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ORIGINAL PAPER

An application of dynamic programming to local adaptation decision-making

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Abstract

Adaptation decision-making in mountain regions necessitates dealing with uncertainties which are driven by the complex topography and the potential interconnections of stochastic events. Such events can lead to amplifying consequences for the exposed communities located at different elevations. In this study, we present a stylized application of stochastic dynamic programming for local adaptation decision-making for a small alpine community exposed to debris flows and floods. We assume that local decision-makers and planners aim at maximizing specific objectives by choosing from a feasible set of adaptation measures and under given constraints on these actions. Our results show that stochastic dynamic programming is a promising tool to address the underlying problem faced by local planners when evaluating the feasibility and effectiveness of adaptation measures. Furthermore, stochastic dynamic programming has some advantages compared to deterministic approaches which assume full knowledge of the system of interest in a world dominated by randomness. We provide an estimation of a best option and an appropriate metric to benchmark adaptation effectiveness for long time horizons. We show how multiple constraints, risk preferences, time horizons and decision periods all influence the decision-making and the overall success of adaptation responses over time.

Keywords Climate risks · Climate change adaptation · Decision making · Dynamic programming · Debris flows · Floods

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1 Introduction

In a world, already committed to 1.5–2 °C of warming under the most conservative RCP scenarios, adaptation has proven essential to reduce climate risks' severity (Magnan and Ribera 2016; Tompkins et al. 2018). Adaptation has been broadly categorized as autonomous or reactive if it takes place in the aftermath of climatic-related extreme events and shocks and proactive if it entails planning ahead for anticipated shocks (Termeer et al. 2017). Proactive or planned adaptation requires the setting of long-term objectives within short-term decision periods (Marchau et al. 2019). However, decisions taken in view of climate change are typically riddled with the results of limited knowledge about the terms of the speed and magnitude of the change and its consequences, and the potential costs and benefits of different adaptation options(Halsnæs and Kaspersen 2018; Pol and Hinkel 2019). The widespread recognition that climate change impacts are felt more acutely at the local level has made evident an urgent need to develop new approaches and model designs to support local governments and their decision-making processes with regard to adaptation (Bierbaum et al. 2013; Nordgren et al. 2016). The challenge for local planners and managers, however, is precisely the limited resources, the short-term goals of constituencies, and the prevalence of objectives other than climate risk reduction (Aguiar et al. 2018). Hence, decision-makers are confronted with the dilemma of how to best allocate scarce resources to mitigate future risks that are of shifting intensity and frequency, with mostly no or little historical precedence within appropriate decision time frames (Lenton et al. 2019). Furthermore, a recent body of literature has pointed at the complex nature of climate risks where more climatic drivers or hazards co-occur and cascade across exposed elements and vulnerabilities to generate extreme impacts (Pescaroli and Alexander 2015; Pescaroli 2018; Pescaroli and Alexander 2018; Zscheischler et al. 2018; Vogel et al. 2019). Thus, achieving the optimal cost saving outcome under such a backdrop of increasing complexity requires an explicit consideration and understanding of uncertainties or else planning in spite of uncertainties (Mechler 2016; Gomez-Cunya et al. 2020).

There exist a number of decision support tools in environmental management to deal with different degrees of uncertainty (Hallegatte 2009; Watkiss et al. 2015; Simpson et al. 2016). Cost–benefit analysis (CBA) is a relatively common decision tool to inform adaptation that is employed for deterministic analysis, where variables such as costs and benefits of projects/programs are known and can be compared to justify interventions that are based on an efficient allocation of resources (Watkiss et al. 2015; Dittrich et al. 2016). At the other end of the spectrum, tools exist that support decision-making under deep uncertainties (DMDU), where many plausible futures are possible and a broad range of solutions or outcomes exist (Marchau et al. 2019; Shepherd et al. 2018). In these cases, DMDU tools such as robust decision-making (RDM) (Groves and Lempert 2007; Lempert 2019), dynamic adaptive policy pathways (DAPP) (Haasnoot et al. 2013; Lawrence et al. 2019) and real option analysis (Guthrie 2019) can be extremely useful.

Uncertainties might not be of a deep nature but instead arise from a lack of information (Hallegatte 2009). In these cases, uncertainties can be dealt with by using iterative risk management (IRM) approaches, which allow the integration of learning processes into decision-making cycles (Marchau et al. 2019; Watkiss et al. 2015). Likewise, stochasticity or randomness can be appropriate representations to deal with uncertainties in systems whose inputs parameters can be described probabilistically (Cai 2019). Recent advances in computational economics have developed and applied methods of numerical dynamic programming that integrate stochastic or random uncertainties into the decision-making process at relatively low computational costs (Cai et al. 2017, 2016; Lontzek et al. 2015). Dynamic programming has been successfully employed in environmental decision-making for solving stochastic problems and it is a well-established approach in environmental management (Fletcher et al. 2019) and in particular in the context of water resource management (Herman et al. 2020). Dynamic programming has been used to address stochasticity in water (Robert et al. 2018; Archibald and Marshall 2018) and flood (Sims and Null 2019) management, as well as to include environmental quality in the decision maker's utility function (Cai et al. 2015). Beside the direct integration of uncertainties into the decision-making process, dynamic programming has several other advantages over alternative methods, one of them being the ability to handle a long-time horizon (e.g., several decades on with monthly intervals) (Robert et al. 2018). A second advantage is that stochastic dynamic programming can use approximation methods to account for continuous decision and state variables (Reimer et al. 2019). In addition, stochastic dynamic programming is a flexible framework able to capture the optimal trade-offs and synergies in adaptation decision-making by modeling the risk preferences of a decision agent under uncertainties (Lontzek and Narita 2011).

In this paper we present an application of dynamic programming for adaptation decision-making under stochastic uncertainties in the case of temporally compound events, e.g. the succession of hazards (debris flows and floods) leading to amplified impacts downstream (Zscheischler et al. 2020). The geographic area under investigation is that of the Grimsel Valley located in the Central Swiss Alps, which has been affected by impacts originated from consecutive debris and flood hazards of a stochastic nature (Bafu 2017).

The aim of the paper is to show how stochastic dynamic programming can address the nature of the challenges of local adaptation decision-making in an upstream–downstream context of interconnected hazards and to provide a related supportive framework for short-term decision-making under long-term planning horizons. The paper is organized as follows. The paper is organized as follows. In the next section we describe the site of our case study. The methods section provides a detailed explanation of the modeling approach. Findings are presented in the results section and discussed in the final section—Discussions and Conclusions.

2 Study area

Guttannen is located in the Grimsel region (Bernese Alps), in the Aare River valley, at around 1000 m asl. (Fig. 1). It is characterized by an inner-alpine climate with relatively large variations in temperature and precipitation throughout the year, exacerbated by the high local relief. A clear positive trend in annual temperature from the long term mean 1961–1990 has been observed since the 1980s for this region (e.g. the northern part of Switzerland above 1000 m.s.l) (CH2018, 2018) (see Fig. 2, top panel). In terms for changes in annual precipitation, trends are less pronounced in this region which is also true for the majority of Swiss regions (CH2018, 2018). Extreme high precipitation (rain) related indices highlighted for Guttannen are show in Fig. 2 (bottom panel). Heavy precipitation events occur throughout the year. Events have been recorded in summer and fall, but also in winter. For instance, one of the strongest heavy rainfall events was in August 2005 when 170 mm were recorded in 48 h (Scheuner et al. 2009).

The future evolution of heavy precipitation events which have the potential to produce great damage to people and infrastructure shows an intensification for all regions of

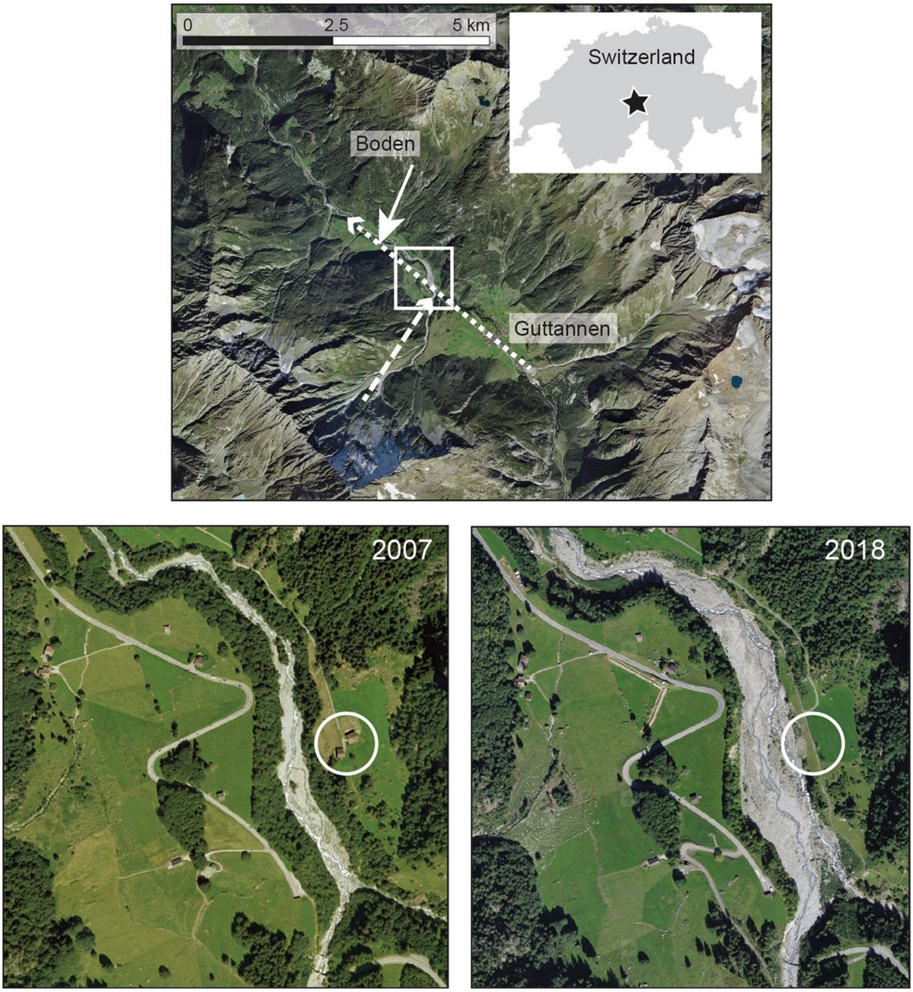

Fig. 1 The study area of Guttannen in the Grimsel valley. Top panel: the short, dashed arrow represents the debris flow trajectory, the long-dotted arrow the floods in the Aare river. The community center of Guttannen and the residential area of Boden are indicated. The white rectangle indicates the location of the two close-up images in the bottom panel. Image source: Swiss Federal Office of Topography swisstopo. Bottom panels: Close-up of parts of the flood area. Debris flows enter the Aare river channel from bottom left of the image and have deposited massive sediment in the riverbed over the past years, which can be easily recognized in a comparison of the two images (2007 representing conditions before the debris flow activity started). The white circle indicates the location of a building which was dismantled due to risk of flooding and people were relocated. Image sources: left: Flotron Perrin Jacquet, 2007; right: Swiss Federal Office of Topography swisstopo, 11/09/2018

Switzerland with absolute value largely depending on emissions scenarios. The intra model spread is also substantial which reflects both internal variability and model uncertainties (CH2018 2018).

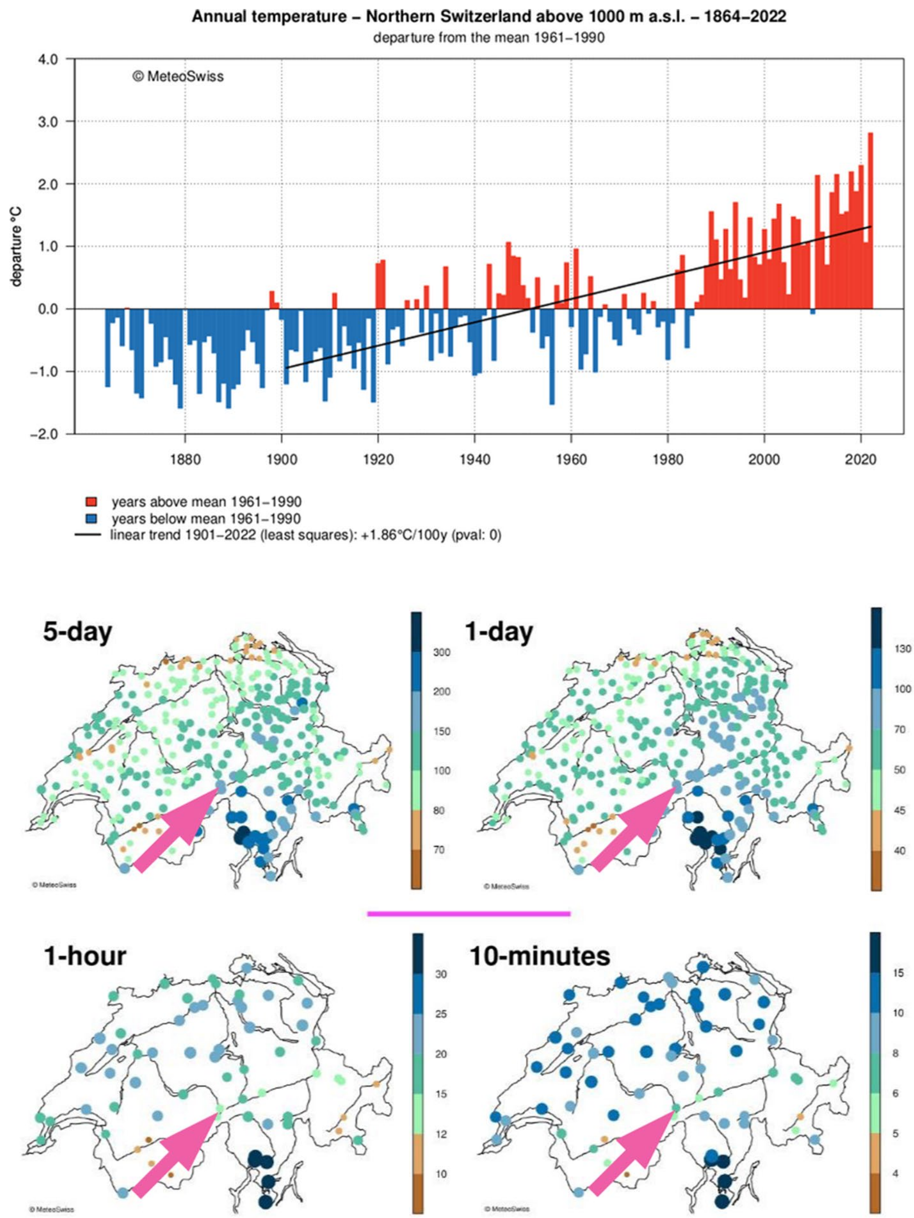

Fig. 2 (Top) Annual temperature anomalies from 1961–1990 for Northern Switzerland Alpine regions to which Guttannen and the Grimsel area belong. (Bottom) Mean annual maxima in mm of 5-day and 1-day precipitation (on the top row) and 1-h and 10-min (on the bottom row). Both figures are generated using data and tools available directly on the MeteoSwiss website and are from MeteoSwiss (CH2018 2018). The magenta arrow indicates the approximate location of measurement stations at Guttannen and Grimsel Ospice

As any other Alpine valley, the Guttannen—Grimsel area is prone to various mass movements, including rock fall, debris flows, snow avalanches, and rainfall triggered floods. In order to design appropriate response options to such complex and interconnected hazards, local authorities are faced with scenarios ranging from a reduction to an intensification of the processes (Paranunzio et al. 2019) During the 2005 heavy precipitation event a large-scale debris flow occurred about 1 km upstream of the community of Guttannen. The debris flow dammed the Aare River and as a consequence, Guttannen was flooded (Huggel et al. 2012; Frank et al. 2015).

For this study, we concentrate mainly on the more recent events in the Spreitlaui catchment, and their interaction with the Aare river system. The Spreitlaui catchment extends from the Aare river at about 950 m asl to the summit of Ritzlihorn at 3263. According to existing permafrost maps the top ~ 500 m of the north/northeast exposed face of Ritzlihorn has permafrost conditions. The north-northeast rock face of the Ritzlihorn consists of strongly shattered and weathered gneiss. Many couloirs carry water, possibly derived from thawing permafrost. Blocky debris and avalanched snow accumulate at the apex of the large Holocene debris fan on which the community of Guttannen is located. The accumulated snow may persist through the summer. The debris fan is drained by the Spreitlaui torrent, which enters Aare River at 950 m asl.

The 2009 and 2011 debris flow events typically entrained large amounts of fan sediments which obstructed the flow of the river. In the aftermath of the events, emergency response actions costing tens of millions of euros had to be deployed due to threats to and destruction of highly sensitive transnational energy and road transport lines, and to newly exposed residential areas. Although such impacts are local, they involve direct and indirect costs and, importantly, make necessary a concrete evaluation of the option of relocating residential areas and critical infrastructures (Huss et al. 2017). Another important debris flow event occurred in September 2015 on the first day of significant rainfall that followed a prolonged dry and hot period (INTERPRAEVENT 2016).

3 Methods

3.1 Defining the problem

Decision-making in the context of climate change requires setting up the decision context and the framing of the decision problem (Moallemi et al. 2020). Our framework is that of a decision problem wherein a local decision-maker or planner aims at maximizing a specific objective by choosing from a feasible set of actions (e.g., adaptation measures) under given constraints on these actions (e.g., socioeconomic constraints). Stochastic dynamic programming has proven suitable in the presence of uncertainty such as those originating in natural systems because it allows to determine an optimal sequence of actions over time that best fulfill the objectives of the decision makers (Marescot et al. 2013). However, in order to operationalize this framework, one that also takes into account the randomness of future outcomes (e.g. debris flows, rock avalanches or wildfires), a stochastic dynamic representation of the problem requires defining a number of problem components or parameters (Robert et al. 2018; Archibald and Marshall 2018; Cai 2019). In our framework, these components are:

(1) The objective which specifies for any decision-making process under conditions of optimality, what need to be optimised and it is expressed through an objective function. For example an objective can be the increase of certain welfare measures such as improvement of security network or ensuring no losses at the minimum possible costs.
(2) Planning horizon and length of a decision period: the planning horizon is the time interval of the optimization problem. The planning horizon can be specified, for example, as the lifetime of a long-lived investment (e.g., dams, roads, etc.). The length of a decision period defines the frequency with which the decision maker can react to events or developments that were not know at the time the decision was taken. A length could be for example a legislation period.
(3) Set of actions (decisions): these represents the potential set of (adaptation) actions that the decision-makers has at his or her disposal. These could be characterized by a combination of both hard-infrastructural measures and soft measures such as early warning systems or fire regulations.
(4) Constraints on decisions and states: constraints can be financial, technological, or social. For example, the decision-maker might dispose of only a limited budget for implementing certain measures. Furthermore, certain measures might need to achieve a certain return in a given time interval.
(5) Uncertainties: This requires identifying the uncertainties that are relevant to the problem at hand. In adaptation, uncertainties can range from the future evolution of climate impacts to the stability of rules and regulations within which the decision-maker can act and the outcomes of certain measures.
(6) Preferences of the decision maker: This category characterizes different types of preferences that a decision entity should consider. These may include preferences regarding the evaluation of welfare at different points in time or preferences regarding risk aversion and the premium the decision-maker would want to incur for resolving uncertainties.

In the following, we evaluate different local adaptation options in the face of uncertain evolution of the magnitude and frequency of debris flow and floods affecting the valley of Grimsel in the Central Swiss Alps. The decision problem is non spatially explicit. The definition of the adaptation options and parameters is, however, explicit to the case of the Grimsel valley.

To design the case study, we consulted experts at the Swiss Federal Office for the Environment (FOEV) and local cantonal authorities from the Directorate of Public Works and Transport of the Canton of Bern (Oberingenieurkreis I, Tiefbauamt des Kantons Bern).[1] Furthermore, a number of reports were also taken into account for the case study design (GEO7 2006; Geotest 2013).

We assume that a decision-making authority (in the following, the decision-maker) faces a certain time interval—for example 50 years—during which the objective is to maximize the present discounted expected assets value of houses at the terminal period. The decision-maker has to identify a set of optimal actions (adaptation measures) under climate impacts given that such impacts might reduce the house asset value. Those impacts are stochastic, which implies that at any time during the decision period the decision-maker has imperfect information about the occurrence of adverse impacts in the next period. This uncertainty eventually leads to a choice of adaptation measures that ex post might turn out to be not optimal. Those measures are, however, optimal ex ante, reflecting a potential risk

[1] https://bvd.be.ch/de/start.html.

premium that the decision-maker is willing to pay. This approach differs fundamentally from a deterministic approach to decision-making where the decision-maker will make a (different) optimal decision for any (different) future outcome—thus bearing no risk premium (Pol and Hinkel 2019; Watkiss et al. 2015).

We investigate the optimality of three adaptation measures: (i) building a flood-protection dam, (ii) relocating the inhabitants of vulnerable residences, and (iii) changing the road infrastructure. The three adaptation measures are all insuring options where a considerable sum of money needs to be invested ex ante to protect against a risk that might or might not materialize. In addition, we investigate a fourth option, i.e. under which conditions a preventive measure of investing little money over time becomes a viable option; in this case we consider excavating the riverbed as a preventive adaptation option. The decision to focus on both insuring and preventive measures is made with the intention of capturing the risk preferences of the decision-maker.

3.2 The decision framework

Here, we concentrate on few binary adaptation options, such as whether to build a flood-protection dam or not, to relocate inhabitant or not as well as the continuous adaptation measure of excavating some portion of the riverbed. In addition, we also consider the cost of an additional road. Adverse impacts are the flooding of residential areas. Our formulation has two stochastic *state* components. One component is the amount of debris flow in each period which follows a stochastic process that could depend on climate change. The other component is the flood which occurs stochastically in each period but whose frequency and intensity is affected by climate change. We calculate the future changes in flood frequency and intensity from the ENSEMBLES project regional climate models (RCM) at a horizontal resolution of 25 km for the northwest section which extends from the central Swiss Alps northwards to the southernmost limits. In order to cover the entire uncertainty envelope of the fourteen ENSEMBLE realisations we calculate future changes under (1) the best estimate model given by the median of the model ensemble); (2) the low impact model represented by the lower uncertainty limit of the model envelope; and (3) the high impact model represented by the upper uncertainty limit (Rajczak et al. 2013). Hereafter we refer to the three realisations simply as climate models. The consistency in precipitation projections for the Alpine region between the ENSEMBLE regional climate models and the more recent EURO-CORDEX further justifies our selection (Ritzhaupt and Maraun 2023). It is worth mentioning that the ENSEMBLE models used here are derived under A1B emission scenario which would correspond to the RCP8.5 scenarios in EURO-CORDEX (Ritzhaupt and Maraun 2023). Detailed calculation of inundation height and flood frequency are given in Annex 1.

For the debris flow events, we derive the annual probabilities of occurrence extrapolated from the records of the past 50 years (the detailed calculation can be found in the Supplementary Information – Sect. 3). Furthermore, we keep track of two additional *state* variables—namely, the contemporaneous height of the riverbed and the maximum historically height of the riverbed, which provides information on the value of already destroyed houses. The decision-making authority has several controls to execute, namely extent of riverbed excavation, the building of a dam, the relocation of the inhabitants of the region, and changing the road infrastructure. A schematic representation of the decision problem is shown in Fig. 3. Given the structure of the maximization problem, in particular the binary

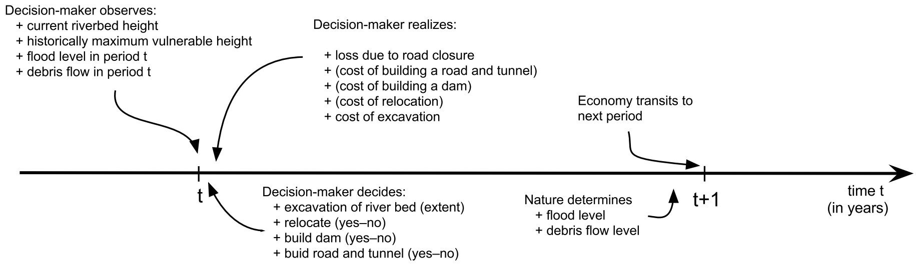

Fig. 3 Schematic representation which illustrates a single period in the dynamic decision framework. Note that at the beginning of each period, the decision maker observes a unique state of the world, i.e. time period t, riverbed height B, historically maximum vulnerable height of house asset H and the realizations of the two shocks related to floods, F and debris flow M. Given that unique state of the world, the decision maker takes into account the possible future stochastic occurrence of floods and debris flow and chooses the optimal level of excavation and if the options of dam building or relocation and the building of an alternative road should be executed

exit options of building a dam, relocate and building an alternative road, the model can be decomposed into smaller separate problems.

3.3 State variables, controls and functional relations

We first define the state variables. We assume that in each time period a flood can either occur or not occur. The binary variable F_t denotes the flood level in meters at time t and we assume that either $F_t = 0$ (i.e., no flood occurring at time t) or $F_t = F^h > 0$, which denotes the flood level in meters. The model is spatially non-explicit, however, in order to include spatially appropriate information in the model calculations we applied the following approach: we analyzed the cumulative number of buildings that are potentially affected along the ca. 1 km long river section (Fig. 2). We then distributed the buildings across a hypothetical river cross section, representing their horizontal and vertical distance from the riverbed in accordance with the topography of their real location. For this purpose, we used a trapezoidal cross section of the river which implies that an increasing consecutive number of buildings will be flooded as the flood height increases. The evolution of the flood level F_t is then given in Eq. (1).

$$F_{t+1} = \begin{cases} f(S_{t+1}), & \text{with}\, \phi_{t+1}\left(S_{t+1}\right) \\ 0, & \text{with}\, 1 - \phi_{t+1}\left(S_{t+1}\right), \end{cases} \tag{1}$$

$\phi_t(S_t)$ is the iid probability of a flood , and S_t is an exogenous regional climate model at time t. We did not find enough evidence to justify that the flood occurrence is dependent on previous periods. Therefore, the probability of flood in each year is constant and equal to 3% with calculation details provided in the Annex 1 of the Supplementary material. Thus, there are two degrees into which the flood is categorized, e.g. either flood or no flood.

In the case of debris flow, we categorize debris flow M_t in meters into three degrees with $M_t = M^h > 0$, $M_t = M^l > 0$, and $M_t = 0$. We assume that the width of the riverbed does not vary with its height. The general evolution of the debris flow level is given by Eq. (2).

$$M_{t+1} = \begin{cases} M^h, & \text{with } \mu_t^h(S_t) \\ M^l, & with\, \mu_t^l(S_t) \\ 0, & \text{with } 1 - \mu_t^h\left(S_t\right) - \mu_t^l(S_t) \end{cases} \tag{2}$$

where $\mu_t^l\left(S_t\right)$ and $\mu_t^h(S_t)$ are the probabilities of a small and large debris flow respectively. As for the case of floods, we did not find enough evidence to justify that the debris flow occurrence is dependent on previous periods. The probability of debris flows in each year is therefore given by 94% no debris flow, 4% small debris flow and 2% of large debris flow. Calculation details are provided in the Annex 1 and Annex 3 of the Supplementary material.

Given flood and debris flow levels F_t and M_t, we assume that the riverbed height B_t evolves with

$$B_{t+1} = \min\left(\overline{H}, \max\left(0, B_t - x_t + M_t + F_t\right)\right); \tag{3}$$

$\overline{H}$ denotes the maximum height of housing asset vulnerability. Furthermore, we keep track of the historically maximum vulnerable height of housing assets, denoted by H_t, evolving as.

$$H_{t+1} = \min\left(\overline{H}, \max\left(H_t, B_t - x_t + M_t + F_t\right)\right), \tag{4}$$

where x_t is the controlled amount (in meters) of riverbed excavation at time t with excavation cost $C_t^x\left(x_t\right)$. In addition to the control action of riverbed excavation, the decision maker has two exit options: relocation O_t^R and building a dam O_t^D, with fixed costs indicated by $C_t^R\left(O_t^R\right)$ and $C_t^D\left(O_t^D\right)$, respectively. Furthermore, one direct impact of debris flow is on the availability of the road passing through the region. The road closure and associated costs can be prevented by building an alternative road not exposed to debris flows. The decision to build an alternative road is denoted by O_t^A. We assign to each of the three binary variables a level of 0 if not active and of 1 if active. Given the structure of the maximization problem, in particular, the binary exit options of building a dam, relocating residents, and building an alternative road, the model can be decomposed into three separate problems: (1) The decision to build an alternative road depends exclusively on the expectations of future debris flows. We can, therefore, compute the optimal level of building an alternative road O_t^A as:

$$O_t^A = \begin{cases} 1(\text{buildroad}), & C_t^A(O_t^A) \leq E\left\{\sum_t^{T-1} \beta^t C_t^M\left(M_t\right)\right\} \\ 0(donotbuildroad), & C_t^A(O_t^A) > E\left\{\sum_t^{T-1} \beta^t C_t^M\left(M_t\right)\right\} \end{cases} \tag{5}$$

where $\mathbb{E}$ represents the expectation operator and β^t is the discount factor (see Lontzek et al. 2015); (2) the decisions regarding relocating residents and (3) building the dam both have a similar structure in the sense that once the decision has been taken to make use of either option, the housing asset value is no longer at risk and excavation will no longer have any value. Thus, the decision maker will always prefer the least costly alternative. The value of building the dam at time t can be calculated as:

$$V_t^D(H_t) = -C_t^D(O_t^D) + \sum_t^T \beta^{tt} U(H_t). \tag{6}$$

Similarly, the value of relocating at time t can be calculated as

$$V_t^R(H_t) = -C_t^R(O_t^R) + \sum_t^T \beta^t U(H_t). \tag{7}$$

where $t\epsilon\{1, 2, \ldots ., T\}$. Equation (6) and (7) represent the value functions $V_t^D(H_t)$ and $V_t^R(H_t)$ and are equal to the discounted value of the remaining house assets $\sum_t^T \beta^t U(H_t)$ minus the cost of the option, where $U(H_t)$ represents the utility function.

The value function of neither building the dam nor relocating residents still involves the optimal excavation decision and therefore constitutes a dynamic optimization problem and can now be expressed in a dynamic programming fashion using the Bellman equation (Bellman 1957). The Bellman equation is used in dynamic programming and decision theory to describe the relationship between the value of a decision-making problem at a given point in time and the value of the same problem at a future point in time. It expresses the optimal expected value of the total reward received by an agent over a sequence of decisions, given the current state of the system and the future rewards that the agent expects to receive based on its actions. The equation is used to solve problems where the optimal decision depends on the future rewards that are uncertain. The Bellman equation, which if satisfied describes the solution to the optimization problem, is given by:

$$V_t(H_t, B_t, F_t, M_t) = \max_{x_t} U(H_t) - L(H_{t,} B_{t,} F_{t,} M_{t,}) - C_t(x_t) + \beta \mathbb{E}\{V_{t+1}(H^+, B^+, F^+, M^+)\} \tag{8}$$

Subject to the assumption that:

$$H_{t+1} = \min\left(\overline{H}, \max(H_t, B_t - x_t + M_t + F_t)\right)$$

$$B_{t+1} = \min\left(\overline{H}, \max(0, B_t - x_t + M_t + F_t)\right)$$

$$F_{t+1} = f(\phi_{t+1}, S_{t+1})$$

$$M_{t+1} = m(\mu_t, S_{t+1}) \tag{9}$$

where $V_{t+1}(H^+, B^+, F^+, M^+)$ is the next stage value function. The optimal action associated with each initial state value function taken as backward recursion from the terminal period T to the present time t = 1 is:

$$V_1(H_1, B_1, F_1, M_1) = \max_{x_t} \mathbb{E}\left\{ \sum_{t=1}^{T-1} -\beta^{t-1} C_t(x_t) + \beta^T V_T(H_T) \right\} \tag{10}$$

The main idea behind the solution method to Eqs. (8)–(10) is that we recursively compute the optimal amount of excavation at each period as a function of the state space containing the riverbed size, the historically maximum vulnerable height of house assets, the flood level and the debris flow level at that period. Thus, the penultimate decision period the decision-maker observes the state of the world (riverbed size, historically maximum vulnerable housing asset level, debris flow level, and flood level) and decides to build a dam, to relocate residents or to do neither. In addition, the decision-maker decides how much of the riverbed to excavate. We use approximation methods to obtain the value function (maximand) for any combination of *Ht,* and *Bt* at the last decision period and compare it to the value of the exit option (dam, relocation). Once the problem has been solved in the second-last period, the value function (the maximand) is computed as a function of the state space. Then the decision-making problem moves one period backwards in time to the third-last-decision period. Here again there are 6 different realization of next period's state (two floods and three debris flow) of the world and for each of these the value function has just been computed. Given the state of the world in the third-last period and the expectation of the next period's value function the decision maker makes the optimal choices. The problem then moves stage-by-stage until the initial time period. The variables in Eq. (8) at time t are presented again here for the sake of clarity:

- x_t: Riverbed excavation
- C_t: Cost of riverbed excavation
- B_t: Riverbed height
- V_t: Value function (of remaining houses) at time t
- S_t: Exogenous regional climate scenario at time t
- ω_t^F: Random process for the occurrence of floods
- ω_t^M: Random process for the occurrence of debris flows
- β^t : the annual discount factor
- $L(H_t, B_t, F_t, M_t)$: the disutility function or loss function

We assume that the cost function is exponential and has excavation cost multipler δ_1 and excavation cost exponent δ_2.

$$C_t(x_t) = \delta_1 x_t^{\delta_2}, \tag{11}$$

We impose quadratic costs of excavation, which we motivate by the non-homogenous (and increasing) width of the riverbed. We assume there is no dynamics in the last period and therefore we define a terminal value function $V_T(H_T)$ which represents the value of the vulnerable houses asset at the last period as:

$$V_T(H_T) = \gamma_1 - \gamma_2 H_t + H_t^2 \tag{12}$$

To simulate our decision problem, we have used the mathematical programming language AMPL and the KNITRO solver for that problem. Our study is not employing inferential statistics—we merely use past observations and data to calibrate the parameters of our model. See the next section for details on the calibration and Supplementary Information section on.

Details of the model calibration can be found in the Supplementary material. The calibration of the model parameters is performed using real data from historic floods and debris flows events. Costs have been provided by local and federal authorities in particular from the head office for construction, traffic and power of the Canton of Bern[1]. An overview of the parameters at time t (t = one year) introduced in the previous sections with their respective values and description is given in Table 1.

Table 1 Parameters and values used in the Eqs. (8)–(10)

Parameter	Value	Description
γ_1	16.20429	Constant of the terminal value function
γ_2	0.369209	Linear multiplier of the terminal value function
γ_3	0.125122	Quadratic multiplier of the terminal value function
δ_1	0.5	Excavation cost multiplier
δ_2	2	Excavation cost exponent
β	0.99	Annual discount factor
T	49	Number of time periods
$H_{\min}$	0	Lower bound on historically maximum height of riverbed at $t=0$ (in meters)
$H_{\max}$	10	Upper bound on historically maximum height of riverbed (in meters)
$B_{\min}$	0	Minimum possible height of the riverbed
$B_{\max}$	10	Maximum possible height of the riverbed
$F_{f,t}$	$\{0, 1.08 + \mu t\}$	The time dependent flood level matrix where μ corresponds to either of the adjustment factors (-0.02, 0.02, 0.01) in yearly flood intensity given in Table 2SM
$M_{m,t}$	$\{0, 2.2, 5.4\}$	Debris flow level matrix with calculation in Annex 3SM

The derivation of these parameters is described in the Supplementary Information. The exogenous climate models are given by the ENSEMBLE regional climate models covering the whole uncertainty envelope which includes the (1) the best estimate model given by the median of the model ensemble); (2) the low impact model represented by the lower uncertainty limit of the model envelope; and (3) the high impact model represented by the upper uncertainty limit. For the purpose of our analysis, we assume linearity between precipitation change and inundation height

4 Results

The result of the stochastic optimization model is a set of optimal control rules for any possible location in the specified state space. Thus, we obtain for each time period, ranging from the present to the terminal decision period, and any state (that is: current size of the riverbed and its historically maximum level) the optimal decision rule regarding how much to excavate or whether to relocate or build the dam.

We initilaise the model by determining the initial time location in the state space (today's location). Today's maximum effective and actual riverbed height are set to zero and at today's decision period there is neither debris flows nor floods. As a response to this initialization our model solution produces an optimal decision in terms of how much to excavate or the execution of the alternative option. In a next step we use the optimal solution to the model to generate a simulation—that is to say, a realization of the model for the specified time interval. That simulation will produce randomly occurring (thus stochastic) debris-flow events and floods which will prompt the decision-maker to react to their occurrences and in expectation of their occurrence in the following periods. We conduct 100.000 of those simulations and present their statistical outcomes and some single paths. Based on randomly generated debris flows over the next 50 years, Fig. 4 (left) shows that following a large debris flow event in period 1, the maximum effective and actual riverbed height increases by 5.4 m. Due to riverbed excavation, the impact of the next high-intensity debris flow event, in 2034, on housing assets is dampened. The two flow events of moderate intensity, simulated for 2045 and 2051, respectively, have limited impact on housing assets, also due to the extent of riverbed excavated, which is roughly 2.5 m per decade over

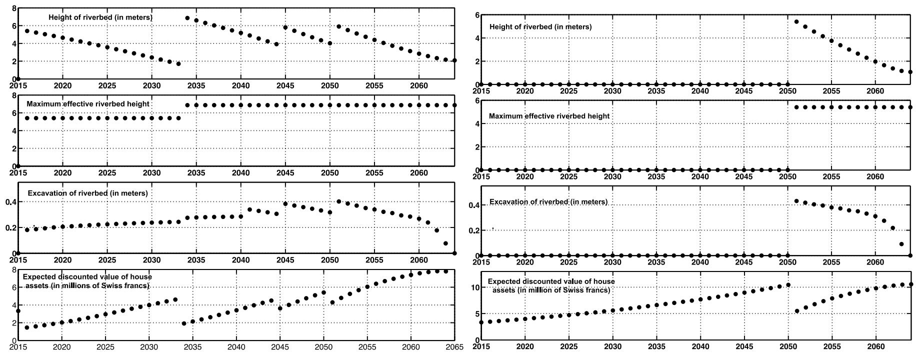

Fig. 4 The dynamics of selected model variables in one simulation of the model. Left panels show the evolution of core model variables for a sample path with two big debris flow events (2016 and 2034) and two small events (2045 and 2051). Right panels show the evolution of core model variables for one sample path with one high-intensity debris flow event in 2051

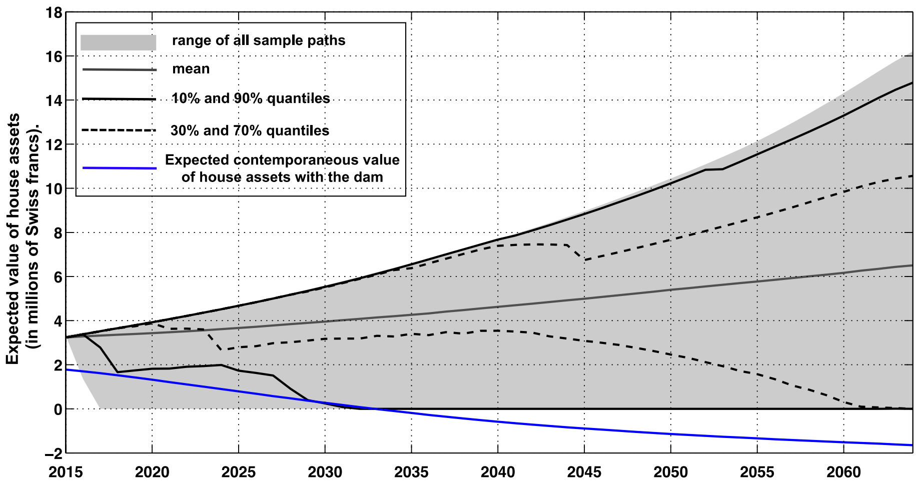

Fig. 5 Statistics for the expected value of housing assets from 100,000 simulated paths. The figure displays the expected value of housing assets from running 100,000 paths. The gray-shaded area shows the possible range of expected values from all simulations. The gray line represents the sample mean; the continuous lower and upper black lines represent, respectively, the 10% and 90% quantiles; the lower dotted and upper dotted lines represent the 30% and 70% quantiles; the blue line represents the expected present value of the housing assets with the dam

the complete time period. Today's expected (discounted) value of housing assets is around CHF 3.5 million Swiss Francs. Figure 4 (right) shows that the present discounted expected value of the house assets is increasing over the course of time as no debris flow events occur until year 2050. A high intensity debris flow event in 2050 destroys 5.4 m in height of the house assets, leading to a drop in the expected house asset level. Riverbed excavation is induced. At the terminal period (2065) riverbed excavation ceases and the contemporaneous house asset value is slightly above 10 million Swiss francs.

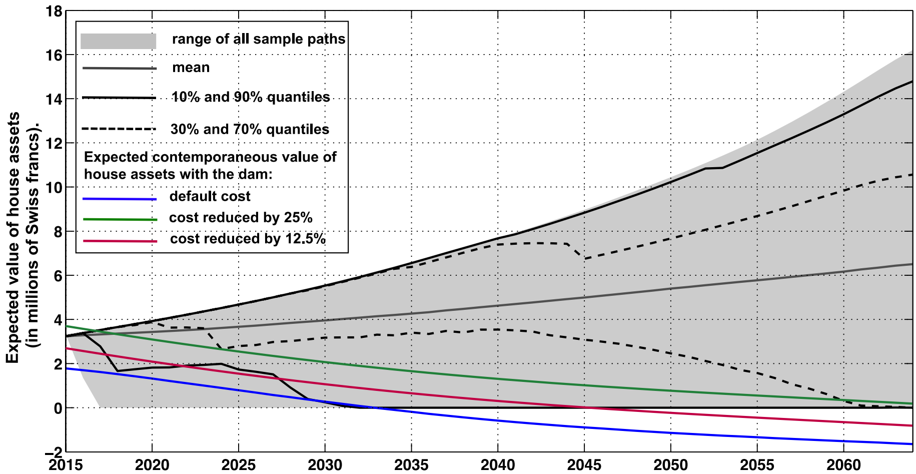

Fig. 6 Statistics for the expected value of housing assets from 100,000 simulated paths and sensitivity regarding the cost of the dam. This figure adds a sensitivity to the reported statistics of Fig. 4. In addition, we display the expected value of the house assets with regards to lower costs of building and maintaining the dam (solid red and green lines)

In Fig. 5, we notice how the range of all possible sample paths covers the entire state variable space, ranging from CHF 0 (i.e., all houses are destroyed) to > CHF 16 million (no house is destroyed). The expected housing asset value (the 50% quantile) increases moderately over time and the expected value of housing assets at the terminal time (year 2065) is around CHF 6.5 million (around 40% of the maximum possible value). A striking result emerges from our simulation of the debris flow probabilities and impacts. In about 30% of cases, debris flows, and floods will destroy all housing assets.

Next, we investigated whether building a dam at a high fixed cost is a preferred choice. The solid blue line in Fig. 5 indicates that at the initial time building the dam is not preferred and that over the time horizon, there is only a small likelihood (indicated by scenarios yielding values below the blue line) that building a dam will turn out to be optimal. Since the relocation of the inhabitants is as costly as building the dam, the same reasoning applies. A sensitivity analysis regarding the cost of the dam (Fig. 6) shows that if the costs of building and maintaining the dam are reduced e.g. by 25%, the exit option (building the dam) is more profitable at the initial period (green line is above the solid black line in period 1).

Further exploring the role of riverbed excavation, we show that this option leads to an optimal reduction in the maximum effective riverbed height (the reference over the modelled time period) of more than 1 m and in the instantaneous height of the riverbed of almost 4 m in the terminal period (Fig. 7). We furthermore observe that excavating the riverbed sets up a 20–35% buffer between the riverbed height and the maximum effective riverbed height. Excavation leads to a significant increase in the expected value of housing assets (Fig. 7C), even after the costs of excavation are accounted for, and is optimal for about 2.2 m per decade (Fig. 7D). Allowing for excavation increases today's expected value of future housing assets by CHF 1.5 million. Even without the option of excavation, building a dam (and incurring costs of CHF 8 million) is not optimal. Regarding the option of building an alternative road to the existing one, model results indicate that today's expected costs of road closure amounts to around CHF 320 k,

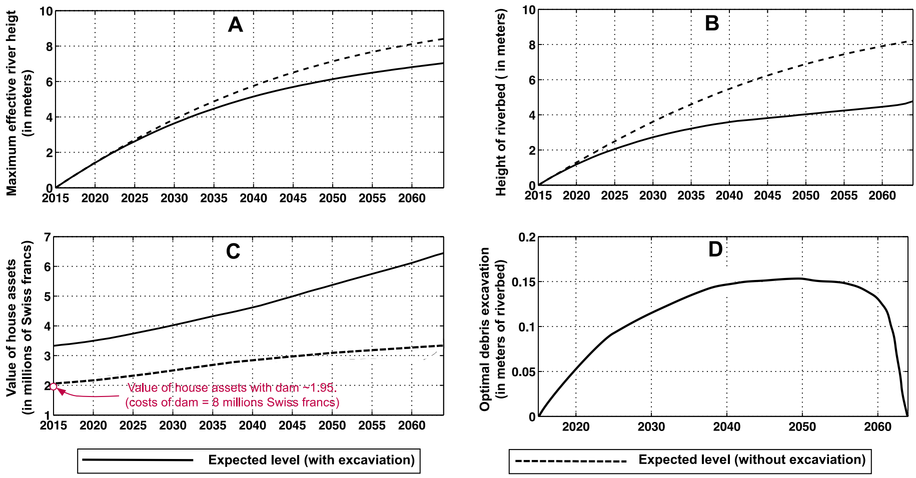

Fig. 7 The effect of riverbed excavation. The figure presents the impact of considering riverbed excavation as a control variable in the decision-making process. The continuous lines in panels A, B, and C represents the expected levels with riverbed excavation while the dotted lines represent the expected levels without river excavation

Table 2 Optimal deterministic solution with different time horizons

Time horizon	25 years	50 years	75 years
Expected annual debris flow (in meters)	0.26	0.26	0.26
Expected flood level (in meters) in period t	0.03 (1.08 + 0.005 t)		
Expected annual height of riverbed (in meters)	0.26	0.26	0.26
Maximum effective riverbed height (in meters) in period t	0.26 + 0.03 (1.08 + 0.005 t)		
Expected annual excavation of riverbed (in meters)	0.26	0.26	0.26
Expected dicounted value of house assets (in millions of Swiss francs) in period t	11.71	8.39	5.81

Here, the decision maker in the initial period expects each period a debris flow of 0.26 m (5.4 m with 4% probability and 2.2 m with 2% probability)

which is considerably less than any estimates of the costs of building an alternative road or a tunnel.

We also contrast our approach to optimal decision-making under randomness with one in which the core of the optimization framework is deterministic. While the underlying problem has stochastic (that is to say, ex-ante unknown) components, one frequently used approach is to compute the expected value of future risks. Here, it is important to point out that this approach transforms the underlying stochastic problem into a deterministic decision problem: while the modeler deals with the uncertainty in that practical manner, the decision maker in the problem is facing complete certainty regarding future outcomes. For our model, we could compute the expected debris flow level and flood size in each period. Table 2 displays the results. Irrespective of the time horizon it is always optimal to extract 0.26 m such that additional debris flow events do no lead to additional damages. The maximum effective riverbed height increases only slightly due to the flood events. For the time-horizon of 50 years, the expected value of house assets in period 1 is much higher than in a stochastic framework. The reason is that the decision-maker considers the expected damages and is not dealing with the stochastic nature of the problem, thus ignoring any risk premia.

5 Discussions and conclusions

The application of stochastic dynamic programming presented in this research represent a useful framework to guide the process of local adaptation decision-making. The study has intentionally been considered at a local level because this is where in reality most of adaptation implementation is taking place (Nordgren et al. 2016; Dilling et al. 2019). Moreover, recent research has highlighted how mountains are hotspots of multi-hazards and their cascading impacts (Pescaroli and Alexander 2018; Moftakhari et al. 2017; Schauwecker et al. 2019; Tilloy et al. 2019; Terzi et al. 2019; Kirschbaum 2019). Therefore, adaptation approaches in mountain regions necessitate an explicit consideration of upstream–downstream dynamics. We thereby incorporate physical climate impact science, including effects of compound heavy rainfall, flood and debris flow and slope stability processes, into the economic optimization approach.

Our proposed approach can be regarded as a "forward looking, inter-temporal decision making". The forward-looking decision maker uses some information about how her decisions which will affect the future state of the world and also takes into account how future states of the world in turn will affect her decision-making process. The decision maker takes this information to make some "decisions", e.g. investments into adaptation in order to maximize some kind of welfare measure. We introduced a conceptual framework for the decision problem under stochastic uncertainties, which we then develop for an Alpine valley in Switzerland that is exposed to cascading impacts from debris flows and floods. Given that adaptation costs and benefits have different periods of realizations, we have explicitly accounted for both insuring and preventive adaptation measures in an attempt to capture the risk preference structure of the decision-maker. Specifically, the decision-making authority must weigh the sunk costs of implementing a certain adaptation measure against the uncertain benefits of the impact-reducing effectiveness of that measure.

Whereas all the options are available in any decision period, a response pathway can be inferred from our results in Figs. 5, 6, 7. At the initial time and until about 2030, there is a 10% probability that building a dam will have increased the asset value of the houses above the initial value and turned out to be optimal. Beyond 2030, building a dam is suboptimal. Our study indicates that from a broad portfolio of adaptation options, river excavation performs best under uncertainties while building a protection dam is sub-optimal and relocation of inhabitants is never optimal. This outcome, however, depends, among other, on (monetized) values assigned to people, assets and adaptation measures, i.e. on what and how much we value. The sensitivity analysis indeed shows that if the costs of building and maintaining the dam are reduced by 25% the exit option of building a dam is more profitable at the initial period. Clearly, a shorter time horizon will lead to less debris flow and flooding events and thus increases the expected values of house assets at the initial period. Thus, with shorter time horizons, the option to build a dam becomes less attractive. Table 2 also confirms that the longer the time horizon the more excavation will be needed because of the higher expected damage from debris flow events and thus the value of the house assets will be reduced accordingly.

We have compared our approach to one where the decision maker has perfect information about the future (Table 2). In the deterministic case, the decision maker knows exactly how much to excavate (0.26 m) and thus the final value of the house asset is higher than in the stochastic model where the decision maker will excavate more than would be needed if she/he knew exactly the magnitude of the debris flow (Table 2). However, the limitations of a deterministic approach in dealing with stochastic events becomes evident here, e.g. for example the option of building a dam would never be attractive if we knew for sure that no events will happen in the future, which is not a realistic assumption in the topographic context explored here. Hence, our results confirm that our model has some advantages to the one assuming perfect information or foresight to deal with events of stochastic nature.

The decision problem highlights the dilemma of a decision agent faced with either providing insuring options (building a dam) that has more potential to remove the hazard ex-ante but require high investment/maintenance cost or preventive options, which require continuous small investment over time, but can only mitigate the hazard magnitude (Sims and Null 2019).

Notwithstanding, our case study has revealed that river excavation indeed performs well across a broad range of hazards intensities and frequencies. We were able to infer an optimal level of excavation, which offers a metric to benchmark the effectiveness and economic feasibility of response options in the context of adaptation (Singh et al. 2020).

Furthermore, while local realities of flood exposed people and assets are included, the method is spatially non-explicit. Hence, the method offers a high potential of replicability in other mountain regions providing that good quality data are available alongside an open and collaborative exchange with local experts and authorities. Riverbed excavation after flooding events or with regular frequency to increase riverbed flood capacity and thus reduce probability of flooding is a flexible, incremental adaptation measure (Hegger, et al. 2016). However, additional constraints such as the direction of subsides would probably show different results (Simonet and Fatorić 2016). Current governance mechanisms in Switzerland and in many other countries are not supportive for what is here assessed as economically optimal because subsidies from higher governance levels (sub-national and national) are typically limited to larger infrastructure investments. Riverbed excavation would fall under maintenance costs which needs to be borne by local communities, implying that economically optimal solutions are not necessarily a preferred option at the local level due to relative higher financial burdens. Our study therefore confirms that adaptation decision-making is anchored in local setting and realities (Nalau et al. 2015; Nordgren et al. 2016). Whereas we do not presume to capture the full extent of the decision states and variables, the approach does consider above all the nature of the problem local decision-makers are confronted with when deciding on adaptation—that is to say, cost problems, the feasibility of options (what we have), decision periods, and time horizon, and risk preference. We demonstrated that all these factors can influence how adaptation is going to perform, and thus a formulation that is aware of the nature of the problem can potentially be instrumental to signal both effectiveness and a feasibility of adaptation responses.

However, we also need to be considerate concerning the limitations of our approach in the adaptation decision process. While our approach is replicable in other local contexts which face similar upstream and downstream impacts, we also recognize that adaptation decisions would not be based exclusively on the outcomes of our model. In some contexts, such as for instance in developing countries, financial constraints may be higher, and non-monetary, equity or culture related factors may play a more important role for decisions. Non-monetary, intangible values (e.g. people's attachment to place) could, in principle, be included in the model if data, such as based on surveys, would indicate a ranking of options and non-monetary costs. More fundamentally, though, we envision this approach being an element in a broader co-production of knowledge process towards identifying appropriate adaptation solutions. Such frameworks have been proposed and evaluated for climate adaptation (Hegger et al. 2012; Howarth and Monasterolo 2017; Muccione et al. 2019). For our case this implies that the results of our study would inform a decision process where different perspectives are evaluated and negotiated, and thus ensure that adaptation decisions are embedded in the local socio-political context.

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Authors' contributions VM developed the paper and wrote every section of the manuscript. TSL and CH wrote and edited substantial sections of the main texts and supplementary material. TSL and PO developed the model and wrote the Method section together with VM. VM, TL, and CH wrote the Result section. VM, CH and NS wrote the Discussion and Conclusion section. Everyone contributed to the supplementary material. PO contributed with model calibration. Correspondence and requests for materials should be addressed to veruska.muccione@geo.uzh.ch.

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Data availability Additional climate and hydrology data are submitted as part of the supplementary material and as separate excel file.

Code availability The data in this study were obtained and analyzed with a commercial programming language AMPL and the commercial solver KNITRO.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical statement We confirm that the present manuscript is in compliance with the Ethical standards of the journal.

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