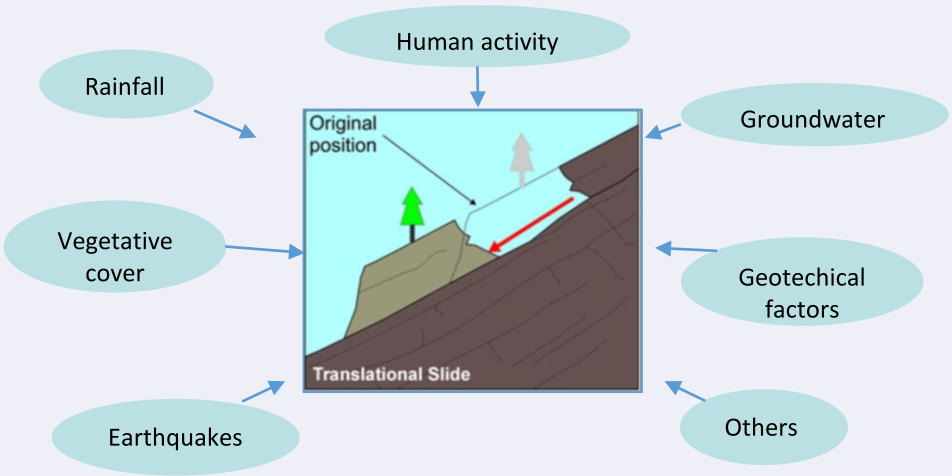
Risk Analysis for Slope Stability with Advanced Bayesian Networks

Introduction

Shallow landslides can be analyzed as infinite slopes, whose failure is induced by various geotechnical factors, external environment, and anthropogenic influence. To identify the main inducing factors for the instability of slopes is of importance for geotechnical design, disaster prevention, and decision-makers. For solution Bayesian Networks (BNs) are proposed, which are causal graphical models for quantifying the uncertainty, having been developed and successfully applied to natural hazards, safety, and reliability engineering for over two decades.



The following problems need to be solved:

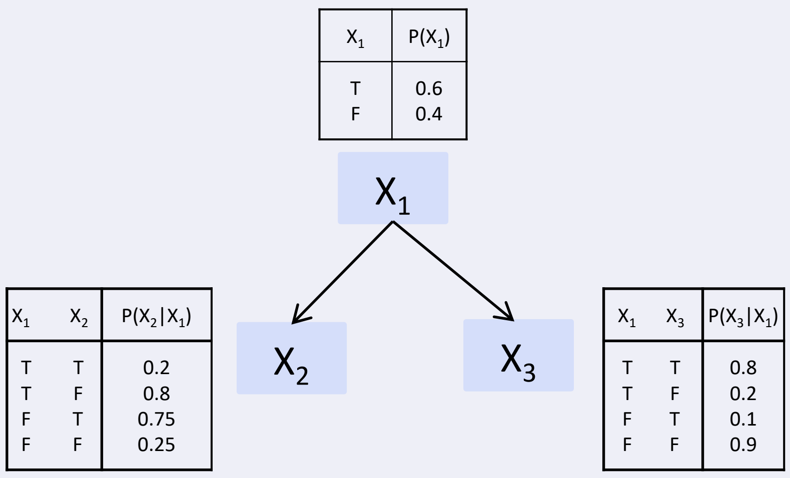
- Identify the key influence factors on the slope stability
- Predict the probability of slope failure

Bayesian Networks

Traditional Bayesian networks are precise probabilistic models by means of directed acyclic graphs, with no cycles. Each node represents an event with random variables. Between the nodes parent-child relations are formulated, represented by an arrow denoting the conditional dependencies between the variables. Conditional Probability Tables are attached to each node, considering all the possible states of a variable. For a simple Bayesian network, according to the chain rule of BNs, the equation of the factorization of joint probability distribution is

$$P(X_1, X_2, X_3) = P(X_1)P(X_2)P(X_3|X_1, X_2)$$

where the node X_1 is the parent of X_2 and X_3, and all of them are discrete variables.



X_1	$P(X_1)$
T	0.6
F	0.4

X_1	X_2	$P(X_2\|X_1)$
T	T	0.2
T	F	0.8
F	T	0.75
F	F	0.25

X_1	X_3	$P(X_3\|X_1)$
T	T	0.8
T	F	0.2
F	T	0.1
F	F	0.9

Figure 1: A simple Bayesian network

BNs provide efficient algorithms for probability updating, allowing to take evidence as input. For instance, considering the observation $X_2 = e$, the update from the prior probabilities to the posterior probabilities is described as

$$P(X_1, X_3|e) = \frac{P(X_1, e, X_3)}{P(e)} = \frac{P(X_1)P(e)P(X_3|X_1, e)}{P(e)}$$

and $P(e)$ should be computed by marginalisation calculation when it cannot be obtained directly.

Enhanced Bayesian Networks

Enhanced BNs (eBNs), integrating BNs and structural reliability methods (SRMs) into a coherent model, enable effective computation of continuous nodes with stochastic distributions. Then by means of SRMs, these continuous nodes lose the causal dependencies with their deterministic nodes. Finally, all the continuous nodes can be removed from eBNs according to a node elimination algorithm, thus reducing the original BNs to discrete BNs.

Credal Networks

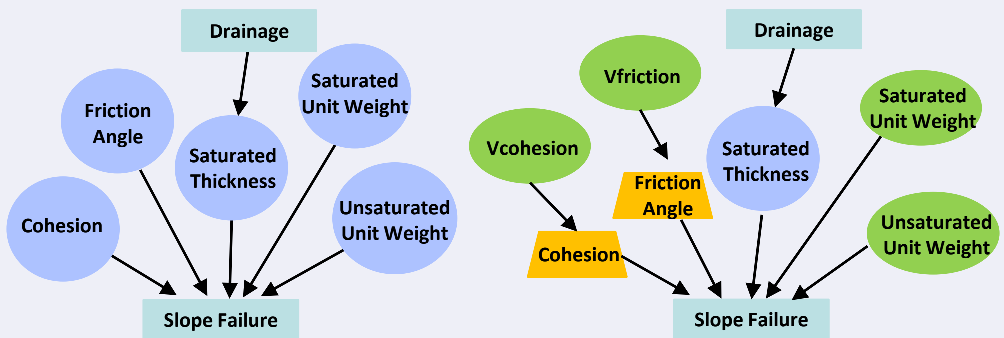
Credal networks (CNs) are a generalization of Bayesian networks to implement imprecise discrete variables in the form of intervals. In the case that imprecise probabilities are introduced to Bayesian networks, the node corresponding to an imprecise event is associated with a credal set

$$K(x_i) = CH\{P(x_i)|P(x_i) = \prod_{i=1}^{n} P(x_i|\pi_i)\}$$

The calculation of the marginal probabilities of variables is based on the joint credal set definition to calculate the bounds of each node. The inference for CNs is more complex than for BNs, still being in its infancy stage of development. Currently, there are some exact and approximate inference algorithms used for the reasoning of CNs.

The Application in the Infinite Slope Problem

In this study, advanced BN approaches are proposed to deal with the slope stability. As Figures 2a and 2b show, the model includes six factors and one failure event. The main strength parameters of the soil, cohesion and friction angle are the resisting forces preventing the occurrence of failure. In the light of the influence of water in the slope, the factors: Unsaturated Unit Weight, Saturated Unit Weight and Saturated Thickness are selected in the slope model. Furthermore, the node Saturated Thickness represents the depth of saturated soil, which is the level of the water table. This random variable is governed by the drainage condition. The results provide key information for the decision makers and demonstrate that advanced BN approaches are effective and feasible to assess the risk regarding slope stability subjected to drainage state.



a. The eBN of the slope   b. The CN of the slope

Figure 2: The advanced BN models

Reference

Longxue He, António Topa Gomes, Matteo Broggi, and Michael Beer. *Risk Assessment for Slope Stability with Enhanced Bayesian Networks Methods. Proc. of the 6th ISRERM conference, 2018.*

Longxue He, António Topa Gomes, Matteo Broggi, and Michael Beer. *Risk Analysis of Infinite Slope Failure using Advanced Bayesian Networks. Proc. of the 8th International Workshop on REC2018.*

Note

This work is supported by the Chinese Scholarship Council.

Institute for Risk and Reliability

www.irz.uni-hannover.de