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RANDOM LARGE DEFORMATION ANALYSIS OF UNSATURATED SLOPES USING DATA-DRIVEN AND PHYSICS-INFORMED METHOD

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Abstracts:Landslides would travel certain distances during the post-failure period. Once occur, the human's lives and properties along its runout route will be threatened, underlining that the accurate estimation of landslide consequence is of great necessity. In this study, a data-driven and physics-based random coupled Euler-Lagrange (RCEL) method is proposed to evaluate the unsaturated slope horizontal runout distance. During the slope initial failure stage, both the site investigation data and field monitoring data are adopted to conduct the Bayesian updating and then the conditional random fields can be generated. Both the spatial variability and the epistemic uncertainty can be considered. During the subsequent post-failure stage, the RCEL analysis is performed and the influence of the soil strain softening on the landslide runout behaviours is also discussed. A case study of Baishuihe landslide in the Three Gorges Reservoir area of China is selected as an example to demonstrate the application of the developed method. It is found that both Bayesian updating and soil strain softening effect cannot be overlooked, otherwise the landslide runout distance would be underestimated.

Keywords: Random large deformation analysis, spatial variability, unsaturated slopes, coupled Euler-Lagrange method, strain softening, data-driven and physics-informed.

1. Introduction

Landslide is a catastrophic geohazard which could cause serious threats to the human's lives and properties (Augarde et al. 2021; Chen et al. 2021b; Lu et al. 2023). Therefore, it is of great significance to conduct an accurate prediction of the slope performance and its failure consequence, which would provide valuable guidelines for disasters mitigation and facilitate the life-cycle risk management.

Although the conventional reliability analysis can provide an estimation for the slope failure probability (P_f), just those areas with great possibility of landslide occurrence can be identified(Zhu et al. 2013; Chen et al. 2021a; Guardiani et al. 2021; Ng et al. 2024). As for the detailed influential range and geohazard consequence, it would be difficult to conduct the assessment during the landslide initialization period. To reasonably and quantitatively estimate the landslide disaster consequences, a series of studies have been performed in recent years, such as field monitoring via sensors and numerical modelling. For example, several typical techniquesare commonly used for surface deformation monitoring, i.e., Global Positioning System (GPS), synthetic aperture radar interferometry (InSAR) and traditional geodesy(Yin et al. 2010; Benoit et al. 2015; Schulz et al. 2017).As for the deep displacement of landslide, drilling inclinometer, flexible inclinometer and optical fiber sensing technology are mainly used for monitoring(Kang et al. 2009). However, compared with the on-site monitoring, the latter numerical modelling may be low-cost and time-efficient. As such, the numerical modelling is widely adopted by many researchers to investigate the landslide post-failure behavior.

Currently, common numerical methods for slope large deformation analysis include smooth particle fluid dynamics (SPH), discrete element method (DEM), matter point method (MPM), coupled Euler-Lagrange method (CEL)(Augarde et al. 2021; Chen et al. 2021a; Chen et al. 2021b; Ren et al. 2023).Chen et al. (2021b)developed a slope instability criterion based on energy sudden change within CEL framework. Zhang et al. (2020) used the random SPH method to explore the mechanism of the influence of the spatial variability of friction angle on the deformation behavior during the post-landslide failure stage. Wang et al. (2018)employed the MPM to investigate the large deformation and failure process of the slope after rainfall instability, and the strain softening effect of the soil strength parameter was taken into account.Chen et al. (2021a) developed the CEL method, where the evaluation of the entire failure process of rainfall landslide was achieved and the influence of soil strength parameter strain softening effect was also quantified. Within this framework, Chen et al. (2020) studied the influence mechanism of large deformation failure of submarine landslides and its influence the adjacent pipelines. It can be obtained that most researchers are mainly focused on the impacts of spatial variability and the strain softening effect on the landslide large deformation evaluation results. However, aside from the spatial variability, there exist many other types of uncertainties in geotechnical engineering, such as the epistemic uncertainty. Also, most studies primarily employed the conditional random field theory to carry out the random large deformation analysis. Thirdly, the newly emerged method, namely data-driven and physics-informed, is a research hotpot in recent years. And how to extend the application of such method in the estimation of landslide large deformation behaviors deserves to be further studied.

This study aims to propose a novel data-driven and physics-informed random large deformation framework to investigate the large behaviors for unsaturated slopes. Both the spatial variability and the epistemic uncertainty of geotechnical parameters can be simultaneously considered. Then, the Baishuihe landslide example in the Three Gorges Reservoir area of China is used to illustrate the proposed framework.

2. Data-driven and physics-informed random large deformation analysis

The proposed data-driven and physics-informed method (see Fig. 1) is composed of the following two steps. The first is to conduct the back analysis of geotechnical parameters using the field monitoring data, followed by the characterization of the conditional random fields for the soil profile based on the site investigation data. Then, the final generated random fields can be input into the finite element software and thereby the landslide runout behaviours can be estimated. Herein, it should be mentioned that the data-driven is reflected in the first step and the generated soil profile is as close as possible to the reality by fully utilizing the data available. Due to the employment of finite element software to predict the landslide runout distance, the physics-informed seepage analysis, the slope stability analysis and the subsequent CEL analysis are completed by turn. The calculated pore water pressure, saturation and the node stress obtained during the landslide initialization stage will be the initial conditions for the latter large deformation analysis. More detailed information about CEL can be found inChen et al. (2021a). During the landslide post-failure stage, the strain softening may occur and the soil strength parameters would decrease with the development of the soil deformations. And in this study, a widely used strain softening model (see Fig. 2) is selected(Rafiei Renani and Martin 2020), as shown in Eq. (1).

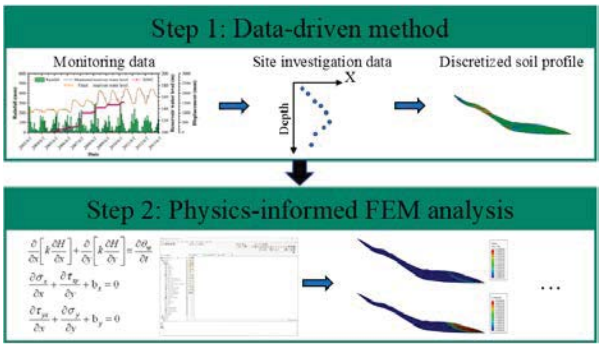

Fig. 1Flow chart of the proposed method

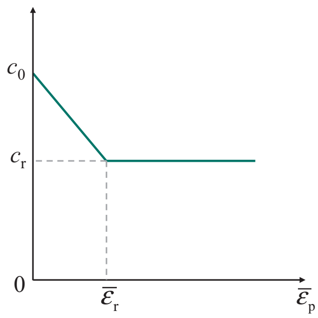

Fig. 2 Strain-softening model

$$c = \begin{cases} c_0 - (c_0 \text{-} c_r) \cdot \bar{\varepsilon}_p / \bar{\varepsilon}_r, & \bar{\varepsilon}_p \le \bar{\varepsilon}_r \\ c_r, & \bar{\varepsilon}_p > \bar{\varepsilon}_r \end{cases}$$
$$\varphi = \varphi_0 \qquad , \quad \text{Arbitrary } \bar{\varepsilon}_p \tag{1}$$

where$c$ and Æare the cohesion and friction angle of soil when considering the strain softening effect. c_0 and Æ0 are the initial soil cohesion and friction angle without considering the strain softening effect, whilec_r is the soil residual cohesion after strain softening. $\bar{\varepsilon}_p$ is the soil's cumulative plastic strain and $\bar{\varepsilon}_r$ is the soil's residual cumulative plastic strain when the cohesion reaches the residual value.

3. Illustrative example

Baishuihe landslide is 56 km west of the Three Gorges Dam, located at the Ziguicounty, Hubei Province, China. A cross-section 1-1' is selected for investigation, including two constituents (i.e., Zone A and Zone B). Compared with Zone B, Zone A is the sliding area. Consequently, the RCEL analysis is just conducted for Zone A using the data-driven and physics-informed framework. As for this area, the primary components are the quaternary deposits. Fig. 3 displays the cross-section 1-1'of Baishuihe landslide discussed inthis study. The statistical information for the geotechnical parameters is tabulated in Table 1. In this study, a total of four cases are designed for comparison. In Case 1 and 2, Bayesian updating is not conducted while the effect of strain softening is analysed. As for Case 3 and 4, the impact of the soil strain softening is selected for compared after performing Bayesian updating. Herein, three Markov chains with 5000 samples on each chain can guarantee the convergence. The time-series monitoring data can be found in Gu et al. (2024).

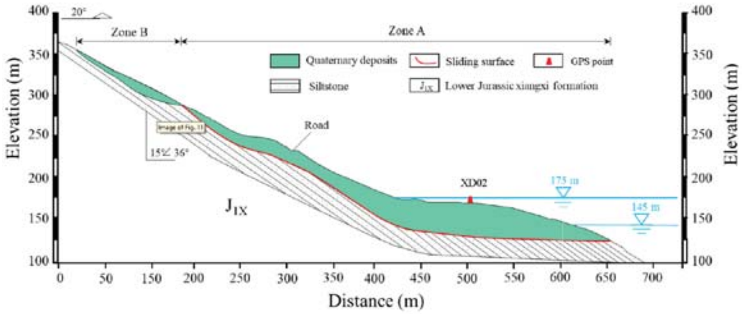

Fig. 3Cross-section 1-1'of Baishuihe landslide

Table 1. Basic information of geo-parameters at Baishuihe landslide.

Parameter	Mean	COV	Distribution	Min	Max
c' (kPa) ※	42.8	0.3	Lognormal	2	50
Æ(°)※	18	0.2	Lognormal	12	21.9
E (MPa)	10	0.2	Lognormal	8	11.5
k_s (m/month) ※	16.459	0.5	Lognormal	12.2	20
± (kPa^{-1})	0.233	0.25	Lognormal	0.17	0.28
n	1.255	0.15	Uniform	0.93	1.58
Á (kg/m^3)	2070	-	-	-	-
½	0.2	-	-	-	-
´$_h$ (m)	48	-	-	-	-
´$_v$ (m)	4.8	-	-	-	-

Note: Notations with superscript "※" denote the spatially varying parameters.

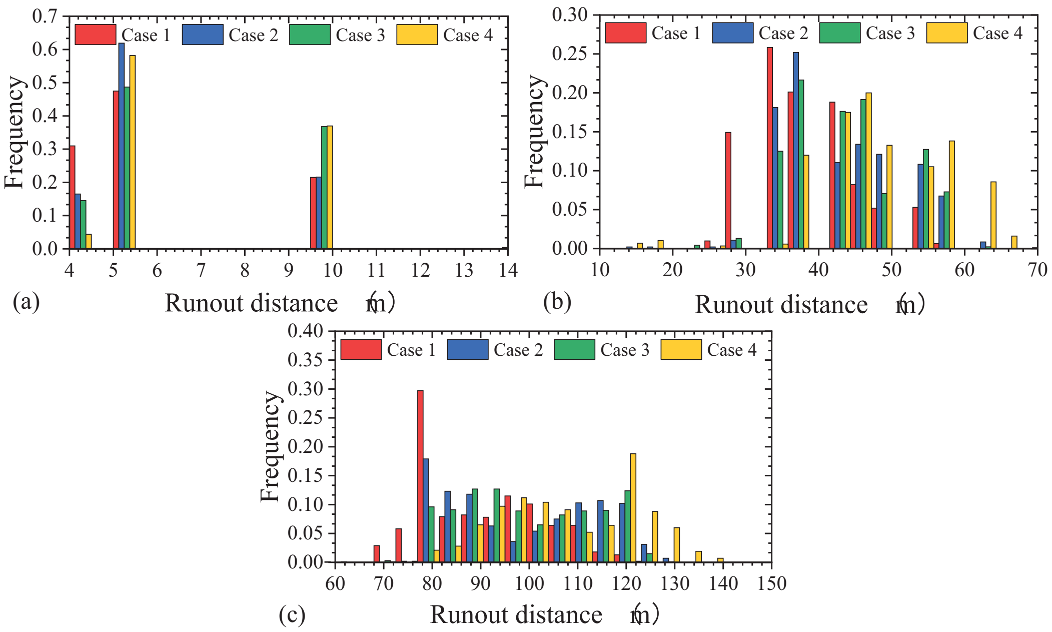

Fig. 4Influence of Bayesian updating and strain softening effect on Baishuihe landslide runout distance: (a) t=2 s; (b) t=4 s and (c) t=6 s

Thefrequency histograms of horizontal runout distance under different conditions are plotted in Fig. 4, where the influences of Bayesian updating and strain softening are discussed. It can be observed that the landslide horizontal runout distance is slightly affected by the spatial variability of soil strength parameters during the initial sliding stage (i.e., t=2s), as shown in Fig. 4(a). With the intensification of the sliding trend, the landslide horizontal runout distance will be significantly affected by the spatial variability of soil parameters, as shown in Fig. 4(b) and 4(c), highlighting the necessity of the RCEL method for reasonably predicting the potential sliding distance of the Baishuihe landslide. Otherwise, inaccurate predictions may be provided when ignoring the spatial variability.

Also, it can be further derived from Fig. 4 that the Baishuihe horizontal runout distance would travel further when considering the soil strain softening. And this may not be influenced by whether to firstly implement Bayesian updating. However, according to a comparison between Case 1 and Case 3 (or between Case 2 and Case 4), it can be found that characterization of soil parameter profile is of great significance after Bayesian updating using the field monitoring data. This can avoid the underestimation of the landslide horizontal runout distance.

4.Conclusions

In this study, a data-driven and physics-informed framework is developed to be combined with random coupled Euler-Lagrange method (RCEL) analysis. Baishuihe landslide is selected as an example to showcase the application of the proposed method. Results showed that the spatial variability, epistemic uncertainty and the soil strain softening effect should be taken into account. This can contribute to the reasonable estimation of the landslide runout distance.

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