Sensing time-variant risk of rainfall-induced landslides using slope digital twins

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ABSTRACT: Digital twin is deemed as a core technology for building a smart city and Industry 4.0, and it has great potential to be applied to quantitatively sense the time-variant risk of a rainfall-induced landslide by developing a slope digital twin. A slope digital twin is a virtual slope model that can continuously learn from various field observations (e.g., monitoring data, site investigation data, slope performance records) collected from its physical counterpart to enhance the performance of the slope model. This study develops a slope digital twin for a real slope in Hong Kong using monitoring data and slope survival records, and uses the slope digital twin to predict time-variant soil hydraulic responses (e.g., pore water pressure) and slope stability (e.g., factor of safety and slope failure probability) under rainfall infiltration. A two-level Bayesian updating scheme is adopted to learn from field observations and update the slope model. Results show that incorporating monitoring data and slope survival records leads to reduced uncertainties in soil hydraulic and strength parameters. The updated slope model predicts time-variant soil hydraulic responses under rainfall infiltration consistent with the field measurements. The predicted time-variant slope factor of safety and slope failure probability properly reflect rainfall infiltration mechanism and are verified by field observations. Slope digital twins provide a novel tool for sensing the time-variant risk of rainfall-induced landslides.

Rainfall-induced landslides are a major geo-hazard in mountainous regions. Rainfall infiltration can decrease soil matric suction and elevate groundwater table, and potentially induce a slope failure. Under a changing environment, slope stability is closely associated with time-variant slope responses (e.g., pore water pressure (PWP), displacement) and environmental factors (e.g., rainfall) (Lu and Godt, 2013). In addition, soil parameters often contain large uncertainties due to a lack of site investigation data (Phoon and Kulhawy, 1999). Therefore, landslide risks vary with time and are challenging to be quantified.

Digital twin has been deemed as a core technology for building a smart city and Industry 4.0 (Grieves and Vickers, 2016). A slope digital twin is a virtual slope model that can continuously learn from various field observations (e.g., monitoring data, site investigation data, slope performance records) collected from its physical counterpart to enhance the performance of the slope model (Liu et al., 2022). Although a slope digital twin could leverage various types of field observations and provide a tool for lifetime landslide risk management, its development and application have rarely been investigated in previous studies.

Liu et al. (2022) proposed a slope digital twin framework for sensing time-variant risk of rainfall-induced landslides. The framework is applied in this study to develop a slope digital twin for a real slope in Hong Kong using monitoring data and field observations. The slope digital twin is used to predict time-variant soil hydraulic responses (e.g., PWP) and slope stability (e.g., factor of safety (*FS*) and slope failure probability (*PF*)) under rainfall infiltration. A two-level Bayesian updating scheme is adopted to learn from field observations and update the slope model. The framework for developing a slope digital twin is introduced in Section 1, followed by the two-level Bayesian updating scheme in Section 2. Section 3 presents the application of the slope digital twin to a real slope in Hong Kong. Finally, key conclusions are drawn in Section 4.

1. FRAMEWORK FOR DEVELOPING A SLOPE DIGITAL TWIN

Figure 1 schematically illustrates a framework for developing a slope digital twin with five major modules (Liu et al., 2022):

Modules (a) & (c): A soil slope in the physical space may be vulnerable to rainfall-induced landslides. Slope stability is closely related to some time-variant soil responses and environmental factors, such as PWP, rainfall, crack length, displacement, groundwater table, and slope performance records (stable or failed). These quantities can be automatically monitored by different types of monitoring instruments or sensors, such as piezometers, rain gauges, wire crack meters, inclinometers, observation wells, and video cameras (Marr, 2013). For example, a piezometer buried in the soil can monitor the time series of PWP at a certain depth. In addition, the field observations that a slope stays stable during past rainfall events (i.e., slope survival records) are also a valuable source of qualitative information (actual *FS* > 1, Zhang et al., 2011), and they can be visually obtained from a video camera installed on the slope. Monitoring data measured from different sensors can be gathered and transferred to a cloud server via networks (e.g., cellular network, Internet of Things) in real time or periodically. Thus, all slope monitoring data can be stored, visualized, and analyzed online and in real-time to develop a slope digital twin.

Module (b): Although establishing a purely data-driven slope model may be an attractive way for developing a slope digital twin, slope monitoring data (e.g., monitoring data associated with slope failure) and site investigation data are often insufficient for training an accurate data-driven slope model. A physics-based slope model, or several candidate slope models, are established in this study for the development of slope digital twin. Physics-based slope models have been widely used in geotechnical practice and are able to predict soil hydraulic and mechanical responses (e.g., PWP, displacement) under rainfall accurately. The slope model should be able to perform slope seepage and stability analyses under rainfall infiltration and contain virtual monitoring points that correspond to the actual locations of monitoring instruments. A fully coupled or two-stage slope model may be established according to slope geometry, stratigraphy, and measurements of soil properties (Lu and Godt, 2013).

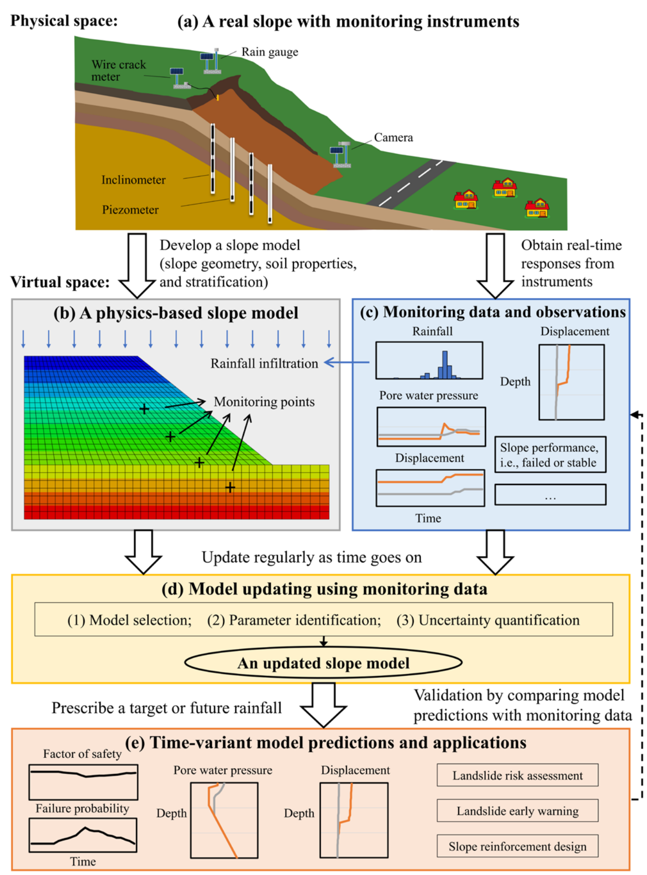


Figure 1: A framework for developing a slope digital twin (after Liu et al., 2022).

Module (d): The slope model developed in module (b) inevitably contains uncertainties and errors, and its performance would be degraded as time goes on. The model updating using monitoring data is a key module for developing a slope digital twin, leading to an updated slope model. Bayesian updating or probabilistic back analysis under a Bayesian framework provides a rigorous tool for incorporating different types of field observations (e.g., monitoring data, site investigation data, prior knowledge) (e.g., Vardon et al., 2016; Yang et al., 2021). It is able to utilize field observations to reasonably select the most suitable slope model, identify soil parameters, and quantify various types of uncertainties (e.g., spatial variability of soil parameters). For example, Liu and Wang (2021) developed a Bayesian method to select the most suitable slope hydraulic model and identify the most probable soil hydraulic parameters using monitoring data of PWP.

Module (e): After model updating using monitoring data, the updated slope model is used to predict time-variant slope responses, such as PWP, displacement, *FS*, and *PF* during a target or future rainfall event. These model predictions can be compared and verified by actual monitoring data measured from the slope in future. These model predictions may provide useful references for landslide risk assessment, landslide prediction and early warning, and slope reinforcement design. The slope digital twin framework may provide a useful tool to utilize existing monitoring data and mitigate landslide risks.

2. A TWO-LEVEL BAYESIAN UPDATING SCHEME

Figure 2 shows a two-level Bayesian updating scheme developed by Liu et al. (2022) for the abovementioned model updating and prediction modules. In this scheme, a slope digital twin is developed using site-specific observations and prior knowledge, including the existing databases of soil hydraulic and strength parameters, monitoring data of PWP and rainfall, and slope survival records from past rainfall events. A slope seepage and stability analysis model is first developed for a real slope. The existing databases of soil parameters are used to determine prior distributions of uncertain soil parameters. Then, monitoring data of PWP and rainfall in the slope are used to perform the first level of model updating or Bayesian updating, which aims at selecting the most suitable slope hydraulic model, identifying the most probable soil hydraulic parameters, and quantifying the uncertainties in soil hydraulic parameters. Then, model updating results obtained from the first model updating are used as prior knowledge for the second level of model updating, which utilizes slope survival records to update soil parameters, especially soil strength parameters that significantly affect slope stability but are not updated in the first level of model updating. Thus, the two-level model updating identifies both soil strength and hydraulic parameters and quantifies their uncertainties for model prediction. Then, a target rainfall is imposed on the updated slope model to predict PWP, *FS*, and *PF*. The detailed formulation for the Bayesian updating scheme is referred to Liu et al. (2022).

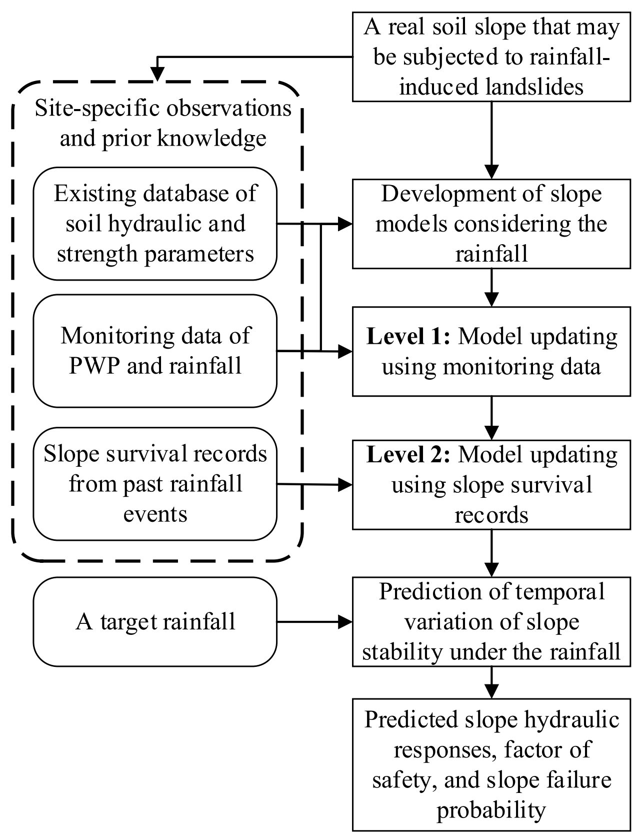


Figure 2: A two-level Bayesian updating scheme for model updating and prediction (after Liu et al., 2022).

3. A REAL SLOPE EXAMPLE

The proposed slope digital twin framework is applied to a terrain slope made of colluvial/residual soil in Hong Kong for illustration. As shown in Figure 3, the slope is located at Tung Chung East on North Lantau Island of Hong Kong, and it is vulnerable to rainfall-induced landslides. The Geotechnical Engineering Office of Hong Kong launched a slope monitoring program in 1999 to monitor slope displacement and hydraulic responses at the site using different types of monitoring instruments, such as rain gauges, shallow piezometers, movement marks, etc (Evans and Lam, 2003).

Figure 4 shows monitoring data of PWP measured from shallow piezometer SP3 and hourly rainfall from rain gauge R2 from 22 – 30 June 2001. PWP measurements increased from about -0.8m to a maximum value of 0.2m when the hourly rainfall reached a maximum value of 31mm on 27 June, and decreased to negative values when there was negligible rainfall afterward. In addition, movement marks showed that no failure or significant movement occurred at the slope site during this period.

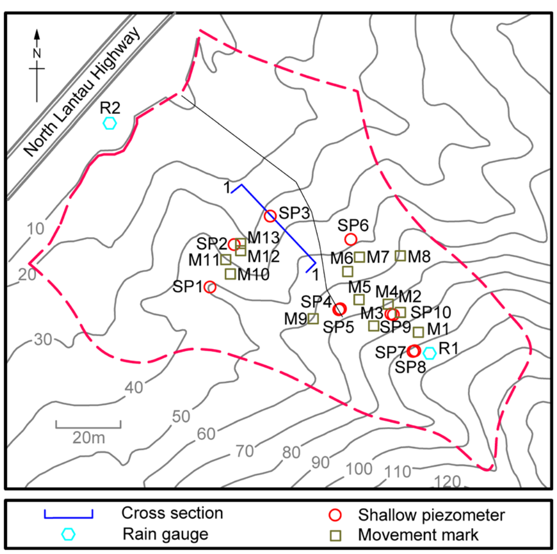


Figure 3: A terrain slope with monitoring instruments at Tung Chung East, Hong Kong (modified from Evans and Lam (2003) and Yang et al. (2021)).

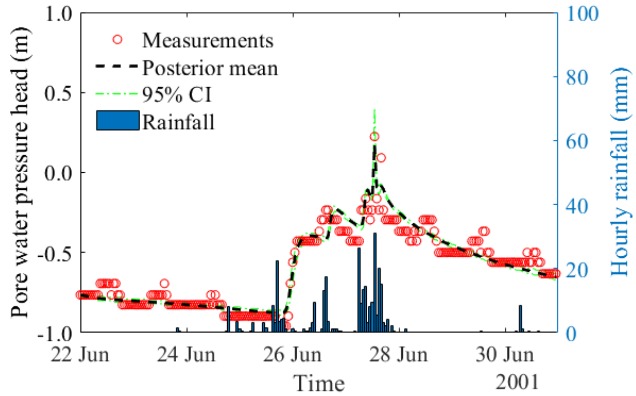


Figure 4: Monitoring data of PWP and rainfall during 22 – 30 June 2001 at the slope site and back analyzed PWP responses.

The monitoring data of PWP and rainfall shown in Figure 3 and the observed slope survival record from the rainfall event are utilized in this study to develop a slope digital twin for cross-section 1-1. This cross section is represented by an infinite slope model under rainfall infiltration with an inclination of 40° and a vertical depth of 5m. Note that the proposed method is equally applicable to two- and three-dimensional slope models. The slope model contains a transient seepage analysis performed using the open-source software HYDRUS-1D and a stability analysis for calculating *FS*. The most suitable slope hydraulic model was developed for the slope by Bayesian updating with subset simulation (Liu and Wang, 2021). The slope model has a drainage boundary condition at the slope bottom, and its initial PWP profile is constant along the depth. The van Genuchten-Mualem model (van Genuchten, 1980; Mualem, 1976) is adopted, respectively, as the soil water characteristic curve (SWCC) and hydraulic conductivity function (HCF) of soils. Soil strength and hydraulic parameters used in the slope model are taken as uncertain parameters, including saturated hydraulic conductivity K_s, saturated volumetric water content θ_s, SWCC parameters α and n, standard deviation (SD) of PWP residuals σ_y, effective cohesion c', effective friction angle ϕ' and model error δ for calculating *FS*. Their prior distributions are determined based on measurements from previous studies (e.g., Carsel and Parrish, 1988) and can be found in Liu et al. (2022). The spatial variability of K_s, c', and ϕ' are considered and modeled by lognormal random fields. The scale of fluctuation in the vertical direction is taken as 5m. Although the cross correlation among uncertain soil properties is not modeled, it could be updated by probabilistic back analysis and observed from posterior samples (e.g., Liu and Wang, 2021).

3.1. Model updating results

The abovementioned slope model and uncertain soil parameters are used to perform the proposed two-level Bayesian updating. For the first level of Bayesian updating, a total of 50,000 posterior samples of uncertain soil hydraulic parameters are generated. These 50,000 posterior samples are then used as prior knowledge to perform the second level of Bayesian updating considering the slope survival records. A total of 21,783 samples of soil hydraulic and strength parameters are identified as the posterior samples.

Figure 4 shows posterior mean and 95% confidence interval (CI) of PWP responses obtained from the 21,783 posterior samples, and they are consistent with the PWP measurements, verifying the effectiveness of model updating. Table 1 compares prior and posterior statistics of soil hydraulic parameters. For example, the posterior SD of α significantly reduces from 2.1 to 0.070, indicating an obvious reduction of uncertainty in α. A similar phenomenon is observed for other parameters, indicating that the uncertainties of soil hydraulic parameters are significantly reduced by model updating using monitoring data of PWP and rainfall. Since uncertainties of soil hydraulic parameters reduce significantly, Figure 5(a) shows that the posterior 95% CI of SWCC becomes much narrower than the prior one. Figure 5(b) shows that the posterior 95% CI of HCF also becomes much narrower. This shows that monitoring data of PWP and rainfall may be used to effectively identify SWCC and HCF through the proposed model updating. Figure 6 shows the posterior mean and 95% CI of K_s along the vertical depth. A non-stationary trend of K_s is identified from the model updating, even though the prior distribution of K_s is represented by a stationary random field.

Table 1: Prior and posterior statistics of uncertain soil hydraulic parameters.

Parameter	Prior distribution		Posterior results from the second level of model updating	
	Mean	SD	Mean	SD
α (m^{-1})	3.6	2.1	3.054	0.070
n (-)	1.56	0.11	1.216	0.003
θ_s (-)	0.43	0.10	0.307	0.004
σ_y (m)	0.05	0.02	0.070	0.002

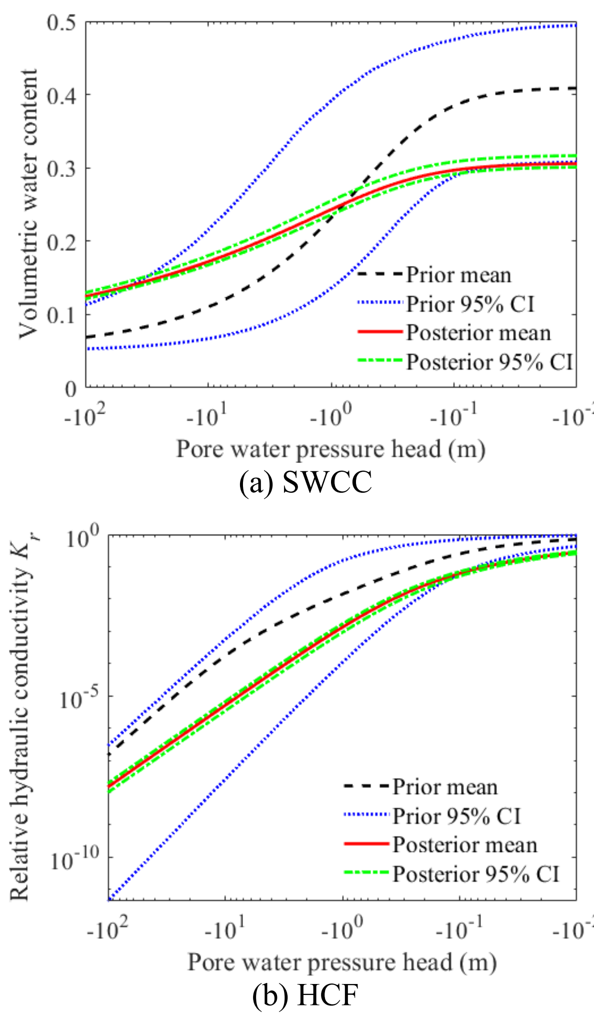


Figure 5: Posterior mean and 95% CI of SWCC and HCF.

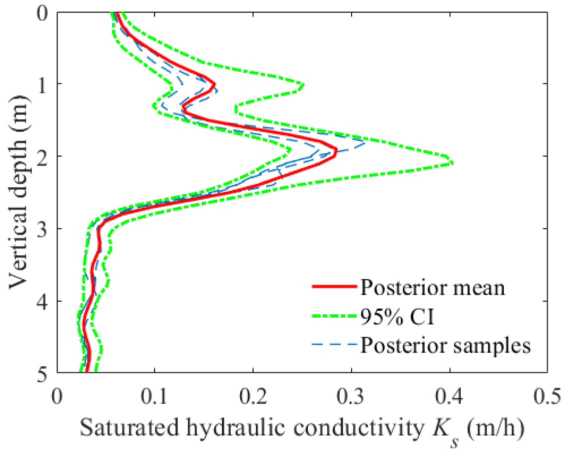
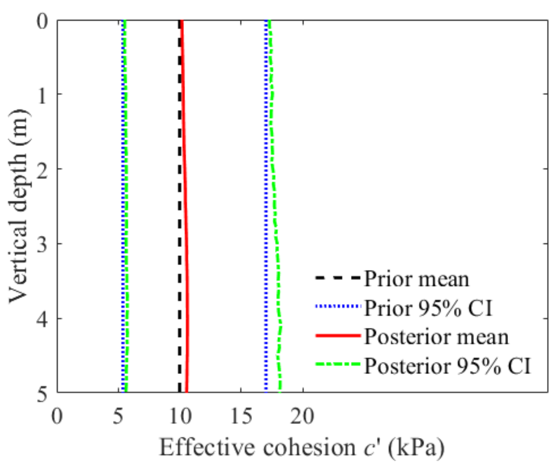
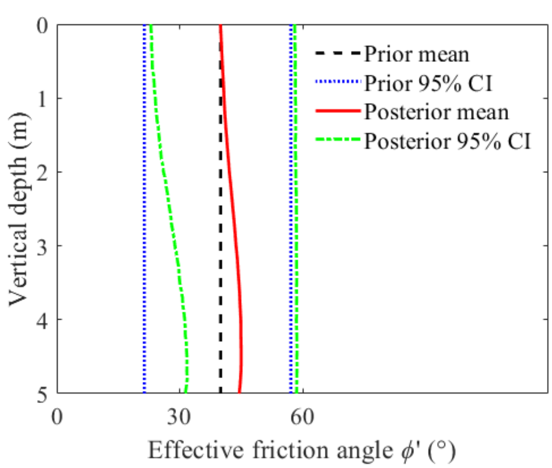


Figure 6: Posterior mean and 95% CI of K_s.



(a) *c'*



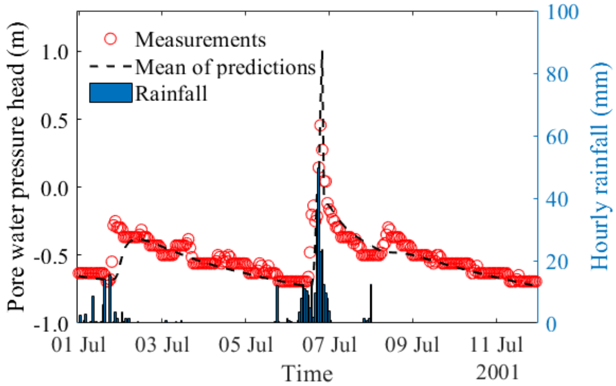
(b) ϕ'

Figure 7: Posterior mean and 95% CI of effective cohesion c' and effective friction angle ϕ'.

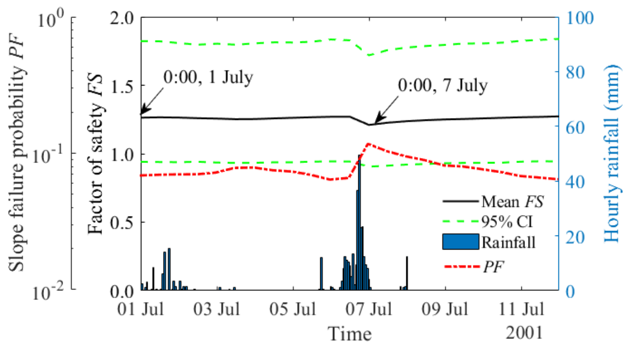
Figures 7(a) and (b) show the posterior mean and 95% CI of *c'* and ϕ' along the depth, respectively. The posterior mean and 95% CI increase slightly after model updating considering the slope survival record. Figure 7(b) shows that the lower bound of ϕ' is larger than the prior one, especially at the slope bottom, leading to reduced uncertainties. This is reasonable since the sliding force at the slope bottom is larger than that at the slope surface. The upper bound of ϕ' stays relatively unchanged because it is represented by a lognormal random field truncated within [0°, 60°] according to measurements from previous studies (Ching et al., 2017).

3.2. Model prediction results

Based on the abovementioned model updating results, a future rainfall event from 1 – 11 July 2002 at the slope shown in Figure 8(a) is imposed on the updated slope model to simulate PWP responses. The initial matric suction is constant along the depth, taken as the first PWP measurement shown in Figure 8(a). Figure 8(a) shows that the predicted PWP responses from the updated slope model agree favorably with PWP measurements, showing the updated slope model accurately predicts PWP responses in the slope. Figure 8(b) shows the predicted mean *FS*, 95% CI of *FS* for the rainfall, and slope failure probability (*PF*) during the rainfall. When the rainfall increased to a maximum of 49.5mm at 18:00 on 6 July, the mean *FS* and *FS* bounds decreased slightly, and *PF* almost doubled from 0.066 to 0.117. These results suggest that the slope was not highly likely to fail during this rainfall event. This finding was consistent with the field observation that the slope stayed stable during the rainfall event. These results show that monitoring data can be used to develop a slope digital twin for predicting temporal variations of PWP, *FS* and its uncertainty, and *PF* under a future event, thus sensing the time-variant risk of rainfall-induced landslides.



(a) PWP



(b) *FS* and *PF*

Figure 8: Predicted PWP responses, FS, and PF from the slope digital twin for a future rainfall event.

4. CONCLUSIONS

This study developed a slope digital twin for a real slope in Hong Kong using monitoring data and slope survival records, and used a slope digital twin to predict time-variant soil hydraulic responses (e.g., PWP) and slope stability (e.g., *FS*, *PF*) under rainfall infiltration. Results showed that incorporating monitoring data and slope survival records led to reduced uncertainties in soil hydraulic and strength parameters. The updated slope model predicted time-variant soil hydraulic responses under rainfall infiltration consistent with the field measurements. The predicted time-variant slope factor of safety and slope failure probability properly reflect rainfall infiltration mechanism, and they were verified by field observations. Slope digital twins provide a novel tool for sensing time-variant risk of rainfall-induced landslides.

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