Quantitative risk assessment for earthquake-triggered landslides using Bayesian network

Évaluation quantitative du risque associé aux glissements de terrain déclenchés par séisme en utilisant un réseau Bayésien

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ABSTRACT: Strong earthquakes in mountainous regions usually trigger many landslides that lead to damage and destruction. Separate investigations of single hazard processes (earthquake and landslide) might lead to a misjudgement of the risks associated with this type of cascading hazards. The assessment and mitigation of the risks require a multi-risk analysis approach that can account for the interactions among the threats and among the vulnerabilities to these threats. In this paper, a quantitative risk assessment model using Bayesian network is proposed to estimate the risk for the buildings exposed to the threat of earthquake-triggered landslides. A sensitivity analysis was done to identify the optimum and appropriate risk reduction strategy in a multi-hazard perspective.

RÉSUMÉ : De forts séismes dans les régions montagneuses déclenchent habituellement des nombreux glissements de terrain qui mènent à dommages et destruction. Si l'on traite les aléas singuliers séparément, par exemple un tremblement de terre et un glissement de terrain, une estimation erronée des risques associés à ce type d'aléas cascadés peut être obtenue. L'évaluation et l'atténuation des risques nécessitent une approche multi-risques qui doit tenir compte des interactions entre les dangers et les vulnérabilités à ces dangers L'article propose un modèle d'évaluation quantitative des risques en utilisant un réseau Bayésien pour estimer le risque aux bâtiments exposés aux glissements de terrain déclenchés par un séisme. Une analyse paramétrique a été réalisée pour identifier une stratégie optimale et appropriée pour réduire le risque dans une perspective multi-aléas.

KEYWORDS: Landslides, Earthquake, Quantitative risk assessment, Bayesian network

1 INTRODUCTION

Earthquake-triggered landslides are one of the most common secondary disasters caused by earthquake in mountainous areas. In the Wenchuan earthquake of May 2008, more than 15 000 landslides of various types were triggered in the steep mountain slopes (Huang 2008). The landslides caused more than 20 000 fatalities (Yin *et al* 2009) and caused extensive damage to housing settlements and irrigation channels (Tang *et al* 2011).

In earthquake-triggered landslide risk assessment, complex interactions are present between the earthquake and landslide threats. The vulnerabilities of the elements at risk are sometimes also correlated to the threats. Amplified risk resulting from hazard and vulnerability interactions has to be considered. Unfortunately, to date, the risk assessment involving multiple hazards is commonly done with independent analyses neglecting possible cascade effects (Marzocchi *et al* 2012) and standard approaches for dealing with the multi-risk situations are not available (Kappes *et al* 2012). In this paper, a quantitative risk assessment model using Bayesian network is proposed to estimate the risk for the buildings exposed to the threat of earthquake-triggered landslides.

2 BAYESIAN NETWORKS

A Bayesian network (BN), also called a belief network, Bayes net or casual network, is an increasingly popular method for reasoning under conditions of uncertainty and modelling uncertain domains. It has been applied to a number of civil and environmental engineering problems, ranging from avalanche risk assessment (Grêt-Regamey and Straub 2006), dam risk analysis (Smith 2006), earthquake risk management (Bayraktarli *et al* 2005; Bensi *et al* 2011), design of early warning system for landslide hazard mitigation (Medina-Cetina *et al* 2007) and environmental modelling and management (Aguilera *et al* 2011).

A BN is a probabilistic model based on directed acyclic graph

$$B_s = G(Z, E) \tag{1}$$

where B_s represents the structure of the network, Z is the set of random variables ($Z_1, Z_2, \ldots Z_n$), and $E \in Z\times Z$ is the set of directed arcs, representing the probabilistically conditional dependency relationships among random variables. Each variable Z_i can be defined in a discrete and finite outcome space (discrete random variable) or as a continuous outcome space (continuous random variable).

One important property of the Bayesian network is that the joint probability function of all random variables in the network can be factorized into conditional and unconditional probabilities implied in the network (Jensen 2007). Thus, the joint distribution can be expressed in the compact form as

$$P(z_1, z_2, \ldots, z_n) = \prod_{i=1}^{n} P\left(z_i \,\middle|\, pa\left(Z_i\right)\right) \tag{2}$$

where $pa(Z_i)$ is the parent set of z_i. It should be noted that if child node z_i has no parents, then the equation reduces to the unconditional probability of $p(z_i)$.

A simple Bayesian network with five nodes and five arcs is illustrated in Fig.1. These nodes are: Magnitude (M), Distance (D), Seismic severity (S), Landslide severity (L), and Building damage (B). These nodes are connected via the arcs: M-S, D-S, S-L, S-B and L-B. The prior probability of B, $P(B = B_1)$ can be calculated by

$$P(B=B_1)=\sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{k=1}^{2}\sum_{m=1}^{2}P\left(B=B_1, M=M_i, D=D_j, S=S_k, L=L_m\right) \tag{3}$$

where P = probability, B_1 = no damage, M_1 = small magnitude, M_2 = large magnitude, D_1 = small distance, D_2 = large distance, S_1 = low seismic severity, S_2 = high seismic severity, L_1 = low landslide severity, L_2 = high landslide severity.

In this case, as both *M* and *D* are the parents of *S*, *S* is the parent of *L*, and both *S* and *L* are the parents of *B*, the joint probability can be derived according to Eq. 2:

$$P(B = B_1, M = M_i, D = D_j, S = S_k, L = L_m)$$
$$= P(M = M_i) \times P(D = D_j) \times P(S = S_k \mid M = M_i, D = D_j)$$
$$\times P(L = L_m \mid S = S_k) \times P(B = B_1 \mid S = S_k, L = L_m) \quad (4)$$

where the (conditional) probabilities on the right hand side of the equation are quantified with available information (e.g., statistical data, expert knowledge, and physical approaches).

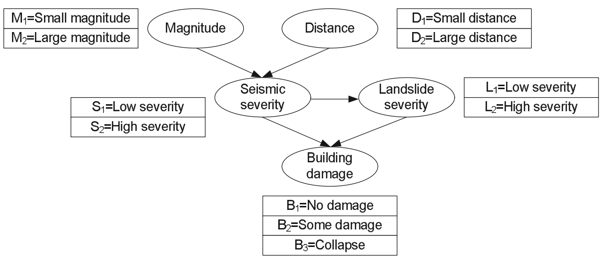

Fig. 1 A simple Bayesian network.

The BN allows one to enter evidence as input, meaning that probabilities in the network are updated when new information is made available, for instance, a case with a small magnitude and large distance. This information will propagate through the network and the posterior probabilities of *B*, $P(B = B_1)$ can be calculated as:

$$P\left(B = B_1 \middle| M = M_1, D = D_2\right) = \frac{P\left(B = B_1 \middle| M = M_1, D = D_2\right)}{P\left(M = M_1, D = D_2\right)} \quad (5)$$
$$= \frac{\sum_{j=1}^{2}\sum_{i=1}^{2} P\left(B = B_1, S = S_j, L = L_i, M = M_1, D = D_2\right)}{\sum_{k=1}^{3}\sum_{j=1}^{2}\sum_{i=1}^{2} P\left(B = B_k, S = S_j, L = L_i, M = M_1, D = D_2\right)}$$

where the joint probabilities in the above equation are calculated with Eq. 3 on the basis of Baye's theorem (Ang and Tang 2007).

3 BAYESIAN NETWORK FOR EARTHQUAKE-TRIGGERED LANDSLIDE RISK ASSESSMENT

According to the ISSMGE Glossary of Risk Assessment Terms, 'Risk' is the measure of the probability and severity of an adverse effect to life, health, property, or the environment. Quantitatively risk is the product of the threat times the potential worth of loss and can be expressed as:

$$Risk = Probability\ of\ Threat \times Worth\ of\ Loss \quad (6)$$

Otherwise expressed (e.g. Einstein 1997):

$$Risk = P(T) \times P(E|T) \times U(E) \quad (7)$$

where $P(T)$ is probability of threat, $P(E|T)$ is conditional probability of damage of the element(s) at risk exposed to threat, i.e. vulnerability, and $U(E)$ is utility of element(s) at risk.

A comprehensive Bayesian network (modified after Einstein *et al* 2010) for estimating the risk of buildings in an assumed earthquake-triggered landslide case was built with an open-source MATLAB package BNT (Bayes Net Toolbox) (Murphy 2001) as shown in Fig. 2. There are 11 nodes and 16 arcs in the network. Each node is characterized by several discrete states as shown in Table 1.

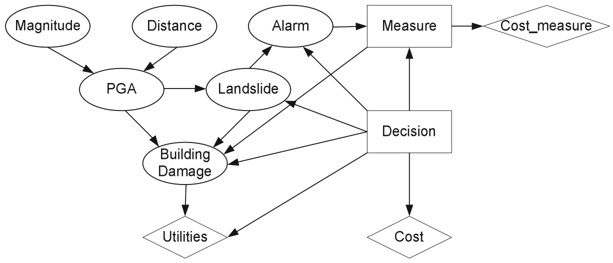

Fig. 2 Bayesian network for earthquake-triggered landslide risk assessment with possible decisions (modified after Einstein *et al* 2010).

Table 1 Nodes and their states of the Bayesian network in Fig. 2

Nodes	No. of states	States
Magnitude (M_w)	6	4.0-4.5-5.0-5.5-6.0-6.5-7.0
Distance (km)	6	22-25-28-31-34-37-40
PGA (g)	6	0-0.08-0.16-0.24-0.32-0.40-0.48
Landslide	2	Happens; Does not
Building damage	3	No damage; Some damage; Collapse
Alarm	2	Yes; No
Measure	2	Yes; No
Decision	4	Passive; Active; No action; Warning system
Cost_measure	-	
Cost	-	
Utilities	-	

4 QUANTIFYING THE NETWORK

4.1 *Seismic hazard*

The seismic source is assumed as a line source in this study. Using the geometric characteristics of the source, the distribution of distances can be calculated as shown in Fig. 3.

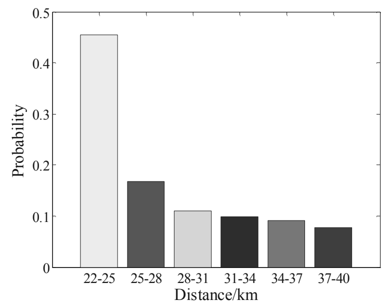

Fig. 3 Specification of the discrete probabilities of distance.

The annual probabilities for each range of Mw are calculated using the Gutenberg-Richter magnitude recurrence relationship (Gutenberg and Richter 1994), as shown in Fig. 4.

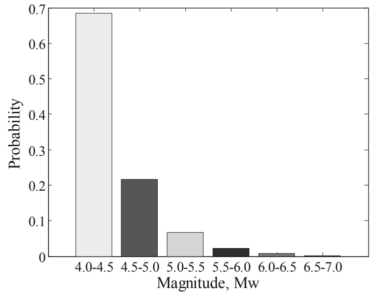

Fig. 4 Specification of the discrete probabilities of magnitude.

The conditional probabilities of PGA given the magnitude and distance to epicenter are calculated with the ground motion equation proposed by Ambraseys *et al* (2005), using Monte Carlo simulation in Microsoft Excel. The joint probabilities of

PGA are obtained based on inference of Bayesian network, as shown in Fig. 5

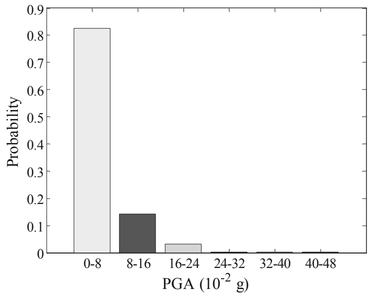

Fig. 5 Specification of the discrete probabilities of PGA.

4.2 *Landslide hazard*

Approaches developed to assess the stability of slopes during earthquake fall into three general categories: (1) pseudo-static analysis, (2) stress-deformation analysis, and (3) permanent displacement analysis. In this paper, dynamic performance of slopes is modelled using permanent displacement analysis developed by Newmark (1965). The critical acceleration of a landslide block can be calculated by

$$a_c = (FS\text{-}1)\ g\ sin\alpha \quad (8)$$

where *FS* is the static factor of safety; *g* is the acceleration of Earth's gravity; and *α* is the angle of the sliding surface, which can generally the approximated as the slope angle.

The static factor of safety (*FS*) for an infinite slope is

$$FS = c'/(\gamma z\ sin\alpha\ cos\alpha)+(1\text{-}m\ \gamma_w/\gamma)tan\varphi'/tan\alpha \quad (9)$$

where *c'* and *φ'* are the effective cohesion and friction angle of the soil; *z* is the depth of the failure surface; *α* is the slope angle; *γ* is the soil unit weight; and γ_w is the specific weight of water.

In the present study, the Newmark displacement is estimated using Eq. 10 reported by Ambraseys and Menu (1998):

$$Log\ D_n = 0.9+log[(1\text{-}a_c/a_{max})^{2.53}\ (a_c/a_{max})^{-1.09}] \quad (10)$$

where D_n is the Newmark displacement in centimeters, a_c and a_{max} are critical acceleration and peak ground acceleration in *g's* respectively.

The probability of slope failure as a function of Newmark displacement, as described by Jibson *et al* (2000) is estimated using the following equation

$$P(f) = 0.335\times[1\text{-}exp\ (\text{-}0.048\times D_n^{1.565})] \quad (11)$$

The soil and slope properties used in this study are shown in Table 2.

Table 2. Soil and slope properties.

Variable	Mean	St. Dev
c' (N/m^2)	10 000	2 000
φ' (degree)	30	2
z (m)	2.5	0
α (degree)	35	0
γ (N/m^3)	27 500	0
γ_w (N/m^3)	10 000	0
m	0.4	0

The probabilities of slope failure computed by Eq. 11 for various ranges of PGA are listed in Table 3. Countermeasures made to landslide could reduce risk. Specifically, active actions can reduce the probability of slope failure, passive actions and warning system can reduce the vulnerability of element(s) at risk. The assumed probability of slope failure when active actions are taken is shown in Table 4.

Table 3. The probability of slope failure

PGA (10^{-2} g)	0-8	8-16	16-24	24-32	32-40	40-48
P(f)	0.124	0.256	0.305	0.328	0.339	0.346

Table 4. The probability of slope failure when active actions are taken

PGA (10^{-2} g)	0-8	8-16	16-24	24-32	32-40	40-48
P(f)	0.025	0.03	0.035	0.04	0.045	0.05

4.3 *Other nodes*

In the case of a building subjected to a multi-hazard situation involving additive load effects (e.g. earthquake + landslide), the damage will be increased. Herein, the conditional probabilities of building damage are modified from Einstein *et al* (2010). For other nodes, we adopt from Einstein *et al* (2010). These probabilities (conditional probabilities) are shown in Tables 5-11.

Table 5. Four combinations of conditional probabilities of Building damage

Parent nodes	PGA	0-0.08			
	Measure	Yes			
	Decision	Passive		Active	
	Landslide	Happens	Does not	Happens	Does not
Building damage	No damage	0.4	0.1	0.52	0.1
	Some damage	0.3	0.1	0.43	0.1
	Collapse	0.3	0.8	0.05	0.8

Table 6. Four combinations of conditional probabilities of Measure

Parent nodes	Alarm	Yes			
	Decision	Passive	Active	No action	Warning system
Measure	Yes	0	0	0	1
	No	1	1	1	0

Table 7. Four combinations of conditional probabilities of Alarm

Parent nodes	Landslide	Happens			
	Decision	Passive	Active	No action	Warning system
Alarm	Yes	0.5	0.5	0.5	0.9
	No	0.5	0.5	0.5	0.1

Table 8. Four combinations of conditional probabilities of Alarm

Parent nodes	Landslide	Happens			
	Decision	Passive	Active	No action	Warning system
Alarm	Yes	0.5	0.5	0.5	0.9
	No	0.5	0.5	0.5	0.1

Table 9. Conditional probabilities of Cost

Parent nodes	Decision	Passive	Active	No action	Warning system
Cost		-1250	-2000	0	-500

Table 10. Conditional probabilities of Utility

Parent nodes	Damage	No damage	Some damage	Collapse
Utilities		0	-10000	-20000

Table 11. Conditional probabilities of Cost_measure

Parent nodes	Measure	Yes	No
Cost_measure		-1000	0

5 RESULTS

The results obtained using the described Bayesian network of the entire risk assessment and decision are shown in Fig. 6. Different mitigation measures result in different utilities. The warning system, showing the lowest (negative) utility is the optimal mitigation measure.

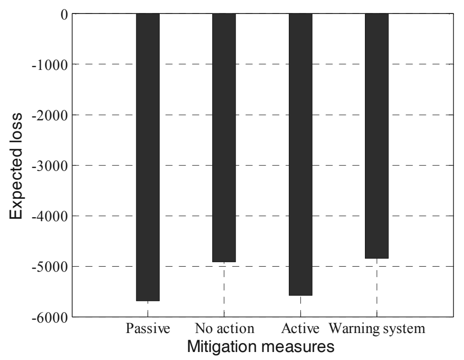

Fig. 6 Comparison of results for Passive countermeasure, No action, Active countermeasure, and Warning system.

This result is based on many parameters that can vary, for instance, the costs; the probability of slope failure or the reliability of the warning system. Therefore, sensitivity analyses were conducted to assess the effects of these variations on the results. Fig. 7 investigates the effect of changing the probability of landslide occurrence against different measures. As expected, for very low failure probabilities, no action is preferred; otherwise a warning system is the best choice, except for very high probabilities where active countermeasures are preferred. It is worth noting that this is only one example, and the sensitivity of the decision to other factors needs to be similarly investigated.

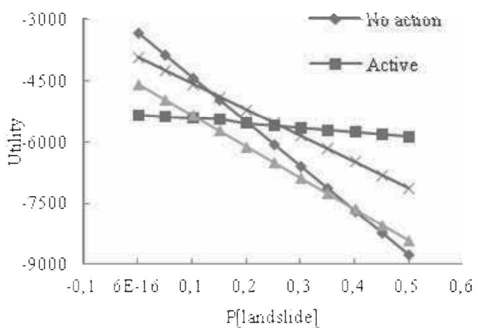

Fig. 7 Sensitivity analysis of the resulting risk arising from varying the probability of slope failure while employing different mitigation actions.

6 CONCLUSIONS

This paper present a new model for evaluating the risks associated with earthquake-triggered landslide using a Bayesian network. The model considered the interactions between different threats in a systematic structure, and accounted for the uncertainties and expert judgments, which are always present in risk analysis. The results obtained in this study are a preliminary step in furthering the earthquake-triggered landslide risk assessment and similar multi-hazard risk assessments. Some of the subjective and empirical parameters in the model need to be further calibrated with the addition of objective data, experience and observations.

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