Interactive Landslide Simulator: A Tool for Landslide Risk Assessment and Communication

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3 authors:

Pratik Chaturvedi
Defence Research and Development Organis…

Akshit Arora
University of Colorado Boulder

Varun Dutt
Indian Institute of Technology Mandi

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Pratik Chaturvedi, Akshit Arora and Varun Dutt

Abstract Understanding landslide risks is important for people living in hilly areas in India. A promising way of communicating landslide risks is via simulation tools, where these tools integrate both human factors (e.g., public investments to mitigate landslides) and environmental factors (e.g., spatial geology and rainfall). In this paper, we develop an interactive simulation model on landslide risks and use it to design a web-based Interactive Landslide Simulator (ILS) microworld. The ILS microworld is based on the assumption that landslides occur due to both environmental factors (spatial geology and rainfall) as well as human factors (lack of monetary investments to mitigate landslides). We run a lab-based experiment involving human participants performing in ILS and we show that the ILS performance helps improve public understanding of landslide risks. Overall, we propose ILS to be an effective tool for doing what-if analyses by policymakers and for educating public about landslide risks.

Keywords Early warning systems · Interactive landslide simulator (ILS) · Landslide risk communication · Feedback · Learning

P. Chaturvedi (✉)
Defence Terrain Research Laboratory (DTRL), Metcalfe House,
Delhi 110054, India
e-mail: prateek@dtrl.drdo.in

P. Chaturvedi · V. Dutt
Applied Cognitive Science Laboratory, Indian Institute of Technology (IIT) Mandi,
Mandi 175001, H.P, India
e-mail: varun@iitmandi.ac.in

A. Arora
Thapar University, Patiala 147004, Punjab, India
e-mail: akshit.arora1995@gmail.com

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1 Introduction

Over the past few decades, catastrophic and disastrous effects of landslides have caused extensive damage to life, property, and public utility services world over. Thus, ensuring effective Early Warning Systems (EWSs) for landslides is essential for the survivability of people in case of occurrence of a disastrous event. To be effective, EWSs need to have not only a sound scientific and technical basis, but also a strong focus on people, who are actually exposed to risk. Unfortunately, such risk communication systems only address part of the existing challenge; the other important part being related to the properties of human perceptual-cognitive factors (cooperation; attitude; and effects of economic and educational background) [1–3]. Moreover, recent surveys in developing countries (like India) show only mediocre knowledge and awareness about causes and consequences of landslide disasters among the general public [4–6]. For example, a recent survey conducted in Mandi town of Himachal Pradesh, India, showed a big gap between experts and general public on understanding of hazard zonation maps and probability of landslides [4]. The existence of this gap is problematic because zonation maps, developed by landslide experts, are currently the common medium to communicate the susceptibility of a region to landslides.

An important aspect of EWSs is related to the development, evaluation, and improvement of risk communication, which helps in transferring risk related knowledge (like causes, consequences and what to do in case a disaster event takes place) and warnings in a manner easily understandable to the local community. A promising way of improving existing risk communication among EWSs is via simulation tools (also called microworlds), which are able to integrate human factors in landslide risk mitigation in addition to physical factors. Such simulation tools, and the models they are built upon, could help risk managers since personal experience and the visibility of processes are the two main influencing factors for improving people's mental models about natural disasters. Promising recent research has shown that regular feedback from a system likely provides an effective tool for people to improve their understanding about the system (Dutt and Gonzalez 2011, 2012). For example, research has documented some benefits of repeated feedback in computer-based microworlds in reducing people's misconceptions about Earth's climate [7]. Dutt and Gonzalez (2012) developed Dynamic Climate Change Simulator (DCCS) microworld and used it as an intervention to help participants understand basic characteristics of the climate system [8]. DCCS helped provide feedback to people about their decisions and enabled them to reduce their misconceptions compared to no DCCS intervention. As DCCS-like tools seem to be effective in improving people's understanding on problems, there is a need to develop simulation models that are able to integrate human factors in landslide risk mitigation in addition to physical factors. Such simulation models could be helpful for the risk managers since personal experience and the visibility of processes are the two main influencing factors explaining the content of people's mental models [9, 10].

Furthermore, affect or emotional response to stimuli is seen to influence risk perception and decision making [11, 12]. For example, Finucane et al. [12] have provided the "affect heuristic," where this heuristic allows people to make decisions and solve problems quickly and efficiently, in which current emotions of fear, pleasure, and surprise influences decisions [12]. According to Finucane et al. [12], the orientation of one's feelings (negative or positive) could be an effective tool for risk communication [12].

In the present work, an interactive simulation model of landslide is developed for understanding the influence of monetary contributions for landslide risk mitigation. Furthermore, the interactive simulation model is used to design a web-based Interactive Landslide Simulator (ILS) too. The ILS tool is based on the assumption that landslides occur due to the presence of both physical factors (spatial geology and rainfall) as well as human factors (monetary investments made for landslide risk mitigation). Thus, even in the presence of physical factors (which are outside of one's control), the landslide risk could be reduced by increasing community investments towards landslide mitigation. Beyond considering human factors in the landslide problem, the ILS also models the damages due to the occurrence of landslide events in terms of fatality, injury, and loss of property. It considers how such damages might impact one's daily income as well as property wealth. In summary, the ILS tool allows participants to make decisions on the landslide risk mitigation, observe the consequences of their decisions (via real-time feedback), and enable participants to try new decisions.

In this paper, we highlight the use of the interactive landslide model as well as the ILS tool in educating the general public about landslide risks. Specifically, we use affect heuristic in the ILS by creating affect-rich feedback to enable people to perceive risks and benefits for investments made against landslides. This will also enable them to develop a deeper causal understanding about landslide disasters and their consequences. Our hypothesis is that monetary contributions against landslides (which is an indicator of improved understanding) will be larger when affective feedback about monetary losses is high compared to low. Based on results of a lab-based experiment involving human participants, we propose a number of benefits of the ILS tool for educating people and for policymaking in terms of generating "what-if" analyses. As part of our outreach activities, we plan to popularize the use of the ILS tool among students in K-12 schools and colleges in mountain areas in India that are prone to landslide risks.

2 Interactive Simulation Model of Landslides

2.1 Interactive Landslide Simulator (ILS) Model

The ILS model focuses on calculation of total probability of landslides (due to natural factors and due to anthropogenic factors, i.e., investments made by people

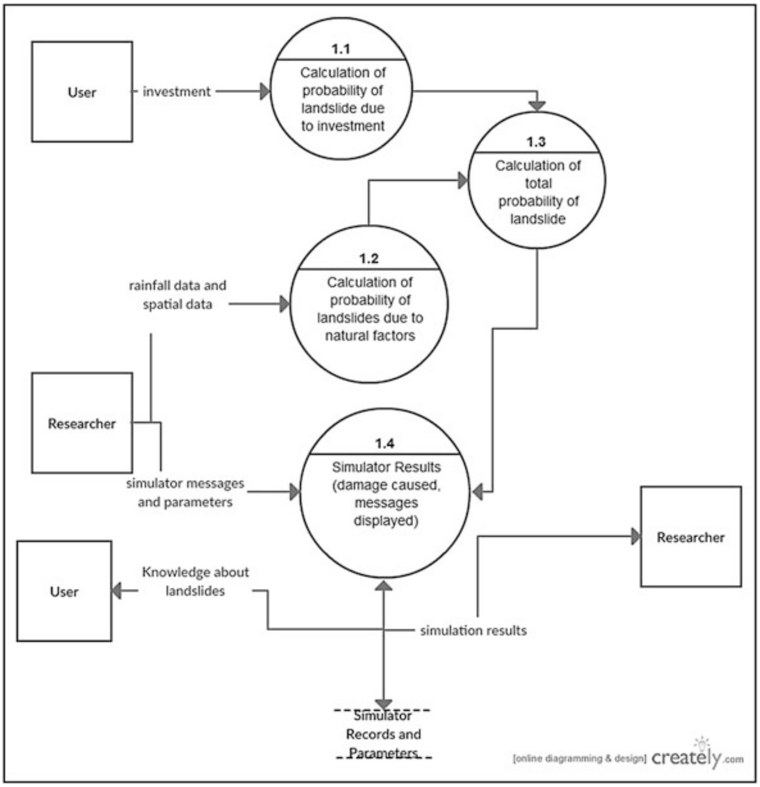

Fig. 1 Probabilistic model of the interactive landslide simulator microworld

against landslides). The model is also capable of simulating types of damages caused by landslides and their effects on people's earnings.

Figure 1 shows the model of ILS proposed in the present research work. In this model, the probability of landslide is calculated as a weighted sum of probability of landslide due to environmental factors and probability of landslide due to people's investments. Probability of landslide due to environmental (natural) factors is a combination of probability of landslide due to rainfall and probability of landslide due to slope and soil properties. Model also simulated the losses caused due to occurrence of landslide events.

The Calculation of Total Probability of Landslides.

$$\text{Total probability of landslide} = (W * P(I) + (1 - W) * P(E)) \quad (1)$$

where W is the weight factor, which is between [0, 1]. In the model, W have been assigned a value = 0.8, which indicates that investments against landslides will cause the system to respond rapidly and reduce the probability of landslide.

The total probability formula involves calculation of two probabilities, P(I) and P(E), which is described below:

Probability of Landslide Due to Investment $P(I)$. The calculation used here is based on expected payoff equation used in Hasson (2009) [13], i.e.,

$$P(I) = 1 - \frac{M * \sum_{i=1}^{n} x_i}{n * B} \tag{2}$$

where,

B Budget available towards addressing landslide (if a person earns a daily income or salary, then B is the same as this daily income or salary).

n Number of time periods (days). In the default formulation of the game, n = 60 simulated days, i.e., the game is played for 60 simulated days.

x_i Investments made by a person at each day i to mitigate landslides; $x_i \leq B$,

M Return to Mitigation, which captures the lower bound probability of P(I) when $\sum_{i=1}^{n} x_i = n * B$, i.e., people invest their entire daily income in mitigating landslides.

P(I) Probability of landslide after an investment is made.

Probability of Landslide Due to Natural Factors $P(E)$. Natural factors include rainfall, soil type, slope profile, etc. These can be categorized into two parts:

- Probability of landslide due to rainfall (P(T))
- Probability of landslide due to soil type, slope profile etc. [spatial probability, P(S)]

The approach used to calculate both of them is based on a research paper [14]. Equation used for calculation of probability of landslide due to rainfall (P(T)):

$$z = -3.817 + DR * 0.077 + 3\,DCR * 0.058 + 30\,DAR * 0.009 \tag{3}$$

$$f(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

$$z: -\infty \text{ to } +\infty, \; P: 0 \text{ to } 1$$

The logistic regression retains the daily (DR), 3-day cumulative (3 DCR) and 30-day antecedent rainfall (30 DAR) as significant predictors influencing slope failure. P(T) = f(z), that is the temporal probability of landslide. The rainfall data was collected as raw data from NASA's TRMM project, from January 1, 2004 to April 30, 2013.

Now,

$$P(E) = P(T) * P(S) = f(z) * P(S) \tag{5}$$

Damage Modeling. The damage caused can be classified into 3 categories:

(a) Property Loss
(b) Injury
(c) Fatality

All 3 of them have different kinds of effects on the player's wealth and income in the simulator. The data used for calculating probabilities of the above damage has been obtained from Parkash [15]. The stochastic nature of landslide occurrence and damages caused by it have thus also been considered. The exact assumptions about damages are detailed ahead in this manuscript.

2.2 Interactive Landslide Simulator (ILS) Microworld

Computer-based decision-making tasks have spread across disciplines and different levels of education [16]. Furthermore, these decision-making tasks have been long used in the study of dynamic decision making behaviour (also called Microworld, see Gonzalez et al. [17]), and many more specialized tasks have been created to provide decision makers with practice and training in organizational system's control; also called Management Flight Simulators [18, 19].

ILS microworld is a computer-based task, where a decision maker's goal is to maximize one's economic level. The economic level (defined by wealth due to income and property in ILS microworld) is influenced by exogenous environment circumstances (spatial and temporal conditions) and the past decisions made by humans. The economic level may decrease (by damages caused due to landslides, like injury, death or property damage) or increase (due to daily income and property wealth). However, the exact functional form governing these increases or decreases was unknown to decision makers. Decision makers could only observe the values that occurred in the previous time period. The level of wealth at time t depends upon the previous time period $t - 1$, a characteristic of dynamic systems called interdependency [20]. Also inherent in dynamic systems are feedback loops, where one observes the effect that one variable has on itself and others. Feedback loops can be positive or negative, "self-reinforcing" or "self-correcting" [21]. Both types of loops are present in ILS because decision makers make repeated investments so as to increase or decrease their economic level.

Figure 2 represents graphical user interface of ILS, which requires a decision maker controlling her economic level and keep it up as much as possible. The economic level is represented graphically as curve of 'Property wealth' and 'Total income not invested in landslides' versus number of times investment decision has been made (since the decision made is one per day the graph is plotted against number of days passed in the simulator). The plot of 'Total probability of landslide'

Fig. 2 ILS microworld graphical user interface [game] (*source* http://pratik.acslab.org)

versus number of days describes the cumulative effect of this variable on probability of landslide. The 'Game Parameters' table on the right hand side describes specific values like daily income, property wealth, probability of landslide, and damages due to landslide.

A decision-maker must enter the investment input in the text field specified on top left of the screen. The investment can only be made between zero (minimum) to the player's current daily income (maximum). Once investment is made, the decision-maker can observe changes in the daily income, property wealth, and damages caused due to landslide [loss of daily income (due to death and injury) and loss of property wealth].

After a decision-maker enters the investment decision and clicks on the 'Invest' button, the system provides feedback on whether a landslide occurred or not. If a landslide occurs, then the system decides what kind of damage the landslide has caused and the resulting economic level is shown as a loss via a negative feedback screen (see Fig. 3). If landslide did not occur, however, a positive feedback screen is shown to the decision maker (see Fig. 4). The user can get back to investment decision screen by clicking on 'Return To Game' button.

Fig. 3 ILS microworld's negative feedback screen where a landslide has occurred (*source* http://pratik.acslab.org)

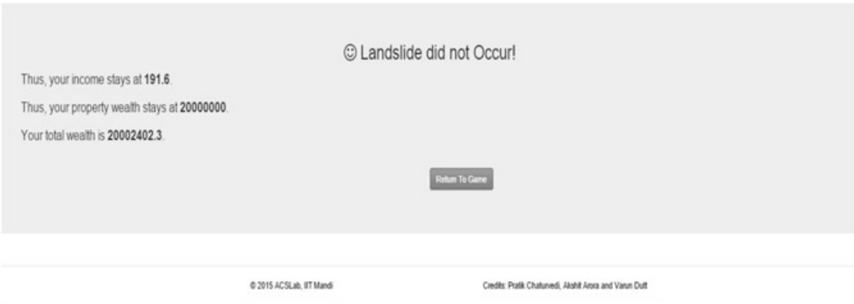

Fig. 4 ILS microworld's positive feedback screen where a landslide did not occur (*source* http://pratik.acslab.org)

Returning to game causes the player to come back to the main graphical user interface of ILS (see Fig. 2). Once a player has played multiple days in ILS (where the end-point is not known), the interface shows the amount of income and property wealth left at the end of the game. Although ILS is made to capture the dynamics of landslides, the tool can actually be deployed for other natural calamities so long as the geological data related to those calamities is available. Lastly, we have setup ILS as a web-application; therefore, it is accessible anywhere in the world at any time and on any web-browser compatible computing device.

3 ILS Experiment: Testing Affective Feedback in ILS

In order to showcase the effectiveness of the ILS tool, we performed a lab-based experiment where we used ILS with human participants. In this experiment, we manipulated the feedback, i.e., the effect of landslides on a person's income and property wealth using two different conditions: high-affect condition (i.e., high probability of death, injury, and property due to a landslide) and low-affect condition (low probability of death, injury, and property due to a landslide). The expectation was that participants will invest more and improve their understanding about landslides in the high-affect condition compared to the low-affect condition. These conditions and results are explained in greater detail below.

3.1 Methods

Experimental Design. Participants were randomly assigned to one of the two between-subjects conditions: high-affect and low-affect. In both conditions, participants were given daily income and were as asked to make daily investment decisions. In high-affect condition, the probability of property damage, fatality and injury were set as 10, 3, and 30 %, respectively. In low-affect condition, the probability of property damage, fatality and injury were 3, 1, and 10 %, respectively. The goal was to maximize the net wealth (coming from property wealth and daily income combined) over multiple rounds of ILS (where the end-point was not known to participants). The nature of functional forms used in ILS were unknown to participants, and participants simply observed the values of the probability of human factors and natural factors and all the damages occurring in an event of a landslide.

The amount of damage (in terms of daily income and property wealth) that occurs in an event of fatality, injury and property damage was kept constant in both the affect conditions. The property wealth decreased to ½ of its value every time property damage occurred in an event of a landslide. The daily income was reduced by 10 % of its latest value in case of injury and 20 % of its latest value in case of fatality loss. The initial property wealth was fixed to INR 2 million, which is the expected property wealth in Mandi district of Himachal Pradesh. The initial daily income of the person was kept 292 INR (taking into account the GDP and per-capita income of Himachal Pradesh, India where the study was carried out). The time duration of the simulation was 30 days (this duration was not known to participants). Weight of human factors in probability of landslide (W) was fixed to 0.8 and that of natural factors $(1 - W)$ was fixed to 0.2. The W value was known to participants on the graphical user interface.

We used decision maker's average investment ratio as a dependent variable for the purpose of data analysis. The average investment ratio was defined as the ratio of investment made to total investment possible averaged across all participants and days. On account of Affect heuristic [12], we expected the average investment ratio to be greater in the high-affect condition compared to in the low-affect condition.

Participants. Forty-three participants at Indian Institute of Technology Mandi from diverse fields of study participated in the experiment. There were 20 participants in high-affect condition and 23 participants in low-affect condition to yield a medium to large effect size (= 0.5) in our results (for Alpha = 0.05 and a Power = 0.80). All participants were students from Science, Technology, Engineering, and Mathematics (STEM) backgrounds and their ages ranged in between 21 and 28 years (Mean = 23.54; Standard Deviation = 4.08). Twenty-eight participants were Master's students, 5 were Ph.D. students, and 10 were B. Tech. students. When asked about their previous knowledge about landslides, 20 participants mentioned having a basic understanding, 16 having little understanding, 5 being knowledgeable, and 3 having no idea. All participants received a base payment of INR 50 and an additional bonus according to their performance in the task.

Procedure. Participants were recruited via an online advertisement circulated via an email at Indian Institute of Technology Mandi. Experimental sessions about 30 min long per participant. Participants were randomly assigned to one of the two conditions, and they were given instructions on the computer before entering the ILS microworld. Participants were encouraged to ask questions after reading instructions. Participants were not given any information concerning the nature of environment or conditions in the microworld. They were told that their goal was to maximize their final income and they were then asked to play ILS for 30 days.

3.2 Results

Data were analyzed for all participants in terms of their average investment ratio in both the high-affect as well as low-affect condition. The result was as per our expectation: Average investment ratios were significantly higher in high-affect condition compared to those in the low-affect condition (see Fig. 5).

As shown in Fig. 5, participants had lesser investment ratios in low-affect condition(M = 0.38, SE = 0.05) compared to those in high-affect condition (M = 0.67, SE = 0.045) [$t(41) = -4.1$, $p < 0.05$, $r = 0.54$]. Thus, our hypothesis related to affect heuristic was satisfied with these results from ILS.

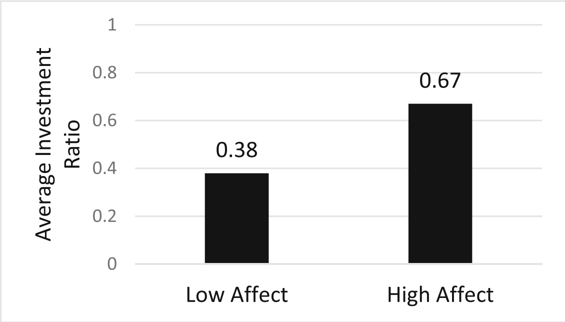

Fig. 5 Average investment ratio in low- and high-affect conditions

4 Discussion and Conclusions

One way of improving existing risk communication practices for landslides is by training people about these risks via simulation tools. That is because personal experience and the visibility of processes are the two main factors for improving people's understanding and seriousness about natural disasters. Interactive Landslide Simulator (ILS) is an interactive simulation model, which could be used by policymakers to do what-if analyses. ILS can also be used as an educational tool for the general public to increase their understanding and awareness about landslides.

In order to showcase the performance of ILS in improving public's perception towards landslide risk, we conducted an experiment involving 43 students of different educational backgrounds and made them invest against landslides for 30 days in different affective conditions. As expected, the result from the experiment suggested that participants making investment decisions in high-affect condition invested much higher than the participants doing the same task in low-affect condition. This result can be explained by previous lab-based research on use of repeated feedback or experience (Cronin et al. 2009; Dutt and Gonzalez 2011) and affect heuristic (Fischoff 2001; Finucane et al. [12]. Affect heuristic allows people to make decisions and solve problems quickly and efficiently, in which current emotions of fear, pleasure, and surprise influences decisions. As the emotional feedback is higher in high-affect condition, participants have made higher monetary contributions in this case. Thus, ILS has exhibited success in terms of improving public's seriousness and awareness towards landslide risk. In future, various other system-response parameters (e.g. w or M), feedback (e.g. numbers, text messages and images for damage) will be varied to study their effect on public's decision making. Here, we would like to evaluate affect and its ability to increase public contributions in the face of other system-response parameters.

Other uses of ILS include packaged education material for classroom and workshops that accounts for factors like feedback, affect, and social norms. We believe that such material, when tailored to specific individuals, will help improve decision making of individuals against landslides. ILS tool can be used for communicating landslide risk in other landslide prone states by customizing the spatial probability (based on geology, soil properties etc.) and temporal probability (based on rainfall) of landslides in such areas. In future, we also plan to use ILS to understand the effects of social norms on people's investment decisions towards mitigation of landslide risk.

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