Quantitative Risk Assessment of Individual Landslides

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Abstract: Slope failures or landslides are reported every year in different countries. In spite of improvements in landslide hazard recognition, prediction, mitigation measures, and warning systems, worldwide landslide activity is increasing. Uncertainty is a dominant feature of all landslides. Various uncertainties arise during the resolution of the problem, from climate data of rainfall, to infiltration rate, to site characterization, to material properties, to analysis, design and consequence assessment. These variabilities are rarely taken into account directly in traditional geotechnical analysis, rather some "average" or suitably "pessimistic" property is assumed to act across the whole region of interest. This keynote will focus on the modelling of spatial variability of soil properties in the quantitative risk assessment of individual landslides. Firstly, infinite (1D), two dimensional (2D) and three dimensional (3D) slope examples are used to demonstrate the importance of modelling spatial variability in the risk assessment of landslides. The infinite slope example shows that ignoring spatial variability will lead to unconservative estimation of slope failure. The 2D slope example shows that the slope failure can have multiple possible failure modes. The 3D slope example shows that ignoring the spatial variability in the third direction can lead to unconservative estimation of slope failure probability if the slope is long. Then the framework of quantitative risk assessment of landslides is discussed. Slope or landslides can fail shallowly or deeply. Because deep failure leads to more severe consequence than shallow failure, each potential failure mode has a specific consequence associated with it. It is thus necessary to redefine risk as mean consequence rather than assuming a constant consequence for all failure modes. One challenge for quantitative risk assessment of landslides is to automatically identify failure modes and assess associated consequences. This issue can be overcome by introducing Machine Learning algorithms within the framework of Monte Carlo simulations.

Keywords: Quantitative risk assessment; landslides; spatial variability; machine learning.

1 Introduction

Slope failures or landslides are reported every year in different countries. Although not as high profile as other natural hazards such as cyclones, storms, floods, droughts or earthquakes in Australia, landslides cause more life loss and injury, along with economical losses due to damage to infrastructure, and mining and agricultural facilities (Geosciences Australia 2017). In spite of improvements in landslide hazard recognition, prediction, mitigation measures, and warning systems, worldwide landslide activity is increasing. This trend is expected to continue in the 21st century because of: (1) climate change, which causes more extreme rainfalls and droughts; (2) urbanisation and developments in landslide-prone areas; and (3) deforestation in landslide-prone areas. To address the problem, governmental agencies need to develop a better understanding of landslide hazard and to make rational decisions on allocation of funds for management of landslide risk.

Uncertainty is a dominant feature of all landslides. Various uncertainties arise during the resolution of the problem, from climate data of rainfall, to infiltration rate, to site characterisation, to material properties, to analysis, design and consequence assessment, as pointed out by Lacasse (2015) in her 55th Rankine Lecture. In recent years, risk analysis and management have become an important tool in addressing uncertainties inherent in landslide hazards. However, the methodologies adopted are still largely qualitative and based on experts' judgements. Further efforts are needed to quantify uncertainties and to understand the propagation of these uncertainties in numerical simulations, to make such analyses more robust for engineering applications. This paper reviews recent research in quantitative risk assessment of individual landslides.

2 Deterministic Approach

By the very nature of their origins, geotechnical materials such as soils and rocks are variable in their engineering properties. This variability is rarely taken into account directly in traditional geotechnical analysis, rather some "representative average" or "appropriately conservative" property is usually assumed to act across

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the whole region of interest. The evaluation of the safety of geotechnical projects is quantified by a factor of safety to keep the probability of failure to an acceptable level. The factor of safety itself can be overly conservative in some cases. It is common to use the same factor of safety for different types of application without regard to the degree of uncertainty or consequence of failure involved in its calculation. Through regulation or tradition, the same factor of safety is often applied to conditions that involve widely varying degrees of uncertainty. High probability events attracting a high factor of safety may have negligible consequences and could be designed more economically. The deterministic approach also does not necessarily reflect the risk tolerance of the client or contractor and does not allow them to make informed decisions.

Currently, the geotechnical community is mainly preoccupied with keeping the probability of failure to an acceptable level using allowable stress design (WSD/ASD), Load and Resistance Factor Design (LRFD, United States), Limit State Design (LSD, Canada) and Partial Factors Design (PFD, Europe, Australia). The emphasis is primarily on the re-distribution of the original global factor of safety in WSD into separate load and resistance factors (or partial factors), where risk is not explicitly quantified. These types of semi-probabilistic design codes lead to a dilemma where geotechnical engineers produce deterministic designs on the assumption that risk is controlled but then find themselves spending the construction period trying to manage variability and risk.

Since the deterministic approach is not a very logical strategy (Duncan 2000), numerous studies have been undertaken in recent years to develop probabilistic methods that deal with uncertainties in a systematic way (e.g., Paice et al. 1996; Low et al. 1998; Griffiths and Fenton 2000; El-Ramly et al. 2002; Griffiths and Fenton 2004; Ching et al. 2009; Griffiths et al. 2009; Huang et al. 2010; Zhang et al. 2011; Li et al. 2015). Of particular importance has been the development of the random finite element (RFEM) to model the spatial variability of soil properties (e.g., Griffiths and Fenton 2004; Fenton and Griffiths 2008).

3 Modeling Spatial Variability and Random Fields

3.1 One dimensional analysis

The infinite slope model is the oldest and simplest slope stability method that assumes identical conditions occur on any vertical section. While the model is not capable of modeling any kind of downslope variability, it is used in this paper to give important insight into the influence of spatial variability on slope failure probability and the location of the critical failure mechanism. The infinite slope equation is usually implemented with the assumption of homogeneous or averaged soil properties in which failure always occurs at the base of the slope. For an undrained slope as shown in Figure 1, the deterministic Factor of Safety (FS) can be calculated analytically using Eq. (1). It can be seen from Eq. (1) that the minimum FS is always at the bottom of the slope.

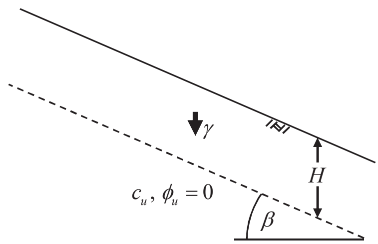

Figure 1. Undrained infinite slope model.

$$FS = \frac{c_u}{H\gamma \sin\beta \cos\beta} \tag{1}$$

where c_u is undrained shear strength and γ is unit weight of soil.

However, if c_u is varying along the depth z, the minimum FS is not necessarily at the bottom, but at the depth where c_u / z reaches a minimum, as shown in Eq. (2).

$$FS = \left(\frac{c_u}{z}\right)_{\min} \frac{1}{\gamma \sin\beta \cos\beta} \tag{2}$$

If one assumes c_u is the only random variable, characterized by its mean and standard deviation, the probability of failure (p_f) based on Eq. (1) can be analytically calculated. Let us assume the probability of failure is p_{f_RV}, where the subscript *RV* denotes the random variable approach.

In the random variable approach, the spatial variability of c_u is not considered. If random field theory is used to model the spatial variability of c_u, an additional parameter, i.e., the spatial correlation length θ_{c_u} is needed. The spatial correlation length describes the distance over which the spatially random values will tend to be significantly correlated. Thus, a large value of θ_{c_u} will imply a smoothly varying field while a small value will imply a ragged field as shown in Figure 2. In this case, a random field simulator is needed to calculate the p_f. Let us assume the probability of failure is p_{f_RF}, where the subscript denotes the random field approach. As shown in Figure 2, if the spatial variability of c_u is modelled, the slope can fail anywhere along the depth. It is thus obvious that p_{f_RF} is always bigger than p_{f_RV}, which means ignoring spatial variability will lead to unconservative results (Griffiths et al. 2011).

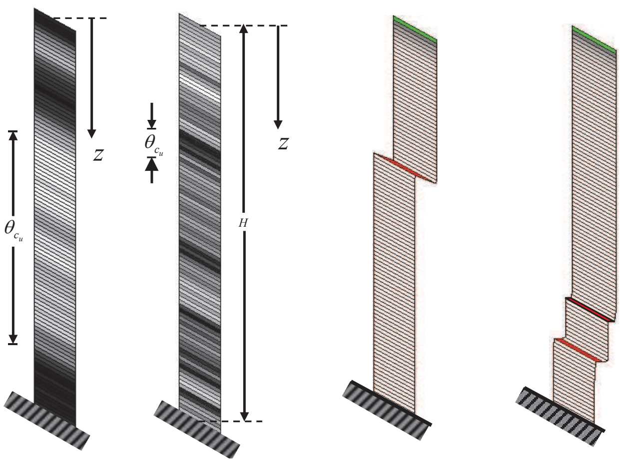

Figure 2. Random field simulations of infinite slope model.

3.2 Two dimensional analysis-system reliability

In a probabilistic slope stability analysis, the probability of failure associated with the most critical slip surface (the one with the minimum reliability index) is known to be smaller than that for the system that comprises all potential slip surfaces. This can be easily understood by looking at a two-layer undrained slope as shown in Figure 3. By varying the undrained shear strength of both the embankment (c_{u_1}) and foundation (c_{u_2}), the contour of factor of safety can be drawn as shown in Figure 4. It can be seen from Figure 4 that there are multiple possible failure modes if both the undrained shear strengths of the embankment and foundation are treated as random variables. In Figure 4, the safe and unsafe zones are separated by the contour line of FS=1. It can be seen from Figure 4 that the unsafe zone (i.e., FS<1) consists of three sub-failure zones, each of which represents a failure mode. The probability of failure of the whole slope system is the integral of the joint probability density function of c_{u_1} and c_{u_2} over all three failure zones. The probability of failure associated with any one of the three failure zones must be smaller than the probability of failure of the whole slope system (e.g., Huang et al. 2010).

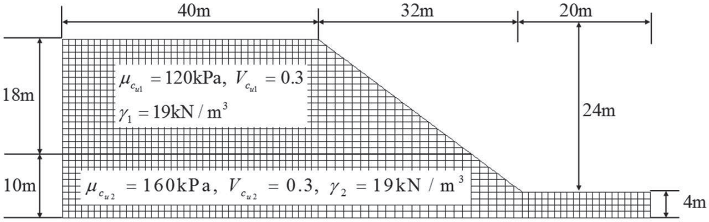

Figure 3. Two-layer undrained slope.

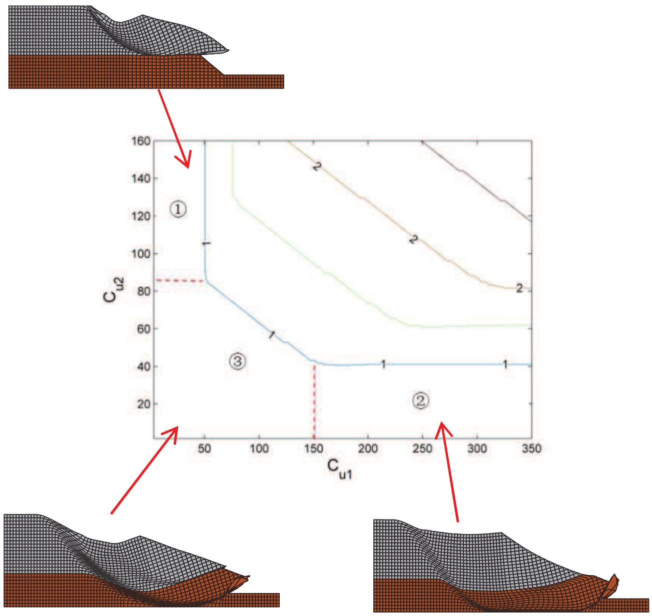

Figure 4. Contour of factor of safety.

3.3 Three dimensional analysis

It is commonly believed that the factor of safety of a slope obtained by 2D plane strain analysis is always smaller than that obtained by 3D analysis. One may say that 3D probabilistic analysis is not necessary because 2D probabilistic analysis always gives more conservative results. The following example shows that if the slope is long enough, 2D analyses actually provide unconservative results, relative to 3D analyses. As shown in Figure 5, if we ignore the spatial variability in the third direction, i.e, simply extend a 2D plane strain model to 3D model, the 3D probability of failure will be smaller than the 2D probability of failure, because the support from the two end boundaries. However, if we model the spatial variability in the third direction, the 3D probability of failure can be larger than the 2D one if the slope is long enough, because the slope can fail locally anywhere along the third direction. This means ignoring the spatial variability in the third direction may lead to unconservative results (e.g., Griffiths et al. 2009).

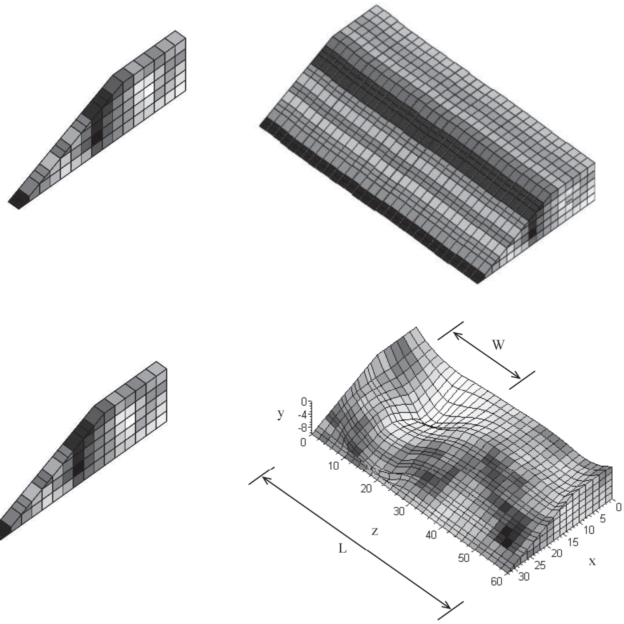

Figure 5. Model the spatial variability in the third direction.

4 Site Specific Data and Conditional Random Fields

Engineering properties of soils vary spatially, however geotechnical tests can only investigate a small proportion of the site. When random field theory (e.g., Griffiths and Fenton 1993; Fenton and Griffiths 2008) is used to model the spatial variability of soils, the associated statistics are inferred from geotechnical tests, however the random fields do not necessarily account for the specific deterministic properties, albeit limited, as measured from the site investigation data. Conditional random fields can be used to model the spatial variability of soil properties taking account of the actual site-specific data (e.g., Jiang et al. 2018; Li et al. 2016), which may significantly reduce the uncertainty compared to traditional random field simulations. The differences between unconditional and conditional random field simulations are shown in Figure 6. The picture on the left top corner shows the real in-situ soil profile. Due to limited site investigations, engineers cannot know the soil profile completely. They can refer to the literature or similar projects to estimate the statistics (e.g., mean, standard deviation, and spatial correlation length) of soil properties (e.g., shear strength), and then use random field simulations to guess the soil profile and perform stability analyses. If such a process is repeated for a large number of simulations, some of the simulations will indicate the slope is unsafe. The probability of failure of the slope is simply the ratio of the number of unsafe simulations to the total number of simulations. The two random field simulations on the left in Figure 6 are such kind of simulations and are called unconditional random field simulations. If site investigation is performed (e.g., a cone penetration test as shown in Figure 6 on the top right corner), engineers would know the shear strength of the tested soils. If these known soil properties are directly used in random field simulations, the randomly generated soil profiles will have constant values at the places where soils have been tested. As shown in the two random field simulations on the right in Figure 6, the soil properties within the red rectangular remain constant from simulation to simulation. Because the simulations use this additional information on the soil properties, the uncertainty in the slope properties must be reduced (e.g., Yang et al. 2019).

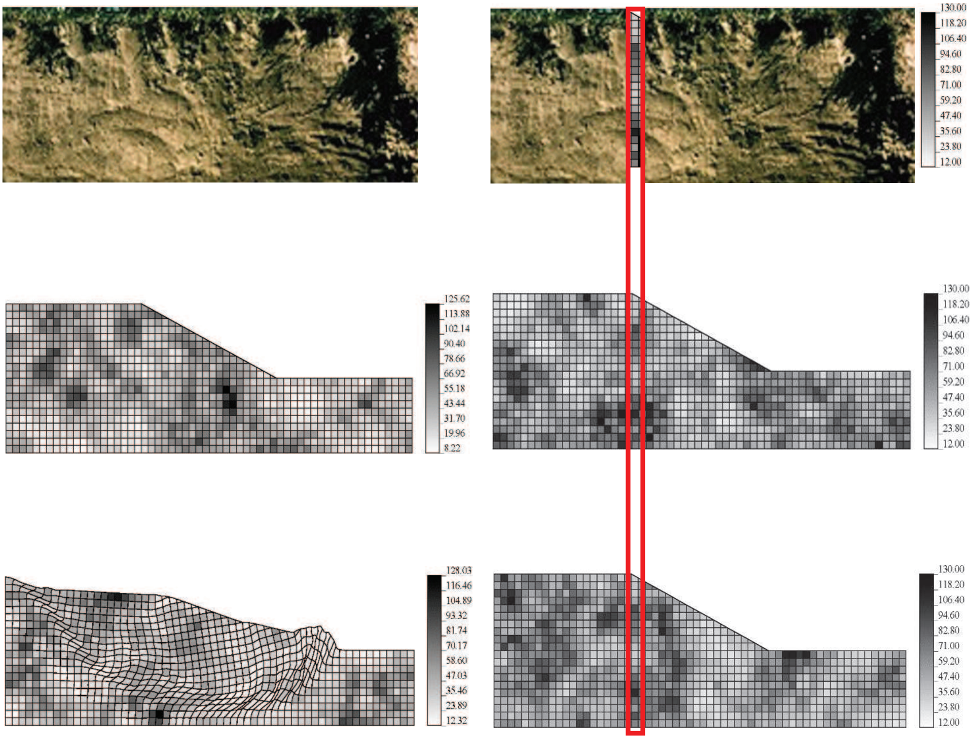

Figure 6. Conditional random field simulations of slopes.

5 Quantitative Risk Assessment

The risk assessment of landslides involves estimating the probability of slope failure (p_f) first and then calculating the risk as

$$R = p_f \times C \tag{3}$$

where R is the risk and C is the failure consequence.

The above method works well for systems that have a single failure consequence. In landslide problems, as noted by Huang et al. (2010), every failure involves a different volume of soil, and thus a different failure consequence. As a result, the consequence associated with each failure should be assessed individually, leading to a modified definition of risk as follows (Huang et al. 2013)

$$R = \sum_{i=1}^{n_f} p_{fi} \times C_i \tag{4}$$

where p_{fi} and C_i are the probability and consequence of the i'th failure , and n_f is the number of slopes which failed during the Monte Carlo simulation.

In Monte Carlo simulation, p_{fi} is approximately equal to the probability of occurrence of that particular simulation, i.e.,

$$p_{fi} = \frac{1}{n_{sim}} \tag{5}$$

where n_{sim} is the total number of simulations.

Equation (4) can thus be rewritten as

$$R = \sum_{i=1}^{n_f} p_{fi} \times C_i = \sum_{i=1}^{n_f} \frac{1}{n_{sim}} \times C_i = \frac{1}{n_{sim}} \sum_{i=1}^{n_f} C_i \tag{6}$$

Equation (6) can be further rewritten as

$$R = \frac{1}{n_{sim}} \sum_{i=1}^{n_f} C_i = \frac{n_f}{n_{sim}} \frac{\sum_{i=1}^{n_f} C_i}{n_f} = p_f C \tag{7}$$

where

$$p_f = \frac{n_f}{n_{nsim}} \tag{8}$$

and

$$C = \frac{\sum_{i=1}^{n_f} C_i}{n_f} \tag{9}$$

is the average consequence. In other words, Eq. (7) states that the risk is equal to the total probability of landslide failure times the average (the mean, in the limit) consequence. Equation (8) is the formula that is used in Monte Carlo simulations to estimate probability of failure. Equation (9) is the average consequence among failures. The expressions of Eqs. (3) and (7) are the same, but it should be noted that consequence C in Eq. (3) is a constant, while it is defined as average consequence among failures in Eq. (7).

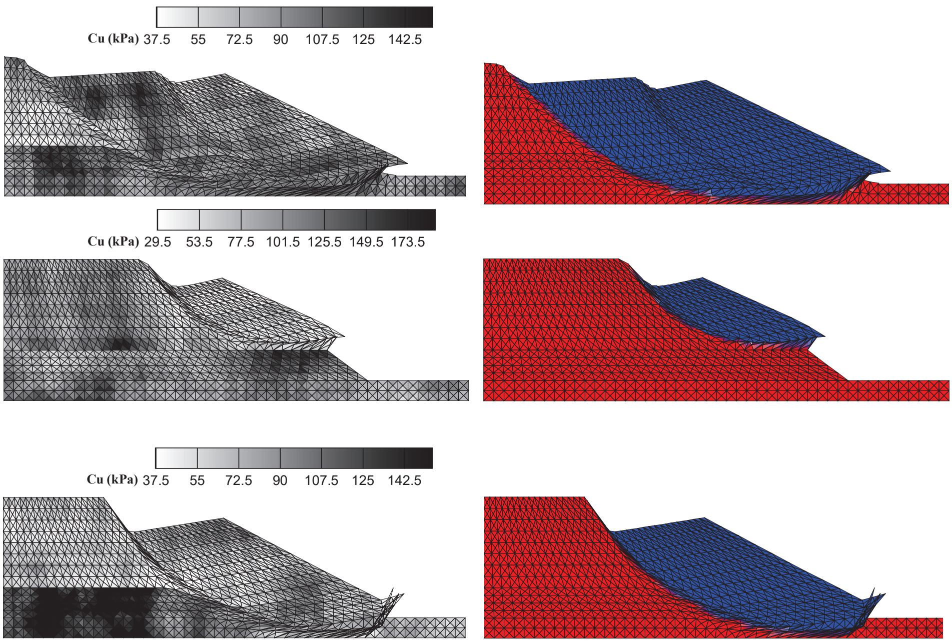

Figure 7. Identify failure mode and consequence automatically.

The main challenge of applying the above redefined risk assessment methodology is to assess the consequence of individual failure automatically in the simulations. Because the volume of the sliding mass is directly related to the consequence of a landslide, this quantity can be used to quantify consequence (e.g., Li et al. 2019). A more complete assessment of the consequence should also quantify the dynamic behaviour of the sliding soil. To identify the volume of the sliding soil used to be thought of as a difficult task, but Figure 7 demonstrates that the classic K-means clustering method (e.g., Bishop 2006) works very well for this purpose. Figure 7 shows the deformed mesh obtained by upper bound finite element limit analyses on the left, and automatically identified sliding mass in blue by the K-means clustering method on the right (Huang et al. 2013). Although only three typical failure modes are shown in Figure 7, there are many possible failure modes for a particular slope. The same approach can be extended to three dimensional analysis. Figure 8 shows a three dimensional quantitative risk assessment of slope instability where spatial variability is directly modelled. The figure on the right shows the sliding volume.

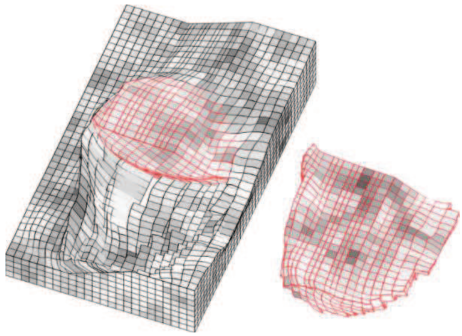

Figure 8. Three dimensional quantitative risk assessment of slope instability where spatial variability is directly modeled.

6 Simulation of Small Probability of Failure

For a landslide whose negative consequences are very high, the designed remedial measures must aim to keep the probability of failure at an acceptably low level. When advanced numerical models are used, the challenge is to efficiently simulate small probabilities of failure, especially when the simulation is transient and is based on Monte Carlo Simulations. Huang et al. (2017) and van den Eijnden and Hicks (2017) developed efficient methods for the simulation of small probability of failure considering spatial variability of soils based on subset simulation (e.g., Au and Beck 2001). The need for the search of factor of safety using strength reduction method is eliminated so that the computational efficiency is significantly improved. However, the method needs to be further developed for time dependent problems.

7 Bayesian Updating and Observational Methods

Once the risk from a potential landslide is identified, measures are required to mitigate the risk. Remedial measures for such slopes in urban areas must involve minimum disturbance and may be thwarted by lack of public access to the respective sites. There are generally three strategies. The first one is to do nothing and accept the consequences of failure. Secondly, the slope can be stabilized and a monitoring program installed to verify the effectiveness of stabilization works. Thirdly, a monitoring program can be used to warn of impending instability so that evacuation can be carried out prior to failure occurring. Decisions on the remedial measures undoubtedly involve a risk assessment study of slope failure based on the observed behaviour of the potential landslide. Bayes Theorem provides a theoretical framework to allow updating the predictions with the monitored data. This could be done in real-time allowing engineers to take advantage of updated predictions (e.g., Zhang et al. 2010; Zhang et al. 2010; Kelly and Huang 2015; Jiang et al. 2018). Quantitative probability of event occurrence could be continuously updated. Sun et al. (2019) used Bayesian Updating for progressive excavation of high rock slopes using multi-type monitoring data. They show that the uncertainties in the prediction of slope instability can be reduced by incorporating more deformation and stress monitoring data.

8 Conclusions

Figure 9 summarizes the approaches of risk assessment of individual landslides. From a probabilistic point of view, the traditional factor of safety approach is usually based on the mean factor of safety. The probability of failure needs an estimate of the mean and standard deviation of the factor of safety. To be able to assess risk, the consequence of failure needs to be quantified. If an individual consequence is assessed for different failure modes, risk is actually the mean consequence times the failure probability. It can be concluded that risk assessment of individual landslides needs to evolve towards using more detailed assessments of each component of risk. It can be predicted that as computer technology advances, the risk assessment of individual landslides will require the simulation of the dynamic process of landslides from initiation, transportation, run-out and final settling.

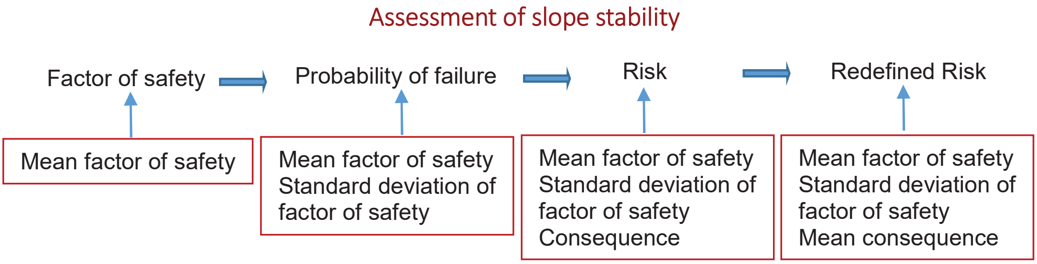

Figure 9. Risk assessment of individual landslides.

Traditional deterministic factor of safety approaches do not take uncertainties directly into account. A more logical way is to use probabilistic approaches for the risk assessment of landslides. Because the engineering properties of soils vary spatially, unconservative results are obtained if such spatial variability is not considered. There are also many possible failure modes for a particular landslide, each of which has individual consequences. In the risk assessment of individual landslides, it is necessary to assess consequences individually for each potential failure mode.

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