

Precipitation data and their uncertainty as input for rainfall-induced shallow landslide models

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Abstract Physical models used to forecast the temporal occurrence of rainfall-induced shallow landslides are based on deterministic laws. Owing to the existing measuring technology and our knowledge of the physical laws controlling landslide initiation, model uncertainties are due to an inability to accurately quantify the model input parameters and rainfall forcing data. An uncertainty analysis of slope instability prediction provides a rationale for refining the geotechnical models. The Transient Rainfall Infiltration and Grid-based Regional Slope Stability-Probabilistic (TRIGRS-P) model adopts a probabilistic approach to compute the changes in the Factor of Safety (*FS*) due to rainfall infiltration. Slope Infiltration Distributed Equilibrium (SLIDE) is a simplified physical model for landslide prediction. The new code (SLIDE-P) is also modified by adopting the same probabilistic approach to allow values of the SLIDE model input parameters to be sampled randomly. This study examines the relative importance of rainfall variability and the uncertainty in the other variables that determine slope stability. The precipitation data from weather stations, China Meteorological Administration Land Assimilation System 2.0 (CLDAS2.0), China Meteorological Forcing Data set precipitation (CMFD), and China geological hazard bulletin are used to drive TRIGRS, SLIDE, TRIGRS-P and SLIDE-P models. The TRIGRS-P and SLIDE-P models are used to generate the input samples and to calculate the values of *FS*. The outputs of several model runs with varied input parameters and rainfall forcings are analyzed statistically. A comparison suggests that there are significant differences in the simulations of the TRIGRS-P and SLIDE-P models. Although different precipitation data sets are used, the simulation results of TRIGRS-P are more concentrated. This study can inform the potential use

of numerical models to forecast the spatial and temporal occurrence of regional rainfall-induced shallow landslides.

Keywords rainfall-induced landslide, SLIDE, TRIGRS, *FS*

1 Introduction

Shallow landslides induced by precipitation, which is the most common trigger of landslides as it causes an increase in local pore water pressure, have posed significant threats to human lives and property in China and the world (Hong et al., 2006; Bogaard and Greco, 2014). When predictions and landslide warnings are issued in advance, people can act to protect themselves from injury and death; furthermore, economic losses can be reduced. Empirical (Guzzetti et al., 2008), statistical (Guzzetti et al., 2005; Guzzetti et al., 2006), or process-based (Montgomery et al., 1998; Baum et al., 2008; Godt et al., 2008; Simoni et al., 2008; Baum et al., 2010; Vieira et al., 2010; Raia et al., 2014) approaches are adopted to predict “where” and “when” landslides are likely to occur. However, the empirical and statistical models provide little information on landslide dynamics. A process-based model attempts to reproduce the triggering mechanisms and is preferred to forecasting the spatial-temporal occurrence of rainfall-induced shallow landslides using detailed mechanical and hydrological information (Montgomery and Dietrich, 1994; Wu and Sidle, 1995; Iverson, 2000; Baum et al., 2008; Arnone et al., 2011). In a process-based model, the Factor of Safety (*FS*) defined as the ratio of resisting to driving forces on a potential sliding surface is used to evaluate the stability of the slope. The slope is considered unstable if the value of *FS* is smaller than 1.

Various sources of uncertainties are recognized in predicting the spatial-temporal occurrence of a landslide by using the process-based model. Several features usually

contribute to such uncertainties, such as 1) those associated with the inherent randomness of natural processes; 2) input model parameters and forcing data uncertainties resulting from inherent non-homogeneity and measurements errors; and 3) poor understanding of the physical laws and the simplified and conceptual models that are currently available (Abbaszadeh et al., 2011). Owing to the existing measuring technology and our knowledge of the physical laws controlling landslide initiation, model uncertainties mainly result from an inability to quantify accurately the model input parameters and rainfall forcing data.

The variation in mechanical and hydrological soil properties plays a crucial role in the infinite slope model, and it is increasingly recognized that the variability of soil properties accounted for by estimating of slope stability may be misleading (Fenton et al., 2008). The uncertainties resulting from model parameters are always assessed by a Taylor series method, the Rosenblueth point estimate method, and the Monte Carlo simulation method. Recently, the Monte Carlo simulation method has been increasingly used as an uncertainty-testing tool for slope stability and as a method for calculating the probability of failure. The Monte Carlo simulation method uses independent sets of parameters for mechanical properties, and similar probabilistic approaches for modeling the slope stability exist in the literature (Pack et al., 1998; Haneberg, 2004; Wang et al., 2010). The uncertainty of the mechanical parameters (e.g., cohesion and the soil friction angle) involved in slope stability is modeled and analyzed (Abbaszadeh et al., 2011). Arnone et al. (2014) implemented a probabilistic approach by randomizing soil cohesion, friction angle, and soil retention parameters in an existing eco-hydrological and landslide model. The TRIGRS-P copes with the natural variability inherent in the mechanical and hydrological properties of the slope materials by allowing values of the input parameters of the TRIGRS model to be sampled randomly from a given probability distribution (Raia et al., 2014).

The process-based model is forced by rainfall data, and the accuracy of landslide simulation results is closely related to rainfall forcing. However, it is difficult to obtain accurate rainfall data where a landslide occurs. Instead, we use the rainfall data from in situ observations or the pixel value of the gridded rainfall data set, which is the closest to the location where the landslide occurred. As significant differences exist in the rainfall characteristics from different rainfall data sources, it is necessary to assess the uncertainty of multi-source rainfall data sets on model simulation.

For the past two decades, the TRIGRS and SLIDE models have been the most widely used methods for analyzing rainfall-induced slope instability. The new code (TRIGRS-P) adopts a probabilistic approach to compute the changes in FS due to rainfall infiltration (Raia et al., 2014). In this study, we propose a newly developed mode SLIDE-P using a similar probabilistic method. Li et al.

(2016) tests the SLIDE model with three representative landslide events in the south-west, south-east, and south central of China during rainstorm. One of the representative landslide caused by Typhoon Fanapi is chosen as a case study in this study in order to assess the precipitation data and their uncertainty as input for rainfall-induced shallow landslide models, especially when some uncertainties exist in the mechanical parameters (e.g., cohesion and the soil friction angle). Owing to the difficulty in obtain accurate rainfall data where a landslide occurs, we are concerned that the time of landslide failure predicted changes with the different rainfall forcing data sets and mechanical parameters by using SLIDE, SLIDE-P, TIRGRS and TRIGRS-P models.

The paper is organized as follows. First, we describe the observation information of the landslide, and summarize the mechanical (unit weight γ_s , cohesion c , soil friction angle ϕ) and the hydrological (water content θ , saturated hydraulic conductivity K_s) properties of the terrain, as well as different rainfall forcing data sets. Next, we summarize the probabilistic extension implemented in the code of TRIGRS-P (Raia et al., 2014). The model adopted in the software code of SLIDE (Liao et al., 2010) and our probabilistic extension implemented in the new code of SLIDE-P are also summarized. The design of numerical experiments used to examine the ability of the different models and the relative importance of rainfall uncertainties with uncertainty in the variables that determine the slope stability are described in Section 2. Section 3 provides performances of the different models and an assessment of uncertainties in rainfall data and their uncertainty as input for rainfall-induced shallow landslide models. Section 4 summarizes the findings of this study.

2 Materials and methods

2.1 Study region and data source

The precipitation from Typhoon Fanapi induced a landslide (22.21°N, 111.37°E) at 01:00 am on September 21, 2010 (GMT) in Liutang village, Magui town, in the southwestern region of Guangdong Province in China (Li et al., 2016) (Fig. 1). The landslide resulted in at least 55 deaths and 44 missing persons. A photograph of the landslide (The Ministry of Land and Resources, 2010) is shown in Fig. 2. Liutang village is mainly covered with Migmatite weathered soil, residual cohesive soil, and sandy cohesive soil, and it is a landslide-prone area because of its highly steep slope, thin soil layer, and poor soil cohesion. The landslide disaster mainly occurred at the interface of soil and rock, with a height of 300–500 m and a soil thickness of about 1 m.

The parameter values for modeling are summarized in Table 1. Important topographic parameters including spatial location, elevation, and slope angle were derived

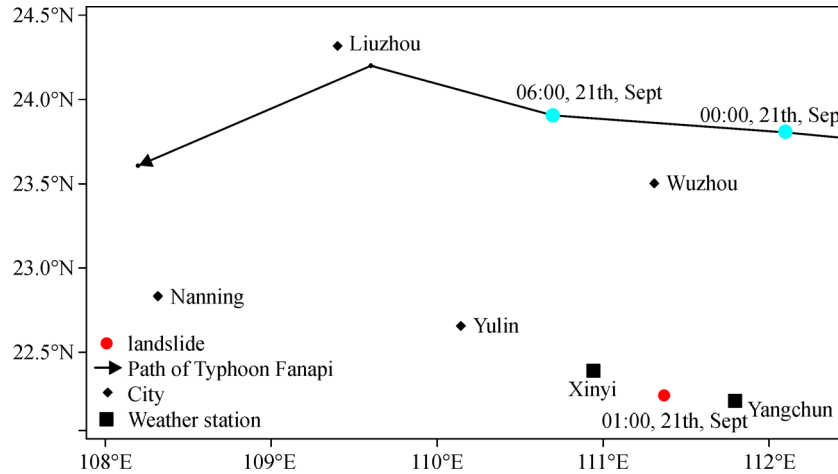


Fig. 1 Location of the landslide and the path of Typhoon Fanapi.



Fig. 2 Landslide triggered by heavy rainfall from Typhoon Fanapi in September 2010 in Liutang village (The Ministry of Land and Resources, 2010).

from the 30 m resolution ASTER GDEM. Soil parameter values, including the soil unit weight and the degree of saturation, were acquired from the soil types of the Food and Agriculture Organization of the United Nations. The water content of soil was obtained from retrieval products of surface soil moisture. There was lots of rainfall in the rainy season, and the soil was assumed to be saturated. We also assumed that the hydrological diffusivity was 100 times more than the hydrologic conductivity, and the infiltration rate was 10^{-8} m/s (Chen et al., 2011). Other parameters were confirmed according to 16 soil texture classifications and a field investigation. All the input parameters listed in Table 1 have been described in detail in Li et al. (2016). Lots of researches show that mechanical parameters should be considered as random variations to account for the uncertainties involved in their determination. The mechanical parameters in Dehua county of Fujian Province are tested in laboratory in 2008. The characteristics of the soil and climate in south-western region of Guangdong is similar to the south-central region of Fujian. Therefore, the mechanical properties (the cohesion and

friction angle), such as the mean, standard deviation, probability density function, maximum value, and minimum value are obtained according to the literature reviews and a field test in Dehua county of Fujian Province.

Different Rainfall forcing fields are used to drive rainfall-induced shallow landslide models:

1) China Meteorological Administration Land Assimilation System version 2.0 (CLDAS2.0) meteorological forcings (Shi et al., 2014). The hourly 0.0625° CLDAS 2.0 precipitation product in China is formed by interpolating fusion precipitation products of the FengYun-2 satellite, gridded precipitation production from the climate prediction center morphing technique (CMORPH) and surface observations.

2) China Meteorological Forcing Data set (CMFD) (Yang et al., 2010). The 3-hourly 0.1° CMFD precipitation data was developed by using the tropical rainfall measuring mission (TRMM) 3B42 and the global land data assimilation system (GLDAS) precipitation product as the background field, and corrected for systematic departures by using gauge observation data from 740 stations.

Table 1 Geotechnical parameters for the model

Properties	Slope angel	Soil type	Parameter shear	Friction angle	Cohesion	Coefficient
Symbol (Unit)	δ (°)	1–16	A (Unitless)	ϕ (°)	c (kPa)	λ, δ (Unitless)
	26	12	100	22	10	0.4, 3.4
Properties	Unit weight of soil	Porosity	Water content	Degree of saturation	Hydrologic conductivity	Capillary
Symbol (Unit)	γ_s (kN/m ³)	N (Unitless)	θ_s, θ_r (Unitless)	S_r (Unitless)	K_s (m/s)	H_c (m)
	12.5	0.40	0.4, 0.9	0.39	1.8×10^{-5}	500

3) In situ observations from China Meteorological Administration. Two weather stations near the location of the landslide are Xinyi and Yangchun stations.

4) The rainfall data from the China geological hazard bulletin (The Ministry of Land and Resources, 2010). According to the record, the total rainfall is 651.1 mm from 16:00 on September 20 to 01:00 on September 21, 2010. There are no records of the rainfall after 01:00 on September 21, 2010. In this study, it is assumed that the rainfall intensity increased linearly from 16:00 on September 20 to 01:00 on September 21, 2010.

2.2 Model description

2.2.1 TRIGRS and TRIGRS-P models

TRIGRS is a raster-based deterministic model for computing the slope stability due to rainfall infiltration (Baum et al., 2010). It is based on a transient vertical infiltration model combined with a simple slope stability model and a simple routing model. The infiltration models are based on Iverson's (2000) linearized solution of Richard's equation and the solution for pore pressure in the case of an impermeable basal boundary at a finite depth. The slope stability model using an infinite slope analysis is characterized by FS , which is the ratio of the resisting basal Coulomb friction to the gravitationally induced downslope basal driving stress. The slope is stable when $FS > 1$, in a state of limiting equilibrium when $FS = 1$, and unstable when $FS < 1$. A simple method for routine of surface runoff from cells is used to compute the excess surface water to adjacent downslope cells where it can either infiltrate or flow farther downslope. Further technical details of the model have been fully described in Baum et al. (2008 and 2010).

TRIGRS-Probabilistic (TRIGRS-P) uses the same model and equations as TRIGRS, but the probability distributions are used to model the slope material and hydrological properties for model input (Raia et al., 2014). The soil cohesion and the friction angle are considered to be the major sources of uncertainty, and these two parameters are considered random variables in the probabilistic analysis. The model parameters appearing in TRIGRS are replaced using a Monte Carlo simulation

by functions of random numbers. The input parameters are transformed into independent variables by a given probability distribution of a set of parameters, that is,

$$c = c(\xi_c), \text{ cohesion;}$$

$$\phi = \phi(\xi_\phi), \text{ soil friction angle,} \quad (1)$$

where ξ is a random number with the subscript used to specify a different parameter, so that the parameters can be varied independently of each other. The normal distribution function and the uniform distribution function can be used to generate the model parameters. Then, we calculate the FS in the study domain for a given set of variables describing the slope material properties obtained by sampling randomly from the probability density function.

2.2.2 SLIDE and SLIDE-P models

The SLIDE model (Liao et al., 2010; Liao et al., 2012), which is modified from Fredlund et al. (1996) and Montrasio and Valentino (2008), defines a direct relationship between FS and the rainfall depth on an infinite slope. SLIDE was tested in Honduras during Hurricane Mitch in 1998 and evaluated using the United States Geological Survey (USGS) landslides inventory data. The agreement between modeling results and landslide observations demonstrates SLIDE's good predictive skills (Liao et al., 2010; Liao et al., 2012). A link between the rainfall amount and the final expression of FS is set up and translated into a simple mathematical formulation as follows:

$$FS_{(z, t)} = \frac{c + c'_\phi(t)}{\gamma_s z_r \sin \delta \cos \delta} + \frac{\tan \phi}{\tan \delta}, \quad (2)$$

where c is soil cohesion, γ_s is the unit weight of soil, δ is the slope angle, and ϕ is the soil friction angle. $c'_\phi(t)$ represents the apparent cohesion related to the matric suction, which in turn, depends on the degree of soil saturation (Montrasio and Valentino, 2008):

$$c'_\phi(t) = A \times S_r \times (1 - S_r)^\lambda \times (1 - m_t)^\delta, \quad (3)$$

where A is a parameter depending on the soil type and is

linked to the peak shear stress at failure, λ and ∂ are numerical parameters that allow estimation of the peak of apparent cohesion related to S_r , the degree of soil saturation. m_t represents the dimensionless thickness of the infiltrated layer, which is a fraction parameter between 0 and 1:

$$m_t = \frac{\sum_{t=1}^T I_t}{nZ_t(1-S_r)}, \quad (4)$$

where I_t is rainfall intensity, n is the porosity, and Z_t is the soil depth at time t and is determined by the infiltration process:

$$Z_t = \sqrt{\frac{2K_s \times H_c \times t}{\theta_s - \theta_r}}, \quad (5)$$

where K_s is the saturated hydraulic conductivity, H_c is the capillary pressure, t is time, θ_s is the water content of the saturated soil, and θ_r is the initial water content of the soil.

In this study, we have modified the SLIDE code by adding the Monte Carlo simulation for input parameters. The Monte Carlo simulation offers a practical approach to reliability analysis because the stochastic nature of the system response can be probabilistically duplicated (Abbaszadeh et al., 2011). The new SLIDE-Probabilistic (SLIDE-P) code uses the same model and equations as the original SLIDE code, but adopts uniform and normal distribution functions, which are also used in the TRIGRS-P model to generate the input parameters for computing FS due to rainfall infiltration and considered to be ideal for assessing how the uncertainty in the model parameters affects the model results (Raia et al., 2014). The model parameters appearing in Eq. (2) are replaced using the Monte Carlo simulation by Eq. (1)

2.3 Numerical experiments

To systematically assess the precipitation data and their uncertainty as input for rainfall-induced shallow landslide models, we propose three groups of experiments for each

model, which are listed in Table 2. The first experiment (hereafter Exp1) is conducted with the input parameter information in Table 1 and forced by rainfall data from different data sets, that is, CLDAS 2.0 data, CMFD data, in situ data (Xinyi station and Yangchun station), and the rainfall data from the China Geological hazard bulletin. This experiment allows us to assess the performances of the different models and their relationships with uncertainty in the rainfall data.

The rainfall data from Xinyi station is considered short-lasting heavy rain data, and the rainfall data from the CMFD is considered long-lasting light rain data. The results of Exp1 show that the performance of the models using Xinyi station and the CMFD as rainfall forcing data are accepted, so Xinyi station and the CMFD are chosen as the rainfall forcing data for Exp2 and Exp3. The SLIDE-P and TRIGRS-P models are used in Exp2 and Exp3, respectively. In Exp2-1 and Exp3-1, the models are forced by rainfall from Xinyi station, and the modeling parameters are generated by a uniform distribution function. The rainfall forcing data used in Exp2-2 and Exp3-2 are the same as those used in Exp2-1 and Exp3-1, but the modeling parameters are generated by a normal distribution function. In Exp2-3 and Exp2-4, the SLIDE-P model is forced by CMFD rainfall data with the mechanical parameters generated by the uniform and normal distribution functions, respectively. In Exp3-3 and Exp3-4, the TRIGRS-P model is forced by CMFD rainfall data with the mechanical parameters generated by the uniform and normal distribution functions, respectively. The randomly generated parameters are combined with the fixed input data to determine a single value for the factor of safety. This process is repeated 5000 times to generate a sufficient number of different factors of safety values. In this study, based on the error analysis, the number of iterations required to achieve an acceptable level of accuracy is estimated to be 5000 for Exp2 and Exp3. A given set of the mechanical variables (cohesion and friction angle), which are sampled randomly from the uniform or normal distribution, is used to calculate the stability conditions in every model.

Table 2 Summary of Numerical Experiments

Experiment Name	Model	Rainfall forcing resources	Mechanical parameters (cohesion, friction angle)
Exp1	SLIDE, TRIGRS	CLDAS 2.0, CMFD, Xinyi station, Yangchun station, Report data	Fixed input parameters
Exp2-1	SLIDE-P	Xinyi station	Uniform distribution
Exp2-2	SLIDE-P	Xinyi station	Normal distribution
Exp2-3	SLIDE-P	CMFD	Uniform distribution
Exp2-4	SLIDE-P	CMFD	Normal distribution
Exp3-1	TRIGRS-P	Xinyi station	Uniform distribution
Exp3-2	TRIGRS-P	Xinyi station	Normal distribution
Exp3-3	TRIGRS-P	CMFD	Uniform distribution
Exp3-4	TRIGRS-P	CMFD	Normal distribution

3 Results and discussion

3.1 Precipitation data and their uncertainty for the SLIDE and TRIGRS models

Five precipitation forcing data sets, including CLDAS 2.0 data, CMFD data, in situ data from the Xinyi and Yangchun stations near the location of the landslide, and report data from the China geological hazard bulletin, were used to drive the SLIDE and TRIGRS models. There were several differences in the total amount and distribution characteristics of the precipitation. According to the China geological hazard bulletin, the total rainfall was 651.1 mm from 16:00 on September 20 to 01:00 on September 21, 2010. The amount of the CLDAS precipitation was as high as 315 mm, and others were between 82.9 to 96 mm. Most of the rainfall occurred from 17:00 on September 20 to 9:00 on September 21, 2010; however, the multi-source precipitation data sets exhibited significant differences in rainfall intensity (Fig. 3). Overall, the total precipitation during Typhoon Fanapi was almost the same, except for the CLDAS precipitation and report data. The main difference among the other three precipitation data sets are the precipitation intensities, that is, the observations from Xinyi station are for heavy precipitation with a relatively short duration and the CMFD and observations from Yangchun station are for the rainfall with a relatively uniform intensity.

The red point in Fig. 1 represents the location of the landslide. Parameter values for the TRIGRS and SLIDE models are summarized in Table 1. Five precipitation forcing data sets are used to drive the models. The FS is calculated by TRIGRS and SLIDE models at 1-h intervals. Figure 4 illustrates FS changes with the time. The TRIGRS model shows that slope instability ($FS < 1$) occurred between 19:00 pm on September 20, 2010 to 6:00 am on September 21, 2010 using the different precipitation data

sets (Fig. 4(a)). The landslide occurred at 01:00 am on September 21, 2010. The times calculated by the TRIGRS model with CLDAS and report rainfall forcing data are earlier than the real time of the landslide's occurrence, and the times calculated with other rainfall forcing data are later than the real time.

The changes in the FS with time are different when different precipitation data are used to force the SLIDE model, and the slope instability appears at 02:00 am to 15:00 pm, September 21, 2010 (Fig. 4(b)). The times calculated by SLIDE model with the CLDAS and CMFD forcing data sets are close to the real time of the landslide's occurrence, and the time calculated with other rainfall data are later than the real time of the landslide's occurrence. It is observed that there is no landslide occurrence forcing by the report data. In general, the results show that the TRIGRS and SLIDE models have the ability to simulate the rainfall-induced landslide, and it is still challenging to predict the exact time when the slope is prone instability. Moreover, precipitation data can exert a certain impact on the model simulation, especially the time of the landslide's occurrence.

3.2 Precipitation data and their uncertainty for the SLIDE-P model

While the total precipitation was nearly constant, the CMFD precipitation and the observed precipitation from Xinyi station can represent two typical types of rainfall. One is rainfall with a low intensity and a long duration, and the other is rainfall with a high intensity and a relatively short duration. These two precipitation data sets are used to drive the SLIDE-P model to assess the uncertainties from the precipitation. The SLIDE-P model runs according to the numerical experiment designs (Exp2), which considered the uncertainties both from the different precipitation data sets and the input mechanical variables. To conduct a

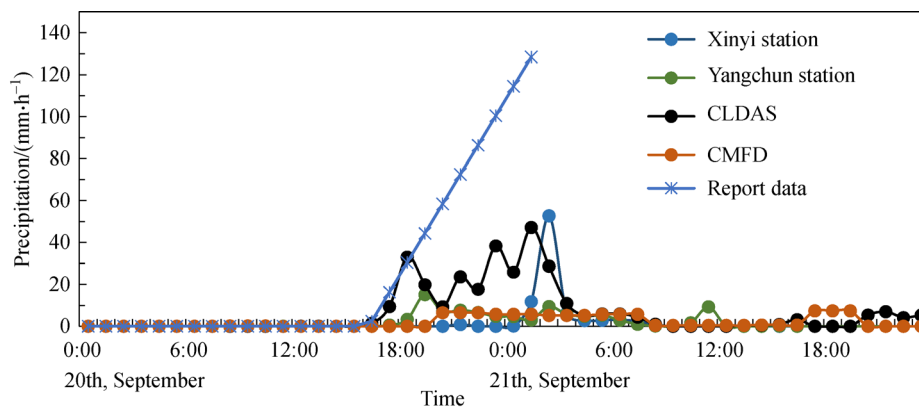


Fig. 3 Comparison of the hourly rainfall intensity for Xinyi station, Yangchun station, CLDAS, CMFD and report data. (Xinyi station: precipitation data from Xinyi station; Yangchun station: precipitation data from Yangchun station; CLDAS: precipitation data from the China Meteorological Administration Land Assimilation System (CLDAS) version 2.0; CMFD: China Meteorological Forcing Data set (CMFD); Report data: precipitation from the China geological hazard bulletin. (Hereinafter the same)).

probabilistic analysis, the random properties of the cohesion and friction angle, such as the mean, standard deviation, probability density function, maximum value, and minimum value were obtained from literature reviews and a field test. In Exp2, the SLIDE-P model runs 5000 times to calculate the FS driven by the CMFD precipitation and the observed precipitation from Xinyi station. In each simulation, the mechanical variables are generated by a normal or uniform distribution function. Figure 5 shows the distribution graphs of strength parameters from a normal distribution function.

In Exp2-1 and Exp2-2, in which the model is forced by rainfall data from Xinyi station, the probability of landslide occurrence is 54.94% using the uniform distribution function and 60.84% using the normal distribution function. Figure 6 shows that the landslide is most likely to occur between 00:00 pm to 06:00 pm on September 21. The results show that the time of landslide occurrence is closely related to the characteristics of precipitation, while the total precipitation is nearly constant.

In Exp2-3 and Exp2-4, in which the model is forced by rainfall data from the CMFD, the probability of landslide occurrence is 52.28% using the uniform distribution function and 69.7% using the normal distribution function.

The landslide is most likely to occur between 12:00 pm to 18:00 pm on September 20. Figure 6 shows the time in which a landslide may occur is more dispersed. It is concluded that there is greater uncertainty in predicting the time of landslide occurrence as the rainfall data uncertainty increases. The probabilities of no landslide occurrence are between 30.3% and 45.06% for SLIDE models with different rainfall forcing data and parameter distribution, that is, even predicting whether landslide occur or not is challenging.

3.3 Precipitation data and their uncertainty for the TRIGRS-P model

The CMFD precipitation and the observed precipitation from Xinyi station were also used to drive the TRIGRS-P model. There are four sets of experiments, which are forced by two precipitation data sets and set up with the cohesion and friction angle parameters generated from the uniform or normal distribution function (Exp3-1, Exp3-2, Exp3-3 and Exp3-4). The TRIGRS model runs 5000 times according to the numerical experiment designs to assess the uncertainties in the forcing data and input parameters in landslide modeling.

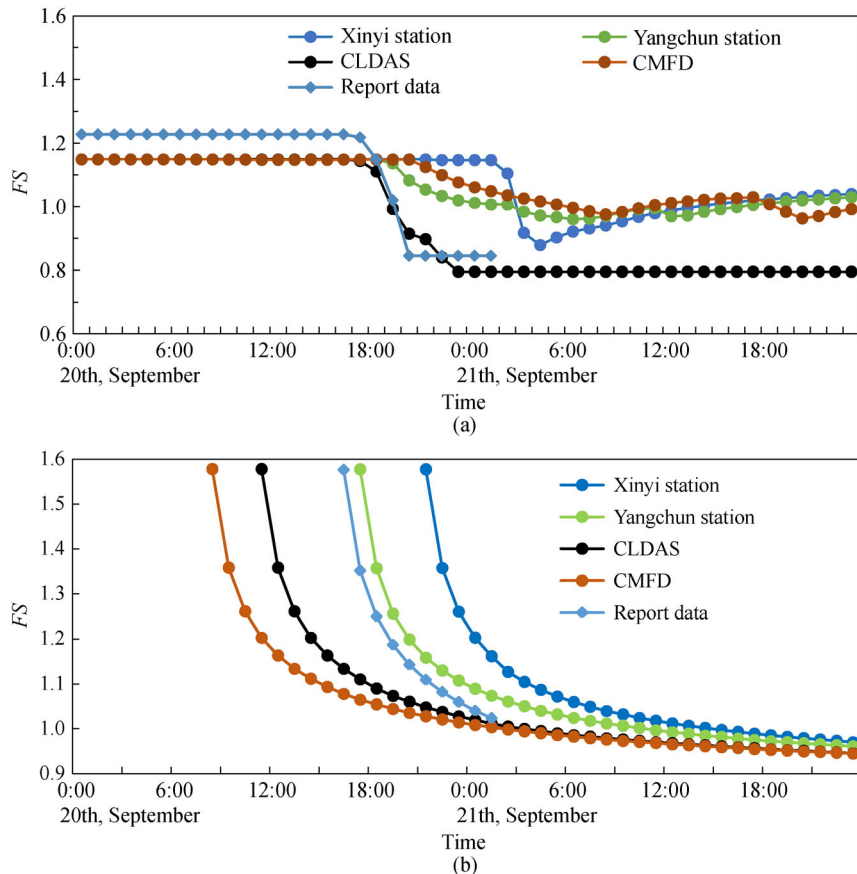


Fig. 4 (a) FS using the TRIGRS model for Typhoon Fanapi; (b) FS using the SLIDE model for Typhoon Fanapi.

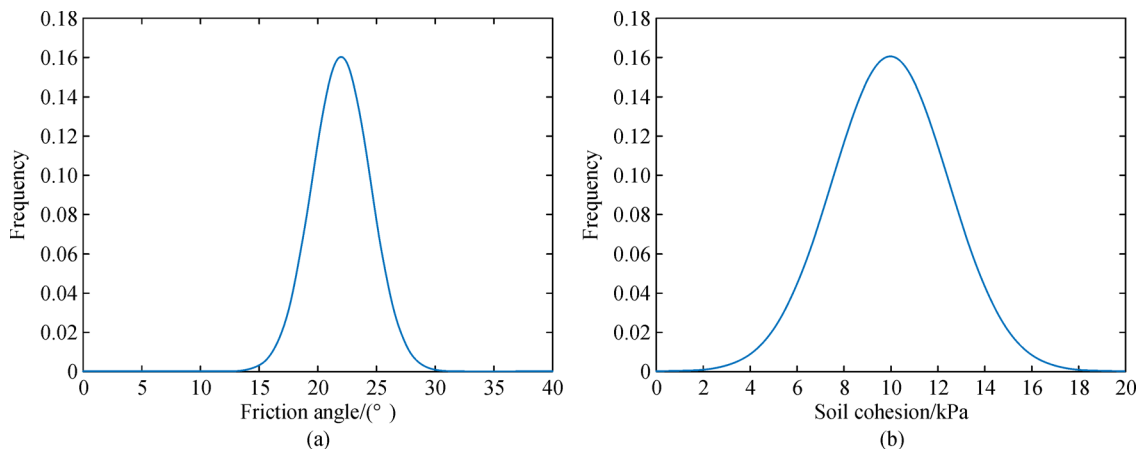


Fig. 5 Distribution graphs of strength parameters: (a) friction angle from the normal distribution function; (b) soil cohesion from the normal distribution function.

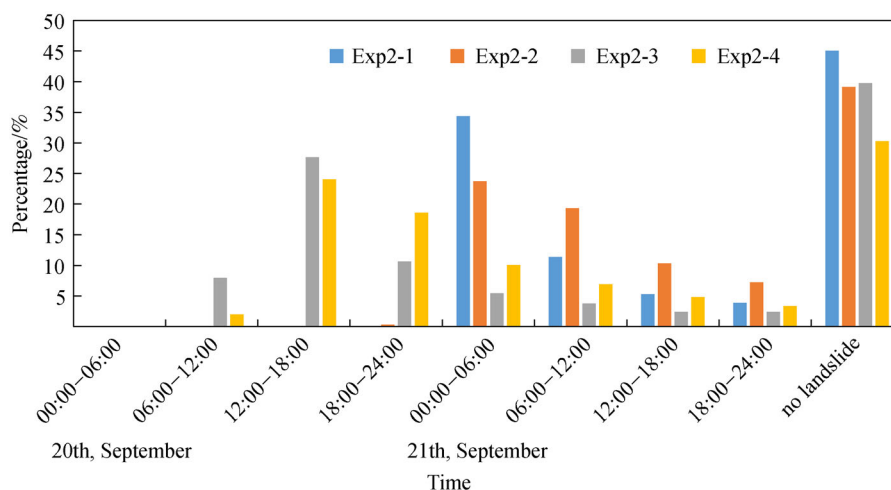


Fig. 6 Probability of landslide occurrence using the SLIDE-P model in Exp2.

In Exp3-1 and Exp3-2, in which the model was forced by rainfall data from Xinyi station, the probability of landslide occurrence was 76.92% using the uniform distribution function and 89.8% using the normal distribution function. In Exp3-3 and Exp3-4, in which the model was forced by rainfall data from CMFD, the probability of landslide occurrence was 50.6% using the uniform distribution function and 68.04% using the normal distribution function. Figure 7 shows that a landslide is most likely to occur between 00:00 pm to 06:00 pm on September 21. The results of *FS* are more sensitive to the parameters forced by the precipitation with light rainfall. The accuracy of model prediction mainly depends on the accuracy of the input parameters, especially in complex areas with great spatial variability. There is great uncertainty in regional simulation using constant parameters in the complex areas.

In Exp3-1 and Exp3-3 using the uniform distribution of the parameters, the probability of landslide occurrence was

76.92% when the model was forced by observed precipitation from Xinyi station and 50.6% when the model was forced by CMFD precipitation. In Exp3-2 and Exp3-4, in which the normal distribution function is used, the probability of landslide occurrence was 89.8% when the model was forced by observed precipitation from Xinyi station and 68.04% when the model was forced by CMFD precipitation. Figure 7 shows that there is a good correspondence between the precipitation and the time of landslide occurrence with rainfall data characterized by a high intensity and a relatively short duration. Furthermore, the accuracy of the prediction may reduce if the model is forced by rainfall data characterized by a low intensity and a long duration with the variability of the input parameters.

4 Conclusions

The key to advancing the predictability of rainfall-induced

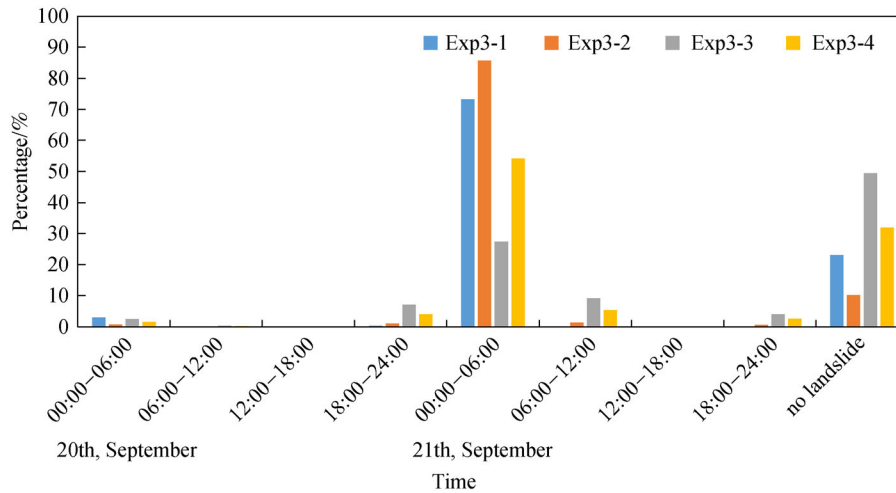


Fig. 7 Probability of the time of landslide occurrence using the TRIGRS-P model in Exp3.

landslides is to use physically based slope-stability models that simulate the transient dynamical response of the soil moisture to spatiotemporal variability of rainfall in complex terrains (Liao et al., 2011). The TRIGRS and SLIDE models have been applied in Liutang village, Magui town, in the south-western region of Guangdong Province in China, where a landslide was triggered by Typhoon Fanapi on September 2010. The different input parameters are described in detail in Li et al. (2016). The rainfall-induced landslide models output hourly *FS*, which are analyzed to assess the timing of potential landslide events. Data from Xinyi and Yangchun station, the CMFD, and the CLDAS, and report data are used as forcing data to evaluate the models. TRIGRS and SLIDE models are evaluated, and the results show that both of them can be used for the rainfall-induced shallow landslide prediction, even the uncertainty of the rainfall data exist. However, TRIGRS model is more sensitive to the rainfall change with the time.

Natural variability of soil parameters and precipitation forcing significantly affects the predictions of slope instability. The values of the TRIGRS-P are sampled randomly from the uniform and normal distribution using a probabilistic Monte Carlo approach (Raia et al., 2014). We have modified the SLIDE model code by allowing values of the model input parameters to be sampled randomly. While the total precipitation was nearly constant, the CMFD precipitation and the observed precipitation from Xinyi station can represent two typical types of rainfall. One is rainfall with a low intensity and a long duration, and the other is rainfall with a high intensity and a relatively short duration. These two precipitation data sets are used to drive TRIGRS-P and SLIDE-P models to assess the uncertainties. Both the TRIGRS-P and SLIDE-P models have a certain ability to predict a landslide induced by heavy rain.

The uncertainties from the precipitation data and input

parameters may affect the results of the models. The analysis quantifies the uncertainties of the TRIGRS-P and SLIDE-P models in simulating the rainfall-induced landslide. The accuracy of model prediction mainly depends on the accuracy of the input parameters and rainfall data. The simulation results of TRIGRS-P are more concentrated comparing with SLIDE-P model, when the significant difference exists in the rainfall forcing data. There is great uncertainty in regional simulation using different rainfall data in complex areas. Precipitation and its uncertainty as input for rainfall-induced shallow landslide models need to be evaluated in detail over large areas in future research.

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