MODELING OF SPATIAL VARIABILITY OF SOIL PROPERTY AND RELIABILITY BASED DESIGN OF PILES

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ABSTRACT: It is the essence of geotechnical design to obtain soil parameters for design that are different from a site to another. Therefore, soil investigations play very important role in geotechnical design. The modeling of the ground based on investigation results is called site characterization, and there are some new developments in this area based on statistical theories. In the new approach, the results are directly related to reliability based design of geotechnical structures, where the resulting uncertainties (e.g. ultimate bearing capacity of a pile, settlement of embankment etc.) related to soil variability and statistical estimations are quantified. This study covers the following contents:

1. Explain some basic statistical concepts and tools that are necessary to understand the statistical site characterization of ground for geotechnical design.
2. Introduce some statistical site characterization examples and describe the procedures to carry out the analysis. The examples include several sites where CPT tests were carried out extensively.
3. Based on the statistical site characterization, vertical bearing capacity of piles is evaluated to see the influence of soil variability and statistical estimation errors.
4. Summary, conclusions and possible future works will be suggested.

Keywords: reliability based design, statistical analysis, cone penetration test, site characterization, pile design

1. INTRODUCTION

One of the distinguish features of geotechnical reliability based design, RBD, compared to other structural reliability design such as concrete and steel structures is material properties are different from site to site, which need to be determined based on filed investigations and laboratory tests.

In the ordinary structural RBD textbook (such as Thoft-Christensen and Baker, 1982), the uncertainties in RBD are classified into the following four sources: (1) physical uncertainty, (2) statistical uncertainty, (3) modeling errors and (4) gross error. It goes without saying that physical uncertainties, especially external actions, are the major source of uncertainty in structural RBD.

Since the spatial fluctuations of soil properties are generally large, people tend to think that the physical uncertainty is the major source of uncertainty in geotechnical RBD. However, this is not necessarily true as repeatedly emphasized by Baecher and Christian (2003a and 2003b) that the statistical uncertainty would have more contribution to the resulting uncertainty in geotechnical RBD. This is because Aleatory uncertainties (uncertainties due to randomness, i.e. physical uncertainty) tend to average out, however effects of Epistemic uncertainties (uncertainties due to lack of knowledge, i.e. statistical uncertainty) do not.

This paper actually tries to add some examples to this statement. The statistical uncertainty and the physical uncertainty are quantified through actual site records to see the relative impacts on the resulting uncertainty in geotechnical RBD.

2. MODELLING OF SOIL PROFILE BY RANDOM FIELD

2.1. Description of Soil Profile

It is general procedure to model soil profile such as concrete and steel structures is material properties are different from site to site, which need to be determined based on filed investigations and laboratory tests.
2.1.1. Trend components by regression analysis
Matsuo (1984) has proposed three types of trend models to describe the soil profiles based on his experience analyzing various kinds of Japanese soil conditions. They are termed Type I, II and III as illustrated in Figure 2. The three types are defined as below where \( x = (x_1, x_2, x_3) \) is a coordinate vector in the space, and \( x_1 \) indicates the depth. \( z(x) \) indicates a soil property at position \( x \):

1. **Type I**: constant trend with constant variance
\[
z(x) = \beta_0 + \sigma \varepsilon(x)
\]
where \( \beta_0 \) and \( \sigma \) are constant. \( \varepsilon \) is a random variable which follows a normal RF with 0 mean, \( \sigma \) variance and \( \theta \) autocorrelation distance. The autocorrelation function is assumed to be of an exponential function type (see 2.2.2 for the details).

2. **Type II**: linear trend with constant variance
\[
z(x) = \beta_0 + \beta_1 x_1 + \sigma \varepsilon(x)
\]
where \( \beta_0, \beta_1 \) and \( \sigma \) are constant. \( \varepsilon \) is a random variable which follows a normal RF with 0 mean, \( \sigma \) variance and \( \theta \) autocorrelation distance. The autocorrelation function is assumed to be of an exponential function type.

3. **Type III**: linear trend with constant COV
\[
z(x) = (\beta_0 + \beta_1 x_1) + \text{Cov}(\beta_0 + \beta_1 x_1) \varepsilon(x)
\]
where \( \beta_0, \beta_1 \) and \text{Cov} are constants. \( \varepsilon \) is a random variable which follows a normal RF with 0 mean, \( \text{Cov} \) variance and \( \theta \) autocorrelation distance. The autocorrelation function is assumed to be of an exponential function type.

Matsuo (1984)’s study is mainly based on the study on undrained shear strength of alluvial clay deposit in Japan, but is considered to be applicable to other sedimentary type soil deposits including ones introduced in this study in the examples.

2.1.2. Random components by random filed
The trend models introduced in the previous subsection all include a random variable \( \sigma(x) \) which consists a stationary (=homogeneous) random filed (RF). The stationarity assumed in this study is that in a weak sense, which implies the RF can be described by the following three statistics:

\[
\mu_z(x_1, x_2, x_3) = \mu_z \quad \sigma_z^2 (x_1, x_2, x_3) = \sigma_z^2 
\]

\[
\rho_z(x_1, x_2, x_3) = \rho(\Delta x_1, \Delta x_2, \Delta x_3)
\]

The first equation states that the mean is constant, i.e. independent of the coordinate \( x = (x_1, x_2, x_3) \). In the present context, this mean value is assumed to be 0. The second equation expresses that the variance is also constant. Finally, the third equation states that the autocorrelation function is given not by the absolute coordinate but by the relative distance between the two coordinate positions.

In addition to the above assumptions, the form of autocorrelation function is specified in this study. Due to the deposition process of soil layers, it is generally assumed that autocorrelation structure for the horizontal direction, i.e. \( x_1 \) and \( x_2 \), and for the vertical, i.e. \( x_3 \), is different. We assume that the autocorrelation function has separable property as suggested by Vanmarcke (1977):

\[
\rho_h(\sqrt{\Delta x_1^2 + \Delta x_2^2}, \Delta x_3) = \rho_h(\sqrt{\Delta x_1^2 + \Delta x_2^2}) \cdot \rho_v(\Delta x_3)
\]

The exponential type autocorrelation function is assumed in this study because Matsuo (1984) has used this type of autocorrelation function. The concrete form of Eq.(5) is given as,

\[
\rho_h(\sqrt{\Delta x_1^2 + \Delta x_2^2}) = \exp \left[ -\frac{\theta_h}{\theta_v} \right] 
\]

where \( \theta_h \) and \( \theta_v \) are so called autocorrelation distance for horizontal and vertical directions respectively. The scale of fluctuation defined by Vanmarcke (1977) is two times of the autocorrelation distance in case of exponential type autocorrelation function.

In some cases, the random component does not show any correlation even within two observations taken in very close distance. In this case, the random component can be considered as independent or a white noise, and the autocorrelation function takes the form as follows:

\[
\rho_h(\sigma(x), \sigma(x_j)) = \delta(x, x_j)
\]

This is known as nugget effect in geostatistics (Jounel and Huijbregts, 1978). In many cases, the random component is a combination of the white noise and the dependent component.

2.2. Parameter estimation and model selection
In fitting the model to observed geotechnical data, it is necessary to prepare several alternative models, estimate parameters for each model, and finally select the best model among the alternative models. The procedure to estimate the parameters is usually termed parameter estimation, whereas that to select the best model from the alternative models is called model selection. In the actual calculations, these two procedures cannot be separated: one chooses the best model after the parameter estimation for all alternative models have been completed.

It is theoretically more sound to simultaneously estimate parameters for the trend component and that for random component simultaneously. However, in many cases they are done in a stepwise fashion: first estimate the trend component parameters assuming the random component is
\( i.i.d. \) (independently and identically distributed), and then estimate parameters for the random components based on the residuals. The former is termed simultaneous estimation whereas the latter stepwise estimation in this study.

The reason the stepwise estimation procedure is taken is that most of the user friendly statistical software available are based on \( i.i.d. \) assumption, and it seems that there is an implicit assumption that the results form the both methods would not be very different. For an example, the variogram fitting procedure in geostatistics is apparently the stepwise estimation procedure (e.g. Wackernagel, 1998).

The present study takes the simultaneous procedure. However, description for this procedure is done in two folds: first the parameter estimation procedure by MLM (the maximum likelihood method) is presented, then model selection by AIC (Akaike information criterion) is introduced.

### 2.2.1. Parameter estimation by the MLM

Any of the three types of models I, II and III introduced in the previous section can be generally described as follows:

\[
z = f(x) + \epsilon \sim N(0, \sigma^2, \Theta)
\]

where

- \( x \): spatial coordinate vector
- \( f(x; \beta) \): a function showing the trend component
- \( \beta \): trend parameter vector
- \( \epsilon(\sigma, \Theta) \): a random field representing the random component
- \( \sigma^2 \): variance of the random field
- \( \Theta \): autocorrelation distance vector
- \( \Theta_v \): autocorrelation distance in vertical direction
- \( \Theta_h \): autocorrelation distance in horizontal direction

Suppose observation vector \( z \) is given which are observed at the coordinate given by a matrix \( X \), which are defined as follows:

\[
X = \begin{pmatrix}
x_1 \\
x_2 \\
\vdots \\
x_n
\end{pmatrix} = \begin{pmatrix}
x_{11} & x_{12} & x_{13} \\
x_{21} & x_{22} & x_{23} \\
\vdots & \vdots & \vdots \\
x_{n1} & x_{n2} & x_{n3}
\end{pmatrix}
\]

\[
z = (z_1, z_2, \ldots, z_n)^T
\]

The likelihood function to obtain \( \beta, \sigma^2 \), and \( \Theta \) is expressed as follows:

\[
L(\beta, \sigma^2, \Theta) = \frac{1}{(2\pi)^{n/2}\sigma^2C(\Theta)^{1/2}} \exp\left(-\frac{1}{2}(z-f(\hat{\beta}))^T \frac{1}{\sigma^2}C(\Theta)^{-1}(z-f(\hat{\beta}))\right)
\]

where \( C(\Theta) \) is the covariance matrix which is described as below:

\[
C(\Theta) = \begin{pmatrix}
\rho_1(x_1, x_1) & \cdots & \rho_1(x_1, x_n) \\
\vdots & \ddots & \vdots \\
\rho_n(x_n, x_1) & \cdots & \rho_n(x_n, x_n)
\end{pmatrix}
\]

Therefore, the loglikelihood function can be written as follows:

\[
l(\beta, \sigma^2, \Theta) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2}\left| C(\Theta) \right|^{-1} + \frac{1}{2}(z-f(\hat{\beta}))^T \frac{1}{\sigma^2}C(\Theta)^{-1}(z-f(\hat{\beta}))
\]

The parameters can be estimated by maximizing Eq.(12). The actual forms of equations are presented here as taking Type II model as an example.

Type II model is given as,

\[
f(x; \beta) = \beta_0 + \beta_1 x_1 = X\beta
\]

where

\[
X = \begin{pmatrix}
1 & x_1 \\
\vdots & \vdots \\
1 & x_n
\end{pmatrix} \quad \beta = \begin{pmatrix}
\beta_0 \\
\beta_1
\end{pmatrix}
\]

Thus, the loglikelihood function, Eq. (12), is expressed as follows:

\[
l(\beta, \sigma^2, \Theta) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2}\left| C(\Theta) \right|^{-1} + \frac{1}{2}(z-f(\beta))^T \frac{1}{\sigma^2}C(\Theta)^{-1}(z-f(\beta))
\]

The maximum likelihood estimator of \( \beta \) is obtained as,

\[
\hat{\beta} = \left(X^TC(\Theta)^{-1}X\right)^{-1}X^TC(\Theta)^{-1}z
\]

The MLE of \( \sigma^2 \) is obtained as below,

\[
\hat{\sigma}^2 = \frac{1}{n}(z-f(\hat{\beta}))^T \frac{1}{\sigma^2}C(\Theta)^{-1}(z-f(\hat{\beta}))
\]

As far as \( \Theta \) is concerned, since \( \Theta \) is non-linear term in Eq. (14), \( \Theta \) is estimated by a trial and error procedure, which implies that Eq. (14) is calculated for possible ranges of \( \Theta \) after \( \beta \) and \( \sigma^2 \) are estimated, and one maximized Eq. (14) is chosen as the best combination of \( \beta, \sigma^2 \), and \( \Theta \).
2.2.2. Model selection by AIC

Akaike (1973) proposed a criterion to choose best model among alternative models based on Kalback-Libler's information criterion or the relative information entropy concept. AIC has replaced model selection procedure based on the hypothesis testing because of its clearly defined concept on model selection problem. Due to its superiority, AIC has become one of the standard tools of model selection in statistical analysis.

The general form of AIC is given as follows:

$$AIC = -2\ln(L) + 2k$$  \hspace{1cm} (17)

where $L$ is the maximized likelihood and $k$ is the number of parameters.

The first term represents the goodness of the fit of the model to the data, whereas the second term can be considered as a penalty for more complex model with more number of parameters. The philosophy of AIC is to adjust the trade-off between the fitness to the data and simplicity of the model (Akaike, 1973, 1974).

The concrete form of AIC to the case of Eq.(8) can be expressed as follows:

$$AIC = n \ln(2\pi) + n \ln(\hat{\sigma}_e^2) + \ln|C_e(\hat{\theta})|$$

$$+ n + 2(\dim(\beta) + \dim(\theta) + 1)$$  \hspace{1cm} (18)

where

$$\hat{\sigma}_e^2 = \frac{1}{n} \sum_{i=1}^{n} (z_i - f(x_i|\hat{\beta}))^2 C_e(\hat{\theta})^{-1}(z_i - f(x_i|\hat{\beta}))$$  \hspace{1cm} (19)

In actual optimization calculation done in this study, the best model was selected among models Type I, II and III, with the autocorrelation distance, $\theta$, for several alternative values.


2.2.3. S plus language

All the calculations done in this study were done by program language S-plus. This is an objective oriented programming language for statistical analyses and is very powerful. It is especially suited for linear calculation of statistical data (Lam, 2001; Venables and Ripley, 1999).

3. GENERAL VS. LOCAL RELIABILITY BASED DESIGN

3.1. Local vs. General RBD

As stated in the introduction, one of the distinguished differences between geotechnical and structural RBD (Reliability Based Design) is material property need to be determined at site based on the site investigation in the former, whereas they are given in the latter. In this context, two different kind of design situation need to be identified in the geotechnical RBD as follows:

**General RBD (General Design):** The material uncertainty considered in the design is that of general uncertainty and not considering relative position of investigation location and structures to be designed. Thus, in this approach, considerable statistical uncertainty remains in determining material property for design. For example, if a large container yard to be designed, the bearing capacity of the ground at an arbitrary location may be evaluated considering general property of ground condition obtained in the whole area. The other case is that, if one specifies general property of a certain soil for a design code used in a certain region or country, one has to specify it based on general information known for that particular soil including the variability.

**Local RBD (Local Design):** The material uncertainty considered in the design takes into account the relative position of investigation and the structure to be designed. Therefore, there would be considerable reduction in the statistical uncertainty in this approach. A straightforward example of this case is that if one wants to design a foundation for a house and made a detailed soil investigation at the spot, one has to consider very little uncertainty to ground condition. This idea extends further. It is possible to generally consider the relative position of the investigation position and the position of structure. It is expected that if a structure is built reasonably far from the position of investigation, Local RBD asymptotically merges to General RBD.

The situation described here as General and Local design are a sort of common situation encountered by geotechnical engineers. The engineers surely have treated these conditions in an implicit way, and modified their design. These are a part of so called engineering judgement in the traditional geotechnical engineering. The difference here is that we explicitly take into account these situations and try to quantify uncertainty, and try to optimise the design.

The method employed to take into account the relative positions of the investigation and the structure is Kriging, which is going to be described in the subsequent section. Since design of a vertically loaded pile will be considered as an example, the design procedure based on A1J foundation design guideline that is used is briefly explained.

3.2. Estimation of Soil Properties by Kriging

One of the most reasonable ways to interpolate obtained data in a stationary RF (random field) is by the ordinary Kriging (Journel and Huijbregts, 1978; Baecher and Christian, 2003 etc.), and this method is adopted in this research as well. It should be noticed that there are some literatures that relates Kriging and reliability design of geotechnical structures already such as (Honjo and Kuroda, 1991) etc.

In driving the formulation, all the assumptions made for the stationary RF in subsection 2.1.2 are preserved. They are the random components of the model we do Kriging to interpolate the soil property, and thus results are superposed to the trend component to obtain the final values for design.
3.2.1. Assumptions
The problem is to estimate \( Z(x) \) at an arbitrary point \( x \) in RF by knowing the mean \( \mu_z \), the variance \( \sigma_z^2 \), the covariance function given by the autocorrelation function \( C_z(\Delta x) = \sigma_z^2 \rho_z(\Delta x) \), and some observed values of \( Z, Z(x_1), \ldots, Z(x_n) \), at \( n \) observation points, \( x_1, \ldots, x_n \).

In the ordinary Kriging, the following three assumptions are made:

(1) Linear Kriging
The estimator is given by the linear combination of observed values:

\[
\hat{Z}(x) = \sum_{i=1}^{n} w_i Z(x_i)
\]  

(20)

Where \( w_i \) (\( i = 1, \ldots, n \)) are weight assigned to each observed values.

(2) Unbiased estimator
The expectation of the estimator coincides with the original mean of the RF:

\[
E[\hat{Z}(x)] = \mu_z
\]  

(21)

(3) The minimum estimation variance estimator
The estimation variance can be obtained by back substituting obtained \( w_{OK} \) and \( \lambda_{OK} \) to Eq.(24), which gives,

\[
\hat{\sigma}_{OK}^2 = C_z(0) + \lambda_{OK} - \sum_{i=1}^{n} C_z(|x-x_i|)w_{OK}^i
\]  

(26)

It is known fact (Hoshiya and Yoshida, 1998) that the solution of the ordinary Kriging is the mean and variance of conditional distribution at \( x \) for the given conditions (i.e. known mean, variance, autocorrelation function and some observations). In this sense, the Local RBD can be called the Conditional RBD. In this context, the General RBD can be said Non-conditional RBD.

3.2.2. Derivation of the solution
The next relationship is obtained by substituting Eq.(20) to Eq.(21):

\[
E[\hat{Z}(x)] = E[\sum_{i=1}^{n} w_i Z(x_i)] = \sum_{i=1}^{n} w_i E[Z(x_i)] = \mu_z
\]  

Therefore,

\[
\sum_{i=1}^{n} w_i = 1.0
\]  

(23)

This is the condition \( w_i \) (\( i = 1, \ldots, n \)) that the estimator should satisfy in order to be an unbiased estimator. Thus Eq.(22) need to be minimized subject to the constraint given by Eq.(23). This can be accomplished by Lagrange multiplier method. By introducing Lagrange multiplier coefficient \( \lambda \), the following function need to be minimized with respect to \( w_i \) and \( \lambda \):

\[
\sigma_{OK}^2 = E[(Z(x) - \sum_{i=1}^{n} w_i Z(x_i))^2] - 2\lambda \left( \sum_{i=1}^{n} w_i - 1 \right)
\]  

(24)

This problem can be solved by considering conditions \( \partial \sigma_{OK}^2 / \partial w_i = 0 \) (\( i = 1, \ldots, n \)) and \( \partial \sigma_{OK}^2 / \partial \lambda = 0 \), which results \( n+1 \) dimensional linear simultaneous equation. We write those \( w_i \) and \( \lambda \) that satisfies this condition as \( w_{OK}^i \) and \( \lambda_{OK} \). The concrete form of this equation is given as,

\[
\sum_{j=1}^{n} C_z(|x-x_j|)w_{OK}^j - \lambda_{OK} = C_z(|x-x_j|)
\]  

(25)

for \( i = 1, \ldots, n \)

3.3. Pile Design Procedure
In the example in this study, vertical ultimate bearing capacity at pile at various location of investigated site is calculated by a design formula employed in a foundation design guideline in Japan (AIJ, 1999). For this reason, this design formula is briefly introduced in this section.

Like most of other Japanese design calculation formula for pile, the method is based on SPT-N value. The ultimate vertical resistance of a pile, \( R_p \), can be obtained by adding the resistance at pile tip, \( R_p \), and side resistance, \( R_f \):

\[
R_p = R_p + R_f
\]  

(27)

The each component is calculated as follows:

(1) pile tip resistance:

\[
q_p \cdot A_p
\]  

(28)

\( q_p \): unit ultimate bearing resistance at the tip (kN/m²)
\( A_p \): the sectional area of the pile (m²)

(2) pile side resistance:

The side resistance consists of two components. Those from non-cohesive layers, \( R_{nj} \), and cohesive layers, \( R_{nj} \):

\[
R_f = R_{fc} + R_{fs}
\]  

(29)

The each term is given as below,

\[
R_{fc} = \tau_c \cdot L_c \cdot \varphi
\]  

(30)

\( \tau_c \): unit ultimate resistance from cohesive soil (kN/m²)
\( L_c \): length of the cohesive soil layer (m)
\( \varphi \): circumference length of the pile (m)

\[
R_{fs} = \tau_s \cdot L_s \cdot \varphi
\]  

(31)

\( \tau_s \): unit ultimate resistance from non-cohesive soil (kN/m²)
\( L_s \) : length of the non-cohesive soil layer (m)

The resistances are estimated from SPT n-values by the relationship presented in Table 1.

Table 1 Estimation of vertical resistances of a pile (AIJ, 1999)

<table>
<thead>
<tr>
<th>unit ultimate bearing resistance at the tip (kN/m²)</th>
<th>unit ultimate resistance from the side (kN/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-cohesive</td>
<td>Cohesive</td>
</tr>
<tr>
<td>Cohesive</td>
<td>Non-cohesive</td>
</tr>
<tr>
<td>( q_p = 100 N ) ( N ) : average SPT N-value between –d to +d at pile tip.</td>
<td>( r_\sigma = 3.3 \sqrt{N} ) (( N \leq 50 ))</td>
</tr>
<tr>
<td></td>
<td>( r_\sigma = C_u ) ( (C_u \leq 100) ) ( (kN/m^2) )</td>
</tr>
</tbody>
</table>

4. EXAMPLES

The soil investigation data analyzed in this study is a series of CPT (Cone Penetration Test) results done at three Alluvial sand deposits beside the rivers done by Public Works Research Institute (PWRI and JGCA, 1998). The purpose of the investigation was to compare the results of CPT, SPT-N value and triaxial test results based on the frozen sampling specimens. Only CPT test results were analyzed in this study due to their intensive sampling intervals.

In this chapter, the investigation data are introduced first in 4.1. Not only the original CPT data but also Robertson’s soil classification method and conversion procedure from CPT results to SPT N-values are explained. In 4.2, the statistical site characterization results are presented, which are based on the statistical procedure presented previously in chapter 2. Finally, reliability of vertically loaded pile is evaluated at one of the site, where methodology introduced in chapter 3 is employed in 4.3.

4.1. Data Description

4.1.1. CPT, Soil Classification and SPT N-value

(1) Piezocone penetration test

It is more convenient to explain about CPT that had been used in this investigation and related matters before describing the actual data employed in this study.

SPT N-value is the most popular soil investigation method in Japan traditionally. Many soil parameters that are used in geotechnical design can be obtained by the empirical formulas that relate those values to SPT N-value. These soil parameters include internal friction angle, relative density, various pile resistances etc. However, there are some problems also in using SPT N-value. For example, SPT N-value does not give good estimate of soft cohesive soils. Also, SPT N-value is an average property of soil for a certain volume, and does not give any detailed soil profile. To overcome these shortcomings, one of the candidate soil investigation methods is CPT. There are some new types of CPT, and combining various types of information, it can be a better alternative to SPT N-value in the near future.

The type of CPT test employed in the present investigation is so called Piezocone, which measures penetration resistance \( q_t \), side resistance \( f_s \) and pore pressure \( P_w \) simultaneously (Suzuki, Tokimatsu and Furuyama, 1996). The diameter of the cone is 36 (mm), whereas the length 500 (mm). It is connected to penetration rod (diameter 45 (mm) with length 100 (cm), and hollow inside), and by connecting these rods, the cone is penetrated into the ground with rate of 2 (cm/sec). The measurements are taken through the wire inside the rods at the ground surface.

(2) Robertson’s soil classification method

Different from SPT, it is not possible to observe the soil directory in CPT. For this reason, soil classification procedure based on CPT results has been proposed by (Robertson et al, 1986), which is employed in this study. In this method, normalized penetration resistance \( Q_t \) and normalized friction ratio \( F_r \) are obtained based on measured penetration resistance \( q_t \), side resistance \( f_s \) and total and effective overburden pressures \( \sigma_v \) and \( \sigma_v' \) as defined below:

\[
Q_t = \frac{q_t - \sigma_v}{\sigma_v'} \\
F_r = \frac{f_s}{q_t - \sigma_v}
\]

Based on these two quantities, soil classification index \( I_c \) is calculated as below, which is used to classify soils as indicated in Table 2:

\[
I_c = \left(3.47 - \log Q_t\right)^2 + (1.22 + \log F_r)^3 \right)^{0.5}
\]

(3) Estimation of SPT N-value and fine contents

Since the pile resistance formula employed in this study (so as other formulas used in Japanese geotechnical standards) depends on SPT N-value. Therefore, SPT N-value needs to be evaluated from CPT observation.

Table 2 Robertson’s soil classification by \( I_c \)

<table>
<thead>
<tr>
<th>( I_c )</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_c \leq 1.31 )</td>
<td>gravel sand to sand</td>
</tr>
<tr>
<td>( 1.31 &lt; I_c \leq 2.05 )</td>
<td>sand</td>
</tr>
<tr>
<td>( 2.05 &lt; I_c \leq 2.60 )</td>
<td>silty sand</td>
</tr>
<tr>
<td>( 2.60 &lt; I_c \leq 2.95 )</td>
<td>silt</td>
</tr>
<tr>
<td>( 2.95 &lt; I_c \leq 3.60 )</td>
<td>clay</td>
</tr>
<tr>
<td>( 3.60 &lt; I_c )</td>
<td>organic soil</td>
</tr>
</tbody>
</table>
The conversion formula adopted here is by (Suzuki, Tokimatsu and Furuyama, 1996), which is given as below:

\[ N_c = q_t / R_N \]  \hspace{1cm} (35)
\[ R_N = 1.3(4.3 - 0.02FC) \]  \hspace{1cm} (36)

where \( N_c \): SPT N-value converted from CPT, \( R_N \): the conversion ratio, \( FC \): fine contents. The same authors have proposed below equation to estimate \( FC \)

\[ FC = I_c^{4.2} \]  \hspace{1cm} (37)

The investigation done by (PWRI and JGCA, 1998) includes 3 sites and at each site, 4 CPT had been carried out within a circle of 10(m) diameter. The CPT was piezocone test type which measures penetration resistance \( q_t \), side resistance \( f_s \) and pore pressure \( P_w \) simultaneously. The site name, components of the measurement, CPT indication name, depth of the investigations, and level of the ground surface at each test are presented in Table 3. The locations of CPT at each site are given in Figure 1.

The penetration resistance \( q_t \), side resistance \( f_s \), and pore pressure \( P_w \) obtained at three sites are presented in Figures 2, 3 and 4 respectively. The four test results are presented in the same figure at each site. Estimated fine content \( (FC) \), soil classification index \( I_c \) and the converted SPT N-value \( (N_c) \) are presented in the same figures.

The characteristics of each site can be described as follows:

**Tone river site**: The site is located west side of Tone river 44 (km) from the river mouth in Sahara city, Chiba prefecture. According to Robertson’s classification, the top 4 (m) is covered by inhomogeneous mixed layers of clay and silt. The dense sand occupies the layer below 4 (m), but \( q_t \) is linearly increasing between 4 to 10 (m), and is constant value below 10 (m). (Figure 2)

**Edo river site**: The site is at east bank of Edo river 25 (km) from the river mouth in Nagareyama city, Chiba prefecture. Up to the depth of 6 (m) is a mixed layer of sand and silt. From 6 to 18 (m), the layer consists of sand with little fine contents, followed by a silty sand layer. \( q_t \) decrease with the depth below 18 (m) depth. (Figure 3)

**Natori river site**: The site is at west bank of Natori river 1 (km) from the river mouth in Sendai city, Miyaghi prefecture. Up to 3 (m) below the ground surface is a mixed layer of silty sand and clay. Below 3 (m) is homogeneous sand layer where the \( q_t \) increases up to 9 (m) and remain constant below this depth. (Figure 4)

### Table 3 Site name, CPT indicator, depth and level.

<table>
<thead>
<tr>
<th>Test Sites</th>
<th>Test items</th>
<th>Test name</th>
<th>Investigation depth (m)</th>
<th>Elevation at GL YP+( m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tone river</td>
<td>qt,fs,Pw</td>
<td>TSR-T1</td>
<td>0.842 ~ 20.986</td>
<td>2.810</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-T2</td>
<td>0.856 ~ 21.140</td>
<td>2.690</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-T3</td>
<td>0.848 ~ 21.083</td>
<td>2.570</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-T9</td>
<td>0.825 ~ 21.097</td>
<td>2.690</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-E3</td>
<td>0.828 ~ 21.232</td>
<td>3.989</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-E5</td>
<td>0.786 ~ 21.265</td>
<td>3.985</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-E7</td>
<td>0.788 ~ 21.265</td>
<td>3.941</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-E9</td>
<td>0.963 ~ 21.223</td>
<td>3.977</td>
</tr>
<tr>
<td>Edo river</td>
<td>qt,fs,Pw</td>
<td>TSR-N1</td>
<td>0.840 ~ 21.150</td>
<td>1.898</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N2</td>
<td>0.858 ~ 21.234</td>
<td>1.819</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N3</td>
<td>0.825 ~ 21.255</td>
<td>1.853</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N4</td>
<td>0.822 ~ 21.373</td>
<td>1.891</td>
</tr>
<tr>
<td>Natori river</td>
<td>qt,fs,Pw</td>
<td>TSR-N1</td>
<td>0.840 ~ 21.150</td>
<td>1.898</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N2</td>
<td>0.858 ~ 21.234</td>
<td>1.819</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N3</td>
<td>0.825 ~ 21.255</td>
<td>1.853</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TSR-N4</td>
<td>0.822 ~ 21.373</td>
<td>1.891</td>
</tr>
</tbody>
</table>

Figure 1 CPT location at each site.

4.2. Results of the Site-Characterization

4.2.1. Procedure of the analysis
The penetration resistance \( q_t \), which is the most dominant quantity in converting CPT results to SPT N-value is analysed in this study.

The procedure employed in the analysis is the one presented in subsection 2.2.1. The trend component which is a function describing the mean value as defined by Eqs. (1), (2) and (3), i.e. Type I, II or III, and the random component defined by the standard deviation and the auto-correlation function, Eqs. (5) and (6), whose parameter is the autocorrelation distance, \( \theta_v \) and \( \theta_h \), are estimated simultaneously by MLM. The best model among the three models is selected based on AIC.

The concrete procedure is presented below taking Tone river site data as an example.
Figure 2 Investigation results at Tone river site

Figure 3 Investigation results at Edo river site
(1) Review the data carefully to determine the identical layers and chose an appropriate trend model type:

$q_t$ in the third layer at Tone river site increases apparently with depth, and variance seems to be constant (Figure 5). It is judged that Type II model

(2) Estimate model parameters by MLM by moving $\theta_v$ in the possible range and chose $\theta_v$ that minimizes AIC.

Type II model was fitted to the data while altering $\theta_v$ from 1 to 5 (m). The minimum AIC was obtained at $\theta_v=2.7$ in TSR-T2 as shown in Figure 6. The estimated $\theta_v$ are slightly different from one investigation to another, thus average value of $\theta_v$ is employed in this study (Table 4).

(3) Estimate $\theta_h$, by fixing other parameters as determined in the previous values of the parameters:

Finally, all 4 CPT data are analyzed together by fixing $\theta_v$ to the value determined in the previous step, and changing $\theta_h$ in a possible range to minimize AIC. All parameters are estimated simultaneously at this step by MLM. The results for the third layer at Tone river site is presented in Table 5 where AIC is minimized at $\theta_h=5.5$ (m).

In this way, model parameters are estimated for every layer at every site as presented in Figs. 6, 7 and 8 as well as Tables 6, 7 and 8.

![Figure 4 Investigation results at Natori river site](image1)

![Figure 5 $q_t$ vs. depth (m) in layer 3 at Tone river site](image2)
4.2.2. Results and Discussions

(1) Results at each site

Tone river site:

The results obtained for Tone river site are presented in Figure 7 and Table 6. Model Type I is fitted to layers 1, 2 and 4, whereas Type II to layer 3. Although the models are fitted according to the procedure described above, the quantity of the data for layer 1 is considerably less, thus the reliability of the results was felt to be poor.

As for the autocorrelation distance for the vertical and the horizontal direction ($\theta_v$ and $\theta_h$), $\theta_h$ is longer than $\theta_v$ in both sand and cohesive soil layers. The former is about three to two times longer than the latter in sand layer, and is about two times in cohesive soil layer.

The relative large variation of $q_t$ in the second layer (cohesive soil layer) may suggest existence of sand seams. This layer exhibits relatively large COV of 50(%) . COV of the first layer is also large (about 40(%) ) due to mixture of sand and clay.

For Tone river site, the side resistance component of CPT, $f_s$, is also fitted as shown in Table 11. The results will be used for pile design in the next section.

Edo river site:

The results obtained for Edo river site are presented in Figure 8 and Table 7. Model Type I is fitted to layers 2 and 3, whereas Type II to layers 1, 4 and 5.

It is observed that the autocorrelation distances are longer in sand layers compared to silty layers. Further more $\theta_h$ is about two times longer than $\theta_v$ in all layers.

COV of layers at Edo river site are larger compared to other sites.

Natori river site:

The results obtained for Natori river site are presented in Figure 9 and Table 8. Model Type I is fitted to layers 1, 2, and 4, whereas Type II to layer 3.

It is observed that $\theta_h$ is about two times longer than $\theta_v$ in all layers.

COV of layers at Edo river site are larger compared to other sites.

(2) Comparison with other results

The results of the analyses are compared with (Phoon et al. 1995, 1999a, 1999b) where soil variability based on many exiting literatures is summarized.

Table 9 compares $q_t$ mean values and COV. The mean values of sand layers in this study are much lager than those of Phoon et al., which simply indicates the layers investigated in this study were denser. COV’s are exhibiting the almost similar values (30-40(%) ) except in clay layer in this study (40(%) ). The clay layers in this study are mixed with silt and sand, thus cannot be compared with COV of homogeneous clay layers presented in Phoon et al. (10(%) ).
Table 6 Estimated model parameters at Tone river site.

<table>
<thead>
<tr>
<th>Site</th>
<th>Layer</th>
<th>Depth (m)</th>
<th>Model Type</th>
<th>Mean Function</th>
<th>Variance</th>
<th>COV (%)</th>
<th>Autocorrelation Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tone river</td>
<td>silt</td>
<td>0 ~ 1.31</td>
<td>I</td>
<td>10.88</td>
<td>-</td>
<td>17.39</td>
<td>38.33</td>
</tr>
<tr>
<td></td>
<td>clay</td>
<td>1.31 ~ 3.36</td>
<td>I</td>
<td>6.18</td>
<td>-</td>
<td>9.58</td>
<td>50.08</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>3.36 ~ 9.26</td>
<td>II</td>
<td>-60.76</td>
<td>23.49</td>
<td>281.942</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>9.26 ~ 20.0</td>
<td>I</td>
<td>206.5</td>
<td>-</td>
<td>1214.94</td>
<td>16.88</td>
</tr>
</tbody>
</table>

Figure 7 Fitted models vs. observation data at Tone river site.

Table 7 Estimated model parameters at Edo river site

<table>
<thead>
<tr>
<th>Site</th>
<th>Layer</th>
<th>Depth (m)</th>
<th>Model Type</th>
<th>Mean Function</th>
<th>Variance</th>
<th>COV (%)</th>
<th>Autocorrelation Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edo river</td>
<td>silty sand</td>
<td>0 ~ 2.431</td>
<td>II</td>
<td>2.04</td>
<td>8.68</td>
<td>82.3</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>2.431 ~ 4.717</td>
<td>I</td>
<td>49.37</td>
<td>-</td>
<td>966.26</td>
<td>62.96</td>
</tr>
<tr>
<td></td>
<td>silt</td>
<td>4.717 ~ 6.535</td>
<td>I</td>
<td>25.06</td>
<td>-</td>
<td>217.81</td>
<td>58.89</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>6.535 ~ 18.774</td>
<td>II</td>
<td>-60.58</td>
<td>18.85</td>
<td>5111.12</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>silty sand</td>
<td>18.774 ~ 21.142</td>
<td>II</td>
<td>1097.1</td>
<td>-49.77</td>
<td>1838.98</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 8 Fitted models vs. observation data at Edo river site.
Table 10 compares the auto-correlation distances for vertical and horizontal directions. As for the vertical autocorrelation distances are concerns, the results from the present study exhibit the longer distances compare to those of (Phoon et al. 1999a, and 1999b). However, the horizontal correlation distances are much shorter in the current study. This is due to the shorter distance between adjacent CPT investigations. The records obtained in this study might not be sufficiently far enough to accurately estimate the horizontal autocorrelation distance.

<table>
<thead>
<tr>
<th>site</th>
<th>layer</th>
<th>depth (m)</th>
<th>Model Type</th>
<th>mean function</th>
<th>variance</th>
<th>COV (%)</th>
<th>Autocorrelation distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natori river site</td>
<td>silty sand</td>
<td>0 ～ 1.17</td>
<td>I</td>
<td>13.87</td>
<td>9.8</td>
<td>22.57</td>
<td>0.07 0.3</td>
</tr>
<tr>
<td></td>
<td>clay</td>
<td>1.17 ～ 2.79</td>
<td>I</td>
<td>9.45</td>
<td>41.23</td>
<td>67.95</td>
<td>0.7 1.7</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>2.79 ～ 8.75</td>
<td>II</td>
<td>-75.88</td>
<td>33.25</td>
<td>930.07</td>
<td>- 0.9 0.5</td>
</tr>
<tr>
<td></td>
<td>sand</td>
<td>8.75 ～ 20.0</td>
<td>I</td>
<td>169.78</td>
<td>1268.41</td>
<td>20.98</td>
<td>1 3.5</td>
</tr>
</tbody>
</table>

Table 8 Estimated model parameters at Natori river site

4.3. Results of the Reliability Analysis

4.3.1. Method of calculation

The vertical ultimate bearing capacity of cast in place concrete piles with diameter 1 (m) and length 20 (m) are calculated by formulas explained in section 3.3. \( q_t \) and \( f_0 \) obtained in CPT test results are converted to SPT N-value by Eqs. (35) and (36). Then Eqs. (27) to (31) are employed to evaluate the bearing capacity.

It is apparent that the design formulas include model uncertainty, and conversion from \( q_t \) to SPT N-value includes uncertainty (also is a model error). In this study, however, these model uncertainties are ignored and physical uncertainty (i.e. the spatial variability) and statistical uncertainty are highlighted.

Figure 9 Fitted models vs. observation data at Natori river site

<table>
<thead>
<tr>
<th>item</th>
<th>layer</th>
<th>mean value</th>
<th>COV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>range</td>
<td>range</td>
</tr>
<tr>
<td>( q_t ) (MN/m²)</td>
<td>sand</td>
<td>3.15-21.37</td>
<td>0.4-29.2</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>14.2</td>
<td>4.1</td>
</tr>
<tr>
<td>( q_t ) (MN/m²)</td>
<td>silty sand</td>
<td>0.83-1.89</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>1.4</td>
<td>-</td>
</tr>
<tr>
<td>( q_t ) (MN/m²)</td>
<td>silt</td>
<td>0.59-2.83</td>
<td>0.5-2.1</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>1.79</td>
<td>1.59</td>
</tr>
<tr>
<td>( q_t ) (MN/m²)</td>
<td>clay</td>
<td>0.47-1.65</td>
<td>0.4-2.6</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>0.84</td>
<td>1.32</td>
</tr>
</tbody>
</table>

Table 9 Comparison of \( q_t \) with other studies.
The calculation is done by utilizing data obtained from Tone river site. For given point, mean value of $q_t$ and $f_s$ are estimated by Kriging given in Eq. (25), and estimation variance by Eq. (26). Then $q_t$ and $f_s$ are converted to SPT N-value for both mean value and variance. Then the bearing capacities of the piles are estimated by the formulas given in section 3.3. The uncertainties associated with the calculation are evaluated by FOSM (first order second moment) method.

Fig. 10 presents the location of CPT investigations at Tone river site, which are TSR-T1, TSR-T2, TSR-T3, and TSR-T9. The ultimate bearing capacity at each investigation point is estimated. Also it is estimated at points A4, D1 and F. Point F is not shown in Fig. 10 because it is 100 (m) away from the origin.

The parameters employed in the Kriging are summarized in Table 12, where the autocorrelation distance for both $q_t$ and $f_s$ are assumed to the values obtained for analyzing $q_t$ data in the statistical analysis.

### Table 10 Comparison of autocorrelation distance with other studies.

<table>
<thead>
<tr>
<th>item</th>
<th>layer</th>
<th>vertical autocorrelation distance $\theta_v$(m)</th>
<th>horizontal autocorrelation distance $\theta_h$(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_t$ (MN/m²)</td>
<td>sand</td>
<td>0.6-2.7</td>
<td>0.05-1.1</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>1.37</td>
<td>0.45</td>
</tr>
<tr>
<td>$q_t$ (MN/m²)</td>
<td>silty sand</td>
<td>0.3-1.1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>0.54</td>
<td>-</td>
</tr>
<tr>
<td>$q_t$ (MN/m²)</td>
<td>silt</td>
<td>0.02-0.8</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>0.355</td>
<td>-</td>
</tr>
<tr>
<td>$q_t$ (MN/m²)</td>
<td>clay</td>
<td>0.13-1.0</td>
<td>0.1-0.25</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>0.48</td>
<td>0.15</td>
</tr>
</tbody>
</table>

### Table 11 Modeling of $f_s$ at Tone river site

<table>
<thead>
<tr>
<th>layer</th>
<th>model type</th>
<th>mean function $\beta_0$, $\beta_1$</th>
<th>variance $\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>silt</td>
<td>I</td>
<td>0.27, 0.27</td>
<td>0.02</td>
</tr>
<tr>
<td>clay</td>
<td>I</td>
<td>0.16, 0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>sand</td>
<td>II</td>
<td>-0.37, 0.17</td>
<td>0.03</td>
</tr>
<tr>
<td>sand</td>
<td>I</td>
<td>1.49, 0.21</td>
<td>0.21</td>
</tr>
</tbody>
</table>

### Table 12 Input values at Tone river site for Kriging

<table>
<thead>
<tr>
<th>layer</th>
<th>soil</th>
<th>thickness (m)</th>
<th>$\sigma_v$</th>
<th>$\sigma_h$</th>
<th>$\theta_v$</th>
<th>$\theta_h$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>silt</td>
<td>1.31</td>
<td>4.86</td>
<td>0.12</td>
<td>0.02</td>
<td>0.50</td>
</tr>
<tr>
<td>2</td>
<td>clay</td>
<td>2.05</td>
<td>3.10</td>
<td>0.07</td>
<td>0.26</td>
<td>0.70</td>
</tr>
<tr>
<td>3</td>
<td>sand</td>
<td>5.90</td>
<td>16.79</td>
<td>0.16</td>
<td>1.80</td>
<td>5.50</td>
</tr>
<tr>
<td>4</td>
<td>sand</td>
<td>10.74</td>
<td>34.86</td>
<td>0.46</td>
<td>1.30</td>
<td>2.50</td>
</tr>
</tbody>
</table>
The bearing capacity at site D1 has mean value of 8.63 and s.d. 0.65. Because of very short horizontal correlation distances employed in this analysis, the influence of the investigation points decays very quickly, and do not contribute very much to the estimation of bearing capacity at point D1. It seems, however, the mean value, 8.63 (MN), is slightly affected by the closest investigation results of TSR-T2, whose mean value is 8.74.

The estimated result at point F, which is very far from all the investigation points, actually gives general uncertainty one encounters at Tone river site. The mean is 8.54 (MN) and s.d. 0.66 (MN).

The horizontal autocorrelation distance estimated in this study, as pointed out in the previous section, is considered to be too short. The bearing capacity of pile at D1 is re-estimated by changing the horizontal autocorrelation distance of layer 4, the thick sand layer that actually controls the bearing capacity, from 2.5 (m) to 20 (m). The result is presented in Table 14 and Figure 12.

The result presented in Figure 12 clearly indicates the considerable reduction of s.d. as well as strong influence of TSR-T2.

4.3.3. General vs. Local RBD

Local and General RBD are discussed in section 3.1. From this view point, the evaluation of vertical ultimate bearing capacity of piles at the investigation points can be called (pure) Local Design (LD), and that at point F can be called General Design (GD). The variation of resulting variability at the investigation points reflects the pure spatial variability of soil properties. In LD, no statistical uncertainty exists, whereas in GD, the resulting uncertainty comes from both the statistical uncertainty and the soil spatial variability.

The evaluations at points A4 and D1 are intermediate cases between the two extreme cases discussed above. However, they can be called, more or less, LD because relative location of the pile and the investigation points are important when the horizontal autocorrelation distances are relatively long.

5. SUMMARY AND CONCLUSIONS

The intensive CPT investigation results at three different sites are used to statistically characterize the spatial variability of soil properties. The statistical procedure based on the maximum likelihood method (MLM) combined with AIC to select the model types are proposed and used in this study. The random component is modeled based on random field (RF) theory where the autocorrelation distance is the key parameter.

Kriging method is employed to interpolate the soil parameter based on the observations. The interpolated values are strongly influenced by the relative position of the investigation points and point estimation is made, autocorrelation distance and variance.
It is important to distinguish between General and Local RBD. It is shown through the example, that there is no statistical and spatial uncertainty in the latter. The resulting variation of the Local Design of pile bearing capacity reflects the spatial variation of soil property. In General RBD, the result include both statistical and spatial uncertainty. Depending on the location of the point the structure is designed, relative influences from statistical and spatial uncertainties change.

Based on the philosophy proposed in this study, following aspects need to be studied further:
(1) Apply the idea to various geotechnical problems to see the importance of distinguish between GD and LD.
(2) Relate the idea to find better location of investigation as well as quantity of investigation.
(3) Combine Kriging with other geotechnical design.

ACKNOWLEDGEMENTS
The authors are grateful to Mr. Yasutsugu Suzuki of Kajima Corporation for providing and advising us on CPT data. We also thank Mr. Yusaku TAMAKI and Dr. Budhi Setiawan for their help in processing data in this study.

REFERENCES