

March 18th, 2018

Dr. Stefano Luigi Gariano
Editor, *Journal of Natural Hazards and Earth System Sciences*

Dear Dr. Gariano:

I write to you concerning a manuscript, "Learning in an Interactive Simulation Tool against Landslide Risks: The Role of Strength and Availability of Experiential Feedback," that I co-authored with my Ph.D. advisor, Dr. Varun Dutt and Mr. Akshit Arora.

We want to thank you for considering our work to the special issue on "Landslide early warning systems: monitoring systems, rainfall thresholds, warning models, performance evaluation and risk perception" of NHESS journal.

As per your kind suggestions, we have now extensively modified our manuscript as per your and referee comments. We are now submitting a revised version of the manuscript with point-to-point replies against the comments and suggestions given by you and referees. These point-to-point replies are attached with this covering letter as an annexure "A".

We would like to mention that our focus in the manuscript was not to develop a very precise model of landslide occurrence, which considers all possible technical-social-economic parameters. Rather, our focus was on developing approximate models, which could be used in improving people's understanding about landslide disasters. We have mentioned this part both in response to referee comments as well as in the manuscript draft.

We look forward to hearing from you on our revision.

Sincerely,

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Comments to the Author:

Dear Authors,

your paper passed through a second round of review and received again constructive comments.

I still believe that your paper has potential but need a huge improvement before being considered publishable. Some drawbacks remains in your paper, both in the contents and in the presentation.

I suggest to reconsider all the comments made by reviewers in the first round of revision and to address all of them. In some case, you did not provide precise answers to the referees' comments.

Moreover, I suggest to follow the suggestions proposed by the referees in the second round of revision. In particular, please:

- i) include a section related to previous events in the area;**
- ii) justify the values of weights adopted to calculate hazard probability;**
- iii) clarify the link between hazard and risk;**
- iv) improve the discussion of the methods used for assessing landslide probability and susceptibility;**
- v) discuss other economic issues (such as the sensitivity of the different social classes in relation to their economic and cultural resources; the public/private intervention in the investments; and a cost-threshold).**

Finally, I suggest an amelioration of the manuscript presentation, in particular regarding the figures, which are still improvable.

My decision is that your manuscript need again major revisions before being reconsidered for publication. The reviewed manuscript will be checked again by referees and editor before proceeding for next steps.

Authors: Thank you for summarizing our contribution and providing encouragement to our work. As per the referees' comments, we have now clarified

several improvements to the manuscript based upon review comments in the second round. In agreement with reviewers, we have now also added a section about the study area (previous landslide events, their features, and associated damages) in this paper (pgs. 5-6). We have also added a simulation result showing effect of weight parameter on landslide probability calculation and how having high values of W parameter gave salient feedback on actions to our participants (pgs. 19-20). We have now clarified the link between hazard and risk in the revised manuscript (pg. 7). As per our paper, $\text{risk} = \text{hazard} = \text{probability} * \text{consequence}$. Furthermore, the damage modelling and spatial probability calculation from hazard maps in ILS tool have been better elaborated and explained (pgs. 11-13). As per your suggestion, we have also explained the economic issues related to model used in ILS. To express the limitations of the current ILS model, we have now added a separate section titled “Limitations” before the “Conclusions” section (pgs. 29-31). Finally, we have now also improved the quality of figures in the revised manuscript.

Point by point replies to referee 1

General Comments

I confirm my positive feelings about the significance of investigated topic and the type of approach used in this perspective. In some parts, on my view, the paper results highly improved after the revision but on the other sections, some weaknesses persist. For example, a section about previous events, suffered damages and features of landslides in the area is again lacking. Moreover, several weights adopted to calculate hazard probability are not properly justified and the results could be highly dependent by such choices (for example, for W parameter). Furthermore, the link between hazard and risk should be clarified (see section “Damages due to landslides”). In the revised version, all the assumptions result clearly reported in Conclusions. Nevertheless, a section devoted to them could be added prior to the “Conclusions”.

Authors: Thank you for summarizing our contribution and providing encouragement to our work. As per your review comments, we have now clarified several improvements to the manuscript based upon review comments. In agreement with you, we have now added a section about the study area listing previous landslide events, their features, and associated damages (pgs. 5-6). Also, we have now added a simulation result showing the effects of weight parameter on landslide probability calculation (pgs. 19-20). Specifically, we have now shown that a high W value allowed us to give human participants salient feedback on how their decisions changed total probability of landslides (pgs. 19-20). Furthermore, we have now explained how we computed the damages, rainfall probability of landslides, and spatial probability of landslides in the study area (pgs. 9-12). As per your kind suggestion, we have now explained all the assumptions in the current study in detail in a limitation separate section prior to conclusions (pgs. 29-31).

Specific comments:

Abstract: again, the text should be improved. Too few details were given about the approaches, the context, and the scopes of the work. On the other side, some findings

are reported also if they could be not clearly understood by the readers at this stage. I suggest you reorganizing the text to improve its appealing.

Authors: Thank you for your kind suggestions. We have now improved the language of the abstract section to improve its appeal and understandability.

L10: please divide the two parts of the sentence.

Authors: Thank you for your kind suggestion. We have now divided this sentence into two parts as suggested by you.

L64-65: it practically replies the previous sentence; in my view, it could be removed

Authors: Thank you for your kind suggestion. We have now removed the extra sentence as per the suggestion in the revised manuscript.

L79: probably, other anthropic interventions could be cited. The word “likely” appears overused in the text; please check and, when possible, use synonyms.

Authors: Thank you for your kind suggestions. In agreement with you, we have now added the following anthropogenic interventions: a retaining wall, planned road construction, provision of proper drainage, and planting of crops with long roots. Furthermore, we have now cut the repetitive use of the word “likely” in the text in the revised manuscript.

Figure 1: please, attempt improving it in quality; moreover, check capital letters and punctuation.

Authors: We have now improved the figure quality, corrected the use of capital letters and other typos in the revised manuscript.

L127: I suggest reporting the footnote directly in the text; moreover, reducing landslide risk could entail also avoiding profitable investments (then loss of revenue); it should be cited in the text.

Authors: Thank you for your kind suggestions. We have now removed the footnotes everywhere and made them part of the main text. In agreement with you, we have now mentioned that by reducing the landslide risk, people also have lesser ability in investing in other profitable investments (pg. 7).

L157-158: the sentence should be clarified; at the moment, it is not really clear the meaning of M.

Authors: The meaning of the return to mitigation parameter (M) has been clarified by an example in the main text (pg. 9).

L180-182: the approach does not result consistent; five years represent a too short interval to climatologically characterize an area. According WMO indications, 30 years are required. Moreover, linking to a single day could be not a proper way as rainfall patterns could be characterized at seasonal scale but not for single rainfall days.

Authors: We plotted the distribution of rainfall averaged over a 30-year period and this distribution was similar to the one that was computed over the past 5-year period.

There was a peak during the monsoon months (mid-June to mid-September) in the average rainfall distribution.

As our primary objective was not to accurately predict rainfall or other landslide parameters; rather, to educate people about landslide disasters, we have used an approximate model of the complex landslide phenomena in the ILS simulation tool. There is a large body of literature on using approximate simulation tools for improving people's understanding about natural processes like climate change and other natural disasters. The development and use of the ILS tool follows the same line of research and tradition. We have now added these arguments to a "Limitations" section in the paper before the conclusions section (pgs. 29-31).

L190-198: please avoid confusing between susceptibility and hazard in the text; if you consider susceptibility, occurrence probability is not taken into account; please display a map with landslide susceptibility map.

Authors: Thank you for your comments. We used the landslide hazard zonation map (now shown as Figure 4 (A) in the manuscript) for computing the spatial probability of landslide occurrence. We have now clarified our method of computing the spatial probability using the area and the colors on the map in the manuscript (pgs. 11-13). We have also shown the cumulative density function for the landslide spatial probability that we used in the ILS tool (Figure 4 (B)). As explained in the manuscript, we have used a point value of the spatial probability from this cumulative distribution for each participant in the ILS tool. Again, please note that this exercise was not meant to accurately determine the spatial probability of landslide in the area of interest. Rather, the primary objective of this exercise was to develop an approximate model that accounts for the spatial probability in the in the ILS, where the tool was meant to improve people's understanding about landslide risks (pgs. 13 and 29-31).

L200-208: do the areas account for invaded zones?

Authors: We have now added the details of the study area in a separate section to the manuscript to improve the depiction of the invaded zones (pg. 5-6).

L211-220: the dynamics regulating “Damages due to landslides” are not clearly reported at the moment; please attempt improving them; in the specific, the role of random U and in which way it is related to total probability.

Authors: Thank you for your comments. We have now improved the exposition of the dynamic aspects in the ILS tool in the manuscript (pg. 8-13). Specifically, we have now explained that the use of a uniformly distributed random variable was to simulate the total probability of landslides as well as the probability of damages due to landslides (pg. 8).

L225: I’m not native English speaker but I suppose that “to help” requires –ing form after.

Authors: Thank you for your kind suggestions. We have now corrected the grammatical mistakes and other typos in the revised manuscript.

L252-256: Is it taken into account where the mitigation measurements are designed to be performed? (e.g. where the player decides the investments).

Authors: Thank you for your kind comments. As part of the instructions, the players were told that the mitigation measures will be taken close to the places where they reside in the district in the ILS tool. We have now added this detail in the methods section of the manuscript (pg. 14).

L256-265: to take into account damages, could you refer to previous landslide events monitored in the area?

Authors: As suggested by you, we have used Prakash (2011) to estimate the historical damages in the study area. However, please note that, in this manuscript, we vary this probability in the experiment. Thus, the exact value of the probability from literature is not required in the simulation (pg. 13). However, we have tried to keep the probability values to those found by Prakash (2011) for this study area.

L322-324: you should carefully justify this choice

Authors: As suggested by you, we have now carefully justified our choice of values on these lines (pgs. 19-20).

Figure 5: the “Instructions” could be reported as Appendix to make them clearer.

Authors: Thank you for your kind suggestions. We have now removed instructions in figure 5 and report them as a part of the appendix section as per your kind suggestions.

L363: do you confirm that these percentages reflect those of communities affected by landslides in the area?

Authors: Yes, as suggested by our citations, we feel that people residing in the study area are well educated. Thus, these percentages more or less reflect the general population of the area (pg. 21).

Footnote7: on my view, you should avoid the use of footnotes not commonly used in NHESS research papers

Authors: Thank you for your kind suggestions. We have now removed the footnotes everywhere and made them part of the main text to match the format of NHESS.

L436: please check the use of Capital letters.

Authors: Thank you for your kind suggestions. We have now corrected the use of capital letters and other typos.

Point by point replies to referee 2

The authors present a simulator (ILS model) that aims to evaluate the interactions between economic investments of the population and reduction of the risk related to landslides. Despite the bibliographic citations, the model is presented inadequately and it is not clear whether the results obtained can be subjected to a validation phase.

Authors: Thank you for summarizing our contribution and providing encouragement to our work. As per your review comments, we have now clarified several improvements to the manuscript based upon your comments. We have improved the description about the model behind the ILS tool in the revised manuscript (pgs. 9-13) so that it can be subjected to a validation phase. Furthermore, now the damage modelling in ILS tool have been better elaborated and explained (pg. 13). In addition, to express the limitations of the current ILS model, we have now added a separate section titled “Limitations” before the “Conclusions” section in the manuscript (pgs. 29-31).

Moreover, many aspects relating to the sensitivity of the different social classes in relation to their economic and cultural resources are neglected. The problem of the amount of the necessary economic investments, that imply an indispensable public intervention instead of the private one, is not addressed. It would therefore be appropriate to indicate a cost-threshold for interventions which, when exceeded, causes the model stop.

Authors: Thank you for your comments. We have now discussed the sensitivity of different social classes to their economic, geographical, and cultural resources, where, in the absence of insurance payments, people mostly use their own finances to overcome the challenges put by natural disasters like landslides (ICICI, 2018) (pg. 7 and pg. 30). Furthermore, as part of “Limitation” section, we have now compared large public investments against landslides with respect to people’s other investments and the reasons for the same (pg. 29-31). Also, we have now discussed future research where we plan to compare public investments against landslides to

their likely socio-economic cost thresholds given that people may need to spend their wealth in other areas (pgs. 29-31).

The methods for assessing the probabilities and the susceptibility to landslides are presented inadequately.

Authors: The exposition of methods for assessing the probabilities and the susceptibility to landslides have been improved now. We used the landslide hazard zonation map (now shown as Figure 4 (A) in the manuscript) for computing the spatial probability of landslide occurrence. We have now clarified our method of computing the spatial probability using the area and the colors on the map in the manuscript (pgs. 11-13). We have also shown the probability density function for the landslide spatial probability that we used in the ILS tool (Figure 4 (B)). Please note that this modeling exercise was not meant to very accurately determine the spatial probability of landslides in the study area. Rather, the primary objective of this exercise was to develop an approximate model that accounted for the spatial probability in ILS, where the tool was meant to improve people's understanding about landslide risks (pgs. 13 and 30-32).

Finally, even the rain data used for the application seems insufficient: it is not realistic that after a few days we pass from probabilities higher than 0.8 to values below 0.3 (see Fig. 2). These irregularities indicate a poor representation of the sample used compared to an average trend.

Authors: Thank you for the comment. The total probability of landslides is influenced by spatial probability of landslides, rainfall probability of landslides, and the human probability of landslides. Any of rapid changes in total probability of landslides as observed by you in the Figure could be a result of changes in any of these constituting probabilities (pg. 11-13). To improve the exposition of our methods, we have now plotted the distribution of rainfall that was averaged over a 5-year period and this distribution was found to be similar to the one over a 30-year period. Also, we have now improved the explanation of calculation of the spatial probability of landslides in the study area (pg. 11-13).

Please note that our primary objective in the manuscript is not to accurately predict rainfall or other landslide parameters; rather, our objective is to understand how people improve their understanding about landslide disasters in a simulation that provides an approximate representation of the complex landslide phenomena. There is a large body of literature on using approximate simulation tools for improving people's understanding about natural processes like climate change and other natural disasters. Again, these simulation tools only use an approximate models of the real phenomena. The development and use of the ILS tool follows the same line of research and tradition. We have added these points to a "limitations" section in the manuscript (pgs. 29-31).

Learning in an Interactive Simulation Tool against Landslide Risks: The Role of Strength and Availability of Experiential Feedback

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Abstract. Feedback via simulation tools is likely to help people improve their decision-making against natural disasters. However, little is known on how differing strengths of experiential feedback and feedback's availability in simulation tools influences people's decisions against landslides. We tested the influence of differing strengths of experiential feedback and feedback's availability on people's decisions against landslides in Mandi, Himachal Pradesh, India. Experiential feedback (high or low) and feedback's availability (present or absent) were varied across four between-subject conditions in an interactive landslide simulation (ILS) tool: high-damage feedback-present, high-damage feedback-absent, low-damage feedback-present, and low-damage feedback-absent. In high-damage conditions, the probabilities of damages to life and property due to landslides were 10-times higher than those in the low-damage conditions. In feedback-present conditions, experiential feedback was provided in numeric, text, and graphical formats in ILS. In feedback-absent conditions, the probabilities of damages were described, however, there was no experiential feedback present. Investments were greater in conditions where experiential feedback was present and damages were high compared to conditions where experiential feedback was absent and damages were low. Furthermore, only high-damage feedback produced learning in ILS. Simulation tools like ILS seem appropriate for landslide risk communication and for performing what-if analyses.

1 Introduction

Landslides cause massive damages to life and property worldwide (Chaturvedi and Dutt, 2015; Margottini et al., 2011). Imparting knowledge about landslide causes-and-consequences as well as spreading awareness about landslide disaster mitigation are likely to be effective ways of managing

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landslide risks. The former approach supports structural protection measures that are likely to help people take mitigation actions and reduce the probability of landslides (Becker et al., 2013; Osuret et al., 2016; Webb and Ronan, 2014). In contrast, the latter approach likely reduces people's and assets' perceived vulnerability to risk. However, it does not influence the physical processes. One needs effective landslide risk communication systems (RCSs) to educate people about cause-and-effect relationships concerning landslides (Glade et al., 2005). To be effective, these RCSs should possess five main components (Rogers and Tsirkunov, 2011): monitoring; analysing, risk communication, warning dissemination, and capacity building.

Among these components, prior research has focused on monitoring and analysing the occurrence of landslide events (Dai et al., 2002; Montrasio et al., 2011). For example, there exist various statistical and process-based models for predicting landslides (Dai et al., 2002; Montrasio et al., 2011). Several satellite-based and sensor-based landslide monitoring systems are being used in landslide RCSs (Hong et al., 2006; Quanshah et al., 2010; Rogers et al., 2011). To be effective, however, landslide RCSs need not only be based upon sound scientific models, but, they also need to consider human factors, i.e., the knowledge and understanding of people residing in landslide-prone areas (Meissen and Voisard, 2008). Thus, there is an urgent need to focus on the development, evaluation, and improvement of risk communication, warning dissemination, and capacity building measures in RCSs.

Improvements in risk communication strategies are likely to help people understand the cause-and-effect processes concerning landslides and help them improve their decision-making against these natural disasters (Grasso and Singh, 2009). However, surveys conducted among communities in landslide-prone areas (including those in northern India) have shown a lack of awareness and understanding among people about landslide risks (Chaturvedi and Dutt, 2015; Oven, 2009; Wanasolo, 2012). In a survey conducted in Mandi, India, Chaturvedi and Dutt (2015) found that 60% of people surveyed were not able to answer questions on landslide susceptibilities maps, which were prepared by experts. Also, Chaturvedi and Dutt (2015) found that a sizeable population reported landslides to be "acts of God" (39%) and attributed activities like "shifting of temple" as causing landslides (17%). These results are surprising as the literacy-rate in Mandi and surrounding areas is quite high (81.5%) (Census, 2011) and these results show numerous misconceptions about landslides among people in landslide-prone areas. Overall, urgent measures

need to be taken that improve public understanding and awareness about landslides in affected areas.

Promising recent research has shown that experiential feedback in simulation tools likely helps improve public understanding about dynamics of physical systems (Chaturvedi et al., 2017; Dutt and Gonzalez, 2010; 2011; 2012; Fischer, 2008). Dutt and Gonzalez (2012) developed a Dynamic Climate Change Simulator (DCCS) tool, which was based upon a more generic stock-and-flow task (Gonzalez and Dutt, 2011a). The authors provided frequent feedback on cause-and-effect relationships concerning Earth's climate in DCCS and this experiential feedback helped people reduce their climate misconceptions compared to a no-DCCS intervention. Although the prior literature has investigated the role of frequency of feedback about inputs and outputs in physical systems, little is known on how differing strengths of experiential feedback (i.e., differing probabilities of damages due to landslides) influences people's decisions over time. Also, little is known on how experiential feedback's availability (presence or absence) in simulation tools influences people's decisions.

The primary goal of this research is to evaluate how differing strengths of experiential feedback and feedback's availability influences people's mitigation decisions against landslides. A study of how the strength of experiential feedback influences people's decisions against landslides is important because people's experience of landslide consequences due to differing probabilities of landslide damages could range from no damages at all to large damages involving several injuries, infrastructure damages, and deaths. Thus, due to differing probabilities of landslide damages, some people may experience severe landslide damages and consider landslides to be a serious problem requiring immediate actions; whereas, other people may experience no damages and consider landslides to be a trivial problem requiring very little attention.

In addition, the availability of feedback in simulation tools is also likely to influence people's decisions against landslides. When feedback is absent, people are only likely to acquire descriptive knowledge about the cause-and-effect relationships governing the landslide dynamics (Dutt and Gonzalez, 2010). However, when feedback is present, people get to repeatedly experience the positive or negative consequences of their decisions against landslide risks (Dutt and Gonzalez, 2010; 2011). This repeated experience will likely help people understand the cause-and-effect relationships governing the landslide dynamics.

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Chaturvedi et al. (2017) proposed a computer-simulation tool, called the Interactive Landslide Simulator (ILS). The ILS tool is based upon a landslide model that considers the influence of both human factors and physical factors on landslide dynamics. Thus, in ILS, both physical factors (e.g., spatial geology and rainfall) and human factors (e.g., monetary contributions to mitigate landslides) influence the probability of catastrophic landslides. In a preliminary investigation involving the ILS tool, Chaturvedi et al. (2017) varied the probability of damages due to landslides at two levels: low probability and high probability. The high probability was set about 10-times higher compared to the low probability. People were asked to make monetary investment decisions, where people's monetary payments would be used for mitigating landslides (e.g., by building a retaining wall, planned road construction, provision of proper drainage or by planting crops with long roots in landslide-prone areas; please see Patra and Devi (2015) for a review of such mitigation measures). People's investments were significantly greater when the damage probability was high compared to when this probability was low. However, Chaturvedi et al. (2017) did not fully evaluate the effectiveness of experiential feedback of damages in ILS tool against control conditions where this experiential feedback was not present. Also, Chaturvedi et al. (2017) did not investigate people's investment decisions over time and certain strategies in ILS, where these decisions and strategies would be indicative of learning of landslide dynamics in the tool.

Prior literature on learning from experiential feedback (Baumeister et al., 2007; Dutt and Gonzalez, 2012; Finucane et al., 2000; Knutty, 2005; Reis and Judd, 2013; Wagner, 2007) suggests that increasing the strength of damage feedback by increasing the probabilities of landslide damages in simulation tools would likely increase people's mitigation decisions. That is because a high probability of landslide damages will make people suffer monetary losses and people would tend to minimize these losses by increasing their mitigation actions over time. It is also expected that the presence of experiential feedback about damages in simulation tools is likely to increase people's landslide-mitigation actions over time (Dutt and Gonzalez, 2010; 2011; 2012). That is because the experiential feedback about damages will likely enable people to make decisions and see the consequences of their decisions, however, the absence of this feedback will not allow people to observe the consequences of their decisions once these decisions have been made (Dutt and Gonzalez, 2012). At first glance, these explanations may seem to assume people to be economically rationale individuals while facing landslide disasters (Bossaerts and Murawski,

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2015; Neumann and Morgenstern, 1947), where one disregards people’s bounded rationality, risk perceptions, attitudes, and behaviours (De Martino, Kumaran, Seymour, and Dolan; 2005; Gigerenzer and Selten, 2002; Kahneman and Tversky, 1979; Simon, 1959; Slovic, Peters, Finucane, and MacGregor, 2005; Thaler and Sunstein, 2008; Tversky and Kahneman, 1992). However, in this paper, we consider people to be bounded rational agents (Gigerenzer and Selten, 2002; Simon, 1959), who tend to minimize their losses against landslides slowly over time via a trial-and-error learning process driven by personal experience in an uncertain environment (Dutt and Gonzalez, 2010; Slovic et al., 2005).

In this paper, we evaluate the influence of differing strengths of experiential feedback about landslide-related damages and the experiential feedback’s availability in the ILS tool. More specifically, we test whether people increase their mitigation actions in the presence of experiential damage feedback compared to in the absence of this feedback. In addition, we evaluate how different probabilities of damages influence people’s mitigation actions in the ILS tool. Furthermore, we also analyse people’s mitigation actions over time across different conditions.

In what follows, first, we detail the characteristics of the study area, and then a computational model on landslide risks that considers the role of both human factors and physical factors. Next, we detail the working of the ILS tool, i.e., based on the landslide model. Furthermore, we use the ILS tool in an experiment to evaluate the influence of differing strengths of experiential feedback and feedback’s availability on people’s decisions. Finally, we close this paper by discussing our results and detailing the benefits of using tools like ILS for communicating landslide risks in the real world.

2 Study area

In this paper, the study area was one involving the local communities living in the Mandi town (31.58° N, 76.91° E), a township located in the state of Himachal Pradesh, India (see Figure 1). The Mandi town has an average elevation of 850m above mean-sea level, 23 square km area, and a population of 26,422 people (Census, 2011). Literacy rate in Mandi town is 81.5% and most of the population are Hindus by religion. Mandi is a highly religious place with a huge number of Hindu temples all around the town (Census, 2011). Geologically, Mandi town is located on the folds of the lesser Himalayan mountains and it lies in the earthquake Zone IV and V, the highest earthquake zones in the world (Hpsdma, 2017). Apart from inherent geological weaknesses that

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may cause landslides in Mandi town, other anthropogenic activities such as road construction, deforestation of hill slopes, building construction on slopes, and debris dumping may also trigger landslides in the area surrounding the town (Hpsdma, 2017). As per Kahlon, Chandel, and Brar (2014), around 90% of the Mandi town is prone to landslides, where 25% of this area falls under the severe landslide hazard risk category. Landslide occurrences during the past 39 years (from 1971 to 2009) exhibit Mandi to account for 99 landslide events (11%) out of a total 919 landslide events in Himachal Pradesh, forming the 4th highest ranked district in terms of number landslides behind Shimla, Solan, and Kinnaur (Kahlon et al., 2014). The problem of landslides is accelerated in the monsoon season (mid-June to mid-September) in the town. The per-capita income of people in the Mandi town is close to INR 292 per day (Census, 2011). In addition, as per the tenancy laws of Himachal Pradesh, most people own land, which cannot be sold to people from outside the state (Himachal, 2012). The average per-capita property value in the state would be close to INR 20 million (Census, 2011). These values of per-capita daily income and property wealth were used in the ILS tool and these values have been detailed ahead in this paper. Furthermore, the prevailing rainfall pattern and the landslide hazard zonation map of Mandi town, which were used in the ILS tool, have also been detailed ahead in this paper.

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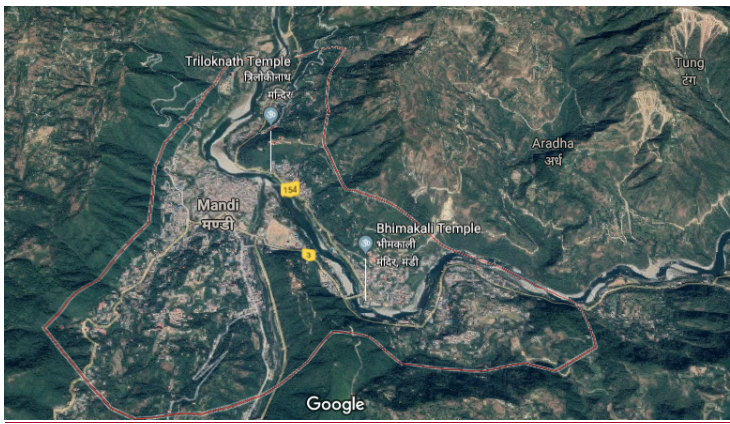


Figure 1. The 3D satellite view of Mandi town and adjoining areas. The town is located in a valley around river Beas with high mountains that are prone to landslides on both sides. Source: Google Maps.

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- Deleted: In fact, the Mandi area has frequently experienced landslides in the recent past (Chaturvedi and Dutt, 2015).

3. Computational model of landslide risk

Chaturvedi et al. (2017) had proposed a computational model for simulating landslide risks that was based upon the integration of human and physical factors (see Figure 2). Here, we briefly detail this model and use it in the ILS tool for our experiment (reported ahead). As seen in Figure 2, the probability of landslides due to human factors in the ILS tool is adapted from a model suggested by Hasson et al. (2010) (see box 1.1 in Figure 2). In Hasson et al. (2010)'s model, the probability of a disaster (e.g., landslide) due to human factors (e.g., investment) was a function of the cumulative monetary contributions made by participants to avert the disaster from the total endowment available to participants. Thus, investing against the disaster in mitigation measures reduces the probability of the disaster and not investing in mitigation measures increases the probability of the disaster. However, by reducing the landslide risk, people also have lesser ability in investing in other profitable investments due to loss in revenue. Although we assume this model to incorporate human mitigation actions in the ILS tool, there may also be other model assumptions possible where certain detrimental human actions (e.g., deforestation) may increase the probability of landslides or the risk of landslides (where, risk = probability (hazard) * consequence). We plan to consider such model assumptions as part of our future research. In addition, there may be contributions made by the national, regional, and local governments for providing protection measures against landslides in addition to the investments made by people residing in the area (Hpsdma, 2017). Such investments may be made based upon the past occurrences of landslides in the study area. Furthermore, people may also be able to buy insurance that covers for the damages caused by landslides. However, in India, in the absence of assistance from the government, mostly people tend to rely on their own wealth for adaptation to landslide occurrence. Thus, purchasing insurance against disasters is less common and unpopular as insurance companies mostly do not pay insured amounts in the event of natural disasters like landslides (ICICI, 2018). In this paper, we restrict our analyses to only people's own investments influencing landslides. We plan to consider the role of government contributions for mitigation and adaptation (mostly after landslide events) and partial insurance payments as part of our future research.

Furthermore, in the landslide model, the probability of landslides due to physical (natural) factors (see box 1.2) is a function of the prevailing rainfall conditions and the nature of geology in the area (Mathew et al., 2013). In this paper, we restrict our focus to considering only weather (rainfall)-induced landslides. As shown in Figure 2, the ILS model focuses on calculation of total

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probability of landslide (due to physical and human factors) (box 1.3). This total probability of landslide is calculated as a weighted sum of probability of landslide due to physical factors and probability of landslide due to human factors. Furthermore, the model simulates different types of damages caused by landslides and their effects on people’s earnings (box 1.4).

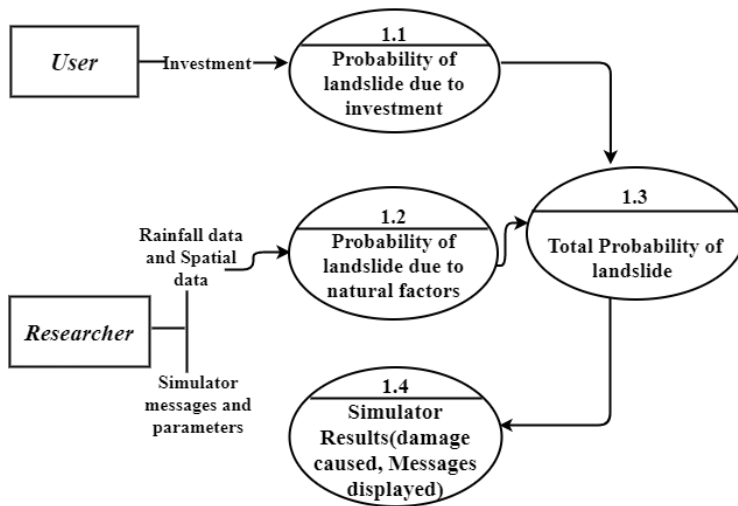


Figure 2. Probabilistic model of the Interactive Landslide Simulator tool. Figure adapted from Chaturvedi et al. (2017).

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3.1 Total probability of landslides

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As described by Chaturvedi et al. (2017), the total probability of landslides is a function of landslide probabilities due to human factors and physical factors. This total probability of landslides can be represented as the following:

$$P(T) = (W * P(I) + (1 - W) * P(E)) \quad (1)$$

Where W is a free weight parameter in [0, 1]. The total probability formula involves calculation of two probabilities, probability of landslide due to human investments ($P(I)$) and probability of landslide due to physical factors ($P(E)$). These probabilities have been defined below. According to Equation 1, the total probability of landslides will change based upon both human decisions and environmental factors over time. **In the ILS model, we simulate the total probability of landslides**

$P(T)$, where a landslide occurs when a uniformly distributed random number ($\sim U(0, 1)$) is less

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than or equal to $P(T)$ on a certain day. If a uniformly distributed random number in $[0, 1]$ ($U(0, 1)$) is less than or equal to a point probability value, then it simulates this point probability value. For example, if $U(0, 1) \leq 30\%$, then $U(0, 1)$ will be less than or equal to the 30% value exactly 30% of the total number of times it is simulated; and, thus this random process will simulate a 30% probability value.

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3.1.1 Probability of landslide due to human investments ($P(I)$)

As suggested by Chaturvedi et al. (2017), the probability $P(I)$ is calculated using the probability model suggested by Hasson et al. (2010). In this model, $P(I)$ is directly proportional to the amount of money invested by participants for landslide mitigation. The probability of landslide due to human investments is:

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

Where,

B = Budget available towards addressing landslides for a day (if a person earns an income or salary, then B is the same as this income or salary earned in a day).

n = Number of days.

x_i = Investments made by a person for each day i to mitigate landslides; $x_i \leq B$.

M = Return to Mitigation, which is a free parameter and captures the lower bound probability of $P(I)$, i.e., $P(I) = 1 - M$ when a person puts her entire budget B into landslide mitigation ($\sum_{i=1}^n x_i = n \cdot B$); $0 \leq M \leq 1$.

People's monetary investments (x_i) are for mitigation measures like building retaining walls or planting long root crops.

3.1.2 Probability of landslide due to physical factors ($P(E)$)

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Some of the physical factors impacting landslides include rainfall, soil types, and slope profiles (Chaturvedi et al., 2017; Dai et al., 2002). These factors can be categorized into two parts:

1. Probability of landslide due to rainfall ($P(R)$)
2. Probability of landslide due to soil types and slope profiles (spatial probability, $P(S)$)

For the sake of simplicity, we have assumed that $P(S)$ is independent of $P(R)$. Thus, given $P(R)$ and $P(S)$, the probability of landslide due to physical factors, $P(E)$, is defined as:

$$P(E) = P(R) * P(S) \quad (3)$$

In the first step, $P(R)$ is calculated based upon a logistic-regression model (Mathew et al., 2013) as follows:

$$P(R) = \frac{1}{1+e^{-z}} \quad P(T) : \quad (4a)$$

And,

$$z = -3.817 + (DR) * 0.077 + (3DCR) * 0.058 + (30DAR) * 0.009$$

$$z: (-\infty, +\infty) \quad (4b)$$

Where, the DR , $3DCR$, and $30DAR$ is the daily rainfall, the 3-day cumulative rainfall, and the 30-day antecedent rainfall in the study area. This model in equations 4a and 4b was developed for the study area by Mathew et al. (2013) and we have used the same model in this paper. The rainfall parameters in the model were calculated from the daily rain data from the Indian Metrological Department (IMD). We compared the shape of the $P(R)$ distribution by averaging rainfall data over the past five years with the shape of the $P(R)$ distribution by averaging rainfall data over the past 30-years. This comparison revealed that there were no statistical differences between these two distributions. Thus, we used the daily rainfall data averaged over the past 5-years (2010-14) to find the average rainfall values on each day out of the 365-days in a year. Next, these averaged rainfall values were put into equations 4a and 4b to generate the landslide probability due to rainfall ($P(R)$) over an entire year. Figure 3 shows the resulting shape of $P(R)$ distribution as a function of days in the year for the study area. Due to the monsoon period in India during mid-June – mid-September, there is a peak in the $P(R)$ distribution curve during these months. Depending upon the start date in the ILS tool, one could read $P(R)$ values from Figure 3 as the probability of landslides due to rainfall on a certain day in the year. This $P(R)$ function was assumed to possess the same shape across all participants in the ILS tool.

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Deleted: Five years of daily rain data (2010-14) from IMD was averaged to find the average rainfall values on each day out of the 365 days in a year. Next, these averaged rainfall values were put into equations 4a and 4b to generate the landslide probability due to rainfall ($P(R)$) over an entire year. Figure 4 shows the shape of $P(R)$ as a function of days in the year for the study area.

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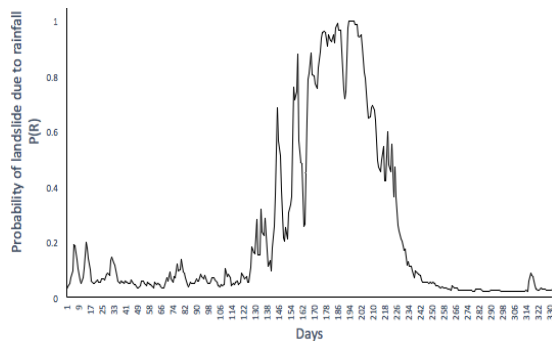
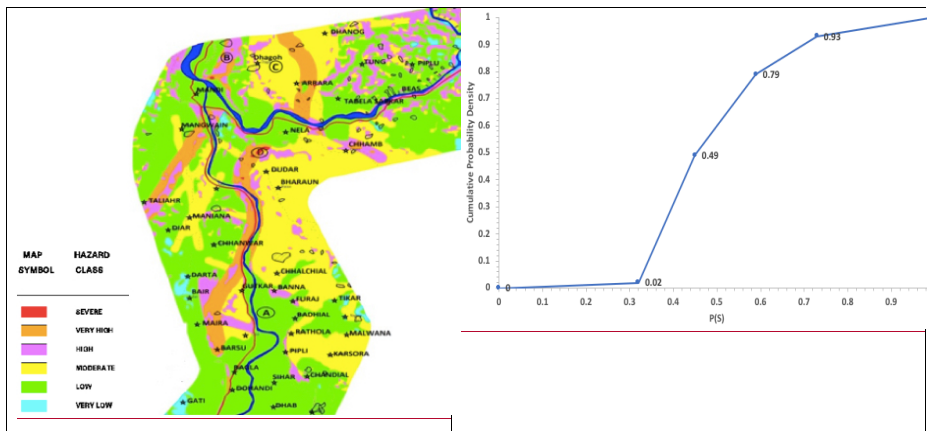


Figure 3. Probability of landslide due to rainfall over days for the study area. The probability was generated by using equations 4a and 4b.

The second step is to evaluate the spatial probability of landslides, $P(S)$. The determination of $P(S)$ is done from the landslide hazard zonation (LHZ) map of the study area (see Figure 4A; Anbalagan, 1992; Chaturvedi et al., 2017; Clerici et al., 2002), which are based on various causative factors of landslides in the study area (e.g., geology, geometry, and geomorphology). As shown in Figure 4A, we computed the spatial probability of landslides in the study area based upon the Total Estimated Hazard (THED) rating of different locations on a LHZ map (see legend) and their surface area of coverage (the maximum possible value of THED is 11.0 and its minimum possible value is 0.0). Table 1 provides the THED scale to report the susceptibility of an area to landslides (Anbalagan, 1992).



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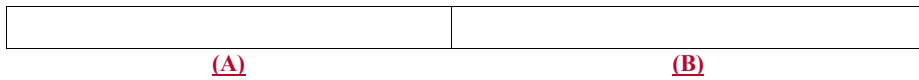


Figure 4 (A): Landslide hazard map of study area. **(B):** The cumulative density function of the spatial probability of landslides ($P(S)$). The $P(S)$ is shaped by geological and other causative factors in the study area.

Table 1. Total Estimated Hazard (THED) scale for evaluating the susceptibility of an area to landslides across to different hazard classes

Hazard Zone	Range of corrected THED	Hazard class
I	THED < 3.5	Very low hazard (VLH) zone
II	3.5 < THED < 5.0	Low hazard (LH) zone
III	5.0 < THED ≤ 6.5	Moderate hazard (MH) zone
IV	6.5 < THED ≤ 8.0	High Hazard (HH) zone
V	THED > 8.0	Very high hazard (VHH) zone

First, from Table 1, the critical THED values (e.g., 3.5, 5.0, 6.5, and 8.0) were converted into a probability value by dividing with the highest THED value (= 11.0). Next, we used the LHZ map of the study area (Figure 4A) to find the surface area that was under a hazard class (very low, low, moderate, high, and very high) and used this area to determine the cumulative probability density function for $P(S)$. For example, if a THED of 3.5 (low hazard class) has a 20% coverage area on LSZ (Figure 4A), then the spatial probability is less than equal to 0.32 (=3.5/11.0) with a 20% chance. Similarly, if a THED of 5.0 (moderate hazard class) has a 30% coverage area on LSZ, then the then the spatial probability is less than equal to 0.45 (=5.0/11.0) with a 50% chance (30% + 20%). Such calculations enabled us to develop a cumulative density function for $P(S)$ (see Figure 4B). As shown in Figure 4B (the cumulative density function of $P(S)$), 1.94% area belonged to the very low hazard class ($P(S)$ from 0/11 to 3.5/11), 46.61% area belonged to the low hazard class ($P(S)$ from 3.5/11 to 5.0/11), 30.28% area belonged to the moderate hazard class ($P(S)$ from 5.0/11 to 6.5/11), and 13.71% area belonged to the high hazard class ($P(S)$ from 6.5/11 to 8.0/11), and 7.43% area belonged to the very high hazard class ($P(S)$ from 8.0/11 to 11/11).

In the ILS tool, using Figure 4B, we used a randomly determined point value of the $P(S)$ from its cumulative density function for each participant in the ILS tool (see Figure 4B). This $P(S)$ value stayed the same for this participant across her performance in the ILS tool. Please note that

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Deleted: participant was assumed to belong to a location in the study area and this study area determined the $P(S)$ value.

Deleted: We have used a point value of the spatial probability from this probability density function (PDF) for each participant in the ILS tool (see Figure 3B).

this exercise was not meant to accurately determine the spatial probability of landslide in the area of interest, where more accurate and advanced methods could be used. Rather, the primary objective of this exercise was to develop an approximate model that could account for the spatial probability in the ILS based upon the LHZ map and THED scale, (the ILS tool was primarily meant to improve people's understanding about landslide risks and not for physical modeling of landslides).

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3.1.3 Damages due to landslides

As suggested by Chaturvedi et al. (2017), the damages caused by landslides were classified into three independent categories: property loss, injury, and fatality. These categories have their own damage probabilities. When a landslide occurs, it could be benign or catastrophic. A landslide becomes catastrophic with damage probability value of property loss, injury, and fatality. Thus, once a uniformly distributed random number is less or equal to the probability of the corresponding damage, then the corresponding damage is assumed to occur in ILS tool. Landslide damages have different effects on the player's wealth and income, where damage to property affects one's property wealth and damages concerning injury and fatality affect one's income level. When the landslide is benign, then there is no injury, no fatality, and no damages to one's property. For calculation of the damage probabilities due to landslides, data of 371 landslide events in India over a period of about 300 years was used (Parkash, 2011). However, it is to be noted that in this paper, we vary this probability in the experiment. Thus, the exact value of the probability from literature is not required in the simulation. The exact assumptions about damages are detailed ahead in this paper.

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4 Interactive Landslide Simulator (ILS) tool

The ILS tool (Chaturvedi et al., 2017) is a web-based tool and it is based upon the ILS model described above. The ILS tool was coded in open-source programming languages PHP and MySQL and it is freely available for use at the following URL: www.pratik.acslab.org. The ILS tool allows participants to make repeated monetary investment decisions for landslide risk-mitigation, observe the consequences of their decisions via feedback, and try new investment decisions. This way, ILS helps to improve people's understanding about the causes and consequences of landslides. The ILS tool can run for different time periods, which could be from

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days to months to years. This feature can be customized in the ILS tool. ~~However, in~~ this paper, we have assumed a daily time-scale to make it match the daily probability of landslides computed in equations 4a and 4b.

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The goal in ILS tool is to maximize one's total wealth, where this wealth is influenced by one's income, property wealth, and losses experienced due to landslides. Landslides and corresponding losses are influenced by physical factors (spatial and temporal probabilities of landslides) and human factors (i.e., the past contributions made by a participant for landslide mitigation). The total wealth may decrease (by damages caused by landslides, like injury, death, and property damage) or increase (due to daily income). While interacting with the tool, the repeated feedback on the positive or negative consequences of their decisions on their income and property wealth enables participants to revise their decisions and learn landslide risks and dynamics over time.

Figure 5 represents graphical user interface of ILS tool's investment screen. On this screen, participants are asked to make monetary mitigation decisions up to their daily income upper bound (see Box A). The total wealth is a sum of income not invested for landslide mitigation, property wealth, and total damages due to landslides (see Box B). As shown in Box B, participants are also shown the different probabilities of landslide due to human and physical factors as well as the probability weight used to combine these probabilities into the total probability. Furthermore, as shown in Box C, participants are graphically shown the history of total probability of landslide, total income not invested in landslides, and their remaining property wealth across different days. As part of the instructions, the players were told that the mitigation measures will be taken close to the places where they reside in the district in the ILS tool.

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A

Your investment for landslides for day 4 (between 0.0 and 292):

For no investment, please enter 0.0

Invest [Help](#)

B

Parameter	Value
Day	4
Income available for investment today (M)	292
Total income not invested in landslides (NTM)	754.7
Property wealth (PW)	20000000
Total damage due to landslides (TD)	0
Total wealth (NTM + PW - TD)	20000754.7
Probability of landslide due to human (investment) factor (P(H))	0.88
Probability of landslide due to environmental factors (P(E))	0.43
Probability weight (W)	0.7
Total probability of landslide (W*P(H)+(1-W)*P(E))	0.69

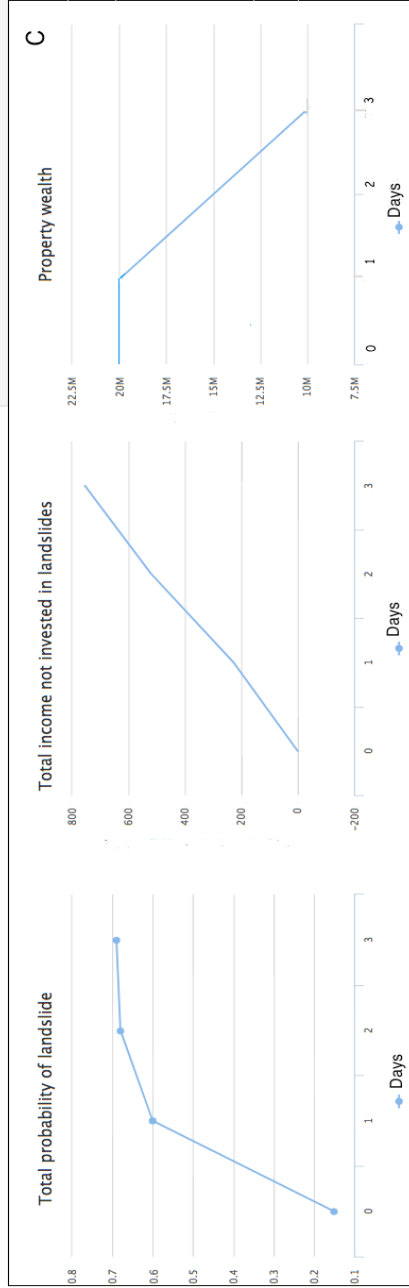


Figure 5. ILS tool's Investment Screen. Box (A): The text box where participants made investments against landslides. Box (B): The tool's different parameters and their values. Box (C): Line graphs showing the total probability of landslide, the total income not invested in landslides, and the property wealth over days. Horizontal axes in these graphs represents number of days. The goal was to maximize Total Wealth across a number of days of performance in the ILS tool. This figure is adapted from Chaturvedi et al. (2017).

1 As described above, participants, i.e., common people residing in the study area, could invest
2 between zero (minimum) and player's current daily income (maximum). Once the investment is
3 made, participants need to click the "Invest" button. Upon clicking the Invest button, participants
4 enter the experiential feedback screen where they can observe whether a landslide occurred or not
5 and whether there were changes in the daily income, property wealth, and damages due to the
6 landslide (see Figure 6). As discussed above, the landslide occurrence was determined by the
7 comparison of a uniformly distributed random number in $[0, 1]$ with $P(T)$. If a uniformly
8 distributed random number in $[0, 1]$ was less than or equal to $P(T)$, then a landslide occurred;
9 otherwise, the landslide did not occur. Furthermore, if the landslide occurred, then three uniformly
10 distributed random numbers in $[0, 1]$ were compared with the probability of injury, fatality, and
11 property damage, respectively. If the values of any of these random numbers were less than or
12 equal to the corresponding injury, fatality, or property-damage probabilities, then the landslide was
13 catastrophic (i.e., causing injury, fatality, or property damage; all three events could occur
14 simultaneously). In contrast, if the random numbers were more than the corresponding injury,
15 fatality, and property-damage probabilities, then the landslide was benign (i.e., it did not cause
16 injury, fatality, and property damage). As shown in Figure 6A, feedback information is presented
17 in three formats: monetary information about total wealth (box I), messages about different losses
18 (box I), and imagery corresponding to losses (box II). Injury and fatality due to landslides causes
19 a decrease in the daily income and damage to property causes a loss of property wealth (the exact
20 loss proportions are detailed ahead). If a landslide does not occur in a certain trial, a positive
21 feedback screen is shown to the decision maker (see Figure 6B). The user can get back to
22 investment decision screen by clicking on "Return to Game" button on the feedback screen.

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(A) Negative Feedback

⚠️ **Landslide Occurred!**

You made **56** investment.

I

Your friend invested: 161

Fortunately, no one in your family died.

Thus, your daily income was not affected and stays at the same value.

Fortunately, no one in your family was injured.

Thus, your daily income was not affected and stays at the same value.

Sorry, your house was destroyed by the debris. Total damage occurred is **10000000**.

Thus, your property wealth is **10000000**.

Your total wealth is **10000631.4**.

II

[Return To Game](#)



41
42
43

(B) Positive Feedback

😊 **Landslide did not Occur!**

You made **180** investment.

Your friend invested: 172

Thus, your income stays at **262.8**.

Thus, your property wealth stays at **5000000**.

Your total wealth is **5000777**.

[Return To Game](#)

44

45 **Figure 6.** ILS tool's feedback screens. (A) Negative feedback when a landslide occurred. Box (I) contains the loss in
46 terms of magnitude and messages and Box (II) contains associated imagery. (B) Positive feedback when a landslide
47 did not occur.

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50 5 Methods

51 To test the effectiveness of strength and availability of feedback, we performed a laboratory
52 experiment involving human participants where we compared performance in the ILS tool in the
53 presence or absence of experiential feedback about different damage probabilities. Based upon
54 prior literature (Baumeister et al., 2007; Dutt and Gonzalez, 2012; Finucane et al., 2000; Knutty,
55 2005; Reis and Judd, 2013; Wagner, 2007), we expected the proportion of investments to be higher
56 in the presence of experiential feedback compared to those in the absence of experiential feedback.
57 Furthermore, we expected higher investments against landslides when feedback was more
58 damaging in ILS compared to when it was less damaging (Chaturvedi et al., 2017; Dutt and
59 Gonzalez, 2011; Gonzalez and Dutt, 2011a).

61 5.1 Experimental Design

62 Eighty-three participants were randomly assigned across four between-subjects conditions in the
63 ILS tool, where the conditions differed in the strength of experiential feedback (high-damage (N=
64 40) or low-damage (N= 43)) and availability of feedback (feedback-present (N= 43) or feedback-
65 absent (N= 40)) provided after every mitigation decision. An experiment involving the high-
66 damage feed-present condition (N = 20) and the low-damage feedback-present condition (N = 23)
67 in the ILS tool was reported by Chaturvedi et al. (2017). This data has been included in this paper
68 with two more conditions, the high-damage feedback-absent (N = 20) and the low-damage
69 feedback-absent (N = 20). Data in all four conditions was collected simultaneously. They were
70 asked to invest repeatedly against landslides across 30-days. In feedback-present conditions,
71 participants made investment decisions on the investment screen and then they received feedback
72 about the occurrence of landslides or not on the feedback screen. Participants were also provided
73 graphical displays showing the total probability of landslides, the total income not invested in
74 landslides, and the property wealth over days. Figures 5 and 6 show the investment and feedback
75 screen that were shown to participants in the feedback-present conditions. In feedback-absent
76 conditions, participants were given a text description and they made an investment decision,
77 however, neither they were shown the feedback screen nor they were shown the graphical displays

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84 on the investment screen. Thus, in the feedback-absent condition, although participants were
85 provided with the probability of damages due to landslides and the results of 0% and 100%
86 investments as a text description, however, they were not shown the feedback screen as well as the
87 graphical displays on the investment screen. The text description and investment screen shown to
88 participants in the feedback-absent conditions is given as Appendix 'A'. In high-damage
89 conditions, the probability of property damage, fatality and injury on any trial were set at 30%,
90 9%, and 90%, respectively, over 30-days. In low-damage conditions, the probability of property
91 damage, fatality and injury on any trial were set at 3%, 1%, and 10%, respectively, over 30-days
92 (i.e., about 1/10th of its values in the high-damage condition). Across all conditions, participants
93 made one investment decision per trial across 30-days (this end-point was unknown to
94 participants). Participants' goal was to maximize their total wealth over 30-days. Across all
95 conditions, only 1-landslide could occur on a particular day. The nature of functional forms used
96 for calculating different probabilities in ILS were unknown to participants.

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97 The proportion of damage (in terms of daily income and property wealth) that occurred in an event
98 of fatality, injury, or property damage was kept constant across 30-days. The property wealth
99 decreased to half of its value every time property damage occurred in an event of a landslide. The
100 daily income was reduced by 10% of its latest value due to a landslide-induced injury and 20% of
101 its latest value due to a landslide-induced fatality. The initial property wealth was fixed to 20
102 million EC, which is the expected property wealth in Mandi area. To avoid the effects of currency
103 units on people's decisions, we converted Indian National Rupees (INR) to a fictitious currency
104 called "Electronic Currency (EC)," where 1 EC = 1 INR. The initial per-trial income was kept at
105 292 EC (taking into account the GDP and per-capita income of Himachal state where Mandi is
106 located). Overall, there was a large difference between the initial income earned by a participant
107 and the participant's initial property wealth. In this scenario, the optimal strategy dictates
108 participants to invest their entire income in landslide protection measures, since participants' goal
109 was to maximize total wealth. The weight (W) parameter in the equation 1 of the ILS model was
110 fixed at 0.7 across all conditions. This high value of the W parameter ensured that participants'
111 investment decisions played a dominant role in influencing the total landslide probability as per
112 the equation 1. To understand the effect of the W parameter on the total probability of landslide in
113 ILS, a Monte-Carlo simulation was performed in the ILS model for different investment conditions
114 over time (see Figure 7A and 7B). It can be seen from both Figures 7A and 7B, in both the extreme

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126 investment conditions over 30-days (i.e., zero investments and full investments from human
 127 players), the value of W determined the range of possible values of the total probability of
 128 landslides, $P(T)$. For example, with a $W = 1.0$, zero human investments over a 30-day period
 129 caused $P(T) = 1.0$ (a sure landslide) and full investments caused $P(T) \sim 0.20$ (landslides to be 20%
 130 likely to occur). Thus, by keeping a higher W value, we could ensure that there was a large possible
 131 change in the $P(T)$ due to human actions, giving human participant salient feedback on how their
 132 decisions changed $P(T)$. The W value was set to be 0.70 in the ILS tool and it was shown to
 133 participants through the investment screen on the ILS tool's interface (see Figures 5). Furthermore,
 134 the return to mitigation free parameter (M) was set at 0.8. Again the value of the M parameter
 135 ensured that probability of landslides reduced to 20% ($= 1 - M$ from equation 2) when participants
 136 invested their daily income in full. Participants performed in the ILS for 30-days, starting in mid-
 137 July and ending in mid-August. This period coincided with the period of heavy monsoon rainfall
 138 in Mandi area (see the $P(R)$ peaks in Figure 3). Thus, participants performing in ILS experienced
 139 an increasing probability of landslides due to environmental factors (due to an increasing amount
 140 of rainfall over days), the investment ratio as a dependent variable for the purpose of data analyses.
 141 The investment ratio was defined as the ratio of investment made in a trial to total investment that
 142 could have been made up to the same trial. This investment ratio was averaged across all
 143 participants in one case and averaged over all participants and days in another case. We expected
 144 the average investment ratio to be higher in the feedback-present and high-damage conditions
 145 compared to feedback-absent and low-damage conditions. We took an alpha-level (the probability
 146 of rejecting the null hypothesis when it is true) to be 0.05 (or 5%).

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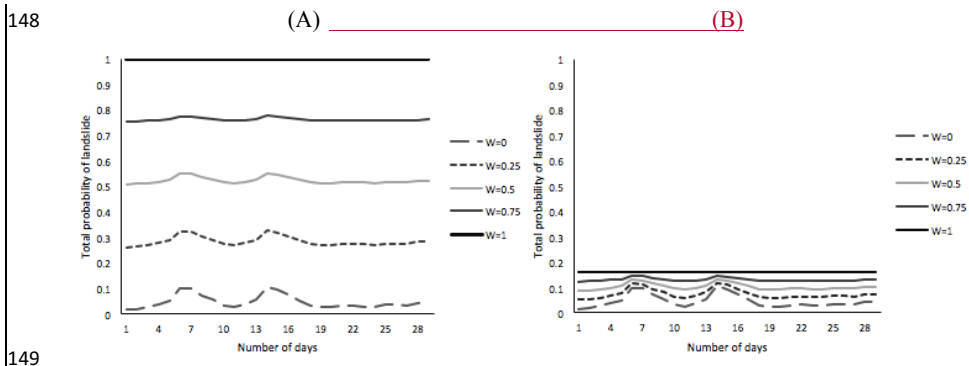
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162 **Figure 7. Simulation of total probability of landslides in ILS for different values of W in zero investment scenario**
163 **(A) and full investment scenario (B).**

164 5.2 Participants

165 Participants were recruited from Mandi town via an online advertisement. The research was
166 approved by the Ethics Committee at Indian Institute of Technology Mandi. Informed consent was
167 obtained from each participant and participation was completely voluntary. All participants were
168 from Science, Technology, Engineering, and Mathematics (STEM) backgrounds and their ages
169 ranged in between 21 and 28 years (Mean = 22 years; Standard Deviation = 2.19 years). The
170 following percentage of participants were pursuing or had completed different degrees: 6.0% high-
171 school degrees; 54.3% undergraduate degrees; 33.7% Master’s degrees; and, 6.0% Ph.D. degrees.
172 The Mandi area is prone to landslides and most participants self-reported to be knowledgeable or
173 possess basic understanding about landslides. The literacy rate in Mandi and surrounding area is
174 quite high (81.5%) (Census, 2011) and our sample was representative of the population residing
175 in this area. When asked about their previous knowledge about landslides, 2.4% claimed to be
176 highly knowledgeable, 16.8% claimed to be knowledgeable, 57.8% claimed to have basic
177 understanding, 18.2% claimed to have little understanding, and 4.8% claimed to have no idea. All
178 participants received a base payment of INR 50 (~ USD 1). In addition, there was a performance
179 incentive based upon a lucky draw. Top-10 performing participants based upon total wealth
180 remaining at the end of the study were put in a lucky draw and one of the participants was randomly
181 selected and awarded a cash prize of INR 500. Participants were told about this performance
182 incentive before they started their experiment.

184 5.3 Procedure

185 Experimental sessions were about 30-minutes long per participant. Participants were given
186 instructions on the computer screen and were encouraged to ask questions before starting their
187 study (See Appendix “A” for text of instructions used). Once participants had finished their study,
188 they were asked questions related to what information and decision strategy they used on the
189 investment screen and the feedback screen to make their decisions. Once participants ended their
190 study, they were thanked and paid for their participation.

192 6 Results

193 6.1 Investment Ratio Across Conditions

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198 The data were subjected to a 2×2 repeated-measures analyses of variance. As shown in Figure
199 8A, there was a significant main effect of feedback's availability: the average investment ratio was
200 higher in feedback-present conditions (0.53) compared to that in feedback-absent conditions (0.37)
201 ($F(1, 79) = 8.86, p < 0.01, \eta^2 = 0.10$). We performed analysis of variance statistical tests for
202 evaluating our expectations. The F-statistics is the ratio of between-group variance and the within-
203 group variance. The numbers in brackets after the F-statistics are the degrees of freedom (K-1, N
204 - K), where K are the total number of groups compared and N is the overall sample size. The p-
205 value indicates the evidence in favor of the null-hypothesis when it is true. We reject the null-
206 hypothesis when p-value is less than the alpha-level (0.05). The η^2 is the proportion of variance
207 associated with one or more main effects. It is a number between 0 and 1 and a value of 0.02, 0.13,
208 and 0.26 measures a small, medium, or large correlation between the dependent and independent
209 variables given a population size. The bracket values are indicative of the F-value, its significance
210 and effect size. This result is as per our expectation and shows that the presence of experiential
211 feedback in ILS tool helped participants increase their investments against landslides compared to
212 investments in the absence of this feedback.

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213 As shown in Figure 8B, there was a significant main-effect of strength of feedback: the
214 average investment ratio was significantly higher in high-damage conditions (0.51) compared to
215 that in low-damage conditions (0.38) ($F(1, 79) = 5.46, p < 0.05, \eta^2 = 0.07$). Again, this result is
216 as per our expectation and shows that high-damaging feedback helped participants increase their
217 investments against landslides compared low-damaging feedback.

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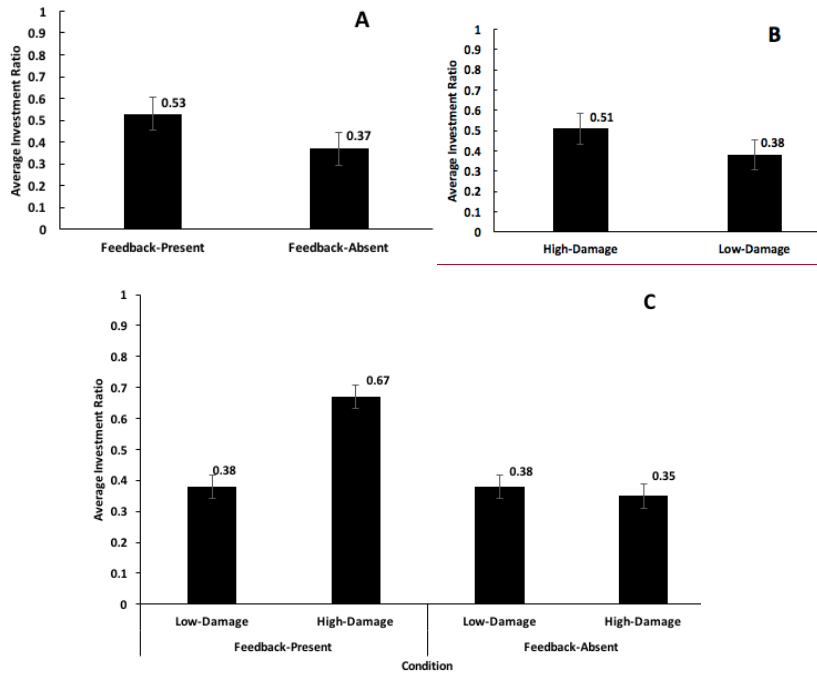
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218 Furthermore, as shown in Figure 8C, the interaction between the strength of feedback and
219 feedback's availability was significant ($F(1, 79) = 8.98, p < 0.01, \eta^2 = 0.10$). There was no
220 difference in the investment ratio between the high-damage condition (0.35) and low-damage
221 condition (0.38) when experiential feedback in ILS was absent, however, the investment ratio was
222 much higher in the high-damage condition (0.67) compared to the low-damage condition (0.38)
223 when experiential feedback in ILS was present (Chaturvedi et al., 2017). Thus, feedback needed
224 to be damaging in ILS to cause an increase in investments in mitigation measures against
225 landslides.

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Figure 8. (A) Average investment ratio in Feedback-present and Feedback-absent conditions. (B) Average investment ratio in low- and high-damage conditions. (C) Average investment ratio in low- and high-damage conditions with Feedback-present and absent. The error bars show 95% Confidence Interval (CI) around the point estimate.

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6.2 Investment Ratio Across Days

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The average investment ratio increased significantly over 30-days (see Figure 9A; $F(8.18, 646.1) = 8.35, p < 0.001, \eta^2 = 0.10$). As shown in Figure 9B, the average investment ratio increased rapidly over 30-days in feedback-present conditions, however, the increase was marginal in feedback-absent conditions ($F(8.18, 646.1) = 3.98, p < 0.001, \eta^2 = 0.05$). Furthermore, in feedback-present conditions, the average investment ratio increased rapidly over 30-days in high-damage conditions, however, the increase was again marginal in the low-damage conditions (see Figure 9C; $F(8.18, 646.1) = 6.56, p < 0.001, \eta^2 = 0.08$). Lastly, as seen in Figure 9D, although there were differences in the increase in average investment ratio between low-damage and high-damage conditions when experiential feedback was present, however, such differences were non-existent between the two

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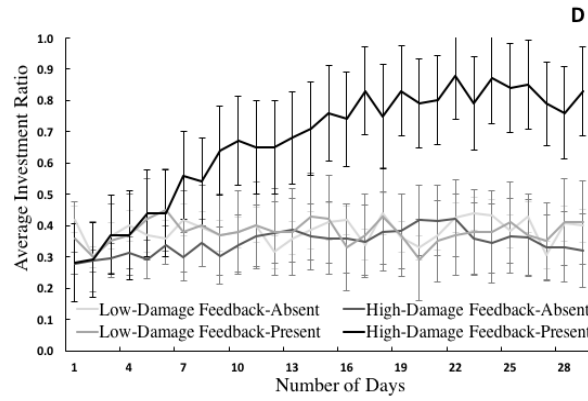
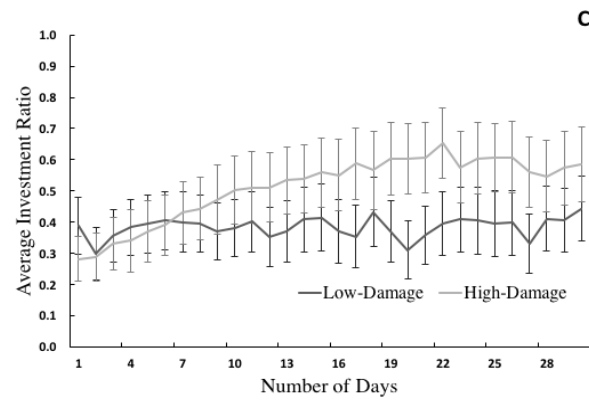
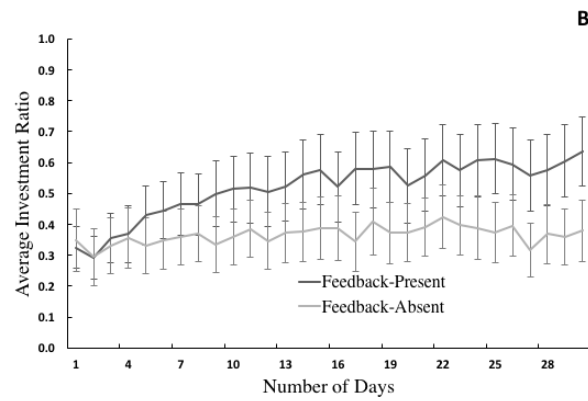
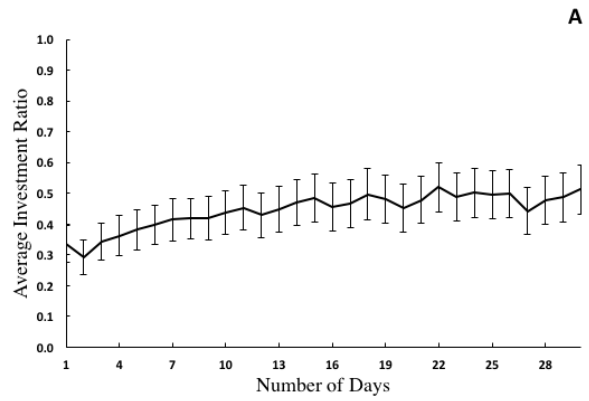
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261 damage conditions when experiential feedback was absent ($F(8.18, 646.1) = 4.16, p < 0.001, \eta^2 =$
262 0.05). Overall, ILS performance helped participants increase their investments for mitigating
263 landslides when damage feedback was high compared to low in ILS.
264



265 **Figure 9.** (A) Average investment ratio over days. (B) Average investment ratio over days in Feedback-present and Feedback-absent conditions. (C) Average
 266 investment ratio over days in low- and high-damage conditions. (D) Average investment ratio over days in low- and high- damage conditions with Feedback-
 267 present or absent. The error bars show 95% CI around the point estim.

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However, in feedback's absence in ILS, participants were unable to increase their investments for mitigating landslides, even when damages were high compared to low.

6.3 Participant Strategies

We analyzed whether an “invest-all” strategy (i.e., investing the entire daily income in mitigating landslides) was reported by participants across different conditions. As mentioned above, the invest-all strategy was an optimal strategy and this strategy's use indicated learning in the ILS tool. Figure 10 shows the proportion of participants reporting the use of the invest-all strategy. Thus, many participants learnt to follow the invest-all strategy in conditions where experiential feedback was present and it was highly damaging compared to participants in the other conditions.

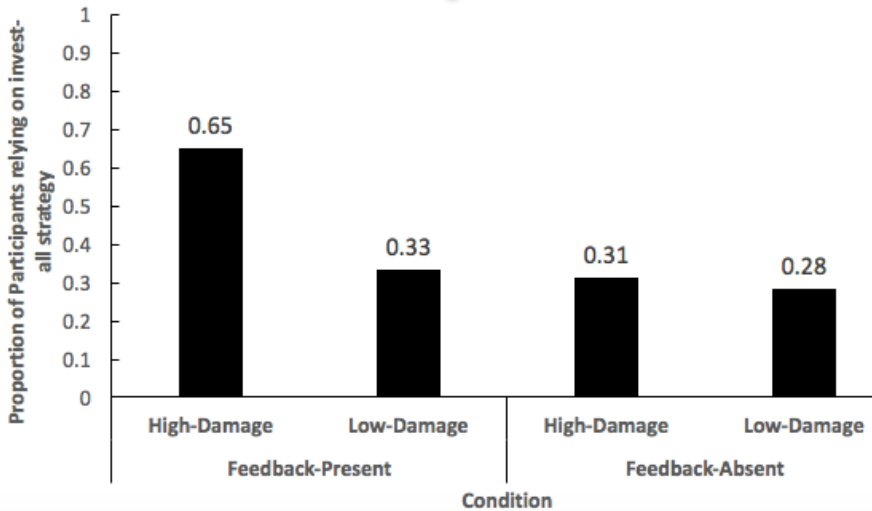


Figure 10. The proportion of reliance on the invest-all strategy across different conditions.

8 Discussion

In this paper, we used an existing ILS tool for evaluating the effectiveness of feedback in influencing people's decisions against landslide risks. We used the ILS tool in an experiment involving human participants and tested how the strength and availability of experiential feedback in ILS helped increase people's investment decisions against landslides. Our results

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agree with our expectations: Experience gained in ILS enabled improved understanding of processes governing landslides and helped participants improve their investments against landslides.

First, the high-damaging feedback helped increase people's investments against landslides over time compared to the low-damaging feedback. Furthermore, the feedback's presence helped participants increase their investments against landslides over time compared to feedback's absence. These results can be explained by the previous lab-based research on use of repeated feedback or experience (Chaturvedi et al., 2017; Dutt and Gonzalez, 2010, 2011; Finucane et al., 2000; Gonzalez and Dutt, 2011a). Repeated experiential feedback likely enables learning by repeated trial-and-error procedures, where bounded-rational individuals (Simon, 1959) try different investment values in ILS and observe their effects on the occurrence of landslides and their associated consequences. The negative consequences due to landslides are higher in conditions where the damages are more compared to conditions where the damages are less. This difference in landslide consequences influences participants' investments against landslides. According to Slovic et al. (2005), loss-averse individuals tend to increase their contribution against a risk over time. In our case, similar to Slovic et al. (2005), participants started contributing slowly against landslides and, with the experience of landslide losses over time, they started contributing larger amounts to reduce landslide risks.

We also found that the reliance on invest-all strategy was higher in the high-damage and feedback-present condition compared to the low-damage and feedback-absent condition. The invest-all strategy was the optimal strategy in the ILS tool. This result shows that participants learned the underlying system dynamics (i.e., how their actions influenced the probability of landslides) in ILS better in the feedback-rich condition compared to the feedback-poor condition. As participants were not provided with exact equations governing the ILS tool and they had to only learn from trial-and-error feedback, the saliency of the feedback due to messages and images likely helped participants' learning in the tool. In fact, we observed that the use of the optimal invest-all strategy was maximized when the experiential feedback was highly damaging. One likely reason for this observation could be the high educational levels of participants residing in the study area, where the literacy rate was more than 80%. Thus, it seems that participants' education levels helped them make the best use of damaging feedback.

We believe that the ILS tool can be integrated in teaching courses on landslide sustainable practices in schools from kindergarten to standard 12th. These courses could make use of the ILS tool and focus on educating students about causes, consequences, and risks of hazardous landslides. We believe that the use of ILS tool will make teaching more effective as ILS will

help incorporate experiential feedback and other factors in teaching in interactive ways. The ILS tool's parameter settings could be customized to a certain geographical area over a certain time period of play. In addition, the ILS tool could be used to show participants the investment actions of other participants (e.g., society or neighbours). The presence of investment decisions of opponents in addition to one's own decisions will likely enable social norms to influence people's investments and learning in the tool (Schultz et al., 2007). These features make ILS tool very attractive for landslide education in communities in the future.

Furthermore, the ILS tool holds a great promise for policy-research against landslides. For example, in future, researchers may vary different system-response parameters in ILS (e.g. weight of one's decisions and return to mitigation actions) and feedback (e.g. numbers, text messages and images for damage) in order to study their effects on people's decisions against landslides. Here, researchers could evaluate differences in ILS's ability to increase public contributions in the face of other system-response parameters and feedback. In addition, researchers can use the ILS tool to do "what-if" analyses related to landslides for certain time periods and for certain geographical locations. The ILS tool has the ability to be customized to certain geographical area as well as certain time periods, where spatial parameters (e.g., soil type and geology) as well as temporal parameters (e.g., daily rainfall) can be defined for the study area. Once the environmental factors have been accounted for, the ILS tool enables researchers to account for assumptions on human factors (contribution against landslides) with real-world consequences (injury, fatality, and infrastructure damage). Such assumptions may help researchers model human decisions in computational cognitive models, which are based upon influential theories of how people make decisions from feedback (Dutt and Gonzalez, 2012; Gonzalez and Dutt, 2011b). In summary, these features make ILS tool apt for policy research, especially for areas that are prone to landslides. This research will also help test the ILS tool and its applicability in different real-world settings.

9. Limitations

Although the ILS tool causes the use of optimal invest-all strategies among people in conditions where experiential feedback is highly damaging, more research is needed on investigating the nature of learning that the tool imparts among people. As people's investments for mitigating landslides in ILS directly influences the risk of landslides due to human and environmental factors, investments indeed have the potential of educating people about landslide risks. Still, it is important to investigate how investing money in the ILS tool truly educates people about landslides. We would like to investigate this research question as part of our future research.

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Currently, in the ILS model, we have assumed that damages from fatality and injury to influence participants' daily-income levels. The reduced income levels do create adverse consequences, but one could also argue that they would be much less of concern for most people compared to the injury and fatality itself. Furthermore, people could also choose to migrate from an area when the landslide mitigation costs are too high, and adaptation becomes impossible, especially due to the differences between the landslide hazard and other hazards such as flood, drought, and general climate risks. As part of our future research, we plan to investigate the influence of feedback that causes only injuries or fatalities in ILS compared to the feedback that causes economic losses due to injuries and fatalities. Also, as part of our future research in the ILS tool, we plan to investigate people's migration decisions when the landslide mitigation costs are too high and adaptation to landslides is not possible.

In this paper, our primary objective was not to accurately predict rainfall or other landslide parameters; rather, to educate people about landslide disasters. Thus, we have used approximate models of real landslide phenomena in the ILS simulation tool. This use of approximate models is in line with a large body of literature on using simulation tools for improving people's understanding about natural processes like climate change and other natural disasters (Dutt and Gonzalez, 2010, 2011; Finucane et al., 2000). As part of our abstraction, we may have missed certain aspects related to the sensitivity of the different social classes to their economic and cultural resources. In future, we would like to compare the proportion of investments in different experimental conditions to people's likely socio-economic cost thresholds given that people may need to spend their wealth in other areas beyond landslide mitigation.

Furthermore, we used a linear model to compute the probability of landslides due to human factors in the ILS tool. Also, the probabilistic equations governing the physical factors in the ILS model were not disclosed to participants, who seemed to possess high education levels. One could argue that there are several other linear and non-linear models that could help compute the probability of landslides due to human factors. Some of these models could not only influence the probability of landslides, but also the severity of consequences (damages) caused by landslides. Also, other generic models could account for the physical factors in the ILS tool. We plan to try these possibilities as part of our future work in the ILS tool. Specifically, we plan to assume different models of investments in the ILS tool and we plan to test them against participants with different education levels.

In the current experiment, we assumed a large disparity between a participant's property wealth and her daily income. In addition, as part of the ILS model, we did not consider support

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from governments or insurance companies against damages from landslides. In India, people mostly use their own finances to overcome the challenges put by natural disasters as insurance or other public methods have only shown limited success (ICICI, 2018). However, in certain cases, especially in developing countries, mitigation of landslide risks may often be financed by government or international agencies. As part of our future work, we plan to extend the ILS model to include assumptions of contributions from government and international agencies. Such assumptions will help us determine the willingness of common people to contribute against landslide disasters, which is important as the developing world becomes more developed over time.

To test our hypotheses, we presented participants with a high damage scenario and a low damage scenario, where the probabilities of property damage, injury, and fatality were high and low, respectively. However, such scenarios may not be realistic, where people may want to migrate from both low and damage areas in even the least developed countries. In future research with ILS, we plan to calibrate the probability of damages, injury, and fatality to realistic values and test the effectiveness of ILS in improving the participants' investment decision making.

Furthermore, in our experiment, when landslide did not occur and experiential feedback was present, people were presented with a smiling face followed by a message. The message and emoticon were provided to connect the cause-and-effect relationships for participants in the ILS tool. However, it could also be that the landslide did not occur on a certain trial due to the stochasticity in the simulation rather than participants' investment actions. Although such situations are possible over shorter time-periods, over longer time-periods increased investments from people will only reduce the probability of landslides.

In this paper, the experiment used a daily investment setting in the ILS tool. However, the ILS tool can easily be customized to different time periods ranging from seconds, minutes, hours, days, months, and years. As part of our future research, we plan to extend the daily assumption by considering people making decisions on longer time-scales ranging from months to years. In addition, in the experiment, we assumed a value of 0.7 and 0.8 for the weight (W) and return to mitigation (M) parameters. These W and M values indicated that landslide risks could largely be mitigated by human actions. However, this assumption may not be the case always, especially for mitigation measures like tree plantations. For example, afforestation alone may not help in reducing deep-seated landslides in hilly areas (Forbes, 2013). Thus, it would be worthwhile investigating as part of future research on how people's decision-making evolves in conditions where investments likely influence the landslide probability (higher values of W and M parameters) compared to conditions where investments unlikely influence the landslide

probability (lower values of W and M parameters). Some of these ideas form the immediate next steps in our ongoing research program on landslide risk communication.

10. Conclusions

It can be concluded from this preliminary research study that simulation tools like ILS that provide feedback about the outcomes of landslides influenced certain people's investment decisions against landslides in the study area. Given our results, we believe that ILS could potentially be used as a landslide-education tool for increasing public understanding about landslides. The ILS tool can also be used by policymakers to do what-if analyses in different scenarios concerning landslides.

Data availability. Data used in this article have not been deposited to respect the privacy of users. The data can be provided to readers upon request.

Author contributions. AA designed the website, administered the account, PC wrote the first draft of website articles and collected data. VD supervised the website contents. AA provided technical support for website maintenance. PC and VD analysed the data and prepared the manuscript. PC and VD revised the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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Appendix A

Instructions of the Experiment

Welcome!

You are a resident of Mandi district of Himachal Pradesh, India, a township in the lap of Himalayas. You live in an area that is highly prone to landslides due to a number of environmental factors (e.g., the prevailing geological conditions and rainfall). During the monsoon season, due to high intensity and prolonged period of rainfall, a number of landslides may occur in the Mandi district. These landslides may cause fatalities and injuries to you, your family, and to your friends, who reside in the same area. In addition, landslides may also damage your property and cause loss to your property wealth.

This study consists of a task, where you will be making repetitive decisions to invest money in order to mitigate landslides. Every trial, you'll earn certain money between 0 and 10 points. This money is available to you to invest against landslides. You may invest certain amount from the money available to you; however, if you do not wish to invest anything, you may invest 0.0 against landslides on a particular trial. Based upon your investment against landslides, you'll get feedback on whether a landslide occurred and whether there was an associated loss of life, injury, or property damage (all three events are independent and they can occur at the same time).

Your total wealth at any point in the game is the following: sum of the amounts you did not invest against landslides across days + your property wealth - damages to you, your family, your friends, and to your property due to landslides. Your property wealth is assumed to be 100 points at the start of the game. The amount of money **not invested against landslides** increases your total wealth. **Your goal is to maximize your total wealth in the game.**

Whenever a landslide occurs, if it causes fatality, then your daily earnings will be reduced by 5% of its present value at that time and if landslide causes injury to someone, then the daily earnings will be reduced by 2.5% of its present value at that time. Thus, the amount available to you to invest against landslides will reduce with each fatality and injury due to landslides. Furthermore, if a landslide occurs and it causes property damage, then your property wealth will be reduced by 80% of its present value at that time; however, the money available to you to invest against landslides due to your daily earnings will remain unaffected.

Generally, landslides are triggered by two main factors: environmental factors (e.g., rainfall; outside one's control) and investment factors (money invested against landslides; within one's own control). The total probability of landslide is a weighted average of probability of landslide due to environment factors and probability of landslide due to investment factors. The money

you invest against landslides reduces the probability of landslide due to investment factors and also reduces the total probability of landslides. However, the money invested against landslides is lost and it cannot become a part of your total wealth.

At the end of the game, we'll convert your total wealth into INR and pay you for your effort. For this conversion, a ratio of 100 total wealth points = INR 1 will be followed. In addition, you will be paid INR 30 as base payment for your effort in the task. Please remember that your goal is to maximize your total wealth in the game.

Starting Game Parameters

Your wealth: **20 Million**

When a landslide occurs:

If a death occurs, your daily income will be reduced by **50%** of its current value.

If an injury takes place, your daily income will be reduced by **25%** of its current value.

If a property damage occurs, your wealth will be reduced by **50%** of your property wealth.

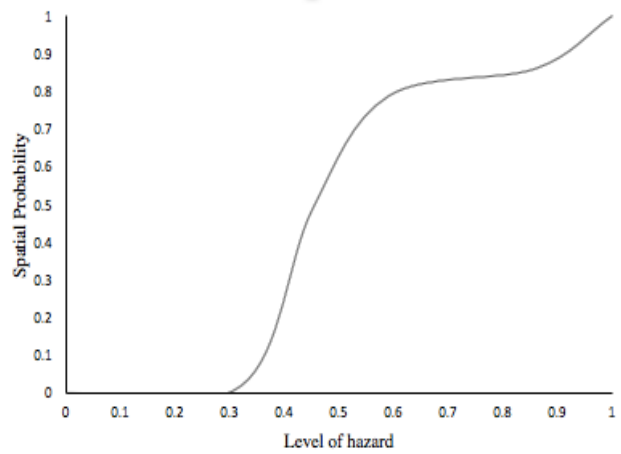
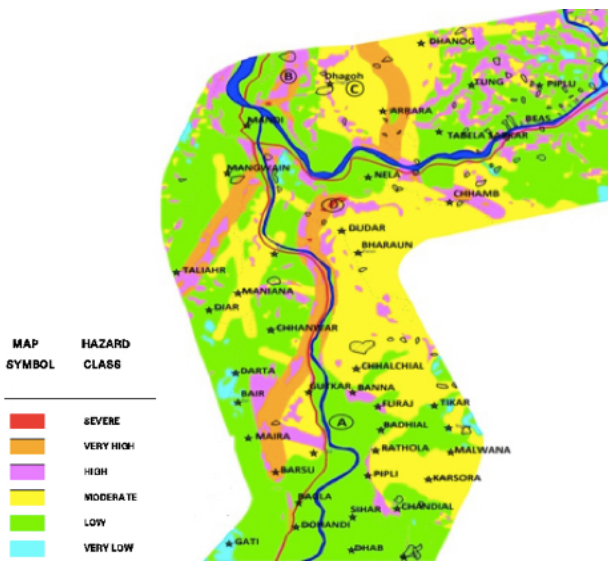
Best of Luck!

Table 1. Total Estimated Hazard (THED) scale for evaluating the susceptibility of an area to l

Hazard Zone	Range of corrected THED	Description of zone
I	$THED < 3.5$	Very low hazard (VLH) zone
II	$3.5 \leq THED < 5.0$	Low hazard (LH) zone
III	$5.0 \leq THED \leq 6.5$	Moderate hazard (MH) zone
IV	$6.5 < THED \leq 8.0$	High Hazard (HH) zone
V	$THED > 8.0$	Very high hazard (VHH) zone

(A)

(B)



A

Your Investment for landslides for day 4 (between 0.0 and 292):

For no investment, please enter 0.0

B

Game Parameters	
Parameter	Value
Day	4
Income available for investment today (M)	292
Total income not invested in landslides (NTM)	754.7
Property wealth (PW)	20000000
Total damage due to landslides (TD)	0
Total wealth (NTM + PW - TD)	20000754.7
Probability of landslide due to human (investment) factor (P(I))	0.88
Probability of landslide due to environmental factors (P(E))	0.43
Probability weight (W)	0.7
Total probability of landslide ($W \cdot P(I) + (1 - W) \cdot P(E)$)	0.69



9

10 **Figure 5.** ILS tool's Investment Screen. Box (A): The text box where participants made investments against landslides. Box (B): The tool's different parameters
 11 and their values. Box (C): Line graphs showing the total probability of landslide, the total income not invested in landslides, and the property wealth over days.
 12 Horizontal axes in these graphs represents number of days. The goal was to maximize Total Wealth across a number of days of performance in the ILS tool. This
 13 figure is adapted from Chaturvedi et al. (2017).

14

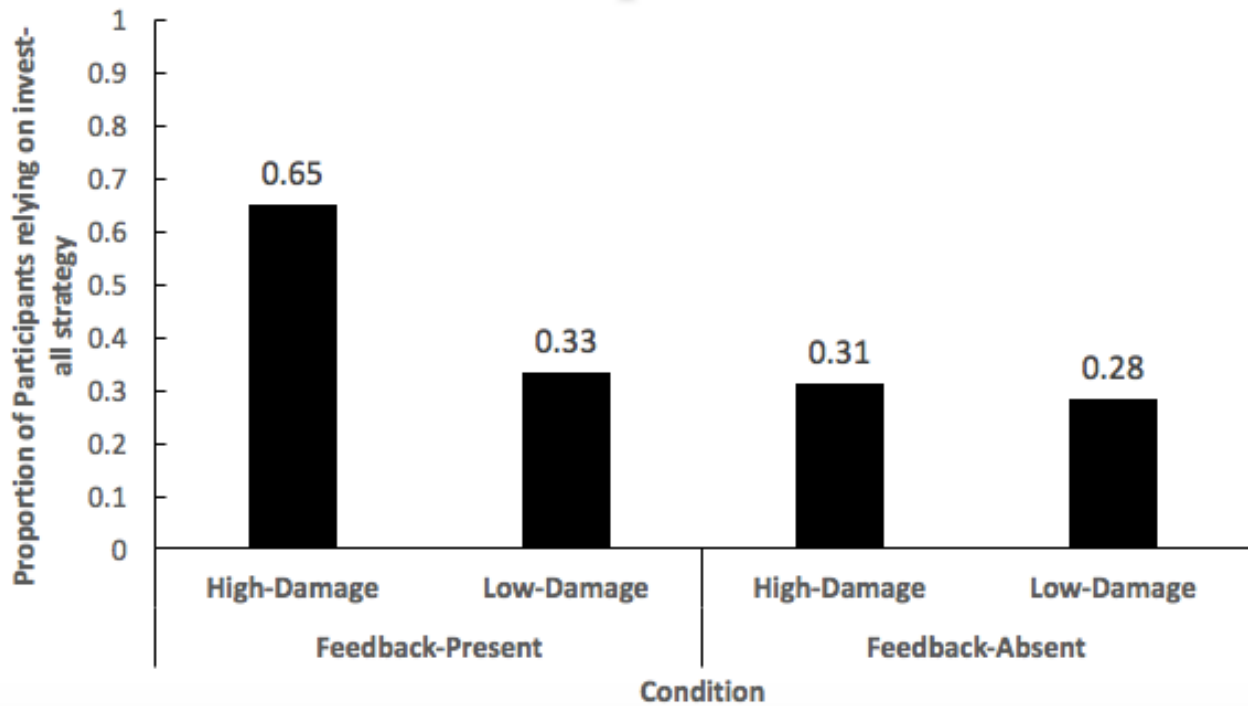


Figure 98. The proportion of reliance on the invest-all strategy across different conditions.

7 Assumptions and limitations

Although the ILS tool causes the use of optimal invest-all strategies among people in conditions where experiential feedback is highly damaging, however, more research is needed on investigating the nature of learning that the tool imparts among people. As people's investments for mitigating landslides in ILS directly influences the risk of landslides due to human and environmental factors, investments indeed have the potential of educating people about landslide risks. Still, it is important to investigate how investing money in the ILS tool truly educates people about landslides.

Currently, in the ILS model, we have assumed that damages from fatality and injury influence participants' daily-income levels. The reduced income levels do create adverse consequences, but one could also argue that they would be much less of concern for most people compared to the injury and fatality itself. Furthermore, people could also choose to migrate from an area when the landslide mitigation cost is too high and adaptation becomes impossible, especially due to the differences between the landslide hazard and other hazards such as flood, drought, and general climate risks. As part of our future research, we plan to investigate the influence of feedback that causes only injuries or fatalities compared to the

feedback that causes economic losses due to injuries and fatalities. Also, as part of our future research in the ILS tool, we plan to investigate people's migration decisions when the landslide mitigation costs are too high and adaptation to landslides is not possible.

In current economical model of ILS, many aspects relating to the sensitivity of the different social classes in relation to their economic and cultural resources are neglected. However, in India, people mostly use their own finances to overcome the challenges put by natural disasters as insurance or other public methods have only seen limited success (Icicilombard.com, 2018). Furthermore, in future we would like to compare the proportion of investments in different experimental conditions to their likely socio-economic cost threshold given that people may need to spend their wealth in other areas.

In the ILS model, we used a linear model to compute the probability of landslides due to human factors. Also, the probabilistic equations governing the physical factors in the ILS model were not disclosed to participants, who seemed to possess high education levels. One could argue that there are several other linear and non-linear models that could help compute the probability of landslides due to human factors. Some of these models could not only influence the probability of landslides, but also the severity of consequences (damages) caused by landslides. Also, other generic models could account for the physical factors in the ILS tool. We plan to try these possibilities as part of our future work in the ILS tool. Specifically, we plan to assume different models of investments in the ILS tool and we plan to test them against participants with different education levels.

We plotted the distribution of rainfall averaged over a 30-year period and this distribution was similar to the one that was computed over the past 5-year period. There was a peak during the monsoon months (mid-June to mid-September) in the average rainfall distribution. In addition, in this paper, we are using the 5-year rainfall data in a simulation (ILS) that is meant to improve their socio-economic understanding of landslide disasters. As our primary objective is not to accurately predict rainfall or other landslide parameters; rather, to educate people about landslide disasters, we have used an approximate model of the real landslide phenomena in the ILS simulation tool. There is a large body of literature on using simulation tools for improving people's understanding about natural processes like climate change and other natural disasters. Again, these simulation tools only use an approximate models of the real phenomena. The development and use of the ILS tool follows the same line of research and tradition.

In the current experiment, we assumed a large disparity between a participant's property wealth and her daily income. In addition, as part of the ILS model, we did not consider any support from government or international agencies against damages from landslides. In certain cases,

especially in developing countries, mitigation of landslide risks may often be financed by government or international agencies. As part of our future work, we plan to extend the ILS model to include assumptions of contributions from government or international agencies. Such assumptions will help us determine the willingness of common people to contribute against landslide disasters, which is important as the developing world becomes developed over time.

To test our hypotheses, we presented participants with a high damage scenario and a low damage scenario, where the probabilities of property damage, injury, and fatality were high and low, respectively. However, such scenarios may not be realistic, where people may want to migrate from both low and damage areas in even the least developed countries. In future research with ILS, we plan to calibrate the probability of damages, injury, and fatality to realistic values and test the effectiveness of ILS in improving the participants' investment decision making.

Furthermore, in our experiment, when landslide did not occur and experiential feedback was present, people were presented with a smiling face followed by a message. The message and emoticon were provided to connect the cause-and-effect relationships for participants in the ILS tool. However, it could also be that the landslide did not occur on a certain trial due to the stochasticity in the simulation rather than participants' investment actions. Although such situations are possible over shorter time-periods, however, over longer time-periods increased investments from people will only reduce the probability of landslides.

In this paper, the experiment used a daily investment setting in the ILS tool. However, the ILS tool can easily be customized to different time periods ranging from seconds, minutes, hours, days, months, and years. As part of our future research, we plan to extend the daily assumption by considering people making decisions on longer time-scales ranging from months to years. In addition, in the experiment, we assumed a value of 0.7 and 0.8 for the weight (W) and return to mitigation (M) parameters. These W and M values indicated that landslide risks could largely be mitigated by human actions. However, this assumption may not be the case always, especially for mitigation measures like tree plantations. For example, afforestation alone may not help in reducing deep-seated landslides in hilly areas (Forbes, 2013). Thus, it would be worthwhile investigating as part of future research on how people's decision-making evolves in conditions where investments likely influence the landslide probability (higher values of W and M parameters) compared to conditions where investments unlikely influence the landslide probability (lower values of W and M parameters). Some of these ideas form the immediate next steps in our ongoing research program on landslide risk communication.

more is needed. The ILS tool's parameter settings could be customized to a certain geographical area over a certain time period of play. In addition, the ILS tool could be used to present investment actions of other decision-makers (e.g., society or neighbours) compared to one's own investment actions. The presence of investment of other decision-makers in addition to one's own decisions will likely enable the use of social norms towards learning (Schultz et al., 2007). These features make the ILS tool very attractive for landslide education in communities in the future.

Furthermore, the ILS tool holds a great promise for policy-research against landslides. For example, in the future, researchers may

vary different system-response parameters in ILS (e.g. weight of one's decisions and return to mitigation actions) and feedback (e.g. numbers, text messages and images for damage) in order to study their effects on people's decisions against landslides. Here, researchers could evaluate differences in ILS's ability to increase public contributions in the face of other system-response parameters and feedback. In addition, researchers can use the ILS tool to do "what-if" analyses related to landslides for certain time periods and for certain geographical locations. The ILS tool has the ability to be customized to certain geographical area as well as certain time periods, where spatial parameters (e.g., soil type and geology) as well as temporal parameters (e.g., daily rainfall) can be defined for the area of interest. Once the environmental factors have been accounted for, the ILS tool enables researchers to account for assumptions on human factors (contribution against landslides) with real-world consequences (injury, fatality, and infrastructure damage). Such assumptions may help researchers model human decisions in computational cognitive models, which are based upon influential theories of how people make decisions from feedback (Dutt & Gonzalez, 2012; Gonzalez & Dutt, 2011). In summary, these features make the ILS tool apt for policy research, especially for areas that are prone to landslides. This research will also help test the ILS tool and its applicability in different real-world settings.

Although we could investigate that the ILS tool causes the use of optimal invest-all strategies among people in conditions where experiential feedback is highly damaging; however, future research should focus on investigating more deeply about the nature of learning that the tool imparts among people. As people's investments for mitigating landslides in ILS directly influence the risk of landslides due to human and environmental factors, investments indeed have the potential of educating people about landslide risks. Still, it is

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