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Landslide susceptibility assessment: Chicken or the egg for the risk analysis?

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Abstract This article explores the complexities of landslide risk assessment, emphasizing the qualitative nature of analysing hazards and consequences. It highlights the necessity for well-defined frameworks to evaluate these risks and the significant role of expert judgment in refining assessments due to inherent uncertainties. The text argues for the development of clear methodologies that stakeholders can understand and accept, incorporating best practices and local knowledge to mitigate legal risks associated with predictive inaccuracies. Additionally, it suggests the use of catastrophe modelling to solve the issues linked with uncertainty.

Keywords Landslide, risk, hazard, susceptibility.

Introduction

Risk management encompasses a more extensive definition of risk than that employed in risk analysis. As per ISO 31000 (2018), risk is conceptualized as:

The "*effect of uncertainty on objectives*".

This notion includes the potential deviation from anticipated events, which could engender negative impacts, opportunities, or a combination thereof, on predefined objectives. Such objectives may be influenced by a myriad of event types at various process levels. Risk is distinguished by elements likely to yield expected or unexpected outcomes on the objective, coupled with their probability of occurrence. This definition is particularly pertinent to risk in decision-making contexts, such as risk management, where it is often contingent upon factors extrinsic to risk analysis.

Moreover, the above definition acknowledges the possibility of risk leading to positive outcomes, a scenario considerably less frequent in the context of landslides. Decision-making and risk management inherently incorporate uncertainty, which, however, can be quantified through probabilities or qualitative assessments thereof (Aven and Renn, 2009).

It is imperative to recognize that risk definitions are context dependent. In epidemiology, for instance, risk is quantified as the proportion of new disease cases in a specified period relative to the initial healthy population (Rothman, 2012).

The methodology for analysing risks associated with slope movements varies case by case. Typically, a particular site is examined to assess potential disaster-related costs or the probable number of casualties. Outcomes may be expressed as the probability of event impacts exceeding a defined threshold within a set timeframe, or as temporal frequencies of costs or fatalities. When calculating individual risk of mortality, it is represented as a death rate over time. This mortality risk is frequently juxtaposed with a societal risk acceptability criterion, defined in relation to the size of the affected population (Hungr and Wong, 2007). Thus, it is evident that:

"*Risk analysis involves applying recipes that may vary based on perspective and available data*."

Identifying the hazard is a primary step, yet quantifying it is often challenging, leading to predominantly qualitative risk assessments, especially when knowledge is limited to susceptibility. The potential impact or vulnerability for given landslide intensities is subject to considerable uncertainty (Galli and Guzzetti, 2007), which means that qualitative assessment is pertinent. In such cases, methodologies like the probability-impact matrix, typically utilized by experts, are beneficial (Haimes, 2009; Porter and Morgenstern, 2013).

Despite its limitations, risk assessment remains a critical tool in decision-making, notably in cost-benefit analyses that guide risk mitigation strategies. Nonetheless, it is essential to acknowledge that risk is not the sole factor in decision-making; socio-economic considerations also play a significant role (Leroi et al. 2005).

The difficulties in quantifying temporal frequency or hazard and consequences are for most landslide risk analyses based on susceptibility, as they are often based on the calibration of both scales.

If the risk framework is clear, the application sensu stricto of risk assessment is rarely carried out, and the use of susceptibility is the most commonly used approach. Furthermore, where the hazard can be assessed quantitatively, it may be subject to considerable uncertainty.

Some sections of this document are inspired by a book in preparation in French on landslides (Jaboyedoff et al. in prep.).

Risk Basics

Basic formulas for risk and hazard (frequency)

Considering the magnitude as a quantity describing the volume, surface area, energy, pressure, etc. the landslide's risk quantification for one landslide scenario of magnitude M_i is classically given by (Corominas et al. 2014):

$$R_{ijk} = f(M_i)\, P(X_j|M_i)\, Exp(t|X_j)\, V_E\left(I(M_i,X_j)\right)\, W(X_j(E_k)) \quad [1]$$

Where $P(X_j|M_i)$ is the probability that an event of magnitude M_i reaches the point X_j, $Exp(t|X_j)$ is the exposure, which means the probability that the object or the person is located in X_i at the time t of the event, $V_E\left(I(M_i,X_j)\right)$ is the physical vulnerability of the object E hit by an event of magnitude M_i with an intensity I depending on the location X_j. $W(X_j(E_k))$ is the value of the object E_k located in X_j or the number of units like people, if there is no object in X_j then W is null. $f(M_i)$ is the temporal frequency of a landslide of magnitude M_i or hazard. In fact, the frequency f or hazard H is calculated for a range of magnitude assuming that $\lambda'(M_i)$ is the frequency density and $\lambda(M_i)$ the cumulative of the temporal frequency to exceed M_i, for a range of magnitude $M_i \pm \Delta M$ it comes:

$$f(M_i) = \mathrm{H}(M_i) = \int_{M_i-\Delta M}^{M_i+\Delta M} \lambda'(m)\, dm \quad [2]$$

knowing that it is not possible to know the time separating two events of the same magnitude; this can only be done by classes of values or using the directly $\lambda(M)$. The relationship between temporal frequency and return period is given by (Hungr et al. 1999):

$$\lambda(m \geq M) = \frac{1}{T(m \geq M)} \quad [3]$$

where $\lambda(m \geq M)$ is the frequency of events of magnitude greater than or equal to M, i.e. a cumulative frequency. The intensity is used to evaluate vulnerability, but often the event frequency is related to the source of the hazard of magnitude M_i and not to the intensity of the event at a given location X. A typical example is the rockfall hazard given by volumes of the source area, but it fragmented along the path (Farvacque et al. 2019; Lanfranconi et al. 2023 Ruiz-Carulla et al, 2016). When the vulnerability V concerns people, it can equal to lethality or a function of the vulnerability of the buildings including injuries (Li et al. 2010).

Relationship Frequency - Probability

The classic example is the distribution of landslide volumes. If $f(M_i)$ is quantified, then the probability that during a period Δt, n events will occur for a class of magnitude M_i using the Poisson distribution, provided that these events are independent:

$$P(n, \Delta t) = \frac{(f(M_i)\Delta t)^n}{n!}\, e^{-f(M_i)\Delta t} \quad [4]$$

The temporal frequency should not be confused with the probability, because some phenomena have a frequency greater than 1, whereas the probability cannot exceed one, which is a common mistake. So, it is only when T>>1 is large that the probability of an event per unit of time so:

$$P \approx \frac{1}{T} \quad [5]$$

In that case the probability of an event not occurring in a year is close to (1-P), and therefore the probability of at least one event occurring in d years is classically given by:

$$P(n \geq 1, d) \approx 1 - \left(1 - \frac{1}{T}\right)^d \quad [6]$$

But this formulation depends on the unit of time, because for T = d = 1 we get 100%, but respecting the hypothesis T>>1, for 8760 hours in a year we get 63.2%. It is therefore preferable to use the Poisson distribution by evaluating the probability that there is no event (Corominas et al. 2014):

$$P(n \geq 1, d) = 1 - P(0, d) = 1 - \frac{(f(M_i)d)^0}{0!}\, e^{-\lambda_i d} = 1 - e^{-f(M_i)d} \quad [7]$$

In fact, we can show that the two formulations are equivalent. In case of multiple events with reconstruction, the use of Poisson's law for n= 1, 2, …, n maybe used, if significant. For small frequency the P≈f, there is less than 2% difference for a ratio f/Δt=f/T>25. To perform a full risk calculation class of magnitude must be used and formally integration or a summation must be performed over M_i, X_j, (implicitly $f(M_i)$) and E_k:

$$R_{total} = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{q} R_{ijk} \quad [8]$$

Second form of risk

An alternative way to present risk is to give a probability of occurrence given by the above formula and the damage or cost:

$$C(E, X_j, M_i) = Exp(t|X_j)\, V_p\left(I(M_i,X_j)\right)\, W(E,X_j) \quad [9]$$

This gives the possibility to create graphs such as consequences-frequency or frequency exceedance. Which is typically f-N or F-N curves (Farmer, 1967; Ale, 2008). The matrix usually represents C versus P or f, but if P is used the period d must be indicated, which is often omitted.

Matrix approach

It is obvious that the F-N curves are a direct transcription of risk equation, it is rather easy create when all the terms of the risk formula are knows. But they present some drawbacks concerning the risk acceptability and tolerability limits, which is not well established for F-N and for the non-cumulative version f-N, they depend on the domain they are applied, at le level of a country or in a local context (Ale et al. 2015).

In addition, the frequencies are not easily accessible like for earthquakes or flooding by their repetitive nature, using respectively Gutenberg-Richer law (Gutenberg and Richter, 1956) or Gumbel's law (Gumbel, 1941). This is also true for the damage estimations. In both case probabilities can be used to assess which class of frequency or damage it belongs.

The methodologies encompassed by Consequences-Frequency Matrices (CFM) are designed to facilitate risk assessment through the hierarchical classification of various hazards (UK-CO, 2017) (Fig. 1). This approach is particularly tailored for individual case studies, addressing key inquiries as posited by Haimes (2008): namely, identifying potential failings, as well as their respective probabilities and repercussions. Concurrently, industrial and insurance sectors implement a systematic process for Risk Filtering, Ranking, and Management (RFRM), which is an efficient and effective identification, prioritization, and administration of risks (Krause et al. 1995; Haimes, 2008; Jaboyedoff, 2023):

1. Scope definitions: what are the problems?
2. Creation of a group of experts concerned by each level of the analyzed risky system.
3. Hazard identification, i.e. identification of potential events and their scenarios
4. Risk filtering and ranking in several sub-stages which implies to establish frequency (probability) and impact classes and their corresponding limits (in loop with point 5)
   1.1. Use decision trees to select for C and f or H
   1.2. Place in risk matrix
5. Establish a ranking.
6. Risk management, including the quantification of the potential risk reduction, which necessitates the understanding of causes and effects
7. Finalization of decision-making process
8. Refinement of the process with the feedback

The CFM must in principle follow certain rules. Cox (2008) highlights an inconsistency in the color-coded risk scale, particularly due to the ambiguity in classifying risks positioned at the boundaries of different categories (Fig. 1). For instance, a data point situated at the juncture of three distinct risk classes may exhibit considerable classification variability. A mere unitary alteration in the axis values could potentially result in a shift of two entire class levels, thereby indicating a significant discrepancy in risk categorization. This phenomenon underscores the inherent challenges in maintaining a consistent and accurate risk assessment framework when utilizing colour-based scales.

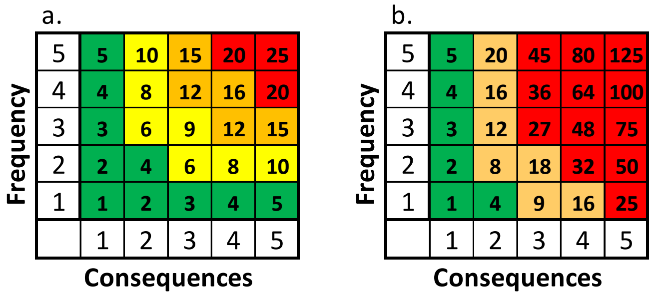

Figure 1 The illustration of 5 × 5 risk matrices presents two distinct configurations: firstly, a hyperbolic risk scale encompassing four classes (a), and secondly, a model incorporating risk aversion, characterized by a reduction to three classes (b). This comparative analysis underscores the variability in risk matrix structures and the impact of scaling and class alterations on risk assessment (modified form Jaboyedoff, 2023).

Example of hazard consequences values

Numerous exemplars of risk matrices exist within the risk domain. Porter and Morgenstern (2013) proposed a matrix for landslide risk assessment being particularly noteworthy (Fig. 2). This matrix provides the order of magnitudes of frequency and the different types of impacts delineating impacts across various domains such as Health and Safety, Environmental, and Social & Cultural factors. It underscores the imperative of maintaining fixed categories for likelihood estimation. However, it allows for the scaling of consequence metrics to align with specific objectives, such as adjusting for the scale of an enterprise or its associated bankruptcy risks. This adaptability renders the matrix a versatile tool in risk assessment.

Defining the classes of consequences and frequency or probability

To choose the membership to a class of consequences or frequency, several strategies can be used. It can be based on a set of indicators with weight which provide a value for one or for both scales as for geotechnical and geomorphic indicators used for quick clays risk analysis (Lacasse et Nadim, 2009).

Decision trees are fundamental tools for the analysis of risks or hazards (Leroueil et Locat, 1998; Haimes, 2008; Lacasse et al. 2008). These methodologies are adept at providing class values for either one or both axes in risk assessment frameworks. The employment of dichotomous branching, as advocated in the context of pandemic analysis by ECDC (2011), is preferred due to the enhanced ease in decision-making it offers. For instance, the frequency or return period (T_i) can be inferred through the process illustrated in Fig. 3, which is dependent on climatic variables, although specific quantitative values are not specified.

Multi-hazard Risk Evaluation Matrix (SAMPLE)									
For the Qualitative Assessment of Natural Hazards									
				Risk Evaluation and Response					
				VH	Very High	Risk is imminent; short-term risk reduction required; long-term risk reduction plan must be developed and implemented			
				H	High	Risk is unacceptable; long-term risk reduction plan must be developed and implemented in a reasonable time frame. Planning should begin immediately			
				M	Moderate	Risk may be tolerable; more detailed review required; reduce risk to As Low As Reasonably Practicable (ALARP)			
				L	Low	Risk is tolerable; continue to monitor and reduce risk to As Low As Reasonably Practicable (ALARP)			
	Partial Risk (annual probability)			VL	Very Low	Risk is broadly acceptable; no further review or risk reduction required			
Likelihood Descriptions	Indices		Probability Range						
Event typically occurs at least once per year	F	Almost certain	>0.9	M	H	H	VH	VH	VH
Event typically occurs every few years	E	Very Likely	0.1 to 0.9	L	M	H	H	VH	VH
Event expected to occur every 10 to 100 years	D	Likely	0.01 to 0.1	L	L	M	H	H	VH
Event expected to occur every 100 to 1,000 years	C	Possible	0.001 to 0.01	VL	L	L	M	H	H
Event expected to occur every 1,000 to 10,000 years	B	Unlikely	0.0001 to 0.001	VL	VL	L	L	M	H
Event is possible but expected to occur less than once every 10,000 years	A	Very Unlikely	<0.0001	VL	VL	VL	L	L	M
	Description of expected negative outcome (Consequence)		Indices	1	2	3	4	5	6
				Incidental	Minor	Moderate	Major	Severe	Catastrophic
			Health and Safety	No impact	Slight impact; recoverable within days	Minor injury or personal hardship; recoverable within days or weeks	Serious injury or personal hardship; recoverable within weeks or months	Fatality or serious personal long-term hardship	Multiple fatalities
			Environment	Insignificant	Localized short-term impact; recovery within days or weeks	Localized long-term impact; recoverable within weeks or months	Widespread long-term impact; recoverable within months or years	Widespread impact; not recoverable within the lifetime of the project	Irreparable loss of a species
			Social & Cultural	Negligible impact	Slight impact to social & cultural values; recoverable within days or weeks	Moderate impact to social & cultural values; recoverable within weeks or months	Significant impact to social & cultural values; recoverable within months or years	Partial loss of social & cultural values; not recoverable within the lifetime of the project	Complete loss of social & cultural values
			Economic	Negligible; no business interruption	<$10,000 business	<$100,000 business	<$1M business	<$10M business	>$10M business
					interruption loss or damage to public or private property				

Figure 2 Illustration of a risk matrix, devised by BGC Engineering Inc. and proposed to the Geological Survey of Canada, is presented as a Sample Qualitative Risk Evaluation Matrix (Porter and Morgenstern, 2013).

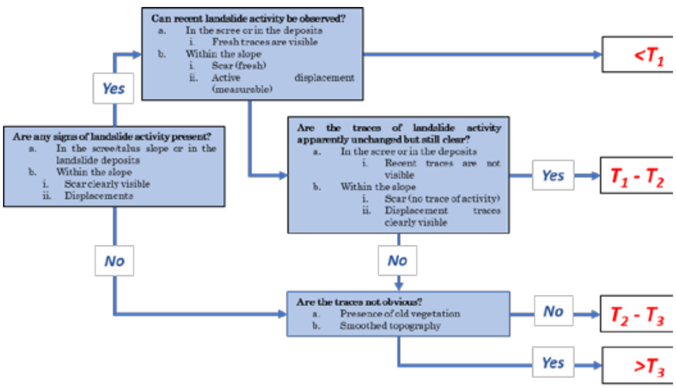

Figure 3 Example of a decision tree to determine the return period.

For the consequences scale, implementing a decision tree to determine the class categories is a feasible method. This approach is exemplified in the case of a landslide threatening a road, as shown in Fig. 4.

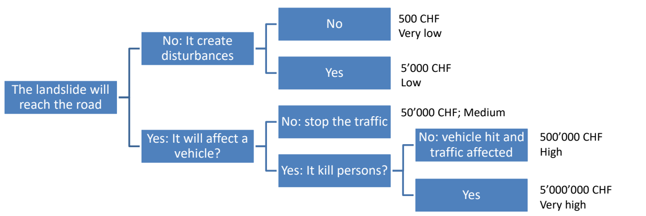

Figure 4 illustrates a decision tree used to ascertain the consequence levels for the Pont Bourquin landslide in Switzerland (from Jaboyedoff, 2023).

Alternatively, experts can be consulted to assign the probability of falling into each class on the scale. This method, as suggested by Vengeon et al. (2001), involves setting the frequency through a probability-delay matrix for landslide failures. This technique is applicable to both consequence assessment and frequency determination.

Temporal frequency and its estimates

Temporal frequencies can be analysed in several ways, in particular using inventories with event chronologies (Jaboyedoff et al. in prep.). But when the data are not sufficient or regional, the lack of local temporal is compensated for data with other information. This information can be weighted to create a local frequency or susceptibility scale. In the case of more detailed studies, seasonality can be integrated.

This involves assessing the temporal frequency for areas ω_i of the territory Ω (from a single landslide to an entire region) for a magnitude class $M_j \pm \Delta M$ which, on average, can be broken down into three terms (modified from Guzzetti et al. 2005):

$$\lambda(\Omega, M_j, t, \omega_i) = \lambda_r(\Omega, t) \times f_r(M_j)\, dM \times PS(\Omega, \omega_i) \quad [10]$$

so (λ_r, Ω, t) is the frequency of landslides in a region Ω at time t. t can be omitted, as the dependency is there simply to highlight the possible seasonal variability. From a practical point of view, we can estimate the temporal frequency for a given region Ω by:

$$\lambda_r(\Omega) = \frac{N_0(\Omega)}{\Delta t} \quad [11]$$

where $N_o(\Omega)$ is the number of landslides that have occurred during a period Δt, per unit area, or not. $f_r(M_j)$ dM corresponds to the relative distribution of magnitudes equal to M_i given that :

$$\int_{M_0}^{M_{max}} f_r(M)\, dM = 1 \quad [12]$$

This formulation can be replaced by a discrete formulation, i.e. a sum of probabilities for several scenarios of different magnitudes. Finally, PS(Ω, ω_i) is the probability of an event occurring within a given perimeter ω_I of Ω, which may be the landslide itself or zones of identical susceptibility. PS(Ω, ω_i) corresponds to a standardised susceptibility scale, i.e. a weighting that can be derived from different types of analysis, for example: counting of criteria favourable to the triggering of landslides (Hantz et al. 2003), regression on these parameters, probabilistic analysis, a neural network, etc. If we assume that s_i is a susceptibility value for one class among n susceptibilities, of m surfaces a_j^i of class i, of any scale, then for a given class PS(Ω, ω_i) we have :

$$PS(\omega_i) = \frac{s_i \sum_{j=1}^{m} a_j^i}{\sum_{i=1}^{n} s_i \sum_{j=1}^{m} a_j^i} \quad [13]$$

With

$$\sum_{i=1}^{n} PS(\omega_i) = 1 \; et \; \Omega = \sum_{i=1}^{n} \omega_i = \sum_{i=1}^{n} \sum_{j=1}^{m} a_j^i \quad [14]$$

Examination of all the variables shows that it is often difficult to estimate them all, and that some are often fixed at 1, which amounts to ignoring them. Many studies use only values of PS(Ω, ω_i), s_i or ω_i and/or expert opinions which produce scales of susceptibility in the broadest sense ranging from *negligible, for* example, through *low, medium and high* to *very high*. Others are based on the distribution of magnitudes f_r such as volumes, with or without the use of λ_r, or simply by choosing a single class of volume i.e. $f_r(M_j)$ dM = 1, PS =1, and λ_r per unit area. This shows the great diversity possible in the assessment of "hazard", or susceptibility. It can exist in very different forms.

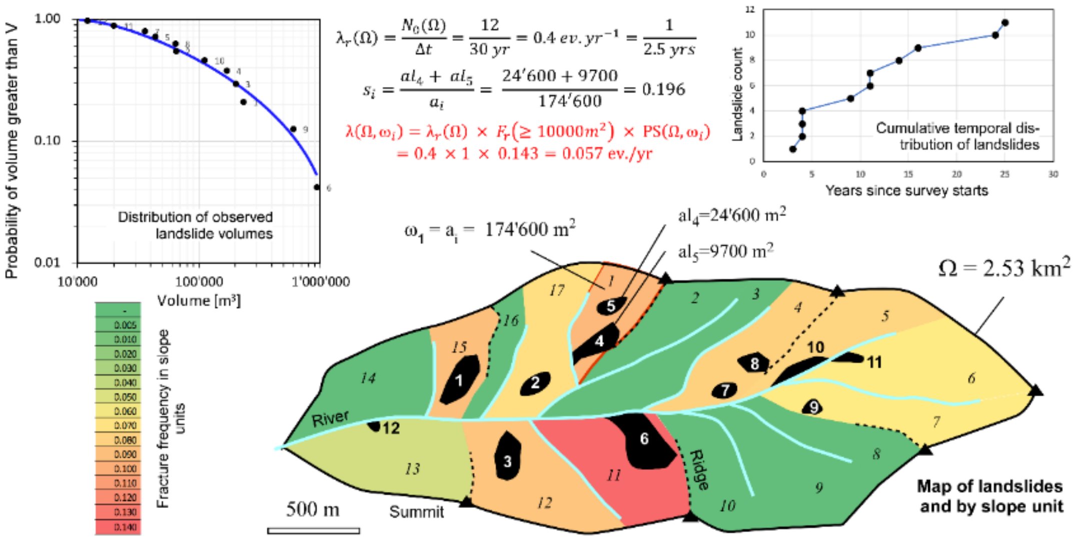

Figure 5 Synthetic illustration of the calculation of the temporal frequency of landslides (in grey) per slope unit. Here, in fact, by simplification, PS(Ω, w_i) is equal to the ratio of the surface area of landslides on a slope unit to the total surface area of all landslides, since the choice to quantify s_i by the ratio of the total surface area of landslides al_j to that of a unit a_i is based on this assumption.

The Fig. 5 an Table 1 show a synthetic example of such an approach. Based on an inventory of landslides in a catchment area that is subdivided into slope units (bounded by rivers and ridges; Carrara et al. 1991; Guzzetti et al. 2005). To simplify matters, the susceptibility s_i is calculated as the ratio of the surface area of the landslides to the surface area of the units containing them, $f_r(M_j)$ dM = 1 for all M_j as only one class of volumes above 10^4 m³ is considered, and PS and λ are calculated according to the formulae set out above. In a true statistical analysis, none of the values of s_i would be zero.

Table 1 Calculation of non-zero frequencies per slope unit of Fig 5..

i	$\omega_i = a_i$ [m]²	Surf. landslides [m²]	s_i	$f_r(v \geq 10^4 m^3)$	PS(ω_i)	λ(ω_i)
1	174'600	34'300	0.196	1	0.143	0.057
4	255'500	21'000	0.082	1	0.087	0.035
5	222'600	18'500	0.083	1	0.077	0.031
6	347'300	5'600	0.016	1	0.023	0.009
7	253'000	5'900	0.023	1	0.025	0.010
11	343'900	80'000	0.233	1	0.333	0.133
12	332'100	27'700	0.083	1	0.115	0.046
13	337'500	4'000	0.012	1	0.017	0.007
15	160'400	30'600	0.191	1	0.127	0.051
17	269'800	12'700	0.047	1	0.053	0.021
				Total	**1.000**	**0.400**

λ_r is often estimated based on historical inventories, observations of signs of activity, or expert opinion. Dating using C^{14} or cosmogenic nuclides, etc. is possible, but difficult to implement on a regional basis; however, analysis using dendrochronology and observations of damage to trees provides interesting results, particularly for debris flows and boulder falls (Stoffel et al. 2010) (Fig. 6).

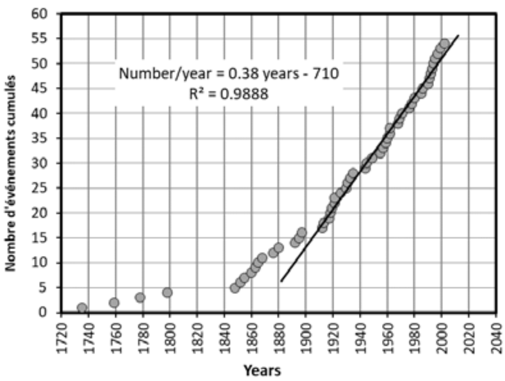

Figure 6 Debris flow activity in the Geisstriftbach (Switzerland), based on observations of tree damage and dendrogeomorphology. From 1910 onwards, the trees were sufficiently well preserved to show stationary activity, with an average of one event every 2 or 3 years (based on data from Stoffel et al. 2010).

Examples

Assessing risk based on matrix approach

As an example of matrix approach for risk analysis, Cardinali et al. (2002). They established a hazard map in Umbria region (Italy). The obtain risk at objects for the area of Rotecastello village. They used first a matrix to assess the landslide intensity (Fig. 7a) by crossing velocities and volumes, which provided a ranking of intensity. The landslide frequency was estimated using four classes, based on the number of landslide events (of the same type) observed within each Landslide Hazard Zone (low 1 event over 60 years, …, very high > 3 ev./60 yrs.). The landslide hazard (LHZ) matrix was obtained by crossing intensity and frequency (Fig. 8).

a.

Volume [m³]		Expected landslide velocity: Fast moving landslide — Boulder falls and rock avalanches	Rapid moving landslide — Debris-flow	Slow moving landslide — Slide
<	0.001	Slight		
0.001 to	0.5	Medium		
0.5 to	500	High	Slight	
500 to	1.0E+04	High	Medium	Slight
1.0E+04 to	5.0E+05	High	High	Medium
5.0E+05 to	6.0E+06	Very High	Very High	High
>	6.0E+06	Very High	Very High	Very High

b.

Landslides Intensity		Elements at risk — Buildings: High population density	Low population density	Industries	Animal farms	Sports facilities	Cemeteries
Light	Falling rocks	A	A	A	A	A	A
	Debris flow	A	A	A	A	A	A
	Landslide	A	A	A	A	A	A
Medium	Falling rocks	F	F	F	F	F	F
	Debris flow	F	F	F	F	F	F
	Landslide	F	F	F	F	F	F
High	Falling rocks	S	S	S	S	S	S
	Debris flow	S	S	S	S	S	S
	Landslide	S	S	S	S	S	S
Very high	Falling rocks	S	S	S	S	S	S
	Debris flow	S	S	S	S	S	S
	Landslide	S	S	S	S	S	S

Figure 7 (a) Landslide intensity matrix based on volumes and velocities, for 3 main types of landslides. (b) Impact of landslides on infrastructures expected for elements at risk. A = superficial (low) damage; F = functional (or medium) damage; S = structural (or total) damage. Intensities are shown in (a) (modified from Cardinali et al. 2002).

The vulnerability was defined based on the intensity scale for each type of landslides for many types of objects (Fig. 7b). As the LHZ matrix is linking frequency and intensity and as the intensity and damage increase it can be considered as a risk matrix (Fig. 8). But observations showed that were not all fitting the scale. Indicating that uncertainty was not included.

Estimated landslide frequency	Landslide intensity Light (1)	Medium (2)	High (3)	Very high (4)
Low (1)	1 1	1 2	1 3	1 4
Medium (2)	2 1	2 2	2 3	2 4
High (3)	3 1	3 2	3 3	3 4
Very high (4)	4 1	4 2	4 3	4 4

Figure 8 Interpretation of the theoretical LHZ matrix of Carinali et al. (2002) in terms of risk: the yellow correspond to low risk, orange to medium, red to high and purple to very high. Not that there is no contact between three classes.

Assessing risk based on indicators

Norway has implemented a straightforward methodology for risk zoning in the context of sensitive clays, as developed by Lacasse and Nadim (2009). This method involves assigning weights wa_i to various indicators Sa_i to derive the susceptibility to landslide which means that it is only based on PS estimations. The hazard is categorized into 4 classes Sa_i: null, low, medium, and high levels, based on a weighted system accounting for 8 parameters, i.e. topography, geotechnical properties, dynamic conditions like erosion, human activity, historical landslide occurrences, etc.

Similarly, consequences are evaluated on a scale Sc_j from not serious to very serious (0-3), considering 7 factors such as loss of life, property damage, and economic or social impacts which are weighted by wc_i.

The risk index (R_I) is calculated for different zones by multiplying the susceptibility index (S_I) and the consequences index (C_I), using a formula that combines the weighted sums of hazard and consequence indicators (Figure 9):

$$R_I = S_I \times C_I = \left(\sum_{i=1}^{8} wa_i \times Sa_i\right) \times \left(\sum_{j=1}^{7} wc_j \times Sc_j\right) \quad [15]$$

This methodology categorizes R_I into five distinct classes ranging from very low to very high. It enables the creation of risk maps through a consequence-susceptibility diagram (Figure 9b), aiding in risk assessment. Associated actions range from geotechnical investigations to mitigation measures. This risk assessment approach is part of a broader spectrum of methods that integrate hazard, impact, and risk estimates, using various parameters and can be adapted to statistical or artificial intelligence methods.

Uncertainty of the frequency estimations

The magnitude- frequency relationship for rockfalls instability sources failure hazard can be characterized using power law frequency cumulative distributions (Hungr et al. 1999; Dussauge et al. 2003; Hantz et al. 2020):

$$F_s(v_s \geq V) = a_s\, V^{-b_s} \quad [16]$$

In this equation, a_s denotes the frequency of volumes exceeding a specified threshold, reflecting the active nature of a region (Figure 10). The b_s-value in the equation is indicative of the frequency of encountering larger volumes which correspond to $\lambda(M_i)$ described above.

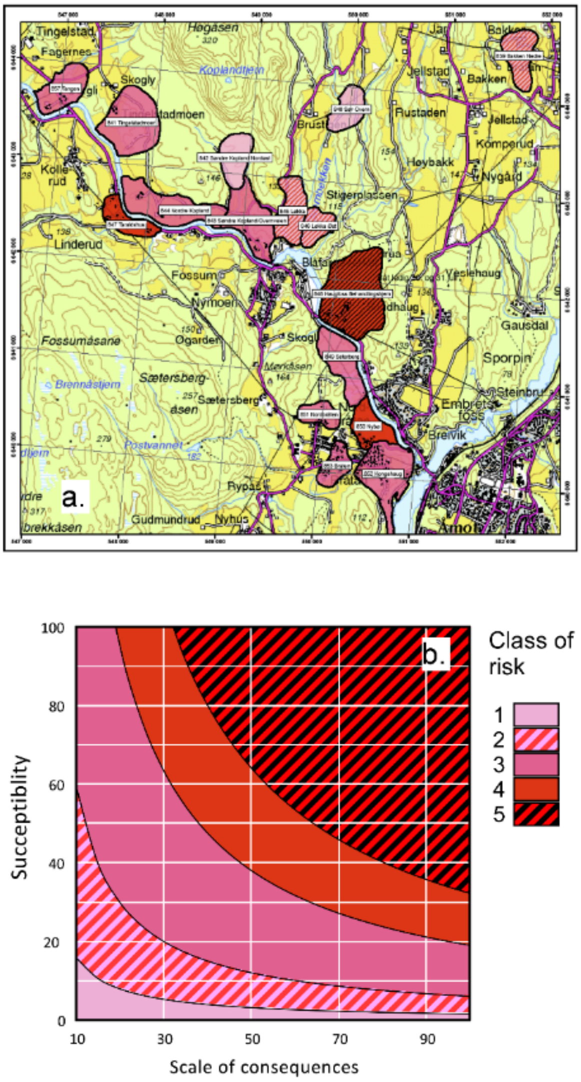

Figure 9 a. Landslide risk map for sensitive clays in the Modum region of Norway (from Lacasse and Nadim, 2009). b. Risk classes in a consequence-hazard or susceptibility diagram (based on the criteria of Lacasse and Nadim, 2009)

The frequency distribution approach, currently a principal method for quantifying hazard in terms of both diffuse failures and released propagated blocks, is not without its limitations. One significant drawback is the potential for substantial uncertainty. The power law used in this approach can be fitted using linear least squares regression or the maximum likelihood estimation (MLE) method, as noted by Dussauge et al. (2003). However, the reliability of this fitting is contingent upon the number of data points available. Despite achieving a perfect fit (R^2 = 1.0) with a reasonable dataset, simulations based on the derived power law will likely yield a lower R^2, indicating inherent uncertainty in such a frequency distribution.

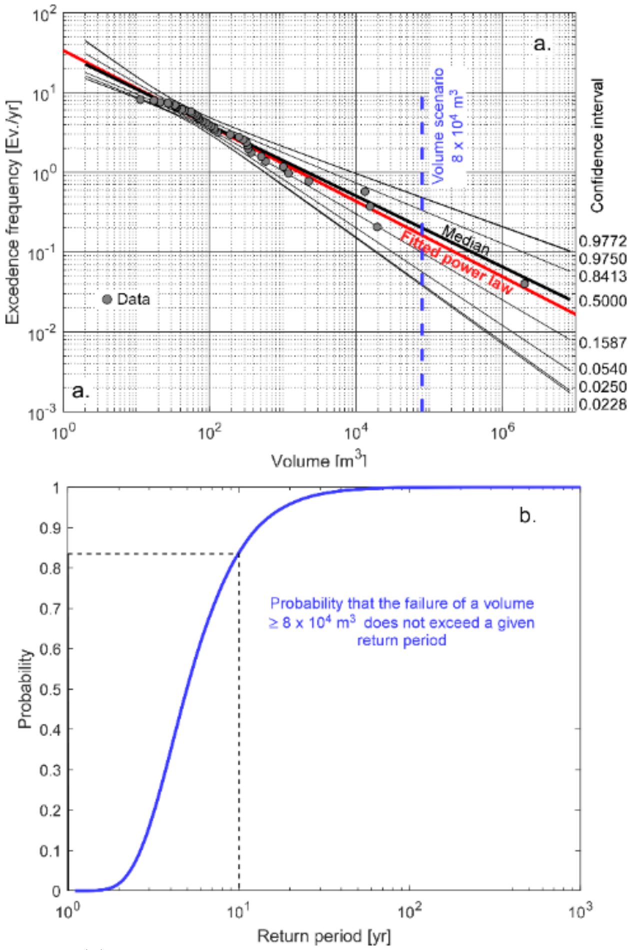

Figure 10 (a) Confidence intervals for the power law, derived from one million Monte Carlo simulations for 42 events. The original data from the La Brenva scar in Italy are represented by grey dots. (b) The probability that a volume equal to or larger than 8×10^4 m^3 will not exceed a certain return period (adapted from Fei et al. (2023)).

To ascertain the probability of a specific volume occurring within a given return period T, one can conduct simulations based on the fitted power laws. Repeated fittings across these datasets will yield a range of T-values for any given volume, as demonstrated by Fei et al. (2023) and illustrated in Figure 10b. For example, there is an 83% likelihood that an event with a volume equal to or greater than 8×10^4 m^3 will have a return period of less than 10 years, highlighting the inherent uncertainty in predicting specific volume occurrences.

Discussion and conclusions

The delineation of risk encompasses multiple facets, elucidated through diverse examples, indicating that risk frequently emanates from a qualitative analysis of two primary dimensions: hazard and consequences. Thus, the appraisal of risk is customarily conducted by experts within the domain. However, the imperative for establishing well-defined guidelines and frameworks for the evaluation of hazards, impacts, and consequentially, risk, is paramount (Corominas et al. 2014). Such a process necessitates meticulous attention towards its formulation, facilitating the quantification of risk to inform decision-making processes. It is essential that stakeholders, encompassing both institutional and private entities, possess the capacity to reconstruct, comprehend, and endorse the methodology employed in deriving the outcome (Corominas et al. 2014). Furthermore, the assessment scale should embody the epitome of current best practices, incorporating extant data and regional expertise. Absence of adherence to these principles significantly escalates the potential for legal disputes in instances of predictive inaccuracies (Griffiths, 1999).

Even in scenarios where risk can be quantitatively evaluated with a degree of precision, such as in rockfall events through simulation techniques and the analysis of rockfall sources failure frequencies, a substantial level of uncertainty persists (Fei et al. 2023). This uncertainty necessitates that final evaluations are frequently refined by domain experts, underscoring the indissoluble link between susceptibility and risk assessments. This principle equally pertains to the evaluation of vulnerability. As a result, the employment of catastrophe modeling (CAT models) (Mitchell-Wallace et al. 2017), which incorporate uncertainty to generate an exceedance probability curve (Macciotta et al. 2016; Jaboyedoff et al. 2021), represents a potential strategy for navigating the inherent paradox presented by the inseparability of susceptibility, vulnerability, and risk assessments.

References

Ale B. 2008, Risk: an introduction: the concepts of risk, danger and chance. Routledge, Taylor and Francis group, 134 p.

Ale, B. Burnap, P. & Slater, D. 2015. On the origin of PCDS – (Probability consequence diagrams). Safety Science, 72, 229-239, doi: https://doi.org/10.1016/j.ssci.2014.09.003.

Aven, T. & Renn, O. 2009. On risk defined as an event where the outcome is uncertain. Journal of Risk Research, 12, 1-11, doi: 10.1080/13669870802488883.

Cardinali, M. Reichenbach, P. Guzzetti, F. Ardizzone, F. Antonini, G. Galli, M. Cacciano, M. Castellani, M. & Salvati, P. 2002. A geomorphological approach to the estimation of landslide hazards and risks in Umbria, Central Italy. Natural Hazards and Earth System Sciences, 2, 57-72, doi: 10.5194/nhess-2-57-2002.

Carrara, A. Cardinali, M. Detti, R. Guzzetti, F. Pasqui, V. & Reichenbach, P. 1991. GIS techniques and statistical models in evaluating landslide hazard. Earth Surface Processes and Landforms, 16, 427-445, doi: https://doi.org/10.1002/esp.3290160505.

Corominas, J. van Westen, C. Frattini, P. Cascini, L. Malet, J.P. Fotopoulou, S. Catani, F. Van Den Eeckhaut, M. Mavrouli, O. Agliardi, F. Pitilakis, K. Winter, M.G. Pastor, M. Ferlisi, S. Tofani, V. Hervás, J. and Smith, J.T. 2014. Recommendations for the quantitative analysis of landslide risk. Bulletin of Engineering Geology and the Environment, 73(2): 209-263.

Cox LA Jr. 2008' What's wrong with risk matrices? Risk Analysis, 28, 497–512.

Dussauge, C. Grasso, J.-R. & Helmstetter, A. 2003. Statistical analysis of rockfall volume distribu-tions: Implications for rockfall dynamics. Journal of Geophysical Research: Solid Earth, 108, doi: 10.1029/2001jb000650.

ECDC, 2011, European centre for Disease Prevention and Control: Operational guidance on rapid risk assessment methodology. Stockholm, ECDC, 68p.

Farmer, F.R. 1967. Siting criteria-a new approach. Containment and Siting of Nuclear Power Plants. Proceedings of a Symposium on the Containment and Siting of Nuclear Power Plants.

Farvacque, M. Lopez-Saez, J. Corona, C. Toe, D. Bourrier, F. & Eckert, N. 2019. How is rockfall risk impacted by land-use and land-cover changes? Insights from the French Alps. Global and Planetary Change, 174, 138-152, doi: 10.1016/j.gloplacha.2019.01.009.

Fei, L. Jaboyedoff, M. Guerin, A. Noël, F. Bertolo, D. Derron, M.-H. Thuegaz, P. Troilo, F. & Ravanel, L. 2023. Assessing the rock failure return period on an unstable Alpine rock wall based on volume-frequency relationships: The Brenva Spur (3916 m a.s.l. Aosta Valley, Italy). Engineering Geology, 323, 107239, doi: https://doi.org/10.1016/j.enggeo.2023.107239.

Galli, M. & Guzzetti, F. 2007. Landslide Vulnerability Criteria: A Case Study from Umbria, Central Italy. Environmental Management, 40, 649-665, doi: 10.1007/s00267-006-0325-4.

Griffiths, J.S. 1999. Proving the occurrence and cause of a landslide in a legal context. Bulletin of Engineering Geology and the Environment, 58, 75-85, doi: 10.1007/s100640050070.

Gumbel, E.J. 1941. The Return Period of Flood Flows. The Annals of Mathematical Statistics, 12, 163-190.

Gutenberg, B. & Richter, C.F. 1956. Earthquake magnitude, intensity, energy, and acceleration: (Second paper). Bulletin of the Seismological Society of America, 46, 105-145, doi: 10.1785/bssa0460020105.

Guzzetti, F. Reichenbach, P. Cardinali, M. Galli, M. & Ardizzone, F. 2005. Probabilistic landslide hazard assessment at the basin scale. Geomorphology, 72, 272-299, doi: https://doi.org/10.1016/j.geomorph.2005.06.002.

Haimes, Y.Y. 2008, 'Risk Modeling, Assessment, and Management'. 3rd Edition. John Wiley & Sons, 1009 p.

Hantz, D. Vengeon, J.M. & Dussauge-Peisser, C. 2003. An historical, geomechanical and probabilistic approach to rock-fall hazard assessment. Natural Hazards and Earth System Sciences, 3, 693-701, doi: 10.5194/nhess-3-693-2003.

Hantz, D. Colas, B. Dewez, T. Lévy, C. Rossetti, J.-P. Guerin, A. & Jaboyedoff, M. 2020. Caractérisation quantitative des aléas rocheux de départ diffus. Rev. Fr. Geotech. 2.

Hungr, O. & Wong, H. 2007. Landslide risk acceptability criteria: are FN plots objective. Geotechnical News, 25, 47.

Hungr, O. Evans, S.G. & Hazzard, J. 1999. Magnitude and frequency of rock falls and rock slides along the main transportation corridors of southwestern British Columbia. Canadian Geotechnical Journal, 36, 224-238, doi: 10.1139/t98-106.

ISO 2018. Risk management–principles and guidelines. ISO 31000:24

Jaboyedoff, M. 2023. Consequence: Frequency Matrix as a Tool to Assess Landslides Risk. In: Alcántara-Ayala, I. Arbanas, Ž. Huntley, D. Konagai, K. Mihalić Arbanas, S. Mikoš, M. V. Ramesh, M. Sassa, K. Sassa, S. Tang, H. & Tiwari, B. (eds.) Progress in Landslide Research and Technology, Volume 2 Issue 2, 2023. Springer Nature Switzerland, Cham, 137-153.

Jaboyedoff, M. Choanji, T. Derron, M.-H. Fei, L. Gutierrez, A. Loiotine, L. Noel, F. Sun, C. Wyser, E. & Wolff, C. 2021. Introducing Uncertainty in Risk Calculation along Roads Using a Simple Stochastic Approach. Geosciences, 11, doi: 10.3390/geosciences11030143.

Jaboyedoff M. Locat J. Merrien V. Michoud C. (in prep): Mouvements de terrain. PPUR. (a French treaty about landslides)

Krause, J.-P. &R. Mock, Gheorghe A.D. 1995, Assessment of Risks from Technical Systems: Integrating Fuzzy Logic into the Zurich Hazard Analysis Method. in: International Journal of Environment and Pollution (IJEP) 5 (2-3), 278-296.

Lacasse, S. & Nadim, F. 2009. Landslide Risk Assessment and Mitigation Strategy. In: Sassa, K. & Canuti, P. (eds.) Landslides – Disaster Risk Reduction. Springer Berlin Heidelberg, Berlin, Heidelberg, 31-61.

Lacasse, S. Eidsvik, U. Nadim, F. Høeg, K. and Blikra, L.H. 2008. Event Tree analysis of Åknes rock slide hazard. IV Geohazards Québec, 4th Canadian Conf. on Geohazards. 551-557.

Lanfranconi, C. Frattini, P. Sala, G. Dattola, G. Bertolo, D. Sun, J. & Crosta, G.B. 2023. Accounting for the effect of forest and fragmentation in probabilistic rockfall hazard. Natural Hazards and Earth System Sciences, 23, 2349-2363, doi: 10.5194/nhess-23-2349-2023.

Leroi, E. Bonnard, C. Fell, R. & McInnes, R. 2005. Risk assessment and management. Balkema, 159-198.Porter, M. and Morgenstern, N. 2013. Landslide Risk Evaluation – Canadian Technical Guidelines and Best Practices related to Landslides: a national initiative for loss reduction; Geological Survey of Canada, Open File 7312, 21 p. doi:10.4095/292234

Leroueil, S. & Locat, J. 1998. Slope movements: geotechnical characterisation, risk assessment and mitigation. Proc. 11th Danube-European Conf. Soil Mech. Geotech. Eng. Porec, Croatia, 95–106. Also published in Proc. 8th Congress Int. Assoc. Eng. Geology, Vancouver, 933-944, Balkema, Rotterdam.

Li, Z. Nadim, F. Huang, H. Uzielli, M. & Lacasse, S. 2010. Quantitative vulnerability estimation for scenario-based landslide hazards. Landslides, 7, 125-134, doi: 10.1007/s10346-009-0190-3.

Macciotta, R. Martin, C.D. Morgenstern, N.R. & Cruden, D.M. 2016. Quantitative risk assessment of slope hazards along a section of railway in the Canadian Cordillera—a methodology considering the uncertainty in the results. Landslides, 13, 115-127, doi: 10.1007/s10346-014-0551-4.

Mitchell-Wallace, K. Jones, M. Hillier, J. & Foote, M. 2017. Natural catastrophe risk management and modelling: A practitioner's guide. John Wiley & Sons.

Porter, M. and Morgenstern, N. 2013. Landslide Risk Evaluation – Canadian Technical Guidelines and Best Practices related to Landslides: a national initiative for loss reduction; Geological Survey of Canada, Open File 7312, 21 p. doi:10.4095/292234

Rothman, K.J. 2012. Epidemiology: an introduction. Oxford university press.

Ruiz-Carulla, R. Corominas, J. & Mavrouli, O. 2016. A fractal fragmentation model for rockfalls. Landslides, 14, 875-889, doi: 10.1007/s10346-016-0773-8.

Stoffel, M. Bollschweiler, M. Widmer, S. & Sorg, A. 2010. Spatio-temporal variability in debris-flow activity: a tree-ring study at Geisstriftbach (Swiss Alps) extending back to AD 1736. Swiss Journal of Geosciences, 103, 283-292, doi: 10.1007/s00015-010-0014-4.

UK-CO (Cabinet Office) 2017. National Risk Register Of Civil Emergencies, retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/644968/UK_National_Risk_Register_2017.pdf

Vengeon, J.-M. Hantz, D. & Dussauge, C. 2001. Prévisibilité des éboulements rocheux. Approche probabiliste par combinaison d'études historiques et géomécaniques. Revue française de géotechnique, 143-154.