



Research Paper

Conditional random field reliability analysis of a cohesion-frictional slope



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ABSTRACT

Discarding known data from cored samples in the reliability analysis of a slope in spatially variable soils is a waste of site investigation effort. The traditional unconditional random field simulation, which neglects these known data, may overestimate the simulation variance of the underlying random fields of the soil properties. This paper attempts to evaluate the reliability of a slope in spatially variable soils while considering the known data at particular locations. Conditional random fields are simulated based on the Kriging method and the Cholesky decomposition technique to match the known data at measured locations. Subset simulation (SS) is then performed to calculate the probability of slope failure. A hypothetical homogeneous cohesion-frictional slope is taken as an example to investigate its reliability conditioned on several virtual samples. Various parametric studies are performed to explore the effect of different layouts of the virtual samples on the factor of safety (FS), the spatial variation of the critical slip surface and the probability of slope failure. The results suggest that whether the conditional random fields can be accurately simulated depends highly on the ratio of the sample distance and the autocorrelation distance. Better simulation results are obtained with smaller ratios. Additionally, compared with unconditional random field simulations, conditional random field simulations can significantly reduce the simulation variance, which leads to a narrower variation range of the FS and its location and a much lower probability of failure. The results also highlight the great significance of the conditional random field simulation at relatively large autocorrelation distances.

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1. Introduction

Slope stability is a serious geotechnical problem that is characterized by various uncertainties [1]. The uncertainties generally originate from the spatial variability of soil properties [2,3], the limited site investigation data, the assumptions and simplifications in the adopted stability model, etc. [4]. Among these sources, the inherent spatial variability of soil properties has been identified as the most dominating source of uncertainty in geotechnical engineering [5–7]. Therefore, random field theory [8] is often utilized to effectively characterize the spatial variability of soil properties in a slope stability model. Based on this framework, slope reliability analysis is then performed using a probabilistic analysis approach.

Various reliability approaches that are able to consider the spatial variability of soil properties have been proposed in recent decades. Some of these approaches are briefly described as follows: El-Ramly et al. [1] employed 1-D weak stationary random fields to consider the spatial variability of soil properties along a slip surface by the limit equilibrium method (LEM). Griffiths and Fenton [9] investigated the effects of spatial variation of the undrained cohesion on the slope system reliability using a random finite element method (RFEM). Cho [10] proposed a numerical procedure-based Monte Carlo simulation (MCS) for probabilistic analysis of slopes in spatially variable soils. Wang et al. [11] implemented an enhanced MCS termed Subset simulation (SS) in a spreadsheet to perform slope reliability analysis with the ability to consider spatial variation of soil properties. Ji et al. [12] proposed two 2-D random field discretization methods known as interpolated autocorrelations and autocorrelated slices for slope reliability analysis in the presence of spatially varying soil parameters. Jiang et al. [13] adopted a multiple stochastic response surface method

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(SRSM) and MCS to efficiently evaluate the failure probability of a slope in spatially variable soils. Other methods are summarized in Table 1 in chronological order.

Based on Table 1, it is found that great achievements have been obtained in the area of slope reliability analysis for spatially variable soils. On the other hand, it is observed that most of the studies focus mainly on the unconditional random field simulation, which is realized using only the statistics (e.g., means, standard deviations and autocorrelation distances) of the limited site investigation data and discards the actual data. Site investigation data generally exist in an engineering project, even though the amount of data may not be excessive. These data reflect the reference true values of the soil properties at certain locations, which should remain invariant in each random field simulation. The traditional unconditional random field discards such known data, which represents a waste of site investigation effort. Additionally, neglecting the known data increases the simulation variance of the underlying random fields, which subsequently affects the responses, such as the factor of safety (FS) and the probability of failure, of the whole slope system. Hence, it is of practical significance to take the known data into account in slope reliability analysis, which can be considered as an effective tool for reducing the uncertainties in slope analysis.

In the literature, there are very few previous works on slope reliability analysis based on conditional random fields [19,22], and these previous works suffer from many deficiencies, which should be addressed. For example, Kim and Sitar [22] only investigated the effect of a specific number of cored samples on the probability of slope failure. However, the effect of the number of samples was not evaluated or quantified. Additionally, only one slip surface was considered in their work, which would obviously underestimate the failure probability of the slope because various works have demonstrated that the system effect of the slope reliability [21,28,29] can be more controlling in many cases. As another example, Wu ZJ et al. [19] studied the effect of conditional samples on the reliability of a homogeneous cohesive slope using RFEM. The isotropic 2-D random field was considered in their paper; however, the spatial variations in the soil properties in the horizontal and vertical directions are quite different in reality [6,26]. Furthermore, the failure probability of the slope analysed in their paper is also very large. However, events with small failure probabilities in slope reliability analysis are of greater interest to

researchers and engineers. Similar problems to those in the works by Kim and Sitar [22] are also identified.

The present work is thus inspired by the limitations of previous works. The objectives of this paper are to (1) propose an effective method for simulating conditional random fields that account for the known data from cored samples, (2) efficiently evaluate the reliability of a slope based on the proposed method, (3) study the effects of different layouts of cored samples on the conditional random field simulation, and (4) investigate the effects of the statistics of soil properties on the conditional simulation results. To achieve these objectives, the remainder of this paper is organized as follows. Sections 2 and 3 introduce the simulation of the unconditional and conditional random fields, respectively. Section 4 describes the probabilistic analysis approach adopted in this study. The implementation procedure for the proposed conditional probabilistic analysis of slope stability is then detailed in Section 5. The stability of a hypothetical cohesive-frictional slope is evaluated as an example to illustrate the proposed method in Section 6. The summary and conclusions of this study are given in Section 7.

2. Simulation of unconditional random field

Random field theory has been extensively applied to characterize spatially variable soils in slope reliability analysis [9,10,13,22,23]. Within the framework of random field theory, the soil parameters at particular locations are often considered as random variables. The resultant random field is called stationary or weakly stationary if the statistics (i.e., means and standard deviations) of these random variables are constant over the domain of the random field; otherwise, the field is non-stationary [30]. In a slope reliability analysis, a weakly stationary random field is usually applied to model the spatial variability of a soil parameter in a homogeneous soil layer, whereas a non-stationary random field is suitable for multi-layered soils [26].

According to Lu and Zhang [31] and Cho [32], in the simulation of a non-stationary random field for a multi-layered soil slope, the simulation domain is required to be divided into several non-overlapping subdomains. Soil parameters at any two points in different subdomains are assumed to be uncorrelated. However, the soil parameters in each subdomain are characterized by stationary or weakly stationary random fields, where the correlation between any two points depends merely on their absolute distance instead

Table 1
Summary of reliability analysis of slopes in spatially variable soils.

No.	References	Reliability methods	Random field discretization methods	Simulation types
1	El-Ramly et al. [1]	MCS	Local average	U
2	Low [14]	FORM	Midpoint method	U
3	Griffiths and Fenton [9]	RFEM	Local average	U
4	Fenton and Griffiths [15]	RFEM	Local average	U
5	Hsu and Nelson [16]	MCS	Local average	U
6	Cho [10]	MCS	Midpoint method	U
7	Hicks et al. [17]	MCS	Local average	U
8	Griffiths et al. [18]	RFEM	Local average	U
9	Wu ZJ et al. [19]	RFEM	Local average	C
10	Cho [20]	MCS	Karhunen-Loève (K-L) expansion	U
11	Huang et al. [21]	RFEM	Local average	U
12	Wang et al. [11]	SS	Midpoint method	U
13	Ji et al. [12]	FORM	Interpolated autocorrelations	U
14	Kim and Sitar [22]	FOSM	Local average	C
15	Jha and Ching [23]	RFEA	Local average	U
16	Low [24]	FORM/SORM	Interpolated autocorrelations	U
17	Jiang et al. [25]	NISFEM	K-L expansion	U
18	Jiang et al. [13]	SRSM-based MCS	K-L expansion	U
19	Li et al. [26]	MRSB-based MCS	Midpoint method	U
20	Li et al. [27]	RFEM-based SS	Midpoint method	U

Note: "U" and "C" in the table denote the unconditional and conditional simulation, respectively.

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