Performing Spatial Variability of Peat Depth by Using Geostatistics

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Abstract. Geostatistics has been knowns as a reliable tool to explore variability in space of any measured parameter. This research aims to study how peat depth change and vary in space using geostatistics aproach. The research took place in a peat land inMuaro Jambi district, Jambi province of Indonesia. The three different areas of peat depth [very deep (area A), deep (area B) and shallow (area C)] were purposely selected to investigate through borehole. From the total 120 boreholes, peat depth data were analyses using ArcGIS geostatistical analyses.The result showed that peat variability in shallow area is higher than that of deep and very deep area.It is also found that the reliable sampling distance in peat exploration should not be less than 230 meter in very deep area, 275 meter in deep area and 41 meter in shallow area.

1 Introduction

Peat is organic material which is accumulated from plant materials which are not completely decomposed due to anaerobic and water-saturated condition[1]. In the lowlands area, peat was formed under the influence of high water levels, so that litter accumulation of plants is growing and will result dome-shaped peats. Ombrogen peats were deposited thousands of years and contain high wood. The thickness of organic accumulation may reach aranges between 0.5 to 25 meter-deep and it spatially variesin space and position[2][3]. A better knowledge of the peat depth has been one of the prerequisites for science-based peatland and water management[4].

Peat depthdoes not only vary but either not distribute randomly in landscape; there is always a spatial correlation that can explain the distribution of its magnitudes[5][6].In order to represent the spatial correlation, geostatistics has been known to be used, especially due to its specific tool called variogram. The method of geostatistics provide a set of statistical tools for incorporating the spatial coordinates of observations in data processing.

Geostatistics works largely based on random function concept[7] and peat depth is regarded as a spatially dependent random variable. Geostatistics estimates the values of

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properties (at unsampled places) that spatially vary from sparse sample data[8]. It has the capability in quantifying an unknown value, creating a map and validating sampling strategy and so improving the sampling[9]. It is here where this research wishes to perform spatial variability of peat depth by using the geostatistical method.

2 Materials and Methods

The studiarea was more less 75 hectares, located in Seponjen Villange, District of Muaro Jambi, Jambi Province (Indonesia) in a peat land, part of the Peat Hidrological Unit Kumpeh river–Air Hitam Laut river (Fig. 1). The three 25-hectare areas which represent different range of peat depth, A) very deep peat (8–15 m), B) deep peat (3–8 m) and C) shallow peat (0–3 m) were borehole-investigated for collecting its peat depth data.

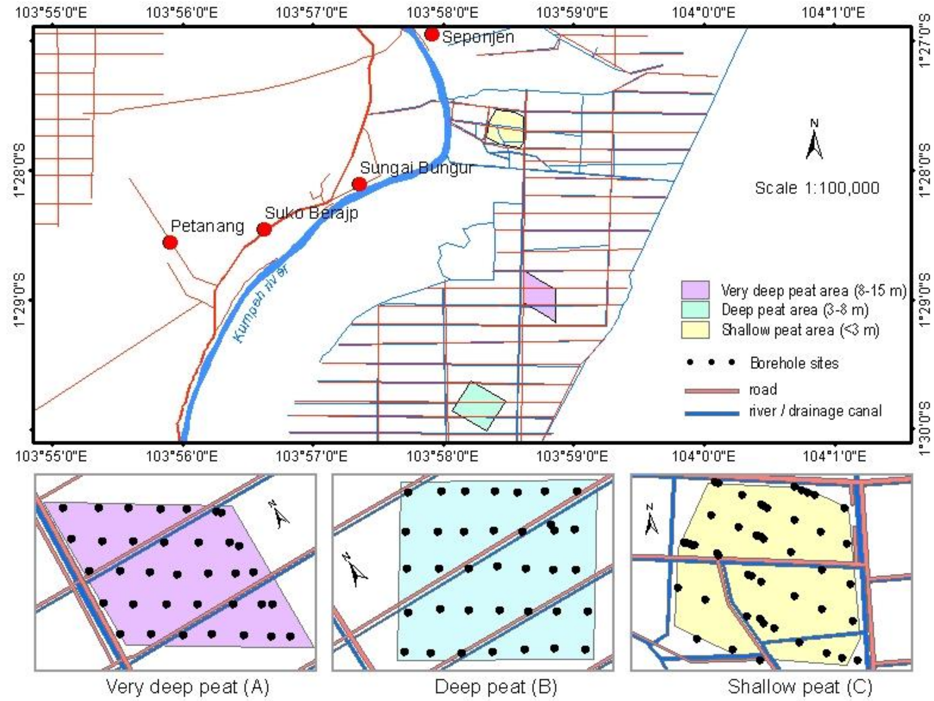

Fig. 1. Research sites location

The study areas were sampled using transects approach. The transects were oriented perpendicular to main river (River of Kumpeh). Borehole investigation was carried out within transect on every 80 meter. Except, when the consecutive borehole appeared significantly vary, the space between borehole was reduced. Using peat augers, and helped by 7 field assistants, peat depth data from the total of 120 boreholes were collected along 16 parallel transects (Figure 1).

Geostatistical analyses and map creationwere performed using GIS software (ArcGIS 10.1 with licence hold by Sriwijaya University). The method used for semi variance analyses and interpolation was ordianary kriging.

3 Results and Discussions

3.1 Exploring datasets

The main descriptive statistics of the three areas are presented in Table 1 and provide information about the central tendency and variability of peat depth. The next three pictures (Figure 2) show their histogram of data distribution,

Table 1. Descriptive statistics of peat depth at the three study areas

Statistics	Area A	Area B	Area C
Number	35	36	49
Minimum	4.60	0.00	0.00
Maximum	11.00	10.00	4.20
Average	9.24	3.33	1.09
Total	323.55	120.05	53.35
Deviation standard	1.45	1.49	1.33
Variance	2.12	2.22	1.77
Skewness	-1.90	2.50	0.78
Kurtosis	6.49	12.94	2.08
1st quartile	9.11	2.70	0.00
Median	9.50	2.95	0.30
3rd quartile	10.00	3.55	2.35

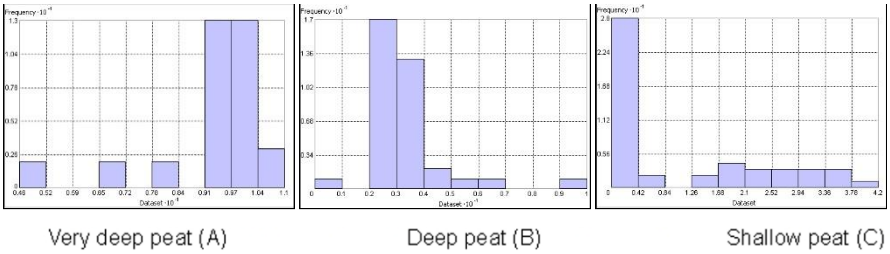

Fig. 2. The histogram of peat depth data from different areas

To be able to analyze in geostatistics, the data which are not distributed normally need to be transformed and the software offered to do it whether by logistic or box cox transformation. The three datasets were considered not normally distributed by the software. So they had been transformed before continued into geostatistical analyses.

Besides, the data trend was also explored as a prerequisite for kriging analyses. The trend is a gradual change through space[10,11]. The software has been equipped with tool to explore the existence of trend in dataset. The next figures show the result of trend detection on each datasets.

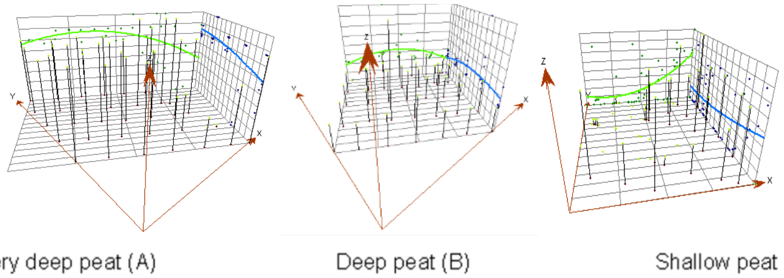

Fig. 3. The histogram of peat depth data from different areas

It can be seen from the Figure 3 that the dataset of shallow peat shows clearly the existence of trend along the transect. It shows that peat depth increase significantly as the distance to east increase. This trend has to be removed before running the Kriging, and would be added backto the output surface.

3.2 Semivariogram

In order to represent the spatial correlation or the structure of variables, geostatistic analyses have the specific tool called variogram. The semivariogram and the variogram are the two basic tools for the analysis of spatial structure[12]. It is defined as a graphical display that shows the relationship (structure) between the variance of pairs of observations as function of the distance separating those observations (h)[13]. In the other word, it describes the variance within a group of distance (y-axis) against the distancebetweenpairsofpopulations(x-axis)(Figure 4).

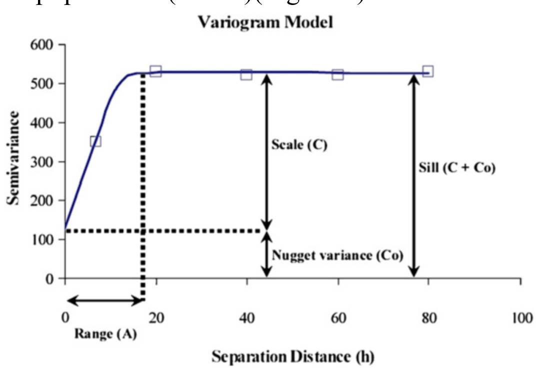

Fig. 4. Variogram parameters.

There are four parameters that can describes variogram model; the sill (C - C_0),thenugget(C_0),thescale(C)andtherange(A). These parameters influence the variogram. especially the shape near the origin until the range. [10]

The variogram model is used to define the weights of the Kriging function [14] and the semivariance is an autocorrelation statistic defined as

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{Z(x_i) - Z(x_i + h)\}^2 \quad (1)$$

where

γ (h) semivariance for interval distance class or lag interval h.
$N(h)$ total number of sample couples or pairs of observations separated by a distance h.
$Z(x_i)$ measured sample value at point i.
$Z(x_{i+h})$ measured sample value at point $i+h$.

The spatial dependence of peat depth on each study area was revealed from study of variography. Each datasets which represent the 3 study areas has been tested with 9 different models. Figure 5 and Table 2 show semivariograms and respective accuration parameters resulted from tested models.

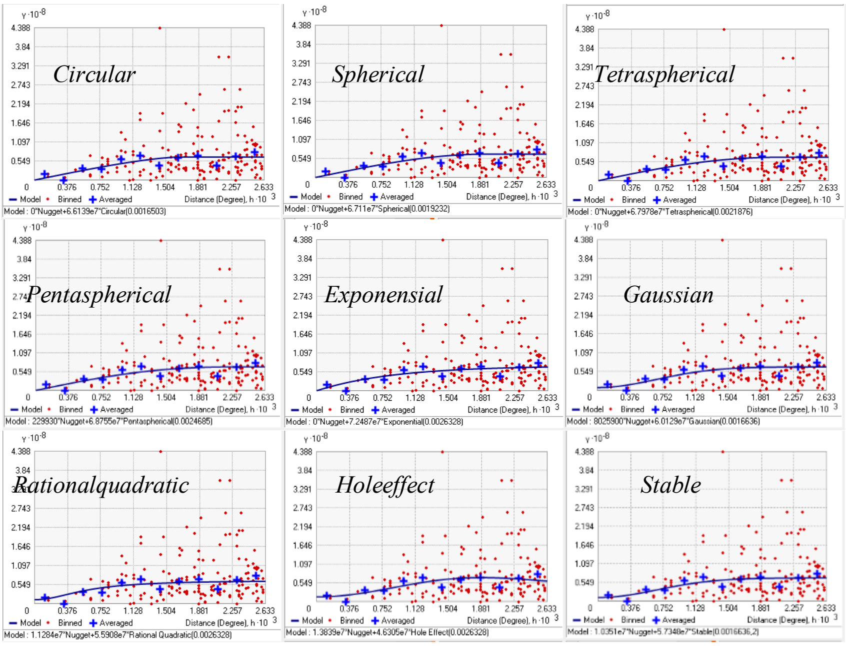

Fig. 5. Semivariograms of dataset A (very deep area) and the curveof tested models

Table 2. The accuration parameters of tested models

Accuration parameters	Circular	Spherical	Tetra-spherical	Penta-spherical	Exponensial	Gaussian	Rational quadratic	Hole effect	Stable
Samples #	35	35	35	35	35	35	35	35	35
Mean	-0.08	-0.08	-0.07	-0.04	-0.04	-0.10	-0.04	-0.01	-0.08
Root-Mean-Square	0.76	0.76	0.75	0.71	0.82	0.66	0.76	0.57	0.69
Mean Standardized	-0.06	-0.05	-0.04	-0.02	-0.02	-0.08	-0.02	-0.01	-0.06
Root-Mean-Square Standardized	0.73	0.70	0.70	0.68	0.71	0.75	0.69	1.01	0.70
Average Standard Error	1.05	1.11	1.10	1.10	1.19	0.96	1.20	0.73	1.01

The best model is the one that has;

- the standardized mean nearest to zero,
- the smallest root-mean-squared prediction error,
- the average standard error nearest the root-mean-squared prediction error, and
- the standardized root-mean-squared prediction error nearest to 1.[10][15]

Therefore, based on these criteria, the best model should be selected for the interpolation or at this study area is the hole effect model that won the whole 4 criteria. The whole result of variogram analyses on the 3 study areas is summarized in the Table 3

Table 3. The best semivariogram model and the parameter on each datasets

Model and the parameters	Area A	Area B	Area C
The best model	Hole effect	Penta-spherical	Gaussian
Nugget	0.042	0.000	0.079
Sill	1.604	2.564	1.264
Range (meter)	230	275	41
Scale	1.562	2.564	1.185
Lag (meter)	9.36	22.95	4.57
Coefficient correlation (R2)	0.922	0.547	0.683
Root mean square error	0.57	1.25	0.96

4 Conclusions

Geostatistics has shown its capability to easily understand the spatial distribution of peat depthin peatland, especially when comparison between or among different areas.

The research has produced a better informative map of peat depth derived from field based point data. The area of shallow peat tends to have higher spatial variability than that of deep and very deep peat area. The minimum distance of peat investigation or sampling interval should not be less than 230 meter in very deep area, 275 meter in deep area and 41 meter in shallow area.

The results of this study highlight the potential of geostatistics and variography to identify and map peat distribution. Map editing through geostatistics and Kriging appears to be an efficient tool to identify changes peat depth in space.

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