Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards

ISSN: 1749-9518 (Print) 1749-9526 (Online) Journal homepage: https://www.tandfonline.com/loi/ngrk20

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To cite this article: Azadeh Mostofi, Robert B. Gilbert, David R. Montgomery & Joseph Wartman (2019) Assessing recurrence probability for Oso 2014 landslide in order to manage risk, Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 13:4, 333-340, DOI: 10.1080/17499518.2019.1623408

To link to this article: https://doi.org/10.1080/17499518.2019.1623408

Published online: 02 Jun 2019.

GEORISK
2019, VOL. 13, NO. 4, 333–340
https://doi.org/10.1080/17499518.2019.1623408

Assessing recurrence probability for Oso 2014 landslide in order to manage risk

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ABSTRACT

In March 2014, a catastrophic landslide in Washington State destroyed a community and killed 43 people. An analysis of the available information using a new approach to manage risk when dealing with rare, high consequence hazards indicates that if the risk for another landslide is accepted, then the expected time between occurrences of massive landslides at this location is about 2000–3000 years, the mean occurrence rate tends to increase with time since the last occurrence, and the alternative of avoiding the risk is preferred if the present worth cost to avoid it (i.e. prevent development) for 100 years is less than about 1/6 the cost of another massive landslide.

ARTICLE HISTORY
Received 14 January 2019
Accepted 21 May 2019

KEYWORDS
Landslides; risk assessment and management; decision analysis; natural hazards; renewal occurrence models; Oso landslide

1. Introduction

In March of 2014, a catastrophic landslide occurred near Oso, Washington (Iverson & George, 2016; Keaton et al., 2014; Stark, Baghdady, Hungr, & Aaron, 2017; Wartman et al., 2016). A 600-m wide section of the 200-m high slope above the valley of the North Fork of the Stillaguamish River collapsed, sending a rapid flow of soil debris nearly 1 km across the floor of the valley (Figures 1 and 2). The debris flow destroyed a community of 49 homes, killed 43 people, cut off the only highway providing access up and down the valley, temporarily dammed the river and flooded the valley upstream.

At the time, a slope failure of this magnitude was unexpected and there were no restrictions on land development in the valley below the slope (Keaton et al., 2014). Over the past century, the lower portion of the slope that failed in 2014 had failed multiple times. However, this slope was only 1/3 the height with a failing mass and debris flow runout distance about 1/10 that of the 2014 failure (Figure 2). These previous smaller failures neither caused loss of life nor impacted the residential homes in the community below the slope.

Assessing and managing the risk from rare but high consequence hazards is challenging because there is limited historical information. The objective of this paper is to analyze the Oso landslide case history using a new approach intended to facilitate risk management when dealing with rare, high consequence hazards. The approach enhances a Bayesian methodology, which is commonly used for assessing landslide hazards (e.g. Einstein & Sousa, 2007; Liu et al., 2015; Medina-Cetina & Nadim, 2008; Nadim & Liu, 2013; Rodríguez-Ochoa, Nadim, Cepeda, Hicks, & Liu, 2015), by establishing a non-informative starting point for the methodology based on risk-management decisions.

2. Risk-management decision

The primary decision in managing risk from natural hazards like the Oso landslide is to either accept the risk or avoid the risk (Figure 3). There are three features of this decision:

- The consequence associated with a slope failure that destroys the residential community. To distinguish this magnitude of a failure from smaller slope failures, it will be denoted as a "characteristic landslide." The consequence of a characteristic landslide, which could be expressed in dollars or more generally as a utility value, will be denoted C_f. For context, the economic consequence of the March 2014 landslide near Oso is on the order of hundreds of million dollars. Of course, the human cost is incalculable to those affected.
- The probability of a characteristic landslide occurring, denoted P_f, during a planning period. Typical

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Figure 1. Aerial photographs of Oso slope before and after the March 2014 failure.

planning periods for land development decisions are between 30 and 100 years; a planning period of 100 years will be used in this analysis.

- The consequence of avoiding the risk due to a characteristic landslide throughout the planning period, denoted C_{avoid}. Practically, this consequence is the present worth cost of not allowing development in the valley below the slope for the duration of the planning period, which could include relocating existing residences and the lost opportunity due to preventing land development in a desirable area.

Following decision theory, the preferred alternative will have the maximum expected utility (or the lowest absolute magnitude of cost):

$$E(\text{utility } A) = -P_f \times C_f \tag{1}$$

$$E(\text{utility } B) = -C_{\text{avoid}} \tag{2}$$

Based on this approach, the alternative of avoiding the risk will be preferred when $C_{\text{avoid}} \leq P_f \times C_f$ or $C_{\text{avoid}}/C_f \leq P_f$ where the cost of avoidance for the planning period is normalised by the cost of a failure due to a characteristic landslide. These costs represent the value

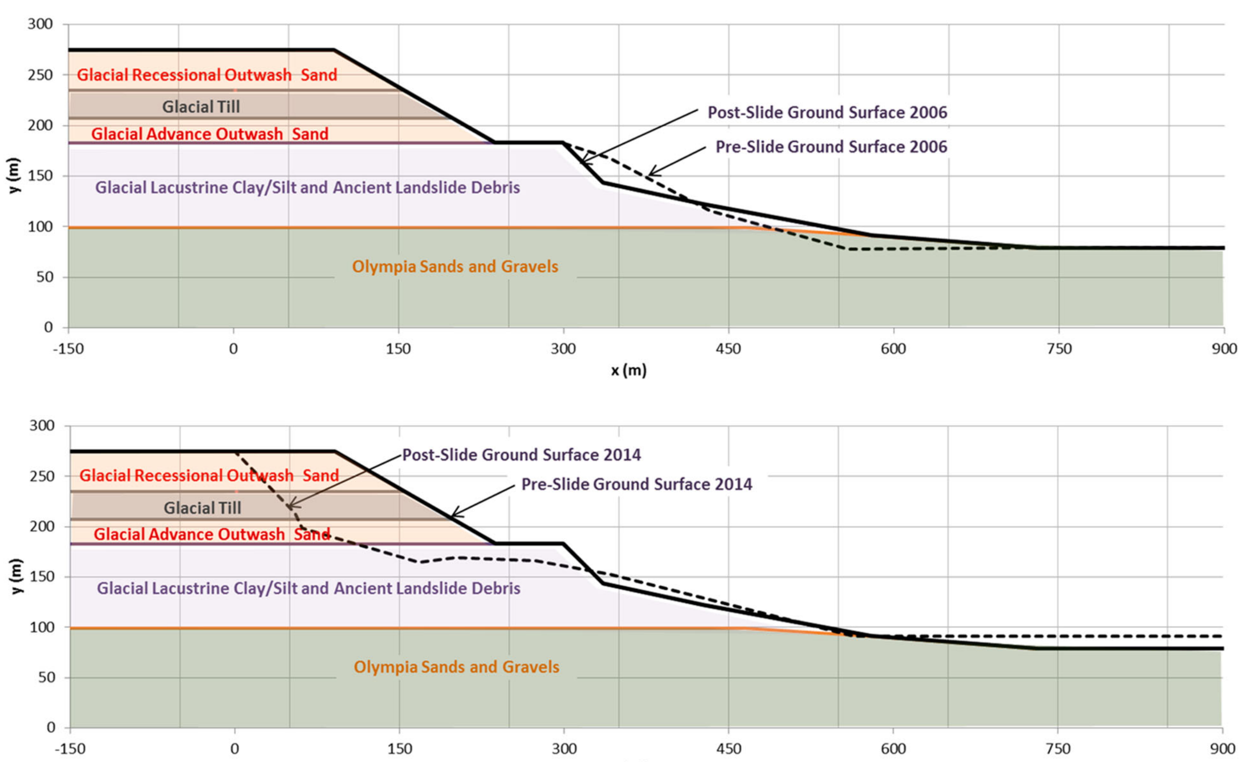

Figure 2. Profiles of the slope after a smaller landslide in 2006 and the large landslide in 2014 (Gilbert, Montgomery, et al., 2016).

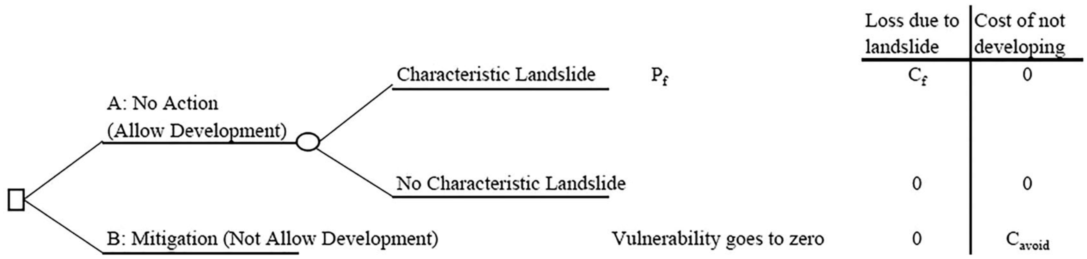

Figure 3. Decision tree for Oso landslide risk management.

system of the stakeholders who are making the decision (e.g. the government) and/or are impacted by the decision (e.g. the residents).

3. Occurrence model for characteristic landslides

The probability of a characteristic (i.e. large and consequential) landslide occurring during the 100-year planning period, P_f, depends on the rate of occurrence for characteristic landslides. A Poisson process is commonly used to model the occurrence of natural hazards, like landslides. However, a Poisson model is not necessarily realistic for landslides because the rate of occurrence may not be constant with time (e.g. Zhang & Tang, 2009). The rate of occurrence for another characteristic landslide at Oso is possibly smaller immediately after a characteristic landslide has occurred because the slope geometry is more stable since the landslide buttresses itself as it decelerates and because soil pore water pressures may decrease in the remaining slope after the weight of the failed mass has been removed. A more general occurrence model is a Weibull renewal model (Cornell & Winterstein, 1988), in which the probability of failure during an interval of time since the last failure, t, is given by:

$$P_f = P[T < t] = 1 - \exp\left(-\left(\frac{\nu_T!\, t}{\mu_T}\right)^{\frac{1}{\nu_T}}\right) \tag{3}$$

where T is a random variable representing the time of recurrence for characteristic landslides, μ_T is the mean or expected time between characteristic landslides, and ν_T is the coefficient of variation for the time between characteristic landslides where $0 \leq \nu_T \leq 1$. When $\nu_T = 1$, this renewal model is a Poisson process and the mean rate of occurrence is a constant with time; when $\nu_T < 1$, the mean rate of occurrence increases with time since the last occurrence (Figure 4).

4. Information about occurrence of characteristic landslides

Since the 2014 landslide, analyses of Lidar data (Haugerud, 2014) and radiocarbon dating of landslide debris (Keaton et al., 2014) indicate at least two characteristic landslides occurred at the location of the 2014 landslide within the 15,000 years since the last glaciation. Also, historical information indicates there had not been a characteristic landslide in this location for at least 200 years before the 2014 landslide. Depending on perspective, there are various descriptions of information:

(1). For a stakeholder who knows nothing about landslide activity, they have no information about the possible occurrence of characteristic landslides. In this case the likelihood of having observed this

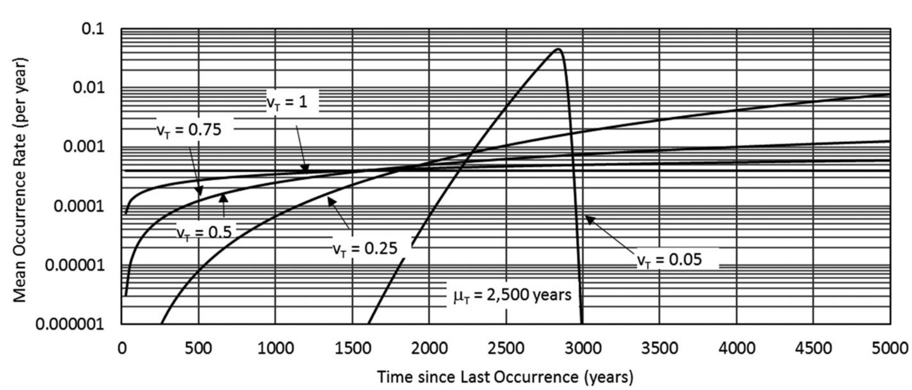

Figure 4. Weibull renewal model.

information as a function of the renewal model parameters, $\boldsymbol{\mu_T}$ and $\boldsymbol{\nu_T}$, (Figure 5(a)) is given by:

$$P(\text{No Information}|\mu_T, \nu_T) = 1.0 \tag{4}$$

(2). For a stakeholder who is unaware that any characteristic landslides have occurred at this location in the past 15,000 years (a typical person prior to March 2014), the likelihood for this information (Figure 5(b)) is given by:

$$P(\text{No Occurrences in 15,000 years}|\mu_T, \nu_T) = \exp\left(-\left(\frac{\nu_T!(15000)}{\mu_T}\right)^{\frac{1}{\nu_T}}\right) \tag{5}$$

(3). For a stakeholder prior to 2014 who is aware of the Lidar studies indicating there have been at least two characteristic landslides at this location in the past 15,000 years, the likelihood for this information (Figure 5(c)) is given by:

$$P(> 2 \text{ Occurrences in } 15,000 \text{ years}|\mu_T, \nu_T) = 1 - \left[1 + \left(\frac{\nu_T!(15,000)}{\mu_T}\right)^{\frac{1}{\nu_T}}\right] e^{-\left(\frac{\nu_T!}{\mu_T}(15,000)\right)^{\frac{1}{\nu_T}}} \tag{6}$$

(4). For a stakeholder today who is aware of all available information, the likelihood for this information (Figure 5(d)) is given by (see Mostofi, 2018 for derivation):

$$\begin{aligned} &P(> 3 \text{ Occurrences in } 15,000 \text{ years and } > 200 \text{ Years between Last Two}|\mu_T, \nu_T) \\ &= \int_{200}^{15,000} \left\{1 - \left[1 + \left(\frac{\nu_T!(15,000 - t_1)}{\mu_T}\right)^{\frac{1}{\nu_T}}\right] \times e^{-\left(\frac{\nu_T!}{\mu_T}(15,000 - t_1)\right)^{\frac{1}{\nu_T}}}\right\} \\ &* \exp\left(-\left(\frac{\nu_T! t_1}{\mu_T}\right)^{\frac{1}{\nu_T}}\right)\left(\frac{1}{\nu_T}\right)\left(\frac{\nu_T! t_1}{\mu_T}\right)^{\frac{1}{\nu_T} - 1} \frac{\nu_T!}{\mu_T} dt_1 \end{aligned} \tag{7}$$

The challenge of limited information in this case is illustrated by the very flat likelihood functions in Figure 6. It is not possible to identify a single combination of $\boldsymbol{\mu_T}$ and $\boldsymbol{\nu_T}$ as most likely based on any of these likelihood functions. In addition, these functions indicate the likelihood of observing the available information as a function of the parameters $\boldsymbol{\mu_T}$ and $\boldsymbol{\nu_T}$; however, the probability of different combinations of $\boldsymbol{\mu_T}$ and $\boldsymbol{\nu_T}$ given available information is needed for decision making going forward.

5. Bayes' Theorem and the Theory of Decision Entropy

For the purposes of making the risk-management decision (Figure 3), the probability of failure in the 100-year planning period is obtained as a function of the renewal model parameters:

$$P_f = \int_{\text{all } \mu_T, \nu_T} \left[1 - \exp\left(-\left(\frac{\nu_T! \text{ (100 years)}}{\mu_T}\right)^{\frac{1}{\nu_T}}\right)\right] P(\mu_T, \nu_T|\text{Information}) d\mu_T d\nu_T \tag{8}$$

where $P(\mu_T, \nu_T|\text{Information})$ is the joint probability for different combinations of μ_T and ν_T given the available information (posterior probability). This joint probability is obtained from Bayes' Theorem as follows:

$$P(\mu_T, \nu_T|\text{Information}) = \frac{P(\text{Information}|\mu_T, \nu_T)P(\mu_T, \nu_T|\text{Decision})}{\int_{\text{all } \mu_T, \nu_T} P(\text{Information}|\mu_T, \nu_T)P(\mu_T, \nu_T|\text{Decision})d\mu_T d\nu_T} \tag{9}$$

where $P(\text{Information}|\mu_T, \nu_T)$ is the likelihood function (Figure 5) and $P(\mu_T, \nu_T|\text{Decision})$ is the joint probability for different combinations of μ_T and ν_T in the original sample space of the decision (i.e. the set of all possibilities prior to incorporating information).

The Theory of Decision Entropy (Gilbert, Habibi, & Min, 2012, 2016) is being developed as a basis to establish non-informative prior probabilities in the context of making a decision, $P(\mu_T, \nu_T|\text{Decision})$. This theory is derived from three principles:

(1). If no information is available about the probabilities of μ_T and ν_T, then a selected alternative is equally probable to be or not to be the preferred alternative.

(2). If no information is available about the probabilities of μ_T and ν_T, then the possible differences in preference between a selected alternative and the preferred alternative are equally probable.

(3). If no information is available about the probabilities of μ_T and ν_T, then the possibilities of learning with new information about the selected alternative

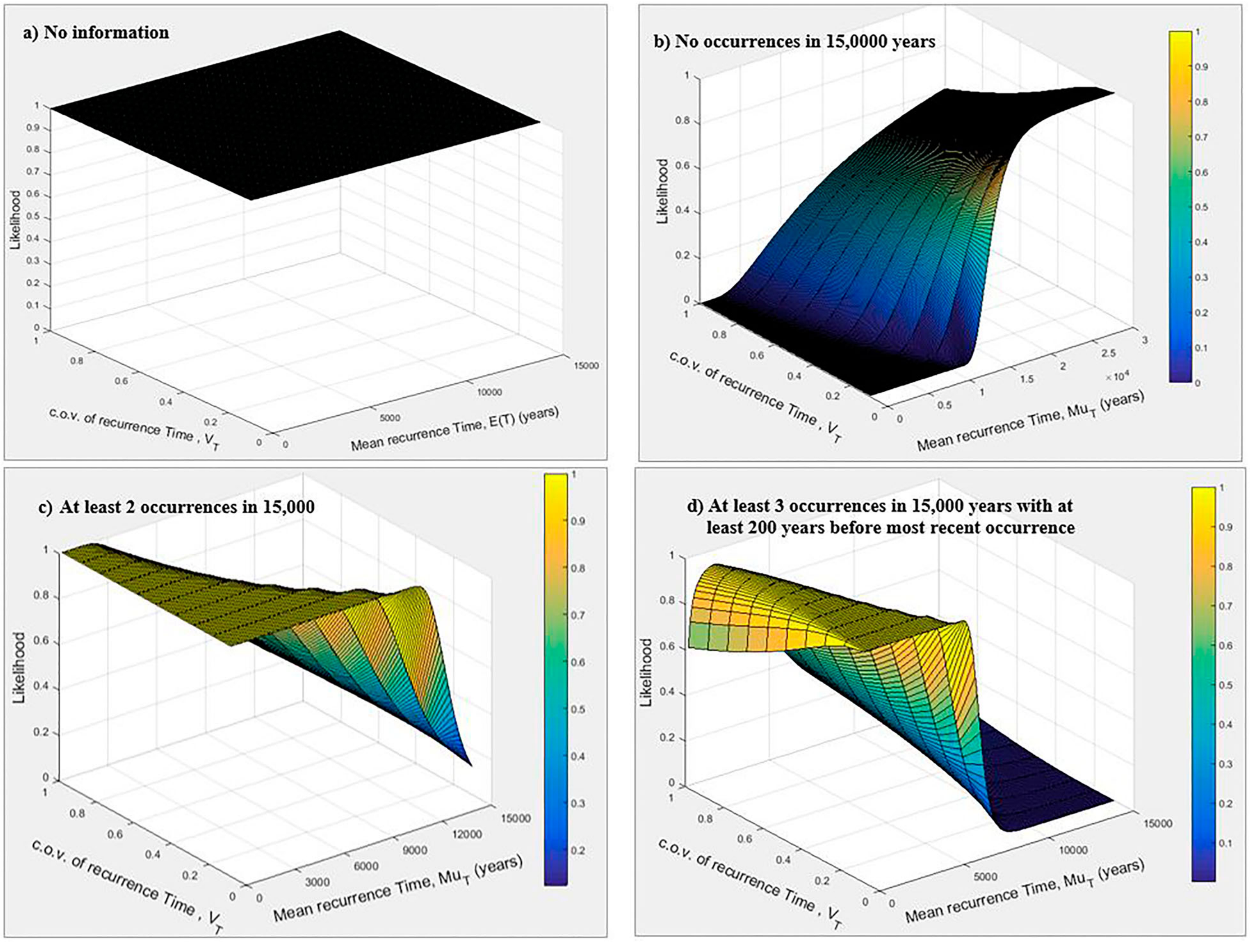

Figure 5. Likelihood of observing different sets of information. (a) No information. (b) No occurrences in 15,0000 years. (c) At least 2 occurrences in 15,000 years. (d) At least 3 occurrences in 15,000 years with at least 200 years before most recent occurrence.

compared to the preferred alternative are equally probable.

The theory is implemented mathematically using the Theory of Information Entropy (Shannon, 1948). The prior probability for a selected decision alternative is obtained by maximising the entropy of the information potential:

$$\begin{aligned}\Delta u(\mu_T, \nu_T, A_j \text{ Selected}) &\\ = u(\mu_T, \nu_T, A_j \text{ Selected}) &\\ - \max[u(\mu_T, \nu_T, A_i \text{ Selected}) \text{ for all } i] &\end{aligned} \quad (10)$$

where $\Delta u(\mu_T, \nu_T, A_j \text{ Selected})$ is the information potential if either alternative A or alternative B is selected and $u(\mu_T, \nu_T, A_j \text{ Selected})$ is the utility if A is selected (Equation 1 where P_f is obtained from Equation 3 as a function of μ_T and ν_T) or if B is selected (Equation 2). The information potential is less than or equal to zero: it equals 0 if A_j is the preferred alternative and it is less than zero if A_j is not the preferred alternative. Accounting for uncertainty in μ_T and ν_T, the preferred alternative will have the maximum expected value of the information potential.

The resulting prior probability distributions (e.g. Figure 6) depend both on the decision alternative (either accept or avoid risk) and on the consequences, C_{avoid}/C_f. They are constructed for each decision alternative such that (i) there are equal probabilities that the information potential is zero and less than zero and (ii) there are equal probabilities for the possible values of information potential less than zero[1]. Once the prior probability distribution is established, then Bayes' Theorem (Equation 9) is used to update the probability for μ_T and ν_T given the available information (e.g. Figure 7).

6. Results

Results of the decision analysis are summarised in Table 1. Given the available information today (following the 2014 failure), the alternative of accepting the risk is preferred if the present worth cost to avoid it (i.e. prevent

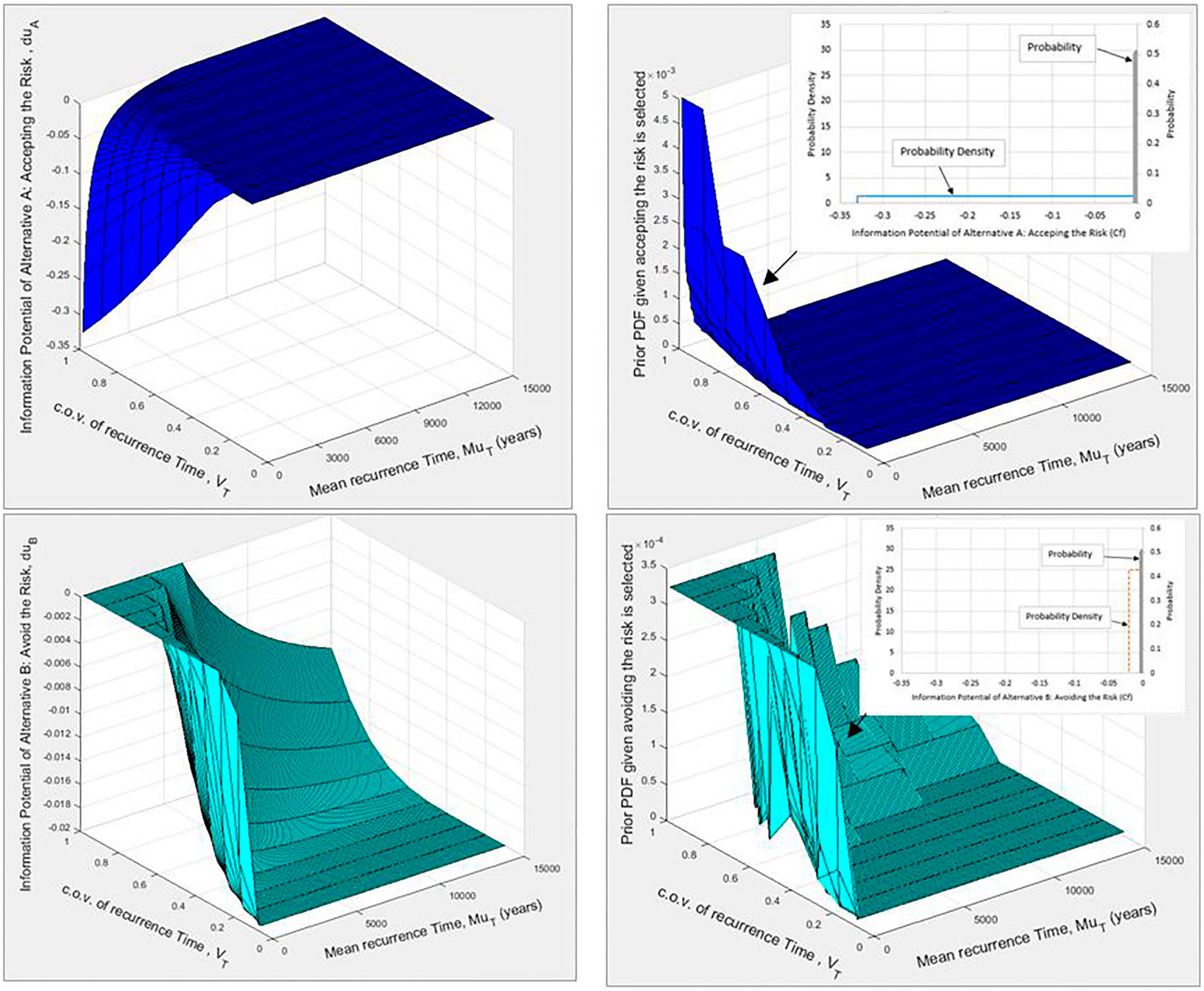

Figure 6. Example construction of prior probability distribution for μ_T and v_T using Theory of Decision Entropy for $C_{avoid}/C_f = 1/50$.

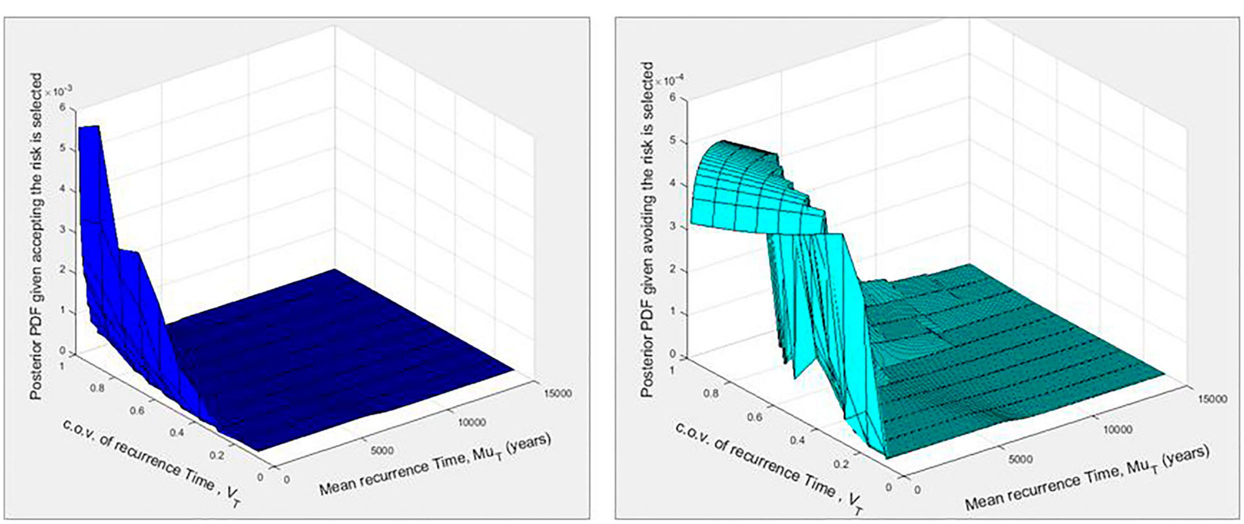

Figure 7. Example updated probability distributions for μ_T and v_T using Bayes' Theorem with information about landslide occurrences at Oso location available today for $C_{avoid}/C_f = 1/50$.

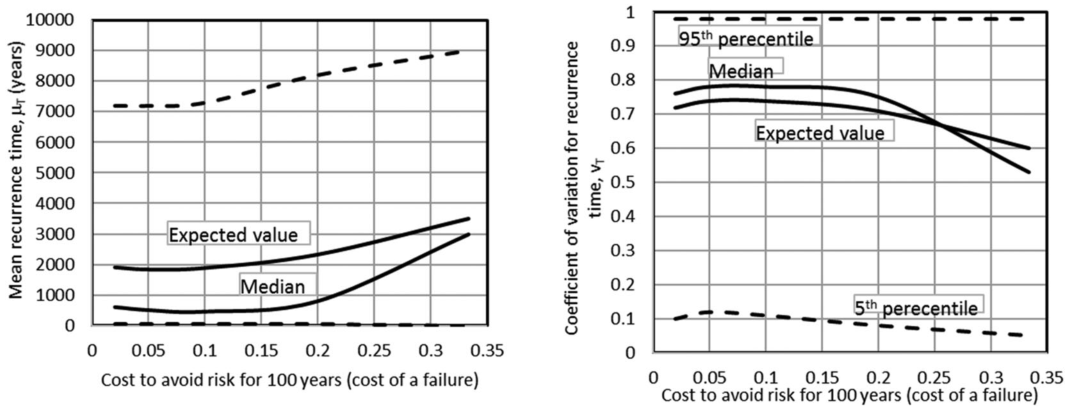

Figure 8. Updated information about renewal model parameters describing the occurrence of characteristic landslides at Oso if one chooses to accept the risk.

development) for 100 years is greater than 1/5.6 the cost of another massive slope failure. If the cost to avoid the risk is at this threshold of 1/5.6, then the value of perfect information about the occurrence frequency of massive landslides in the next 100 years is about 1/20th the cost of a failure (Table 1). If a decision maker prior to the 2014 slope failure ignorantly assumed there had been no previous massive landslides, then the alternative of accepting the risk is preferred if the present worth cost to avoid it is less than 15% of the threshold for accepting the risk today (Table 1).

With the proposed approach, the assessment of the parameters for the renewal model describing the chance for future landslides (μ_T and ν_T) depends both on the available information about previous landslide occurrences at this location as well as how these parameters affect the risk-management decision (i.e. whether or not one chooses to accept the risk and the consequences of accepting and avoiding the risk, C_{avoid}/C_f). Given the available information today and choosing to accept the risk for the next 100 years, the decision-based mean recurrence time for massive landslides at this location is 2000–3000 years, and the coefficient of variation in the recurrence time is 0.6 to 0.7, indicating that the mean occurrence rate tends to increase with time since the last occurrence (Figure 8). However, there is still significant uncertainty in both parameters (Figure 8).

7. Summary

The 2014 landslide near Oso Washington that killed 43 people is an example of a natural hazard that is relatively rare but results in high consequences. A new methodology based on the Theory of Decision Entropy provides a means to assess the probability for a recurrence of this event for the purposes of making risk-management decisions. Given the information available today and choosing the accept the risk of another landslide in the next 100 years, the mean time between occurrences of massive landslides at this location is about 2000–3000 years, and the mean occurrence rate tends to increase as the expected time between occurrences is approached. The alternative of avoiding the risk is preferred if the present worth cost to avoid it (i.e. prevent development) for 100 years is less than about 1/6 the cost of another massive landslide.

8. What do I remember about professor Wu

Robert Gilbert: I remember walking the streets of Paris with TH in the early 1990s. While at a conference together, I mentioned I was a big fan of Ernest Hemingway and F. Scott Fitzgerald and wanted to visit some of their haunts. He suggested we skip an afternoon of the conference and go on an adventure! As we toured Paris, I learned why he was such a great professor: he

Table 1. Results of decision analysis.

	No Information	Ignorance: No Occurrences in 15,000 Years	Pre-2014: > 2 Occurrences in 15,000 Years	Post 2014: > 3 Occurrences in 15,000 Years with > 200 Years before Last One
Threshold Cost of Avoidance beyond which Accepting Risk Preferred (Cost of a Failure)	1/6.2	1/39	1/5.5	1/5.6
Value of Perfect Information about Renewal Model if Cost of Avoidance is at Threshold (Cost of Failure)	0.044	0.016	0.049	0.052

was curious and insightful, he asked questions and listened, and he enjoyed life. I do not remember much from the conference, but I will always remember fondly that afternoon with TH.

Note

1. For combinations of μ_T and v_T that produce the same information potential, each combination is assumed to be equally probable as an approximation to the third principle of the Theory of Decision Entropy.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The authors acknowledge the U.S. National Science Foundation (https://www.nsf.gov/awardsearch/showAward?AWD_ID=1636217&HistoricalAwards=false) for supporting this work with award number 1636217 and through the Geotechnical Extreme Events Reconnaissance (GEER) (https://www.nsf.gov/awardsearch/showAward?AWD_ID=1300744&HistoricalAwards=false) Association (award number 1300744).

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