S−30 INTERNSHIP AT THE HORONOBE DEEP UNDERGROUND RESEARCH CENTER AND ITS APPLICATION TO HYDROLOGICAL ENVIRONMENT MODELING OF SEDIMENTARY ROCKS

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1. Introduction

Horonobe underground research laboratory (URL) is located in northern part of Hokkaido, its aim is to study geological environment as an example of sedimentary formation in Japan and confirm reliability of technologies for geological disposal of High-Level Radioactive Waste (HLW) by applying them to actual geological condition of sedimentary formation. To construct the hydrogeological groundwater flow model in sedimentary rocks environment, it is crucial to get a comprehensive understanding of the spatial distribution of parameters like porosity, hydraulic conductivity, cation and anion index for water. This study is to apply the geostatistics tools in the geological environment research for geophysical, geochemical, and hydrogeological sedimentary environment modeling.

2. Study area

Horonobe URL consists of Neogene sedimentary sequences (ascending orders; Souya coalbearing Formation, Masuhoro Formation, Wakkanai Formation, Koetoi Formation and Yuchi Formation), which are underlain by igneous and Palaeogene to Cretaceous sedimentary basement (Fig. 1). The Wakkanai and Koetoi formations are distributed are mainly composed of diatomaceous mudstone. The mudstone is divided into two depending on degree of the crystallinity of silica mineral (Ota, K., 2007).

The area of URL is about 3 km×3 km, two main faults named Omagari fault and Horonobe fault are in the area. There are 11 Horonobe Deep Boreholes (HDB) drilled from 2001 to 2006 in study area, geophysical investigations and hydrochemical laboratory tests had been executed in these boreholes (Yamasaki, S., 2004).

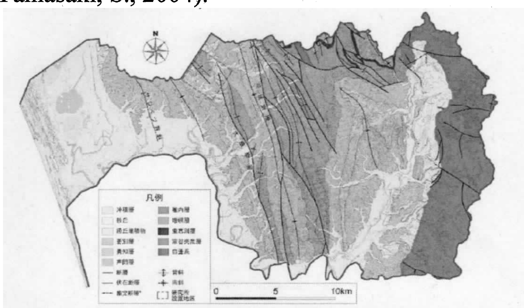

Fig. 1. geological map of Horonobe URL

3. Geostatistical estimation

The main tool for traditional geostatistics is the variogram or its equivalent the covariance. Consider a stationary random function $Z(\mathbf{u})$, and any two of its random variables $Z(\mathbf{u})$ and $Z(\mathbf{u}+\mathbf{h})$ separated by vector $\mathbf{h}$. The relation between these two random variables is characterized by any one of the following 2-point statistics (Journel and Huijbregts, 1978; Goovaerts, 1997):

the covariance:

$$C(\mathbf{h}) = E\{[Z(\mathbf{u})-m][Z(\mathbf{u}+\mathbf{h})-m]\}$$

the variogram:

$$2\gamma(\mathbf{h}) = E\{[Z(\mathbf{u}+\mathbf{h})-Z(\mathbf{u})]^2\} = 2[C(\mathbf{h})-C(0)]$$

if $C(\mathbf{h})$ exists, where $m = E\{Z(\mathbf{u})\}$, $C(0) = \square^{\square}$ $Var\{Z(\mathbf{u})\}$

Kriging has been historically at the source of acceptance of geostatistics (Journel and Huijbregts, 1978); it remains a major data integration tool and is used in most geostatistical estimation and simulation algorithms. Kriging is in essence a generalized linear regression algorithm, extending the data-to-unknown correlation to data-to-data correlation through a non-diagonal kriging matrix. In this study, the ordinary kriging is applied for the estimation. In ordinary kriging the expected value of the random functions is locally re-estimated from local data, while the covariance model is kept stationary. The ordinary kriging has been extended to local estimation of the parameters of a functional trend.

Consider within a stationary field S the estimation of an unsampled value $Z(\mathbf{u})$ from $n(\mathbf{u})$ neighboring data values $Z(\mathbf{u}_\alpha)$, $\alpha = 1,..., n(\mathbf{u})$. If the stationary mean m, is considered locally variable, it can be estimated from the $n(\mathbf{u})$ local data, and the estimate $Z^*(\mathbf{u})$ is restricted to be a linear combination of the data, it is written:

$$z(\mathbf{u}) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha(\mathbf{u}) z(\mathbf{u}_\alpha)$$

where the kriging weights sum to 1.

4. Sequential Gaussian simulation (SGSIM)

Traditional (2-point) simulation algorithm aim at reproducing a prior covariance model, or equivalently a variogram model, that is a statistical relation between any two values in space. The missing information about what should be the relation in space of three or more values taken jointly is then necessary provided by the simulation algorithm retained. The SGSIM algorithm uses the sequential simulation formalism to simulate a Gaussian random function. Let $Y(\mathbf{u})$ be a Gaussian random function with zero mean, unit variance, and a given variogram model $\gamma(h)$, realizations of $Y(\mathbf{u})$ can be generated as Table 1.

Table 1. conception of SGSIM

Sequential Gaussian simulation
1. Define a random path visiting each node of the grid
2. **for** Each node $\mathbf{u}$ along the path **do**
3. Get the conditioning data consisting of neighboring original hard data (n) and previously simulated values
4. Estimate the local conditional cdf as a Gaussian distribution with mean given by kriging and variance by the kriging variance.
5. Draw a value from that Gaussian ccdf and add the simulated value to the data set
6. **end for**
7. Repeat for another realization

5. Estimation and simulation

There are 11 HDBs in the study area, in the following analysis we use 10 HDBs except HDB-2 (Fig. 2). The main reason is because of the range of variogram, the ranges of variogram are all about 1 km but the HDB-2 is far away to the other HDBs.

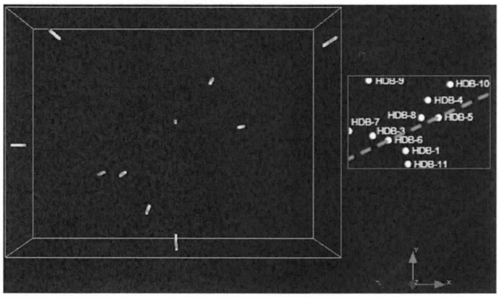

Fig. 2. Distribution of HDB

Study area is usually discretized into identical parallelepipedic blocks (cells) in the X, Y and Z directions respectively, for example 100×130×10 which is referred to as Cartesian grid. The variations of regionalized variable within a cell are considered negligible, and the problem of estimating variable in each block is simplified to estimating porosity at the center of the cells (cell-centered grid).

For the geophysics data, we use ordinary kriging to estimate the 3D distribution of density and porosity, and five sequential Gaussian simulations of density and porosity are generated. One of the deficient in the estimation is due to the sparse data. The study area here is discretized into 80×60×22 identical parallelepipedic blocks (cells) in the X, Y and Z directions respectively, which is referred to as Cartesian grid.

In Fig. 3, we generated three simulations of density at 500 m depth; we could find the simulation3 can well reflect the distribution with depth.

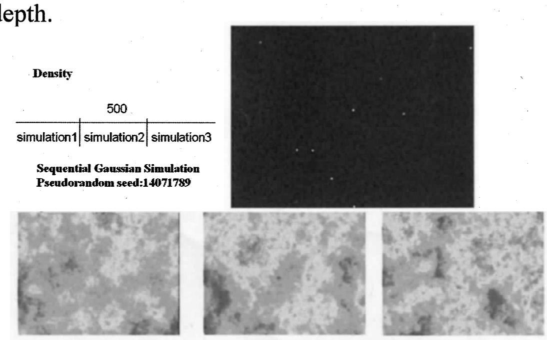

Fig. 3. SGSIM of density at 500 m underground

From the coefficient of correlation of geochemical data like Cl^-, Na^+, Ca^{2+}, Mg^{2+}, K^+, we could find that coefficient of correlation between Cl^- and Na^+ is relatively high, 0.954. In the 3D ordinary kriging estimation of Cl^- and Na^+ (Fig. 4), we could find that they are also relatively equivalent.

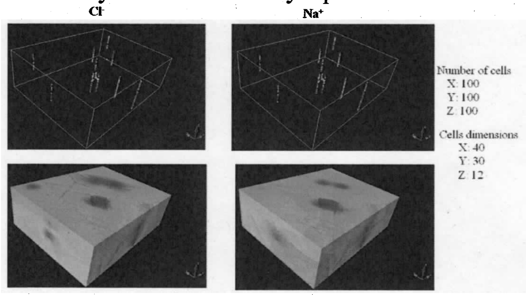

Fig. 4. 3D ordinary kriging estimation of Cl^- and Na^+

Five realizations of Cl^- and Na^+ are shown in Fig. 5, highlight parts of the simulations indicate that the evidence of saline water distribute in deep underground.

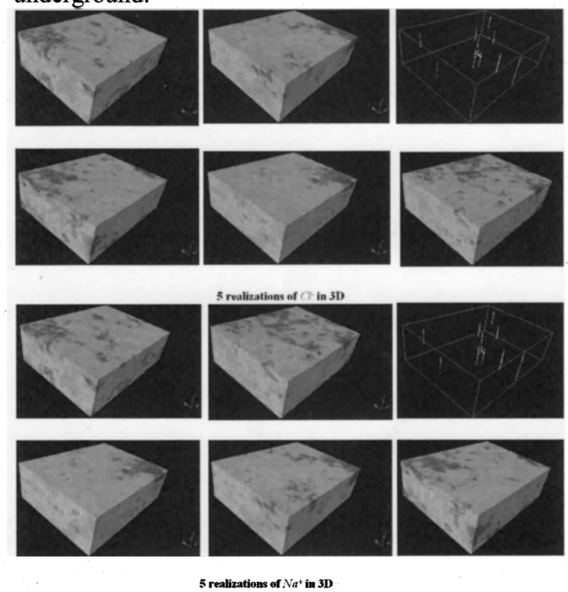

Fig. 5. realizations of Cl^- and Na^+

6. Conclusions

Geostatistics applied in this study approved that it is a useful tool to estimate and simulate the spatial distribution of borehole data.

We applied the stochastic simulation in the study because,

* due to the sparse boreholes, to show the uncertainties.

* from the range and sill of Cl^- at 400 m and deeper, it seems to be anisotropy

The groundwater in study area could be classified into three types: shallow part of $Na\text{-}CO_3$ dominated fresh water; deep part of Na-Cl dominated saline water; and mixtures between fresh water and saline water.

The results of kriging and simulation could be used in the coming groundwater modeling, and to build velocity models for seismic processing and uncertainty analysis etc.

Moreover, this study has not been finished yet. There are some points need to do:

The kriging estimation should be tested by cross-validation and dip may be involved in the calculation.

The kriging estimation or simulation should compare with the 3D geological structure to find out the potential relationship among them.

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