matheron developed it and the new method was called kriging which is a valuation method that uses spatial data. Kriging calculation process can be categorized into several types, namely: the Ordinary Point Kriging, or Simple Point Kriging, and Universal Point Kriging. The difference of these methods based on assumption of mean. The Ordinary Point Kriging method is one that has kriging method assuming an unknown mean [3]. The mean at each location is constant. For example, the data used in this study is data dissemination shear strength of rock in the village Kungkilan, District Merapi Barat Regency South Sumatra [4]. GStat-R Program is a program for the geostatistical model, prediction and simulation in one, two, or three dimensions comprising the sample variogram calculation was made in the software package R as one package containing spatial data processing functions or command processing program in geostatistical applications[5]. In this study, we propose GStat-R program to analyze the method of the Ordinary Point Kriging using algorithm and script from open source R [6].

2 Literature Review

To employ a kriging method (sometimes called optimal prediction), we need to capture the structure of the spatial correlation. In Geostatistics, this problem is known as structural analysis and becomes a key issue in the subsequent kriging process [1]. The accuracy of kriging is based on the functions yielding information about the spatial correlation detected. The functions are called semivariogram, and they must meet a series of requisites. Commonly, a semivariogram that is derived from an

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observed dataset, it is called an experimental semivariogram, does not satisfy such requisites. Once a theoretical semivariogram has been chosen, we are ready for spatial prediction using kriging methods. [2].

Semivariogram is a function for describing the degree of spatial correlation of a spatial random variable. For example in gold mining, semivariogram gives a description for two samples taken from the mining area will be fluctuated in gold percentage depending on the distance between those samples. According to [2], [7] we use intrinsic stationarity assumption in order to capture the structure of the spatial correlation which means that the expectation and variance of the difference $[Z(x+h)-Z(x)]$ should be independent of location x, as follows:

$$E[Z(x+h)-Z(x)]=0 \tag{1}$$

$$Var[Z(x+h)-Z(x)]=2\gamma(h) \tag{2}$$

The function $2\gamma(h)$ is called a variogram and $\gamma(h)$ is a semivariogram. Based on (1) and (2), the experimental semivariogram with stationary intrinsic can be defined as:

$$\hat{\gamma}(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}[(Z(x_i+h))-(Z(x_i))]^2 \tag{3}$$

where :

$\hat{\gamma}(h)$	:	experimental semivariogram value with distance h
$Z(x_i)$	:	value of observations in x_i
$Z(x_i+h)$	:	value of observations in x_i+h
$N(h)$	:	number of point pairs within h

Generally, experimental semivariogram does not have an isotropy property. Isotropy means uniformity in all orientations. The best known isotropic function as theoretical semivariogram are spherical, Gaussion and exponential models. These theoretical models must be fitted to the experimental semivariogram by determining three parameters: sill (c), range (a) and distance (h) as depicted in Figure 1. Range is the value at which the model first flattens out and range is the distance at which the model first flattens out [2].

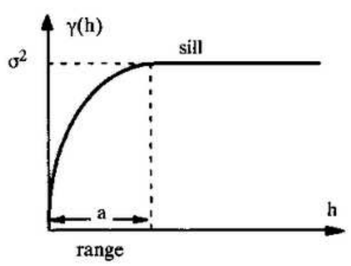

Fig. 1: Semivariogram Plot

An experimental semivariogram is computed by a formula in equation (3). We usually observe the distribution of experimental semivariogram and then identify a reasonable theoretical semivariogram model based on the experimental semivariogram distribution or prior knowledge. The most commonly theoretical semivariogram models are used spherical, Gaussian and exponential models as shown below [2], [7], [8].

Spherical Model

$$\gamma(h)=\begin{cases} c\left[\frac{3}{2}\left(\frac{h}{a}\right)-\left(\frac{1}{2}\right)\left(\frac{h}{a}\right)^2\right], & \text{h< a;}\\ c, & \text{h}\geq \text{a.}\end{cases} \tag{4}$$

Gaussian Model

$$\gamma(h)=\begin{cases} c\left[1-exp\left(\frac{-3h^2}{a^2}\right)\right], & \text{h< a;}\\ c, & \text{h}\geq \text{a.}\end{cases} \tag{5}$$

Exponential Model

$$\gamma(h)=\begin{cases} c\left[1-exp\left(\frac{-3h}{a}\right)\right], & \text{h< a;}\\ c, & \text{h}\geq \text{a.}\end{cases} \tag{6}$$

The Gaussian model reaches a constant and corresponds to infinitely differentiable (see Figure 2). The Gaussian function uses a normal probability distribution curve. This type of model is useful where phenomena are similar at short distances because of its progressive rise up the y-axis. The best model can be chosen by calculating the minimum error sum of squares. Furthermore, we can use the best experimental semivariogram as an input for spatial prediction using the Ordinary Point Kriging [2], [7].

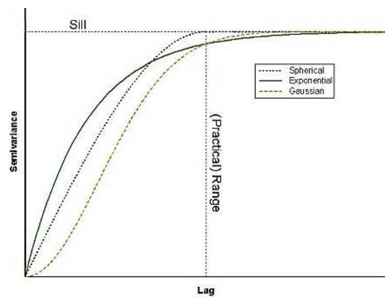

Fig. 2: Spherical, Gaussian and Exponential Models

The Ordinary Point Kriging Method is one of kriging methods that is a prediction method based on spatial data. It can produce maps of optimal predictions and associated standard errors from incomplete and noisy spatial data. The basic idea of kriging is to predict the value of a function at a given point by computing a weighted average of the known values of the function in the neighborhood of the point. Kriging methods are applicable and optimal, when data normally distributed and stationary (mean and variance do not vary significantly in space). The different kriging methods vary in degrees of complexity and in their underlying assumptions. The Ordinary Point Kriging is one of the simplest forms of kriging. It assumes that the data points exhibit unknown local stationarity, i.e., they contain no significant trends over the interpolation search neighborhood.

Furthermore, under the assumptions: a constant but unknown mean μ and a known semivariogram function, we would like to derive the Ordinary Point Kriging. If random variable $Z(x)$ is assumed to be stationary with constant unknown m, then $E[Z(x) = m = E[Z(x_i)]$, and kriging estimators are weighted moving averages of the surrounding data values; that is, they are linear combinations of the data, as follow [2]:

$$\hat{Z}(x) = \sum_{i=1}^{n} \lambda_i [Z(x_i)] \tag{7}$$

where:

$\hat{Z}(x)$: random variable in unobserved location

λ_i : kriging weight in sample location i ; where $\sum_{i=1}^{n} [(\lambda_i) = 1]$

$Z(x_i)$: random variable in sampled location i

The mean of estimation error is:

$$E[\sum_{i=1}^{n} (\lambda_i [Z(x_i) - \hat{Z}(x_i)])] = m = \sum_{i=1}^{n} [\lambda_i - 1] \tag{8}$$

From equation (8), the Ordinary Point Kriging in two locations can be arranged in an equation below [9]:

$$\begin{bmatrix} 0 & \gamma_{12} & 1 \\ \gamma_{21} & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_m \end{bmatrix} = \begin{bmatrix} \gamma_{10} \\ \gamma_{20} \\ 1 \end{bmatrix} \tag{9}$$

From equation (9), we can derive the equations below:

$$\lambda_1 = \frac{1}{2} + \frac{\gamma_{2V} + \gamma_{1V}}{2\gamma_{12}} \; ; \; \lambda_2 = \frac{1}{2} + \frac{\gamma_{1V} - \gamma_{2V}}{2\gamma_{12}} \tag{10}$$

where:

γ_{12} : semivariogram of 2 observed locations 1, 2

$\gamma_{1V};\gamma_{2V}$: semivariogram between observed and unobserved location V

3 Methodology

In this study, we propose to determine the best theoretical semivariogram models, to make an algorithm of the Ordinary Point Kriging method and to display the predicted outcomes through scripts in R software using GStat program based on *gstat* library as following step [10]:

a. The activation process involves the function library of *gstat, sp, Rcmdr*.
b. The process of calculating the value of the experimental semivariogram involving *variogram* function.
c. Fitting the theoretical semivariogram models *fit.variogram* and *vgm* functions.
d. The process of prediction using the Ordinary Point Kriging method involves the function of *krige*.

The GStat-R program has the advantage of determining as many neighbours as possible around a certain location using command *krige*. We use the script of GStat-R for the Ordinary Point Kriging method for the research data as displayed in Figure 3 [6].

```
library(gstat)
library(sp)
library(Rcmdr)
data(shear)
summary(shear)
hist(log(shear[,3]))
elevation<-(shear[,3])
x.range<-as.integer(range(shear[,1]))
y.range<-as.integer(range(shear[,2]))
shear.grid<-
expand.grid(x=seq(from=x.range[1],to=x.range[2],by=1),y=seq(from=y.ra
nge[1],to=y.range[2],by=1))
shear.grid
data(shear.grid)
coordinates(shear.grid)=~x+y
vartem<-log(shear[,3])
semi.expe=variogram(vartem~1,~x+y,shear)
semi.expe
plot(semi.expe)
var(log(geser[,3]))
semi.teor=vgm(psill=0.01846672,model="Gau",range=225)
semi.teor
fitting.semivar=fit.variogram(semi.expe,semi.teor)
fitting.semivar
semi.teor2=vgm(psill=0.01846672,model="Exp",range=225)
semi.teor2
fitting.semivar2=fit.variogram(semi.expe,semi.teor2)
fitting.semivar2
semi.teor3=vgm(psill=0.01846672,model="Sph",range=225)
semi.teor3
fitting.semivar3=fit.variogram(semi.expe,semi.teor3)
fitting.semivar3
plot(semi.expe,fitting.semivar)
plot(semi.expe,fitting.semivar2)
plot(semi.expe,fitting.semivar3)
attr(fitting.semivar,"SSErr")
attr(fitting.semivar2,"SSErr")
attr(fitting.semivar3,"SSErr")
analysis.ok=krige((elevation)~1,~x+y,shear,shear.grid,fitting.semivar
2)
analysis.ok
```

Fig. 3: Script of GStat-R for Ordinary Kriging

Application of the Ordinary Point Kriging methods is used in the prediction of pollutants on the Meuse river floodplain [11], then the predicted contours are developed with projection to google map [12]. Based on these example, the one of the things that can be done in predicting variables that affect the quality of coal is the kriging method [13].

4 Result and Discussion

In this study, we use the drilling data of shear strength of rock from Lahat in Regency South Sumatra, especially the variables of coal quality [4]. The complete data is shown in Table 1. By using the R software, we get statistics descriptive of the data as displayed in Table 2.

Table 1: Drilling Data

Northing	Easting	Elevation	Shear Strength of Rock	Drill Hole
356750,8	9581056	105,967	382,472062	KL-01
356749,3	9581056	105,9479	318,810264	KL-01C
356759,8	9581096	112,8964	404,026844	KL-02
356754,1	9581131	115,1095	462,174628	KL-03
356746,2	9581181	107,5398	428,087996	KL-04
356746,9	9581209	103,1215	418,062516	KL-05
356746,9	9581210	103,0445	436,609654	KL-05C
356998,1	9581398	89,19443	472,701382	KL-06
356999,8	9581347	87,10925	468,189916	KL-07
357003	9581279	87,90373	405,029392	KL-08
357005,2	9581225	88,58064	371,945308	KL-09
357004,2	9581157	92,95112	394,502638	KL-10
357256,5	9581215	97,61149	403,024296	KL-11
357255,4	9581216	97,64733	501,274	KL-11
357255,9	9581280	94,19647	396,00646	KL-12
357344	9581350	99,47483	433,100736	KL-13
357344,5	9581349	99,46436	438,113476	KL-13C
357248,2	9581448	93,19947	497,765082	KL-14RR
357498,3	9581410	94,81862	494,757438	KL-15
357502,7	9581361	101,7601	451,647874	KL-16R
357508,7	9581260	108,5419	488,74215	KL-17
357493,1	9581198	109,8175	310,78988	KL-18
357754,6	9581118	119,3876	345,377786	KL-19
357750,2	9581119	119,2438	341,868868	KL-19C
357754,9	9581175	119,6052	419,065064	KL-20
357755,8	9581232	115,7192	338,35995	KL-21
357755,2	9581233	115,6546	378,46187	KL-21C
357758,4	9581294	110,1865	498,76763	KL-22
357913,4	9581235	106,5125	482,726862	KL-23
357923,2	9581184	107,7467	479,217944	KL-24
357922,2	9581133	116,0664	422,072708	KL-25
357923	9581080	114,9729	467,187368	KL-26
356750,3	9581275	100,3799	489,243424	KL-27
357754,3	9581069	119,7594	362,922376	KL-28
356556,4	9581169	98,84596	473,70393	KL-29
356560,8	9581185	102,2421	487,739602	KL-29CR
356552,5	9581104	109,6523	377,960596	KL-30

Table 2: Table of Descriptive Statistics

	x (m)	y (m)	Shear Strength of Rock (ton/m2)
Minimum	356553	9581056	310.8
1st Quartil	356760	9581157	394.5
Median	357256	9581215	433.1
Mean	357260	9581228	428.2
3rd Quartil	357754	9581280	479.2
Maximum	357923	9581472	501.3

Table 2 shows a summary of the data based on the coordinates of x a minimum value of 356553 m and a maximum value of 357923 m, y coordinates has a minimum value of 9581056 m and a maximum value of 9581472 m, while the elevation has a minimum value of 310.8 and maximum value is 501.3 with an average of 428.2.

To predict the data using the Ordinary Point Kriging method, the data should have the assumption of normal distribution. The histogram plot of the data drilling surface elevation is shown in Figure 4. Based on Figure 4, it can be seen that the data not normally distributed. Furthermore, we transform data using the logarithm to get the data to approach a normal distribution. Figure 5 shows the histogram plots after the data is transformed to logarithm.

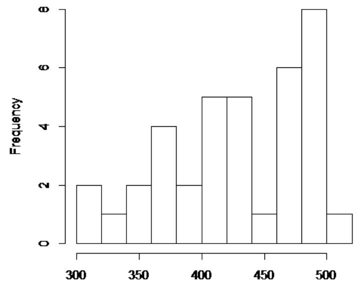

Fig. 4: Histogram Plot Surface Elevation Drilling Data

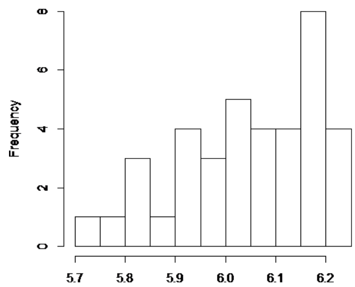

Fig. 5: Histogram for Transformation Data

Based on Figure 5, it can be seen that the graph shapes such as bells, although is not a symmetry. Furthermore, for applying the Ordinary Point Kriging method using GStat-R, we assume that the data approach a normal distribution.

In calculating the experimental semivariogram, the research data is made to be paired with $C(n,2)$ where n is the number of data. From Table 1 it is known that the research data has 38 sample points so that the $C(38,2)$ produced a number of 1.406 pairs of samples. The experimental semivariogram value can be obtained using the R software. The experimental semivariogram from 38 pairs of research data is ordered to be 15 classes based on the distance of each pair of samples and contained the number of point pairs within distance h as shown in Table 3. Furthermore, the experimental semivariogram plot is shown in Figure 6.

Table 3: Experimental Semivariogram Value of Research Data

No	Number of point pairs within h	Distance (m)	Experimental Semivariogram
1	9	9.377134	0.0054004
2	18	51.620463	0.0136946
3	16	73.448691	0.0202425
4	18	114.19442	0.0082679
5	13	150.07553	0.0152569
6	35	173.7514	0.0224448
7	29	206.74603	0.0226132
8	27	240.41966	0.031585
9	48	268.27256	0.0152186
10	24	303.34552	0.0136989
11	22	341.4945	0.0151932
12	4	365.95722	0.0130681
13	12	389.58602	0.024759
14	17	427.63373	0.0308429
15	21	458.82877	0.0158743

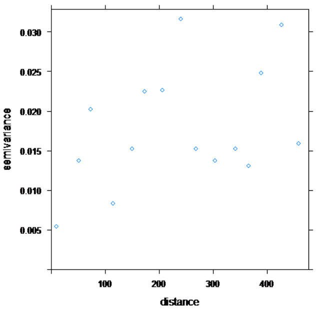

Fig. 6: Experimental Semivariogram Plot of Research Data

Based on Figure 6 we process the selection of the best theoretical semivariogram models in a way fitting the theoretical semivariogram models which correspond to the experimental semivariogram.

Following the procedure of using GStat-R program in section 3, we fitted the research data to theoretical semivariogram models. The first step in fitting the model is to determine the theoretical semivariogram models. This model requires some parameters, especially range and variance. In this study, we choose three types of theoretical semivariogram models: spherical, Gaussian and exponential. In the R software, the Spherical theoretical semivariogram model is written ”Sph” which means Spherical. the Gaussian semivariogram is written ”Gau” and for the Exponential semivariogram is written ”Exp”. Figure 7, Figure 8 and Figure 9 show the plot of theoretical semivariogram models for research data.

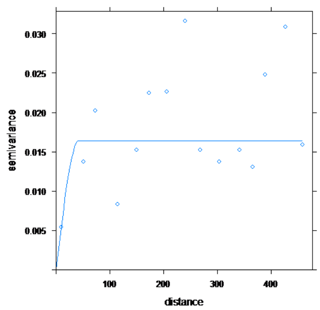

Fig. 7: Spherical Model for Research Data

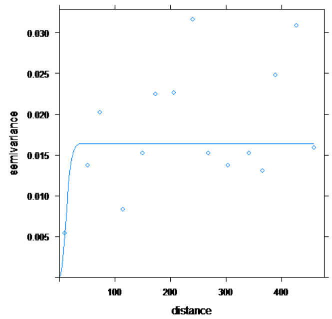

Fig. 8: Gaussian Model for Research Data

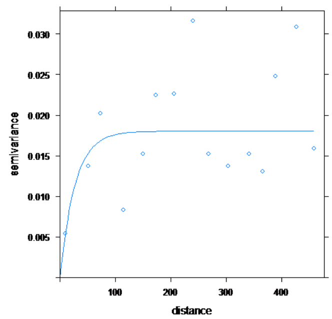

Fig. 9: Exponential Model for Research Data

The best theoretical semivariogram models can be chosen by comparing the sum of squared errors in each lag. The amount of error is obtained from the difference between the experimental semivariogram and the theoretical semivariogram value at each lag. We get the error value of the theoretical semivariogram models. It is displayed in Table 4.

Table 4: SSE of Theoretical Semivariogram for Research Data

SSE Theoretical Semivariogram Model		
Spherical	Gaussian	Exponential
3.90E-07	3.90E-07	3.38E-07

According to Table 4, the best theoretical semivariogram models for research data is the theoretical exponential semivariogram model because it has the minimum Sum Square Error (SSE) among theoretical semivariogram model of spherical and Gaussian, which amounted 3.38E-07.

Table 5: Example Prediction of the last 5 points Unobserved Locations using Ordinary Kriging Method

Locations	Coordinate (m)	Predictions (ton/m2)	Error Variance
...	...	...	...
33329	(356952, 9581080)	431.6267	1.865805e-02
33330	(356953, 9581080)	431.6031	1.865651e-02
33331	(356954, 9581080)	431.5792	1.865494e-02
33332	(356955, 9581080)	431.5552	1.865335e-02
33333	(356956, 9581080)	431.5311	1.865173e-02

After we get the best model of the theoretical semivariogram, we used it as an input for the Ordinary Point Kriging method to predict the observation of spread shear strength of rock in unobserved locations. In Table 5 we give the last 5 examples prediction from 33,333 unobserved locations that can be predicted including coordinate and error of variance. Furthermore, Table 6 explain the statistics for prediction at 33,333 unobserved locations using the Ordinary Point Kriging method.

Table 6: Descriptive Statistics of Prediction at 33,000 Unobserved Locations using Ordinary Kriging Method

	Predictions (ton/m2)	Error Variance
Minimum	311.3	0.00000
1st Quartil	431.1	0.01775
Median	433.1	0.01853
Mean	432.7	0.01762
3rd Quartil	435.6	0.01867
Maximum	497.7	0.01872

Based on Table 6, we can explain that from 38 sample data, we can predict a spread shear strength of rock at 33,333 unobserved locations using the GStat-R program. The average value of the prediction of 432.7 (ton/m^2) approach to the average of the sample data of 428.2 (ton/m^2). The average yield of variance error of 0.01762 indicates that the prediction results obtained is accurate because the average variance of error is $< 5\%$.

5 Conclusion

In this study, we describe the procedure of GStat-R program for the Ordinary Point Kriging method and implemented its algorithms on the spread shear strength of rock at Lahat, Regency of South Sumatera in Indonesia. Using the logarithm data transform, the result shows that:

a.The exponential model as the best theoretical model of semivariogram for research data.

b.The results of prediction of observation at unobserved locations an average approach the average of the sample data and small variance error.

Acknowledgement

The work reported in this paper is supported by Rector Universitas Padjadjaran through Academic Leadership Grant and RKDU 2018. Also thanks to the anonymous reviewers for valuable checking to improve this paper.

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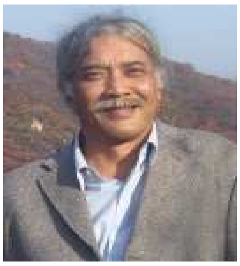

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