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Characterization of Epistemic Uncertainty in River Dike Risk Assessment considering Spatial Distribution of Soil Layer

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This research focuses on quantifying the Epistemic uncertainty in river dike risk management to derive a method to quantify the "oversight risk" of dangerous soil conditions in accordance with the quantity and quality of soil investigations. Specifically, the spatial distribution of the soil layer is modeled by random fields employing Coupled Markov Chain modeling based on statistical analysis using actual soil investigations that had been conducted for 35 km along the target river dike. Furthermore, Epistemic uncertainty depending on limited soil investigations is quantified by reliability analysis to determine its contribution to river dike risk assessment. Finally, the effects on decision-making associated with optimization of soil investigation intervals and countermeasure priorities are discussed.

Keywords: *River dike*, *Coupled Markov Chain*, *Piping*, *Risk assessment*, *Epistemic uncertainty*

1 Introduction

The purpose of this study is to develop a risk assessment framework that is able to extract the high-risk section considering "oversight risk" based on a quantification of risk associated with the statistical estimation error due to lack of soil investigation. Specifically, the spatial distribution of the soil layer is modeled using random fields employing the coupled Markov chain (CMC) model based on a statistical analysis using actual soil investigations that had been conducted for 35 kilometers along the target river dike.

2 Implementation of CMC model

2.1 Outline of CMC model

A basic idea about the spatial distribution of soil layers employing the CMC model proposed by Li et al(2016). is presented. Figure 1 shows a conceptual dialog about estimation of the soil layer in the CMC model. The region estimated by the CMC model is assumed to be discretized by using same-sized cells. Cell (i, j) is assumed to depend on Cell $(i, j-1)$, Cell $(i-1, j)$ and Cell (N_x, j), while the soil classifications in the leftmost and rightmost columns and uppermost row are assumed to be known from preliminary soil investigations. The existence probability for the soil type classification is denoted by:

$$P_{lr,k|q} = \frac{P^h_{lk} P^{h(N_x-1)}_{kq} P^v_{rk}}{\sum_{f=1}^{m} P^h_{lf} P^{h(N_x-1)}_{fq} P^v_{rf}} \tag{1}$$

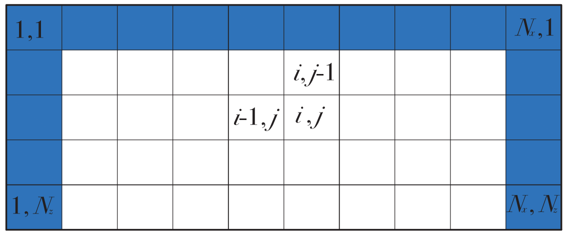


Figure 1 The conceptual dialog about estimation in CMC model

Where, $p_{lr,k|q}$ means the existence probability of Cell(i,j) that the soil classification of the cell is S_k when the soil segments of Cell$(i,j-1)$, Cell$(i-1,j)$, and Cell(N_x,j) are S_l, S_r, and S_q, respectively. Note that P^v and P^h, which are inherent information at the target site, refer to the vertical transition probability matrix and the horizontal transition probability matrix, respectively.

$$P_{ij} = \frac{T_{ij}}{\sum_{f=1}^{m} T_{if}} \tag{2}$$

It is difficult to estimate the horizontal transition probability matrix P^h, since the intervals of soil investigation are basically long in comparison with the auto-correlation distance of the soil layer. A relatively simplified method has already been proposed by Li *et al*(2016). based on Walther's law, which assumes the variance and order for soil layers are the same for both vertical and horizontal deposits. However, this idea, which is assumed after conducting preliminary soil investigations at intervals of several tens of meters, has been developed based on the maximum likelihood estimation method. Therefore, it is difficult to implement directly to the river dike risk assessment problem, on which soil investigations were conducted at very long intervals (i.e. several hundred to thousand meters) along the river dike. In the next section, the possibility of applying the CMC model to practical assessment of the river dike is considered based on grasping the spatial fluctuation characteristics of soil layer composition using actual soil investigations measured along a 35-km first class river dike.

2.2 Estimation transition probability matrix

Figure 2 shows the longitudinal soil layer of the target river dike including foundation ground, where the horizontal axis refers to the distance from the estuary STA (km). The target river dike has already had denser soil investigations conducted than the general river dike, specifically at almost 100 to 200-meter intervals (number of investigations: 62 on right bank, 75 on left bank). In this research, the characteristics of the soil layer composition have been grasped as follows;

STEP 1: The longitudinal soil layer figure is assumed to be true.

STEP 2: The figure is discretized into meshes at intervals of 0.2 meters vertically and 50 meters horizontally.

STEP 3: Scanning the soil classification at each mesh.

From the database, we tried to model the survival probability (the probability can be continued on the same soil classification) using the hazard model Eq. (3) according to the relative distance on each soil classification. Here, the feature of the spatial fluctuation of the soil layer composition is considered by modeling the parameter auto-correlation distance of Eq. (3). Furthermore, the survival probability refers to the diagonal terms of the transition probability matrix.

$$P(Z_{i,j+1} = S_k \mid Z_{i,j+1} = S_k) = \exp(-\frac{\Delta x}{\theta}) \tag{3}$$

Figure 3 (a) shows a scatter diagram representing the relationship between the vertical and horizontal direction auto-correlation distances focused on the difference in survival probability of clay and sand. Note that the survival probability is computed using only shallow data until five-meter depth at two-kilometer pitches along the river dike. Figure 3 (b) shows the auto-correlation distance obtained for each point (2-km intervals) on the left side plotted by soil classification. The upper and lower figures are the vertical and horizontal auto-correlation distances, respectively. Auto-correlation distance has a stationary fluctuation character that is independent of the distance from the estuary. On the other hand, a negative correlation can be confirmed between the autocorrelation distances of clay and sandy soils, such that the autocorrelation distance of clay soil is large, whereas the autocorrelation distance of sandy soil is small. In addition, it was confirmed that the difference between the autocorrelation distances of clay soil and sandy soil increased locally, such as the section surrounded by the red dashed line (2 to 7 km, 9 to 13 km points). Setting the transition probability in the horizontal direction is important, but if we can identify the autocorrelation distance in the vertical direction from the boring investigation, we have the possibility of identifying the autocorrelation distance (transition probability matrix) in the horizontal direction.

3 Trial simulation with simple example

3.1 Calculation conditions

The meaning of the quantification of "oversight risk" is considered in terms of the contribution to reliability based on a relatively simple calculation problem. In this session, we assume a site in which three preliminary boring investigations were conducted at 500-meter intervals. The soil classification was also assumed to be at ground level. In the simplified example in Figure 4 (a), it is assumed that a simple survey is performed to grasp three types of boring investigations (bor1, bor2, bor3) at 500-meter intervals and the surface layer part. Therefore, the prerequisite is that soil classifications are understood for the three sites, where the boring investigations were conducted, and the ground surface in all sections.

In addition, an additional example is computed where the survey interval is halved (bor1, bor2, bor3, add.bor1, add.bor2) as shown in Figure 4 (b).

Figure 5 (a) shows the embankment shape of the river dike used for the calculation. In addition, it is performed assuming that there is no change to the shape of the levee within the study section. Based on this condition, a reliability analysis is performed to confirm whether progressive piping

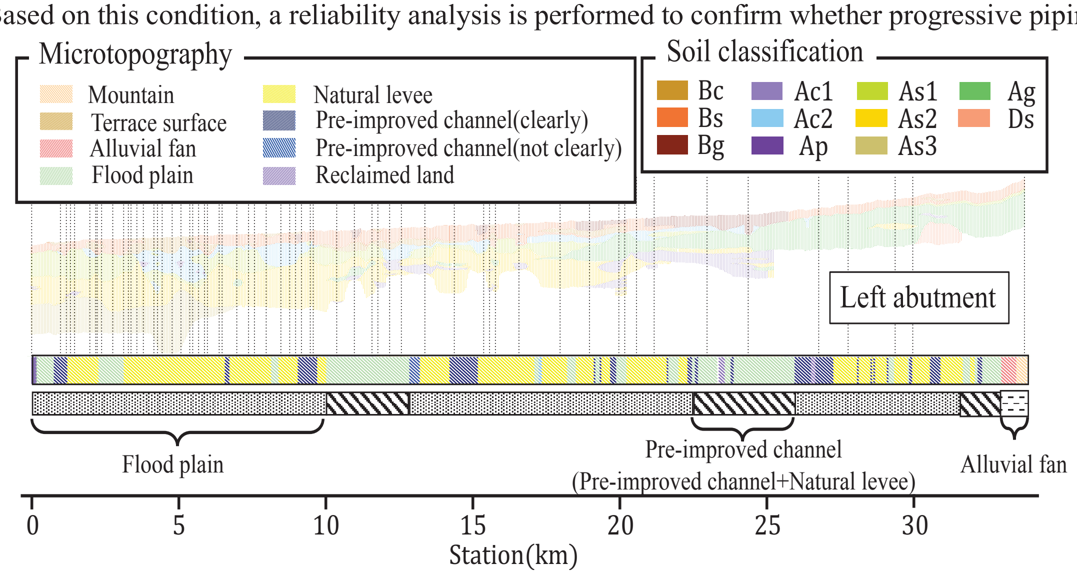
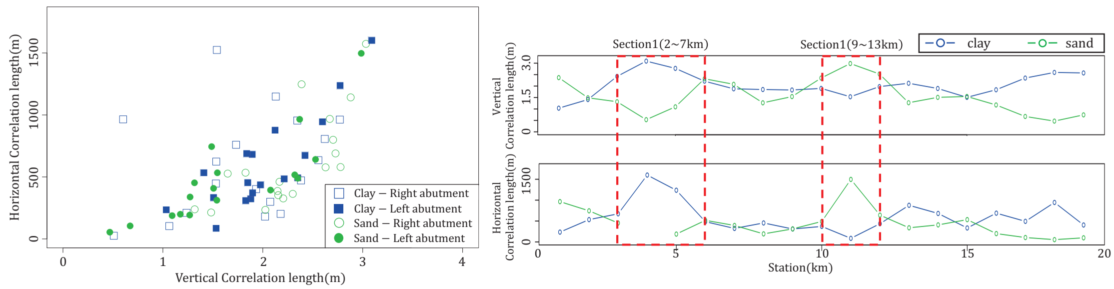


Figure 2 The longitudinal soil layer of the left abutment in target river dike



(a) The relationship between the vertical and horizontal direction auto-correlation distance

(b) The auto-correlation distance on left abutment

Figure 3 The feature of the auto-correlation distance

destruction occurs. The transition probability matrix to be used for the study is set based on two distinctive sections from the analysis of the actual data shown in Figure 3 (b).

(i) Section 1 (2 to 7 km): The auto-correlation distance of clay soil is long and the auto-correlation distance of sandy soil is short.

(ii) Section 2 (9 to 13 km): This shows the opposite characteristic to Section 1; the auto-correlation distance of the sandy soil is long and the auto-correlation distance of the clay soil tends to be short.

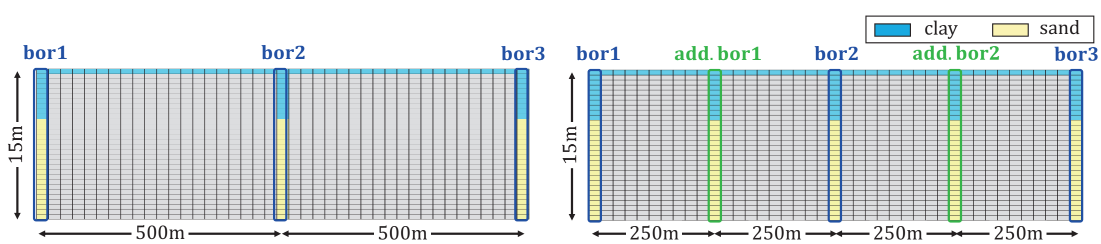
In addition, the transition probability matrix for both sections was picked up from the soil classification for each mesh and was simply calculated using Eq. (2). Figure 5 (b) shows the calculated transition probability matrix. For limitations of this paper, this chapter only shows the results using the transition probability matrix of Section 1, but the results of Section 2 will be presented at the conference.

3.2 Judgment of progressive piping destruction

The calculation procedure as to progressive piping destruction, which has been proposed by Timo (2014) is adopted in this study. Timo (2014) proposed to model the progress of the piping phenomenon as a parallel system of three limit states: UPLIFT, HEAVE and PIPING. The closed form equation for calculation corresponding to each limit state (UPLIFT, HEAVE and PIPING) has adopted the design method in the Netherlands, which was confirmed through many kinds of in-house and field experiments. Where, performance function for UPLIFT Z_u, HEAVE Z_h, and PIPING Z_p are given as follows:

$$Z_h = h_{ch} - h_{obs} \qquad Z_u = h_{cu} - h_{obs} \qquad Z_p = h_{cp} - h_{obs} \tag{4}$$

Where, each performance function is expressed by the difference the limited water level (m) reached in each limit state and the flood water level (m) obtained by actual observation. The basic variables related to the calculation are set the same values as Timo(2014).



(a) 500-meter investigation intervals

(b) 250-meter investigaion intervals

Figure 4 The calculation condition of the boring investigations intervals

3.3 Calculation procedure

STEP 1: Generation of a certain CMC field

A certain random field ( ) for soil layer composition is generated using the CMC model with a transition probability matrix. It is called a CMC field in this paper.

STEP 2: Calculation of conditional failure probability

The limited water level (m) and failure probability are calculated based on the certain CMC field generated by STEP 1 using performance functions. The conditional failure probability is calculated for a certain CMC field by MCS.

$$P(F\,|\,R_i) \cong \frac{1}{n}\sum_{j=1}^{n} I[Z_u \le 0 \cap Z_h \le 0 \cap Z_p \le 0] \tag{5}$$

STEP 3: Calculation of total failure probability

The conditional probability is converted to the total probability by iterative calculation of STEP 1 and STEP 2. Since the generation probability of the CMC field is 1/n, the total probability is obtained by calculating the expectation value of the conditional fracture probability.

$$\begin{aligned} P(F) &= P(F\,|\,R_i)P(R_i) \\ &= \frac{1}{N}\frac{1}{n}\sum_{i=1}^{N}\sum_{j=1}^{n} I[Z_u \le 0 \cap Z_h \le 0 \cap Z_p \le 0] \end{aligned} \tag{6}$$

STEP 4: Calculation of the contribution for “oversight risk”

In this study, the contribution method by Honjo and Otake** is adopted to separate the effect of each uncertainty source. The uncertainty sources consist of two groups, (a) Aleatory Uncertainty (i.e. Model error, Inherent variability of each parameter,) and (b) Epistemic Uncertainty (i.e. Uncertainty of the soil layer modeled using the CMC model). The contribution of each uncertainty source is calculated by Eqs. (9) and (10).

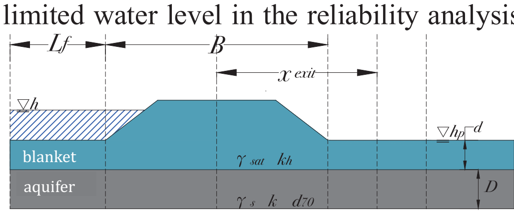
$$\alpha_{Ale}^2 = 1 - \frac{\beta^2}{\beta_{-Ale}^2} \tag{7}$$

$$\alpha_{Epi}^2 = 1 - \alpha_{Ale}^2 \tag{8}$$

Where, β^2 represents the reliability index when considering all uncertainty sources, β_{-Ale}^2 represents the reliability for variance of all basic variables equal to 0. α_{Ale}^2 and α_{Epi}^2 refer to the contribution of Aleatory Uncertainty and Epistemic Uncertainty respectively.

4 Results and Considerations

Figures 6 (a) and 6 (b) show the calculation results for 500- and 250-meter intervals respectively. First, Fig. 7 (a) is focused on. The first figure in Fig. 7 (a) shows an example of the CMC field, and the second and third figures show the piping fracture probability and the distribution of the limited water level in the reliability analysis, respectively. In the fourth figure, the contribution

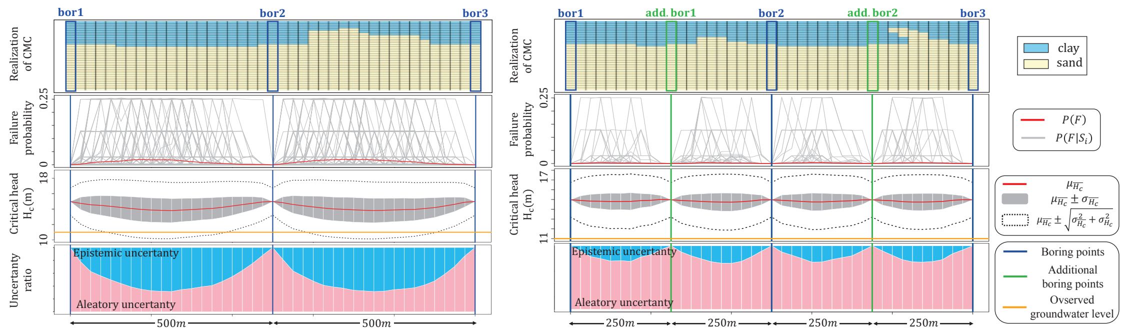


	VTPM			HTPM (from river mouth)			HTPM (from headstream)		
soil type	clay	sand	gravel	clay	sand	gravel	clay	sand	gravel
clay	0.953	0.047	0.000	0.942	0.058	0.000	0.939	0.061	0.000
sand	0.003	0.992	0.005	0.021	0.972	0.007	0.020	0.973	0.007
gravel	0.000	0.040	0.960	0.000	0.052	0.948	0.000	0.052	0.948

(a) The embankment shape of the river dike used for the calculation

(b) The estimated transition probability matrices in section

Figure 5 The basic condition used for calculation



(a) 500-meter investigation intervals (b) 250-meter investigation intervals

Figure 6 The example calculation results according to investigation intervals

ratios of Epistemic Uncertainty and Aleatory Uncertainty are shown. In this study, reliability analysis is performed on 500 CMC fields.

The blue vertical line in the figure at the first figure is an investigation point at 500-meter intervals assuming the initial investigation, and the green line is an investigation point at 250-meter intervals assuming additional investigation. In the distribution of failure probability in the second figure, the red line is the average (total probability) of the fracture probability, and the conditional fracture probability obtained in gray for each CMC field. The farther from the investigation point, the more the fluctuation amount of the failure probability increases and the average (total probability) also increases.

In the distribution of the limited water level in the third figure, the red line shows the average, the black broken line shows the range of one standard deviation, and the black shaded area shows the variation due to epistemic uncertainty. The yellow line is the designed external force (flood level) of 11.0 meters. From these results, in the auto-correlation distance calculated from the actual survey, using a survey interval of about 200 to 250 meters, the uncertainty (Epistemic Uncertainty) due to insufficient investigation becomes the dominant uncertainty factor, and the possibility of oversight increases. Figure 7(b) shows the result when the investigation interval is halved (250-m pitch), but in this case, the Epistemic Uncertainty is greatly reduced and the possibility of overlooking the stratum structure is small. As can be seen from the above consideration, the approach of this study can quantify the risk of overlooking piping ruptures caused by permeability of the foundation ground of the river dike, and it was confirmed to provide important information for reasonable facility management of the river levee.

5 Remarks

In this study, the qualification of "oversight risk" for high-risk sections along the river dike and contributions related to Epistemic uncertainty sources are calculated. In the future, a standard interval will be proposed for similar river dikes based on various kinds of trial calculations and extended to optimization of soil investigation planning employing the VOI concept.

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