Viability, efficiency, resilience and equity: using very diverse indicators to deal with uncertainties of future events

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Article published in Environmental Science and Policy, October 2022

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Abstract

Dynamic models can help adapt to climate change since they inform on the impacts of decisions and future events on sustainability. They make it possible to follow the evolution of variables over time, to model exogenous events and adaptive policies and to compute sustainability indicators. Various model types based on different world-views exist, and they give rise to different indicators. Modellers generally choose only one type of model, limiting the variety of indicators. However, decision-makers, who have to be creative to face global change, need a wider diversity of indicators. The objective of this paper is to show the diversity of insights one can get by using alternative system indicators and their decision implications. We test our "very diverse indicators" approach and illustrate its results for a population at risk of flooding and a water-basin manager who can help the population implement protection measures. We test many variations, including e.g. viability theory and agent-based modelling, and different indicators of viability, resilience, efficiency and equity, based on comparable data sets. We show possible synergies of the obtained diversity of insights: for example, one indicator says that it is urgent to act and another which is the best policy to use. We discuss the difficulties of implementation and the benefits of our approach for the decision-maker.

Keywords: Uncertainty, decision-making, optimization, viability, indicators, floods

1. Introduction

Nowadays, people face strong uncertainties about the evolution of the global climate and the socio-economic system. The changing environment also impacts their personal life, as is the case for instance for people exposed to more frequent and more intense flooding. Changing conditions require both people at risk and decision-makers to adapt to make living sustainable. For this adaptiveness to be effective, one has to consider future events and decisions, as well as their impacts. Dynamic models are models in which one or more variables evolve over time. This evolution may also depend on exogenous events or actions decided by the decision-maker. Hence, dynamic models make it possible to anticipate and inform decision-makers of possible evolutions (e.g. (Barendrecht et al., 2017; Di Baldassarre et al., 2013).

However, designing dynamic models for decision-making requires many choices. Firstly, there are many ways to describe the dynamics of the system: a mean field approach (Mathias et al., 2017; Weidlich, 2002; Picard and Franc, 2001) representing the dynamics of average objects, or a population-based approach representing the various dynamics of each element, through microsimulation (Ballas et al., 2007; Orcutt, 1957), or agent-based models (De Angelis and Gross, 1992; Erdlenbruch and Bonté, 2018; Edwards et al., 2005). Often, the dynamics are too complex to be solved analytically. Thus, they are solved using simulation models.

Secondly, using dynamic models and describing future evolutions requires taking uncertainties into account.There are many ways to translate uncertainty into models (Walker et al., 2003). For example, unknown future floods can be randomly generated according to a distribution function, or can be represented by a worst-case scenario, or a series of scenarios. Finally, viewpoints vary on what constitutes a relevant indicator for decision-making. The more classical view considers that indicators should focus on optimality, another view consists of seeking viability or resilience (Aubin, 1991; Aubin et al., 2011; Martin, 2004, 2019; Saint-Pierre, 1994), i.e., giving the decision maker the temporal sets of actions to undertake to remain forever in a desirable set of states, or equity. These choices especially constrain the modelling scale, the adaptive policies under consideration and the description of uncertain events. Making these choices is similar to picking a particular way to describe the world and its dynamics (McChesney, 1995; Tsoukiàs, 2008). It restricts possible indicators that can be consulted and shapes the conclusions to be drawn from their use (Moallemi et al., 2020; Quinn et al., 2017). These choices are generally made by modellers instead of decision-makers, while the responsibility of the decision lays with the decision-maker.

Some studies tried to go beyond the limitation associated to a particular choice of dynamic model. For example, they compared dynamic approaches (Durrett and Levin, 1994; Edwards et al., 2003; Huet and Deffuant, 2008), discussed the way one may select one model among many (Francois and Laval, 2011; Kelly et al., 2013), or explained ways of coupling models (Abebe et al., 2019; Dai et al., 2020). Others focused on the indicators for decision using different evaluation models, such as multi-criteria analysis (Triantaphyllou, 2000; Raaijmakers et al., 2008) or decisions under deep uncertainty, emphasizing the importance of dynamic policy paths (Haasnoot et al., 2013, 2021; Kwakkel et al., 2016), or indicators of robustness (MacPhail et al., 2018); see also Newman et al. (2017) for a review on decision support systems for natural hazard risk reduction.

However, none of them vary both the choice of dynamic models and the type of decision indicators. Thus, we propose to vary these two sets of choices simultaneously to compute "very diverse indicators" based on comparable data sets and able to address four central questions for the management of dynamic systems under uncertainty. First, a viability question: is there a management option that makes it possible to maintain the system in a desirable set of states? Second, a resilience question: if viability is not ensured, is it possible to recover desirable states given management options and time constraints? Third, an efficiency question: given these management options and constraints, taking costs into account, is one option more efficient in terms of outcome? Fourth, a question of equity: does the information campaign create inequalities in the population? If so, is there a way to reduce inequality or to protect specific parts of the population (the most vulnerable, the poorest, etc.)?

The objective of this paper is to show the diversity of insights one can get by using alternative system indicators and their decision implications. To test our “very diverse indicators” approach, illustrate its results and discuss its advantages and limitations, we consider the following dynamic problem under uncertainty: the case of a population at risk of flooding. People can adopt individual protection measures that reduce the damage in case of a flood. Their motivation to protect themselves is boosted by the occurrence of a flood. However, protection deteriorates over time. The public authorities can encourage the population to adopt these measures by carrying out information campaigns, but this comes at a cost. Management options are then intensity and timing of information campaigns, including the option of doing no campaign.

The article is organized as follows. In Section 2, we discuss several methodological issues: we specify the underlying approaches, the application, the four risk management issues and we detail variations of modelling that should be considered to address these issues. In Section 3, we present some "very diverse indicators" computed from the implemented variations reminding which question they address, how they deal with uncertainty and on which underlying approach they are based. The final section discusses the contributions of our proposal, especially how these indicators can be complementary to help the decision-maker. The appendices give more details on the dynamics and the computation of the indicators, including the related software to compute them.

2. Methods

2.1. Underlying approaches

We base our models on different approaches: viability theory, optimization, numerical simulation and agent-based modelling. The most appropriate approach is chosen in the following to construct our indicators.

Viability theory develops methods and tools to analyse the compatibility between dynamics and constraints. In this framework, the objective is to maintain the system state variables inside a given constraint set, without optimizing a particular objective function (see Aubin (1991); Aubin et al. (2011) for an overview). Optimization consists in defining the decision variables that minimize or maximize an intertemporal objective function given constraints (Agrawal and Fabien, 1999; Bellman, 1957; Pontryagin et al., 1962).

When a particular action policy is considered, answers on its impacts at the individual level (such as its efficiency and its equity) are computed from simulations of an agent-based model. A simulation is an approximate imitation of the functioning of a system, that represents its operation over time (Sokolowski, 2009). Numerical simulation allows to explore the state-space of a system, given a range of parameter values. Agent-based models are particular simulation models which study the interactions between heterogeneous individuals and their environment, over time (Epstein and Axtell, 1996).

2.2. Phenomena under consideration and key variables

We consider a population under threat of flood and a manager who can decide to carry out information campaigns to promote the adoption of individual protection measures against flood damage. In the absence of flood, the living conditions are such that the inhabitants' activities generate wealth. Flood occurrences cause damage that can be measured in terms of wealth losses. Hence, one key variable is the inhabitants' wealth. Wealth tends to increase with time but decreases as it can be partially used by the manager to carry out information campaigns. Wealth can experience a sudden decrease in case of floods. This decrease is lower when the individual has adopted an individual protection measure (Rogers, 1975; Rogers and Prentice-Dunn, 1997; Maddux and Rogers, 1983; Richert et al., 2017). The adoption of a measure is positively influenced by the awareness about the possibility of a flood, which is enhanced by flood occurrence but also by information campaigns. However, protection tends to loose its efficiency over time because of negligence or wear and tear. A second key variable is hence whether inhabitants have an operational protection or not, at the individual level, or the protection rate, at the aggregate level. According to the manager's choices, different information campaign policies can be implemented. Information campaigns are hence a third key variable. All the possible strategies must be specified, described by so-called control variables since they describe the manager's decisions. The impact of these control strategies depends upon the flood occurrences. Finally, the variables describing the possible future flood sequences are also essential.

2.3. Risk management issues and sources of uncertainty under consideration

We assume that the distinction between desirable and undesirable situations only relies on the wealth value: if the wealth is non-negative, the situation is considered as correct, and if the wealth is negative, the situation is considered as problematic by the risk manager. To answer the chosen questions, two types of management issues, as well as two different sources of uncertainty are addressed. They are not independent even if presented separately in the following.

2.3.1. Viability and resilience issues

Considering the above definition of desirable states, viability relates to the possibility of an evolution along which the wealth remains non-negative according to the information campaigns undertaken and despite potential flood events. When positive wealth cannot be ensured, the issue of resilience arises: is it possible to find an evolution (possibly by carrying out information campaigns over time) that allows to reach viable situation in the future? And if possible, how many years does the population have to cope with negative wealth?

2.3.2. Efficiency and inequality issues

If several information campaigns are at hand, of which several may be resilient and viable policies, one can ask which of these policies is the most efficient, in terms of outcomes and costs. Finally, globally viable, resilient or efficient policies may increase inequalities within the studied population and another issue can be the reduction of inequalities or the protection of certain parts of the population.

2.3.3. The uncertainty related to what is known about the parameterization

The current state of the modeled system as well as the parameter of the dynamics are more or less known by the decision-maker and the modeler. Dynamic models generally require to know them to be able to inform on the evolution of the system. This is common to consider some parameters are known, and others can be calibrated (see for example Huet et al. (2017); Lavallée et al. (2019); Xie et al. (2017)). However, calibration is not always possible since it requires data from the past that may not be available. Moreover, it is not obvious such data would be useful for a purpose such as dealing with climate change. Indeed, calibration assumes that the future behavior follows the same tendency as the past one. But what has been observed is an unpredictable change in the frequency and the intensity of the floods. Thus our indicators consider either fixed known parameters with a known starting state (except our indicators based on the viability theory which do not require to know the starting state), or varying values for parameters as proposed by Gao et al. (2016).

2.4. Modelling assumptions

This subsection presents a synthesis of the models which allow to compute our indicators. For the detailed descriptions, see Appendix B to Appendix E. Appendix F makes the mathematical link between the different models.

2.4.1. State variables and their dynamics: individual vs aggregate

We consider a population of individuals[1]. State variables may be described at the individual level or at the aggregate one. In both cases, we assume that two kinds of variables are necessary to describe a given situation of the population :

- at the individual level, one variable is sufficient to represent the wealth ; at the aggregate level, the average wealth (total wealth divided by the population size) is considered.
- the extent of protection against flood is measured at the individual level by a boolean which gives the information whether a protection measure is effective or not ; at the aggregate level, the adaptation rate describes the proportion of individuals in the population having implemented the protection measure.

As far as the dynamics of these variables are concerned, at the individual scale, we use the formalism of agent-based models with discrete time steps ; at the aggregate

[1] Here and in the following, we use equivalently the term "individuals", "households" or "agents" to designate an agent in the individual-based model

scale, we use the formalism of differential equations (stochastic as in Leuenberger et al. (2018) or tychastic as in Martin (2019)).

At both scales, we assume that the dynamics are governed by five interdependent phenomena :

- in absence of any flood event or information campaign, the proportion of protected individuals decreases with time (for instance protective devices deteriorate, people forget the procedure, ...),
- between two flood events, individual and average wealth increases linearly with time,
- a flood causes a damage described by a sudden decrease in wealth which extent depends on the flood height and on the presence or absence of protection measures. At the individual level, the water height which triggers damage for an individual depends on its geographical localisation ; at the aggregate level, the average damage is considered Appendix A,
- both a flood event and an information campaign positively influence the adaptation rate,
- carrying out an information campaign has a cost.

2.4.2. Policies and management strategies: time-dependent or state dependent

The manager has the possibility of implementing policies to influence the evolution of the system. These policies take the form of information campaigns for inhabitants. The campaigns aim to make them aware of the damage that floods can cause and thus encourage them to implement individual protection measures that will reduce their impact. These campaigns may or may not target the most exposed audience:

- policies that are targeted to the specific individual situation are called 'people centred polices'. An expert advice given to a specific household can be a people-centred policy;
- policies that are more general are called 'top-down policies'. For example an exposition or public meeting about floods can be a top-down policy.

Thus, the properties of the system such as viability, resilience, efficiency, inequality, will depend on the policies implemented and the way they are implemented. The number of people who have adopted a protective measure and therefore the extent of the damage caused by future floods will depend on the intensity and frequency of information campaigns, i.e. the management strategy. We can choose to define the relevant management strategies to be implemented:

- according to time (for a given time which campaign has to be carried out), these are time-dependent strategies (or open-loop in the terminology of control);
- or according to the state of the system (for a given state of the system which campaign has to be carried out), these are state-dependent strategies (or closed-loop in the terminology of control).

2.4.3. Upcoming flood events description: scenario, stochastic law or set of possible events

To determine the set of upcoming floods, we will consider three different methods: generating sets of floods following the generation of a sequence of exponential random variables whose parameters are the expected average size of the floods and the average return time; considering the worst future and describing it by the size of the highest expected flood (called big flood), possibly also by the minimum return time of it; writing several time series of big and small floods, called scenarios, over a period of time. Here again, the choice of how to deal with the uncertainty related to floods is not independent of the risk management issues due to the constraints resulting from the theoretical foundations of the underlying approach and the computational limits in memory and time.

Despite considering the same phenomena and key variables, our various indicators, presented in the next section, deal differently with the risk management issues and the sources of uncertainty which implies different modelling choices about the scale (individual or aggregate), the action policies (state or time dependent) and the description of the set of upcoming floods (scenario, stochastic law or set of possible events).

3. A diversity of indicators

We present in the following "very diverse indicators" based on different modeling assumptions which together make it possible to answer questions of viability, resilience, efficiency and equity. The features of each of them are summarized in Table 1.

Indicator 1 is a viability indicator based on a simulation approach (it can easily be adapted to become a resilience indicator based on a simulation approach). Indicator 2 is a viability and resilience indicator, based on viability theory. Indicator 3 is a

	viability theory	simulation	agent-based modeling	optimization
viability	Ind 2/Ind 3	Ind 1		
resilience	Ind 2			
efficiency			Ind 5	Ind 5
equity			Ind 4	

Table 1: Indicator features : underlying approach vs risk management issue

viability indicator, based on viability theory. Indicator 4 is an equity indicator based on agent-based modelling. Indicator 5 is an efficiency indicator based on agent-based modelling and optimization. Note that some indicators are able to respond to two questions, especially those relating to viability and resilience, while others are specific to one question, as the equity indicator. The questions of efficiency or equity, given by indicators 4 and 5, should be computed from the various states of the individuals composing the evaluated population. Such states are only given by agent-based models on which our optimization approach is also based. On the contrary, the questions of viability and resilience, based either on the viability theory or a sensibility analysis by simulation, require a large exploration of the possible states of the model, and is then very costly in terms of computation. Thus, such an exploration can be reasonably done for macro states at the population level, and not for the numerous micro states of the individuals constituting the population. This means in practice that these indicators can be only computed from dynamic models representing the system at a macro level such as a differential equation system.

Despite this difference of dynamic models, all these indicators are computed with comparable sets of data (Appendix F. Indeed, Appendix F makes the mathematical link between the individual and aggregate models. It shows the successive approximations which establish the relations between the parameters of the different models. This makes it possible to calibrate similar parameters for all models.

3.1. Indicator 1: viability under parameters and floods uncertainties

This first indicator aims to provide information on what can happen, considering all possible variations of poorly known parameters of the dynamics of the population and the floods. Moreover, we assume that floods are random processes since the upcoming floods are unknown. The number of floods generated and the intensity of floods (mean water level) follow Poisson distributions. The set of indicators relates to the viability issue: it explores whether there are situations in which, in absence of any policy, wealth becomes negative. For the complete description of the computation of this indicator, see Appendix B. The map presented in Fig. 1 represents results built from the simulated states of the differential equations system presented in 2.4.1. The system is simulated for 30 years. The results are average outcomes of systematic parameter value variations (for the population dynamics and the generation of floods functions), and variations of randomly generated time series of floods (1000 replicas for each set of the parameters values).

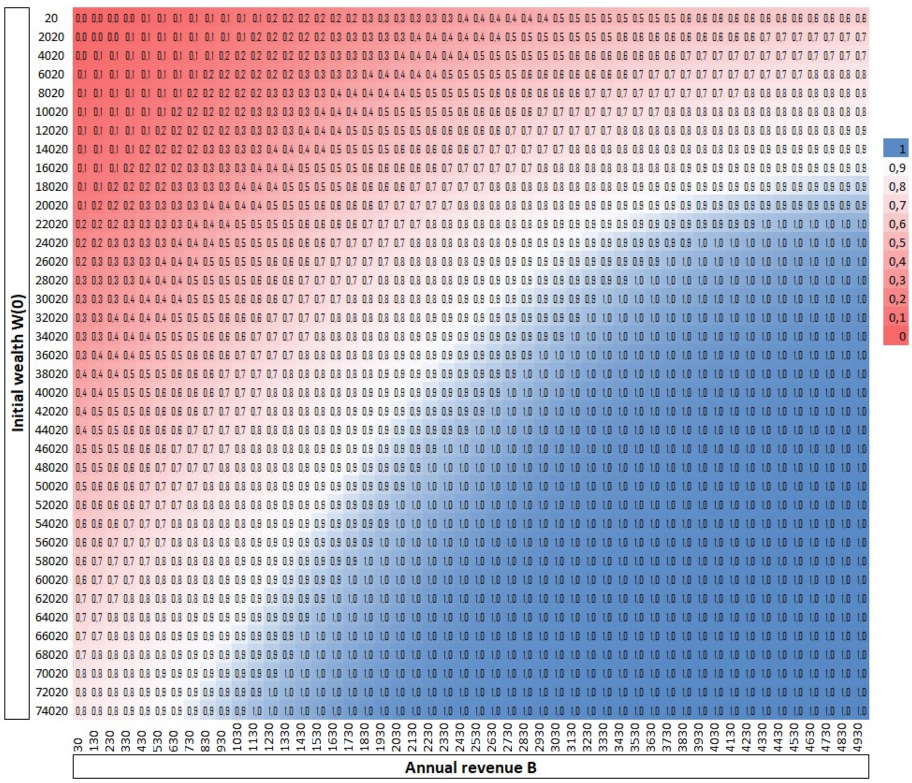


Figure 1: Frequency for a population of having a negative wealth at least once over the next simulated 30 years, depending on the initial wealth W(t=0) (vertical axis) and the annual revenue B (horizontal axis). As indicated by the legend on the right, the color varies from dark red (frequency = 0), to dark blue (frequency = 1), through the white color indicating the frequency considered as acceptable to be safe (in this drawing 0.9).

This indicator takes the form of a map of various results which are depicted for different types of populations, characterized by different levels of initial wealth (vertical axis) and different levels of annual revenue (horizontal axis). The initial wealth and the annual revenue have been chosen as axes for the map since they are values assumed to be more or less known by the decision-maker (contrary to other parameters values). A threshold can be set to distinguish acceptable results (in blue) from unacceptable results (in red). This threshold is drawn in white. Many different results can be presented using this map. For example, it is easy to show the variations of the frequency for a population to be viable over a simulation time of 30 years (as presented in Fig. 1, but also the frequency for a population to be resilient after 30 years (meaning it possibly had a negative wealth during these 30 years but finishes finally with a positive wealth). In the same spirit, it is possible to inform the decision-maker on the variations of the value of the wealth, of the adoption rate for the protection measure, but also on the average size of the floods that do not result in negative wealth during the simulation period, etc.

Such an exploration can help determining whether to act (i.e. defining an information campaign) and which individuals to target. Individuals having acceptable results without any policy intervention may be less urgent to target than individuals who experience unacceptable results (for example a negative wealth at a time) and may suffer more and more from the next coming floods.

3.2. Indicator 2: viability in case of one big and small floods

This second indicator aims at assessing situations in which it is possible, possibly after a delay, to protect the population from the undesirable consequences of a rare big flood (see 2.4.3) occurring now or in the future, in the presence of possible smaller floods, also occurring now or in the future. The big flood is expected to occur only once at an unknown date. Small floods can occur several times. The size of the small floods is supposed to be bounded. For example, in Figure 2, the size of the big flood is 250 cm, and small floods are supposed to have a maximum size of 150 cm. If they follow each other too quickly the population cannot be protected. For each situation the indicator computes the minimum return period under which it is possible to evolve towards states where the population is protected. This indicator is valid until the big flood actually occurs. After this time, if the population was protected before the big flood, it is then only protected against the small floods. The indicator still shows the time without any flood necessary to be protected again against a new big flood.

As in the previous section, being protected means that the average population wealth remains non negative over time. The evolution of the population wealth and adaptation rate is computed from the differential equations system presented in 2.4.1. The parameters of the dynamics are fixed. For the complete description of the indicator computation, see Appendix C.

The maps derived from this indicator can show: in which situations (in terms of mean adaptation rate and wealth) the population is protected now and in the future against a unique big flood of a given size; viable situations where it is protected against this big flood even with occurrences of smaller floods of a given maximum size. The computation gives the minimum period without any flood sufficient to guarantee the viability against the big flood in presence of the smaller floods. It also gives the period of time without any flood which is sufficient to ensure that the population situation evolves towards situations where it is protected. This is an inverse measure of resilience as defined by Martin (2004). The larger this period of time, the less resilient is the situation, since it can evolve to viable states only in the absence of flood. The indicator can also take into account different information campaign policies.

For instance, in Figure 2 the area above the white dashed line depicts situations where the population is protected against a big flood of a size of 250 cm. However, in the region below the plain line (the line above), the population is not protected against the big flood when smaller floods can also occur. In the region above the plain line the population is protected even in the presence of smaller floods, as soon as their succession is not too fast. (Actually, when a small flood occurs when the population state is in the viability area, the wealth of the population is impacted but the state after the flood will stay above the dashed line, so the population is still protected against the big flood). The map shows the minimum period of time without flood necessary to return to the viability area where it is once again protected even in the presence of smaller floods. More precisely, the map shows that the dashed line lies in the area where a time period of 13 years without flood is necessary to reach the viability area. So when small floods succeed one another less frequently than 13 years, with a size smaller than 150 cm, the population whose state is in the viability area is protected forever against the big flood. Other maps which are not shown here allow to verify that after a big flood the population is still always protected from small floods with this return period.

With these maps, it is also possible to decide whether it is necessary to implement a policy or whether it is reasonable to wait doing nothing until the population state reaches the viability area. For example, if small floods are known to succeed one another more frequently than every 13 years, it is not possible to guarantee that the population will ever be protected against the big flood and waiting is not a good strategy. On the contrary, if small floods are known to succeed one another less frequently than e.g. every 15 years, waiting can be a good strategy.

3.3. Indicator 3: viability in case of successive floods given a maximal height of each of them and a minimal period of time between them

This indicator determines from which situations it is possible to maintain the population in a set of acceptable situations regardless of successive floods provided

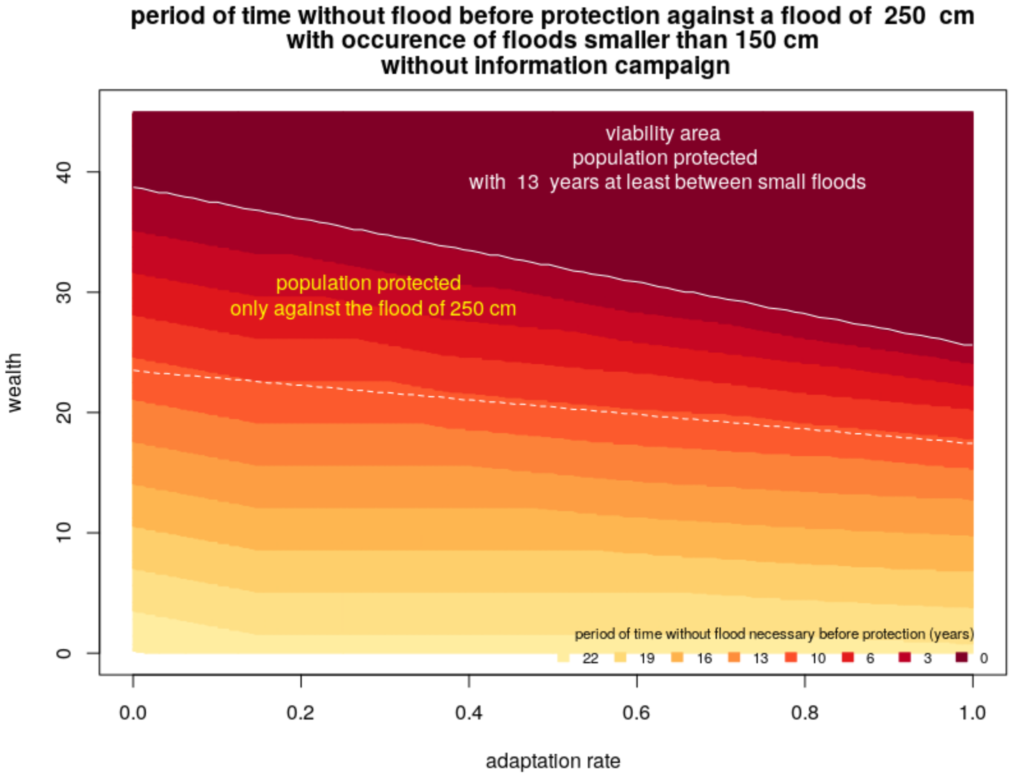


Figure 2: Map of the period of time without flood levels before everlasting protection against a unique big flood of size 250 cm occurring now or in the future, in the presence of smaller floods of maximum size of 150 cm, with no information campaign. The region above the white dashed line describes situations that are protected against the big flood. The region above the white plain line describes situations that are also protected in the presence of smaller flood with a minimum return period that can be seen on the map: It is the level of the period of time without flood that contains the white dashed line. Model described in Appendix C with annual gain of wealth $B = 1,933$ k€.

that they belong to a given set of anticipated floods.
Among the options described in the method section (Section 2), this indicator relies on viability theory methods and addresses viability issues under uncertainty related to the upcoming set of floods. The underlying model is an aggregated model with 3 global variables (the average wealth of the population, the adaptation rate and the time since the last flood) which takes into account the phenomena under consideration described in Subsection 2.2.The wealth and the adaptation rate are computed from the differential equations system presented in 2.4.1. The parameters of the

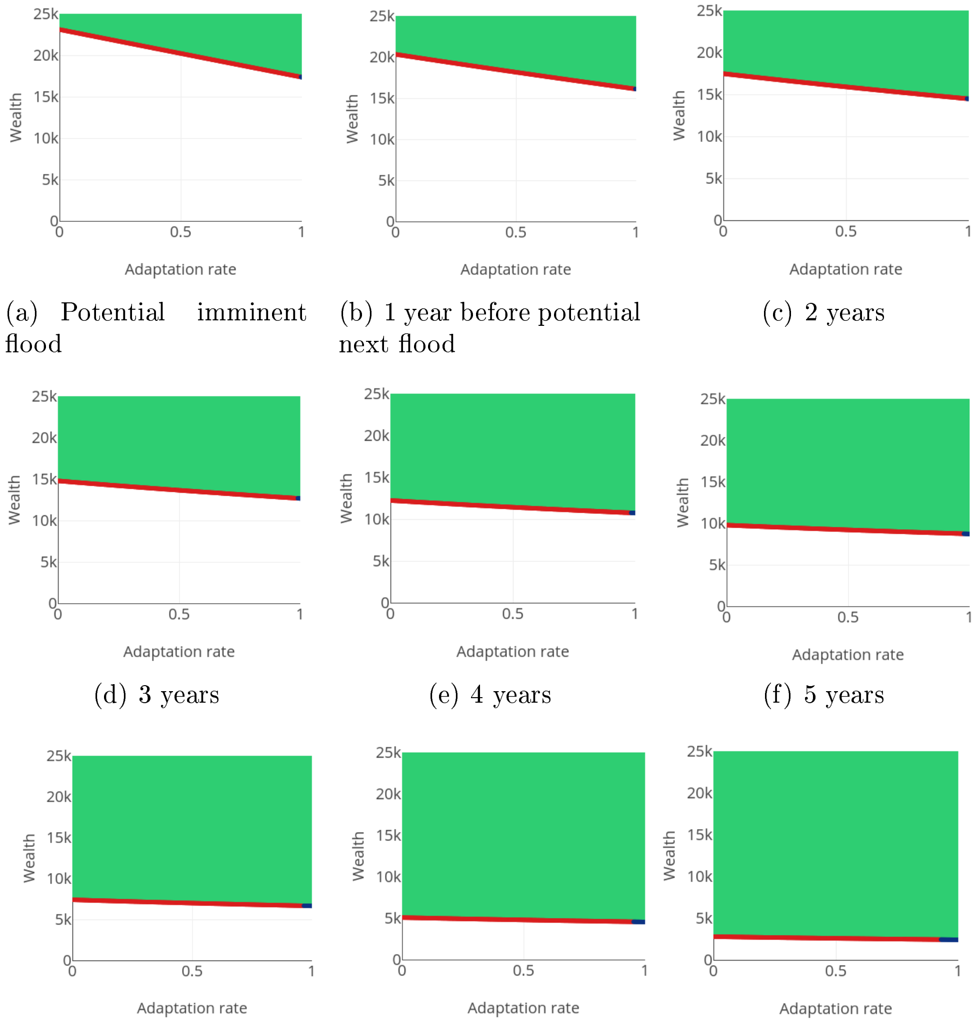
dynamics are fixed.

Given an upper bound for each flood event height (called big flood as presented in section 2.3) and a lower bound for the time period between two floods, the anticipated floods are successive floods that satisfy both bounds. Hence, this indicator proposes to explore the consequences of all possible information campaigns (as indicator 2) and all possible successive floods that belong to the set of anticipated floods, and then to determine situations (called viable) from which there exists at least one sequence of information campaigns over time that produces dynamics with positive wealth whatever the anticipated successive flood occurrences. Moreover, from viable situations, state-dependent management strategies that really ensure the viability over time can be derived. For the complete description of the indicator computation, see Appendix D.

Figure 3 displays the maps that can be associated with this indicator. The parameter values are given in Appendix D. As far as the information campaign parameters are concerned, they correspond to "top-down policies" via the averages described in Appendix F. As for the anticipated successive floods parameters, the height is expected to be smaller than 250 cm and the time period between two floods bigger than 10 years.

The following maps display the situations (pairs of wealth and adaptation rate) for which it is possible to undertake information campaigns in order to maintain the population wealth non-negative whatever anticipated successive floods. Such situations are more numerous when the time before the next flood is longer and leaves more time to undertake information campaigns if necessary. The different panels of the figure depict different expected times before the next flood and the associated viable situations. Moreover, these maps highlight situations (red and blue points) which are viable but which are on the boundary of the viability domain. Red points indicate situations where an information campaign should be undertaken immediately to remain viable. Actually, the management strategies provided by this indicator are state-dependent. For viable green situations, undertaking information campaign may be necessary in the future but not immediately.

If the situation under consideration does not belong to the green area, whatever the information campaigns, there exist successive floods among the anticipated ones that will result in negative wealth. In such situations, the same analysis with higher maximal information campaign intensity would show if increasing the proportion of population reached by the information campaign would allow to maintain a positive wealth despite these successive floods.



(a) Potential imminent flood
(b) 1 year before potential next flood
(c) 2 years
(d) 3 years
(e) 4 years
(f) 5 years
(g) 6 years
(h) 7 years
(i) 8 years

Figure 3: The green areas gather viable pairs (adaptation rate, wealth) from which accurate information campaigns ensure the protection against successive floods of height smaller than 250 cm and time period between two floods bigger than 10 years according to the time period expected before next flood. In red are the situations where information campaigns must be undertaken immediately to remain viable.

3.4. Indicator 4: the impact of policies on inequalities

This indicator details situations at the individual level and at the aggregate level. Its exact formulation as well as the underlying models are described in Appendix E.

Its aim is to discuss inequalities issues.

This indicator and the following are constructed using an agent-based model similar to the one developed in Erdlenbruch and Bonté (2018). The simulations are based on an artificial population of 2760 heterogeneous individuals. The numerous parameters of the dynamics are fixed. Their values have been determined based on a quantitative survey among 331 households conducted in 2015, following statistic and econometric analyses Richert et al. (2017); Erdlenbruch and Bonté (2018). Agents are hit by different flood heights according to their geographical situation in one of three areas around a river. Floods are considered through different scenarios, i.e. different intensities and date of occurrence of events, over a given time-horizon:

- in the first scenario, two small floods occur in years two and three;
- in the second, two big floods occur in years two and three;
- in the third, two big floods occur in years 20 and 21;
- in the fourth, a big flood occurs in year 10 and a small flood in year 20;
- in the fifth, a small flood occurs in year 10 and a big flood in year 20;
- the sixth scenario considers three floods: a small in year two and two big floods in years 20 and 21.

A small flood generates a water height up to 100 cm, a big flood generates a water height between 150 cm and 250 cm. The time horizon is of 30 years.

Figure 4 depicts the distribution of wealth for different flood scenarios at the end of the time horizon. It also indicates the number of poor individuals (red number) as an indicator of inequality. The top line is the situation without any policy: under flood-sequence 1 for example, 133 individuals (out of 2760) have a negative wealth by the end of the simulation horizon.

The second line represents the situation with a people-centred communication policy: for example, under flood-sequence 1, there are 8 individuals less with negative wealth than without policy (125 vs. 133). The third line represents the situation after a top-down communication policy: under flood scenario 1, the policy performs less well than the people centred policy (only 6 individuals are saved from poverty, compared to 8 under a people-centred communication policy); in our examples, a top-down policy always performs worse than a people-centred policy. Generally, whether communication policies are useful depends on the flood scenario considered and on the degree of inequalities that the decision maker accepts.

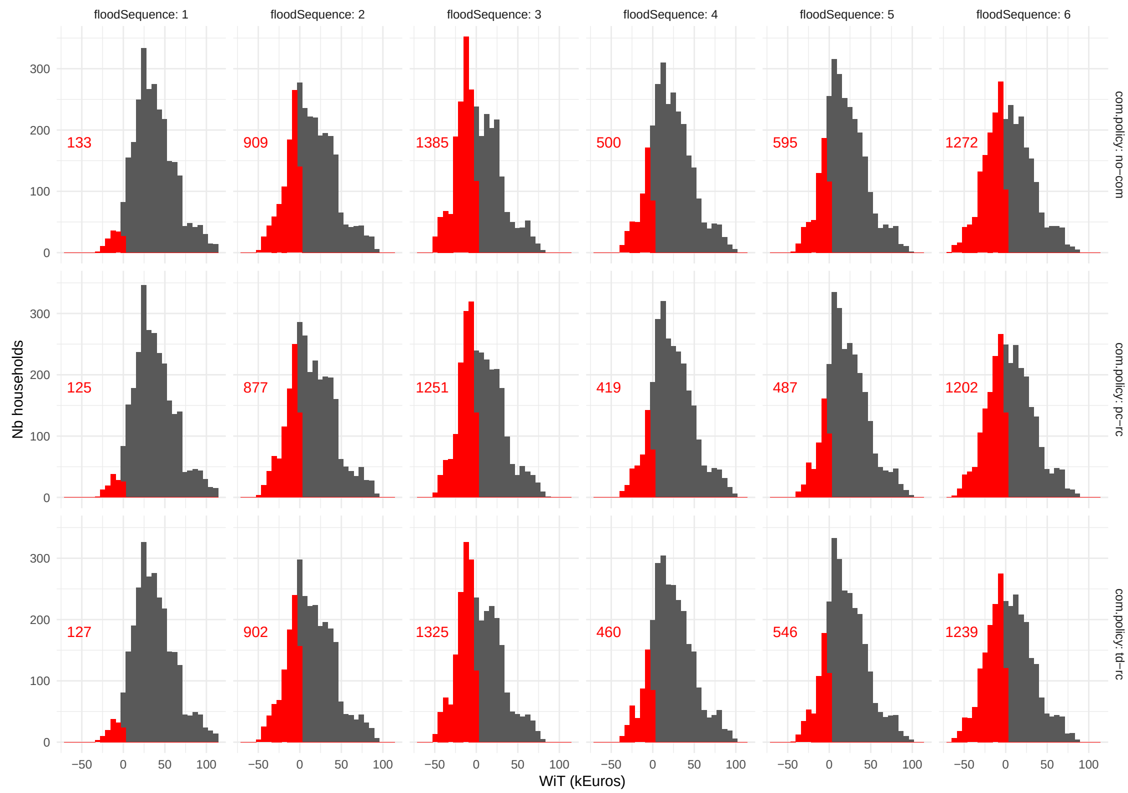


Figure 4: Distribution of wealth of individuals at the end of the time horizon for different flood scenarios (x-axis). First line: without communication policy, second (resp. third) line: with a people-centred (resp. top-down) communication policy. In red: number of individuals with negative wealth.

3.5. Indicator 5: The efficiency of policies

This indicator relies on the same underlying model as the previous indicator: an agent-based model. Details are described in Appendix E. It uses the same assumption on flood scenarios and parameters values. Its aim is to evaluate the efficiency of different types of communication policies.

The most efficient policy does also depend on communication costs. Let us consider the choice between a people-centred communication policy costing 200 EUR per population reached and a top-down communication policy costing 15 000 EUR annually. One can compute the sum of wealth minus costs over the simulation period for different flood-scenarios. Figure 5 presents such a comparison. In red, the net wealth gain without policy intervention (no-com), in green the net wealth gain

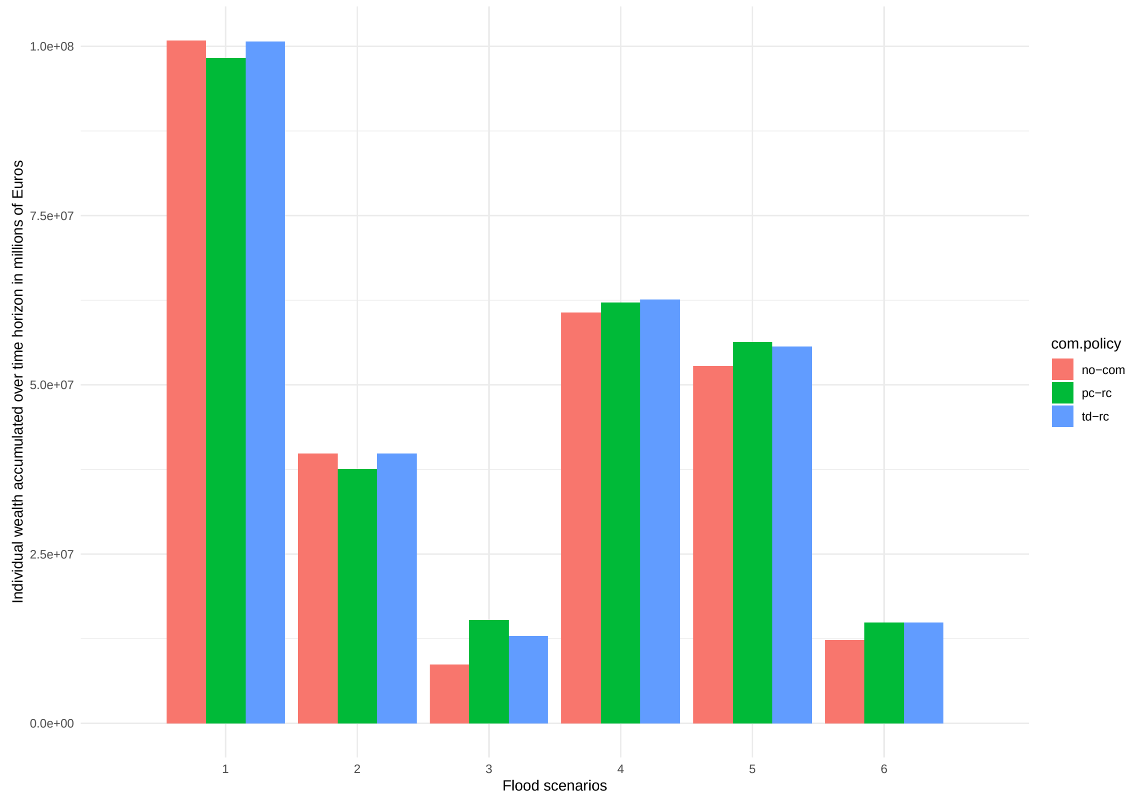


Figure 5: Wealth gain over simulation period minus costs of communication policies, in tens of millions of Euros. Red: no communication policy; Green: people-centred communication policy; Blue: top-down communication policy.

with a people-centred communication policy, in blue, the net wealth gain with a top-down communication policy. One can see that for flood-scenarios with one early occurring flood (flood scenarios 1 and 2), it is not efficient to communicate. It is best to use a top-down communication policy when considering scenario 4. It is best to use the people-centred policy when considering scenarios 3 and 5. Both policies perform equally well when considering scenario 6. Overall, it seems that early occurring floods can not easily be managed with communication policies, the top-down communication policy is more efficient when a big flood occurs in an intermediate time lapse, the people-centred communication policies is more efficient when a big flood occurs in a later time lapse.

4. Conclusion and Discussion

We showed how building diverse indicators conceived from different worldviews such as the viability approach or optimization is possible. These indicators can help a decision-maker protect a population against future floods. Our approach has required formalizing some common principles for the dynamics and a generic dynamic model representing a synthetic abstraction of more detailed models. Despite this effort to make the results of our various models compatible, they still represent different worldviews. Hence, classical multi-criteria analysis methods couldn't be used. Nevertheless, our following discussion will show this point is not necessarily a strong limitation, but can be considered as an advantage. Our 'very diverse indicators' approach implies some issues for modelers and decision-makers. However, it offers a more relevant and very informative description of the impacts of the various uncertainty sources, enabling the decision-makers to make informed decisions.

4.1. Issues for modellers

The first intuitive concern is about complexity for modelers who have to work in an interdisciplinary context. Studies across disciplinary fields are not an easy task. Apart from institutional obstacles, scientists involved in interdisciplinary work must face cognitive obstacles, including methodological and conceptual barriers (MacLeod, 2018; Szostak, 2013). Indeed, in order to understand each other, scientists from various fields of study must share the same language and openness to novelty and difference. They must also recognise the potential contribution of other disciplines in answering key research questions despite their bias toward their own group's contributions (Urbanska et al., 2019).

Thus, dealing with our 'very diverse indicators' approach is very challenging for modelers. First, they should not only build a common view of the phenomena under consideration, but also a formalization of the dynamics which gives comparable results for resolutions. Secondly, they should at least understand each others' formalism and frameworks. This requires a lot more knowledge than working as usual in a unique modelling paradigm. Each paradigm has its own view on what can be of interest for a decision-maker (McChesney, 1995). Working together requires learning not only the methods and the tools of the other modelers, but also the way they think of the problem. However, a real multidisciplinary approach represents a new way of thinking and a promising future for education and research (Darbellay, 2015). Moreover, this is needed to overcome the challenge of climate change (see for example Murphy (2011)).

4.2. Issues for decision-makers

The second intuitive concern is about complexity for the decision-maker. Understanding and assimilating two indicators instead of one is already difficult, but assimilating even more indicators can be cognitively burdensome enough to be more confusing than informative. However, considering our indicators are different answers to different risk management issues, it becomes possible for a decision-maker to deal with our diversity using the complementarity of the various indicators.

At first sight, the best indicator is the one preferred by the decision-maker. Which indicator is favored by the decision maker depends on several elements: firstly, his knowledge about the system; e.g. does he know the current wealth distribution of the population or does he need to guess? Has he already started setting up information campaigns and just wishes to refine their timing or does he want to know what happens if he does not implement any particular policy? Secondly, the indicator depends on his vision of the flood phenomena; e.g. he may think that the probabilistic nature of floods is an essential element or he may prefer elaborating a scenario of protection against a particular flood, such as the 100-year flood. Thirdly, it depends on the decision-maker's objectives: does he want to protect the overall population or certain parts of it? What damage and hence what reduction in revenues is acceptable according to him? Providing different indicators derived from different approaches hence can help decision-makers to define their standpoint and to balance out their opinions.

On the other hand, for indicators 1 to 3 few information is necessary, except the size of the expected biggest flood. Thus the computation of these indicators can be a first cheaper step to define if more detailed approaches, such as the indicators 4 and 5, would be of interest - especially to know more about the most efficient campaign and social and spatial inequalities. Indeed, using several indicators can also improve the decision maker's knowledge of the dynamics of the phenomena under consideration: with indicator 1, he can detect potentially unacceptable situations in which population wealth becomes negative; indicator 2 provides information about the size of the flood that could be withstood; indicator 3 can help define viable policies; indicator 4 can inform about the distribution of wealth and hence the number of poor individuals.

Some indicators respond to similar objectives in a different manner. For example, with indicator 1, one can define the wealth-revenue space for which unacceptable situations arise. With indicator 3, one knows whether unacceptable situations persist after implementing information campaigns. Indicator 1 assumes probabilistic occurrences of floods whereas indicator 3 assumes a maximum flood event and a minimum return period against which the population is protected.

In contrast, some indicators make similar assumptions but respond to different objectives: Indicator 5 aims at efficiency by defining optimal policies given a flood scenario and implementation costs. Indicator 3 aims at viability by defining viable policies given a set of floods and implementation costs. Different objectives can most directly be seen within the same modelling approach: indicator 2 allows knowing the size of the biggest flood that can be withstood immediately without being in a non-viable situation. It also defines the period of time necessary to get back to a viable situation after an even bigger flood. Likewise, indicators 4 and 5 allow defining the most efficient policy to protect against certain floods but also the policy that leads to the greatest equity in the population. The most efficient and most equitable policies are not generally the same.

We can finally stress that indicators 1 and 4 are very rich in terms of information given about the uncertainty related to who is impacted by various scenarios of floods, but very poor in terms of defining policy strategies susceptible to maintain the population protected against floods. On the contrary, indicators 2 and 3 are less able to inform on the variation of the recommendation due to the various cited sources of uncertainty. However, they are extremely precious for their ability to design policy strategies allowing the population to be continuously protected against floods when it is possible. From this point of view, the utility of our 'very diverse indicators' approach becomes obvious. This being said, it would be a challenge to formalize and exemplify further the synergies that can be built from our approach. But this is beyond the scope of this paper.

4.3. A very informative approach regarding uncertainties

The last point relates to how the various sources of uncertainties are informed through our 'very diverse indicators' approach. Whatever the interest of the decision-maker (defining when the population will be viable facing different floods, whether some information campaign can help the population be protected against future floods, etc.), the answer is based on a transition between one set of values of the population state to another set of values. This is the case for viable to non-viable situations for instance. Such transitions, representing a frontier, are always much more sensitive to possible sources of uncertainty than some stable situations of viability or non-viability far from this frontier (Alvarez and Martin, 2011; Huet and Deffuant, 2008). Considering different sources of uncertainty built from different practical constraints guarantees more robust information and decision.

Robustness is an important indicator for decision-making (MacPhail et al., 2018). In our 'very diverse indicators' approach, the way robustness is expressed depends on the indicator chosen: for indicator 1, robustness refers to the ability to stay in an area where wealth is positive following external disturbances or changes in model design parameters; for indicators 4 and 5, it refers to the fact that the ranking of policies stays the same following external disturbances or changes in model design parameters. For indicators 2 and 3, robustness refers to the *guaranteed viability kernel*, i.e. the set of states from which there exists a policy that maintains the system indefinitely in the constraint set, following external disturbances or changes in model design parameters. A decision-maker could use robustness as a meta-indicator to take his decisions about information campaigns.

To sum-up having many diverse indicators is not a limitation but an advantage. Future work should characterize further the synergies that emerge from such a diversity of indicators.

5. Acknowledgements

We acknowledge financial support from Irstea via the "AAP Risques" project RAZ 13 and from Inrae via the "LASID" network.

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Appendix A. Damage evaluation of a given flood

Damage curves depend on the flood height and on the presence or absence of protection measures. We use one of the French official damage curves described in Christin and Peinturier (2014) and adapt it for the presence of two jointly implemented protection measures: a slot-in flood barrier which hinders water to enter the building until a height of 80 cm and the storage of half of the individuals' potentially exposed furniture upstairs. The resulting two damage curves are represented in Figure A.6. These damage curves imply that the adoption of protection measures

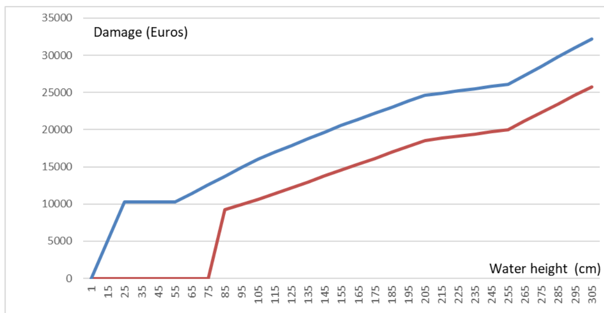

Figure A.6: Damage curve without protection measure (blue, above) and with protection measures (red, below)

reduces flood damage without totally avoiding it, except for small floods with less than 80 cm water height. We use regressions to approximate both damage curves by polynomial functions of degree three, depending on v_i one for each adaptation status b_i:

$$D(v_i, b_i = 0) := Max(0; a_1 v_i - b_1 v_i^2 + c_1 v_i^3 + d_1) \tag{A.1}$$

$$D(v_i, b_i = 1) := \begin{cases} a_2 v - b_2 v^2 + c_2 v^3 d_2 & if \quad v > 80, \\ 0 \quad otherwise. \end{cases} \tag{A.2}$$

with $a_1 = 188.3733$; $b_1 = 0.635664$; $c_1 = 0.0010903$; $d_1 = 2417.68$; $a_2 = 232.5365$; $b_2 = 0.8880617$; $c_2 = 0.0015029$; $d_2 = -5564.097$. At the individual level, the water height, v_i, which triggers damage for individual i according to the general damage function, depends on the geographical localisation of the individual i. At the aggregate level, the average damage is considered. The average damage to be charged on the average wealth when a flood v characterized by height v_i for individual i occurs can be approximated by:

$$D(v, \alpha) := \frac{\sum_i^N D(v_i, 1)}{N} \alpha + \frac{\sum_i^N D(v_i, 0)}{N} (1 - \alpha). \tag{A.3}$$

Appendix B. Formalization of indicator 1

Appendix B.1. Model description

We consider three state variables: the average wealth of the population, w (total wealth divided by the population size), the proportion of individuals in the population having implemented the protection measure, α, and the time since the last flood, T.

This model takes into account the uncertainty due to flood events which are characterized by their average return time and height of water, r and v. It is assumed that flood events occur following a composed Poisson Point Process: times between flood events, as well as heights of the floods, are distributed as exponential variables.

The dynamics of the triplet (T, α, w) is governed by a stochastic differential equation

$$d(T, \alpha, w) = f(T, \alpha)dt + \int_0^\infty \phi(T, \alpha)N(dv, dt)$$

where the deterministic part governs the dynamics in the absence of flood and the stochastic part describes the consequences of a flood event. $N(dv, dt)$ is a Poisson random measure with intensity $\mathcal{L}(v)dv\lambda dt$. This means that λ is the frequency of the flood events and $\mathcal{L}$ is the density of the flood heights.

The functions f and ϕ are defined by:

$$f(T, \alpha) = \left(1, -\frac{ln(2)}{T_m - T_a(v)1_{\tau(t)\leq\tilde{T}}}\alpha(t) + A_1 * A_0(1 + A\alpha(t))(1 - \alpha(t)), B\right) \quad \text{(B.1)}$$

and

$$\phi(T, \alpha) = (-T, \Delta\rho_1(v)(1 - \alpha), -damage(\alpha, v)) \quad \text{(B.2)}$$

where parameter B is the annual revenue, A_1 is the proportion of the non adapted population motivated to protect, A_0 is the ratio of the population convinced to adopt safety measures even when no one has already implemented it, A is the coefficient of the increase of this ratio through the influence of neighbours' adoption. T_m rules the duration of the effectiveness of the protection (the protection becomes inoperative after T_m years for half the population). When a flood occurs, the adaptation rate experiments a sudden increase of a proportion $\Delta\rho_1(v)$ of the non-adapted inhabitants which depends on the flood strength, v ; and the the duration of the effectiveness is reduced by T_a during a $\tilde{T}$ time period.The impact of a flood on the wealth depends on the adaptation rate and the flood height according to damage function (A.3).

Appendix B.2. Indicator formalization

Given a value of the initial wealth of the population, a value of the annual increase of this wealth and a temporal horizon, large sets of virtual experiments translating the various possible dynamics of the population given by the previous model are performed. For each trajectory, tests are carried out (does the wealth become negative, is it negative at the end of the simulation...) and the frequencies of answer "yes" are evaluated.

Appendix B.3. Indicator calculation of subsection 3.1

Equation (B.2) is discretized in time. Simulations are performed with time steps equal to $dt = 0.01$ year and time horizon equal to 30 years. For the behavioural dynamics of the population, the initial wealth $w(0)$ ranges from 20 to 74020 by steps of 2000, B ranges from 30 to 4930 by steps of 100, the initial adaptation rate, $\alpha(0)$ ranges from 0.05 to 1 by steps of 0.1, $\tilde{T}$ from 35 to 43 by steps of 1, $\frac{ln(2)}{T_m}$ from 0.086 to 0.116 by steps of 0.01. The other parameters' value are $A_1 = 1$, $A_0 = 0.00375$, $A = 0.392$, the functions of the height $T_a(v) = T_m - \frac{1}{1/T_m + A_1 x(v)/ln(2)}$ where $x(v)$ is piecewise constant function defined by :

v	0	10	20	30	40	50	60	70	80	90	100
$x(v)$	0.0	0.07895	0.07898	0.07900	0.07900	0.07900	0.07898	0.07896	0.07893	0.07889	0.07884
v	110	120	130	140	150	160	170	180	190	200	210
$x(v)$	0.06554	0.06508	0.06462	0.06417	0.06372	0.06328	0.06285	0.06242	0.06200	0.06159	0.06118
v	220	230	240	250	260	270	280	290	300		
$x(v)$	0.06078	0.06038	0.05999	0.05960	0.05943	0.05926	0.05909	0.05903	0.05903		

and the function $\Delta\rho_1(v)$ is piecewise constant function defined by :

v	0	20	40	60	80	100	120	140	160	180	200
$\Delta\rho_1(v)$	0.0	0.00307	0.00615	0.00922	0.01230	0.01538	0.18464	0.19672	0.20880	0.22088	0.23296
v	220	240	260	280	300						
$\Delta\rho_1(v)$	0.24503	0.25711	0.26587	0.27132	0.27219						

For the flood generation model, the average return time of the flood event r and the average size of flood v vary in couple (r;v) as follows : (3;110), (5;140), (7;175), (9;205), (9;225) and (11;265).

The computation code and the related data are available at
https://www.comses.net/codebases/b999826c-2205-47c5-8f7a-2689cd0df396/releases/1.0.0/

Appendix C. Formalization of indicator 2

Appendix C.1. Model description

The model takes into account two state variables: the proportion α of the population who has adopted protection measures, and the mean population wealth, w. It also takes into account a one-dimensional control variable, u, which stands for the communication effort. Flood events are characterized by their height v.

The variable dynamics are governed by a continuous control dynamical system:

$$\begin{cases} \frac{d\alpha}{dt} &= -\frac{\ln(2)}{T_m}\alpha + A_1(u + A_0)(1 + A\alpha)(1-\alpha) \\ \frac{dw}{dt} &= B - Cu \\ u &\in [0, U_{max}] \end{cases} \tag{C.1}$$

Parameters B, A, A_0, A_1 and T_m have the same meaning as in Appendix B. Parameter $C > 0$ is the unit cost of a communication campaign, U_{max} is the maximum instantaneous effort of a communication campaign, Their values are adjusted to match the mechanism of the agent-based model of Appendix E with hypotheses and methods described in Appendix F. Floods of height $v > 0$ are seen as a perturbation of the dynamics C.1, and they induce a shift $\theta(v)$ in both wealth and protection level. The impact on the wealth is negative whereas it is positive on the protection level.

$$\theta(v) = \begin{cases} \Delta\alpha &= +(1-\alpha)\beta_v(v)(1-\theta_t)(\theta_0 + (\theta_m - \theta_0)\frac{v^2}{v_m^2+v^2} \\ \Delta w &= -\mathtt{damage}(\alpha, v) \\ v &\in \mathbb{R}^{+*} \end{cases} \tag{C.2}$$

Bigger floods have a bigger impact, with a saturation effect on α: a flood of intensity $2v$ has a bigger impact than a flood of intensity v, but not twice the impact. v_m is the flood intensity for which the impact of the flood on the protection shift is half its maximum. $\beta_v(v)$ is the proportion of the population impacted by a flood of size v. It depends on the space configuration. The effect of flood is considered to take place immediately. Parameter $\theta_t > 0$ allow to to take into account the fact that the effect of the flood on the adoption rate can decrease with time. Parameters θ_0 and θ_m adjust the size of the shift according to the mean shift of other models as described in Appendix F.

The effect on the wealth w depends on the flood intensity v following (A.3).

We assume that acceptable situations are those for which aggregate wealth is greater than 0. They are thus defined by: $K := \{(\alpha, w) | w \geq 0\}$.

Appendix C.2. Indicator formalization

To formalize indicator 2, we use the concepts of mathematical viability theory. This indicator is defined using the concept of viability kernel Aubin (1991): given control dynamics and a constraint set (subset of the state space), the viability kernel gathers the states from which there exists at least one control function that governs a dynamics which remains in the constraint set over time; and the concept of capture basin Aubin (2001): given control dynamics, a constraint set and a target, the capture basin gathers the states from which there exists a control function that governs a dynamics which remains in the constraint set until it reaches the target. The set of states supporting a given flood intensity, v, now or in the future, is the viability kernel V_v associated to dynamics (C.1) under constraints $K_v := \{(\alpha, w) \in K \mid (\alpha, w)+\theta(v) \in K\}$. The boundary of V_{250} is shown in white dashed line in Figure 2. The time necessary to reach a situation that ensures the protection against floods of intensity v now and in the future is derived from the capture basin for dynamics (C.1) with an additional variable, T, which measures the elapsed time ($T' = -1$) of the target $V_v \times \{0\}$. Actually, the capture basin is its epigraph. We note $C_S(T)$ the capture basin of subset S in time T. We consider the viability kernel V_{v+v_2} associated to the subset $K_{v+v_2} = \{(\alpha, w) | (\alpha, w) + \theta(v) + \theta(v_2) \in K\}$ to take into account the presence of smaller floods of maximum given intensity v_2. The boundary of $V_{250+150}$ is shown in white plain line in Figure 2. We note T_v the smallest time T such that V_v is included in $C_{V_{v+v_2}}(T)$. We note T_{v_2} the smallest time T such that K is included in $C_{V_{v_2}}(T)$. Then states that belongs to V_{v+v_2} are protected from the big flood v now and in the future in the presence of smaller floods v_2 when their return period is greater than $\max(T_{v_2}, T_v)$.

Appendix C.3. Indicator calculation of subsection 3.2

Approximations of sets K_v, K_{v+v_2}, viability kernels V_v, V_{v+v_2} and capture basins are performed by the ViabiliTree Sofware Rouquier et al. (2015), Alvarez et al. (2016). The computation code and the related data are available at
https://forgemia.inra.fr/isabelle.alvarez/RAZ13_ia.

The parameter values are set according to Appendix F: $T_m = 8$, $A = 0.392$, $A_0 = 0.00375$, $A_1 = 1$, $C = 70.15$€, $B = 1933$€, $U_{max} = 0.456$ (for personalized campaign), $U_{max} = 0.0$ (for doing nothing). Additional parameters due to simplification in this model are the following: $v_m = 100$cm, $\theta_t = 0.0158$, $\theta_0 = 0.0243$, $\theta_m = 0.272$.

Appendix D. Formalization of indicator 3

Appendix D.1. Model description

We consider three state variables: the average wealth of the population, w (total wealth divided by the population size), the proportion of individuals in the population having implemented the protection measure, α, and the time since the last flood, T. The model also takes into account a one-dimensional control variable, u, the communication effort.

The dynamics of the triplet (T, α, w) is governed by an hybrid system: the continuous part governs the dynamics in the absence of flood

$$(T'(t), \alpha'(t), w'(t)) = F(T(t), \alpha(t), u(t))$$

and the discrete part describes the consequences of a flood event

$$(T(t^+), \alpha(t^+), w(t^+)) = \Phi(T(t^-), \alpha(t^-), w(t^-), v(t^-)).$$

F and Φ are maps defined by :

$$\begin{array}{rcl} F(T, \alpha, u) & = & (1, \\ & & -\frac{log(2)}{T_m - T_a 1_{\tau(t) \leq \tilde{T}}} \alpha(t) + A_1(u(t) + A_0)(1 + A\alpha(t))(1 - \alpha(t)), \\ & & B - Cu) \\ u & \in & [0, U_{max}] \end{array} \tag{D.1}$$

and

$$\begin{array}{rcl} \Phi(T, \alpha, w, v) & = & (0, \\ & & \alpha + \Delta\rho_1(v)(1 - \alpha), \\ & & w - damage(\alpha, v)) \\ v \in & & [0, V_{max}] \text{ if } T \geq T_{min} \\ v = & & 0 \text{ otherwise.} \end{array} \tag{D.2}$$

where $u \in [0, U_{max}]$ is the campaign intensity which can vary with time but which is bounded by U_{max}as in Appendix C. Parameters T_m, T_a, A_0, A_1, B, $\tilde{T}$ and functions $damage(\alpha, v)$ and $\Delta\rho_1(v)$ represent the same quantities as in the Appendix B and C and U_{max} represent the same quantities as in the Appendix C.

V_{max} is the maximal flood intensity expected and T_{min} the minimal time period between two floods expected.

Appendix D.2. Set of anticipated floods

We consider the possibility of successive floods, but we only consider the scenarios satisfying the two following constraints: the intensity of each flood is smaller than a given intensity V_{max} and the time period between two successive floods is larger than a positive time T_{min}. The set of admissible perturbations is then defined by :

$$v \in V(T)$$

with $V(T) = [0, V_{max}]$ if $T \geq T_{min}$ and $\{0\}$ otherwise.

Appendix D.3. Set of acceptable situations

We assume that acceptable situations are those for which the aggregate wealth is greater than 0. They are thus defined by:

$$K := \{(T, \alpha, w) | w \geq 0\}.$$

Appendix D.4. Indicator formalization

To formalize indicator 3, we use the concepts of mathematical viability theory Aubin et al. (2011). This indicator is defined as the indicator function of the guaranteed viability kernel of the set K for the dynamics described by F, Φ, U and V.

Appendix D.5. Indicator calculation of subsection 3.3

Approximations of guaranteed viability kernels are performed following Saint-Pierre's algorithm Saint-Pierre (1994). The computation code and the related data are available at
https://www.comses.net/codebases/e5c17b1f-0121-4461-9ae2-919b6fe27cc4/releases/1.0.0/.
The parameter values are the following:

- $T_m = 7$
- $T_a = 2.835$
- $A_1 = 1$
- $A_0 = 0.00375$
- $U_{max} = 0.170$,
- $\tilde{T} = 39.19$,
- $A = 0.392$,
- $B = 2200$,
- $C = 31.98$,
- $V_{max} = 250$,
- $T_{min} = 10$,
- function $\Delta\rho_1(v)$ is piecewise constant function defined by :

v	0	20	40	60	80	100	120	140	160	180	200
$\Delta\rho_1(v)$	0.0	0.00307	0.00615	0.00922	0.01230	0.01538	0.18464	0.19672	0.20880	0.22088	0.23296
v	220	240	260	280	300						
$\Delta\rho_1(v)$	0.24503	0.25711	0.26587	0.27132	0.27219						

Appendix E. Formalization of indicators 4 and 5

Appendix E.1. Model description: an individual based model

In the individual based model, agents' heterogeneity is taken into account. We consider $i = 1, 2, ...N$ heterogeneous agents, which are spatially distributed. Each of them is characterized by individual wealth $w_i \in \mathbb{R}$ and a boolean b_i which indicates if the agent has an efficient protection against floods or not. Time is discrete.

Heterogeneous agents. Individuals are characterized by different attributes, x: e.g. perceived probability of the risk, perceived consequences of the risk, coping appraisal, flood experience, being in a social network. Each individual has an individual specific attribute level, $a_{x,i}$ for example: having no flood experience or having a strong flood experience, varying from 1 to 5.

Probability of adoption. The protection motivation for each individual to adopt adaptation measures is a function of the different attributes and attribute levels:

$$P((a_{x,i})_{x\in X}) := \frac{c\Pi_{x\in X} or_x^{a_{x,i}}}{c\Pi_{x\in X} or_x^{a_{x,i}} + 1} \tag{E.1}$$

where the attributes x belong to X the full set of attributes, or_x the odds ratio for each attribute, $a_{x,i}$ the individual specific attribute level and c a constant parameter.[2] It can, for example, be derived from a logistic regression.

More precisely, in our model, the set X has five elements (perceived probability of the risk, perceived consequences of the risk, coping appraisal, flood experience and a social network) and all attribute levels take their values in set $V := \{1; 2; 3; 4; 5\}$, then P is a function from V^5 to $\mathbb{R}$.

The protection motivation may be transformed into action with a probability of $1/M$, which is the probability for each individual to adopt adaptation measures. Hence the adoption rate for individual i is: $P((a_{x,i})_{x\in X})/M$ during one time step.

Dynamics. Three phenomena may influence positively the adoption rate:

- floods, characterized by variable v, increase the attribute level a_x associated to the "experience" variable of a proportion β_v of the population. In particular the

[2] The odds are defined as the number of events that produce an outcome over the number of events that do not produce this outcome. The odds ratio measures the strength of association between two events: it is the ratio of the odds of event A in absence of event B divided by the odds of event A in presence of event B.

fifth attribute linked with the network is not modified. Hence, their probability of adoption is impacted. Given v, there exists a function f_v which associates for all individual i its attributes before flood v $(i, (a_{x,i})_{x\in\underline{X}})$ with the new attribute levels after flood v with $\underline{X}$ is X minus the network attribute.

- information campaigns increase the attribute levels a_x associated to the "risk perception" and "coping" variables in the probability of adoption. The network attribute level is also not modified. There is a probability β_u that an individual is targeted and reached by the communication message. Given u, there exists a function f_u which associates for each individual i its attributes before campaign u $(i, (a_{x,i})_{x\in\underline{X}}))$ with the new attribute levels after campaign u.

- the social network may increase the attribute level a_x associated to the "social network" variable in the probability of adoption, depending on the number of neighbors who have adopted a measure.

Two phenomena may decrease the adaptation rate over time:

- protection may fade over time, with a probability Q per time step for each individual.

- protection motivation may also fade overtime, the attribute levels of $\underline{X}$ decrease for a proportion β_g of the population at each time step. There exists a function g which associates for every individual i its attributes before decrease $(i, (a_{x,i})_{x\in\underline{X}}))$ with the new attribute levels after decrease.

Individual wealth is determined in the following way:

- in absence of floods, individual wealth, w_i, increases linearly in time with constant earnings, B_i and decreases with tax payments, which are proportional to individual wealth, rw_i,

- when floods occur, individual wealth decreases with the damage of the flood, which depends on the flood water height and the individual adaptation status. We consider 3 different areas in which individuals may be situated, with different distances to the river and hence differentiated water heights. In these areas, small floods generate water heights of maximum 100 cm, big floods of maximum 250 cm. Call v_i the water height at individual $i's$ position when the flood height is v, we have the following damage:

$$D(v_i, b_i = 0) = a_1 v_i - b_1 v_i^2 + c_1 v_i^3 + d_1 \quad \text{(E.2)}$$

$$D(v_i, b_i = 1) = \begin{cases} a_2 v_i - b_2 v_i^2 + c_2 v_i^3 - d_2 & if \quad v > 80 \\ 0 & otherwise, \end{cases} \tag{E.3}$$

with parameter values as in the general damage function, described in equations (A.1) and (A.2). Individual wealth hence evolves as follows:

$$w_i(t + \Delta T) = w_i(t)(1 - r) + B_i - D(i, v_i, b_i) \tag{E.4}$$

The regulator is an agent on its own:

- the regulator can implement communication policies. The cost of a policy, C_u, is function of the regulation effort, u. It can be different for different policies, C_j, here j=1,2, where 1 corresponds to the "people centred" policy and 2 to the "top-down" policy.
- in the baseline scenarios, regulation effort is constant over time.
- the regulator's wealth, w_r increases linearly with tax income and decreases linearly with the costs of regulation.

$$w_R(t + \Delta T) = w_R(t) + r \sum_{i=1}^{N} w_i(t) - C_u. \tag{E.5}$$

Appendix E.2. Indicator formalization

The inequality indicator represented above determines the number of poor individuals, i.e. for which the individual wealth is below a certain threshold noted $\underline{\mathrm{W}}$, at the end of the time horizon:

$$I_{p1} = card(\{i | W_i(T) < \underline{W}\}).$$

The efficiency indicator determines the increase in population wealth, as measured by difference of the wealth at the end and the beginning of the simulation period, after deduction of the costs of information campaigns:

$$I_{e_2} = \sum_{i=1}^{n} (W_i(T) - W_i(0)) - \sum_{t=1}^{T} C(u(t)).$$

Appendix E.3. Parameter values

- $\lambda = 7$, $N = 1$,
- $C_1 = 200$, $C_2 = 15000$, $r = 0.02$,

- $a_{x,i}(0) \in [1;5]$, $W_i(0) = 0$, $W_r(0) = 0$, $\alpha(0) = 0.2464$,
- $B_i(0) = \begin{cases} B_{10} \in [0;900] \\ B_{10-50} \in [901;1700] \\ B_{50-90} \in [1701;3100] \\ B_{100} \in [3101;5000] \end{cases}$,
- $\bar{B}_i(0) = 1932$,
- $D_i \in [0;35000]$,
- Odds ratios: $or_1 = 1.036665763, or_2 = 2.231593606, or_3 = 1.204434523, or_4 = 1.799138048, or_5 = 2.126908471$ with
  1 :'perceived probability', 2 :'perceived consequences' 3 :'coping appraisal' 4 :'appraisal of past flood experience' 5 :'social network'.

The computation code for the indicator and the related data are available at https://www.comses.net/codebases/b6c94b49-51a9-49db-bc9e-fb853f5acf78/releases/1.0.0/.

Appendix F. Formalization of a common aggregate model with homogeneous agents

We make the following assumptions to derive an aggregate model from the individual-based one: individuals who have a protection measure are uniformly distributed in the network. The first aggregate variable we consider is α the mean proportion of individuals who have a protection measure. Its dynamics between times t and $t + \Delta T$ is a combination of the number of new adoptions (Eq. (E.1)) and the number of abandonments:

$$\alpha(t + \Delta T) = \alpha(t) + \frac{1}{M}\frac{1}{N}(\sum_{i=1}^{N} P((a_{x,i})_{x\in X})))(1 - \alpha(t)) - Q\alpha(t) \qquad \text{(F.1)}$$

As we are considering an aggregate model in continuous time, we first linearize the variations during the time step of size ΔT. We are thus considering the time derivative:

$$\alpha'(t) = \frac{\alpha(t + dt) - \alpha(t)}{dt} = \frac{1}{M\Delta T}(\frac{1}{N}(\sum_{i=1}^{N} P((a_{x,i})_{x\in X})))(1 - \alpha(t)) - Q\alpha(t)) \quad \text{(F.2)}$$

Let us first focus on the effect of the social network on the probability to implement the protection measure. For individual i, this effect is taken into account via its attribute $a_{5,i}$

Figure F.7 displays curves of $P((a_{x,i})_{x\in X})$ as a function of $a_{5,i}$ for several values of $(a_{x,i})_{x\in \underline{X}}$ (the set $\underline{X}$ is the set X minus the network attribute).

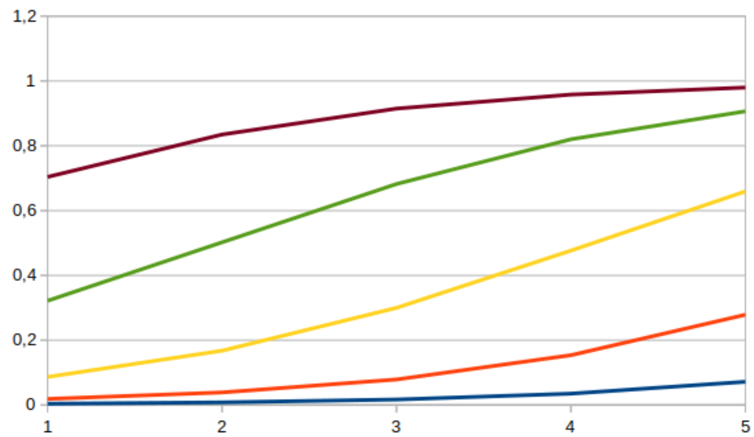

Figure F.7: $P((a_{x,i})_{x\in X})$ as a function of $a_{5,i}$ for several values of $(a_{x,i})_{x\in \underline{X}}$. From the lowest to the highest curve, $(a_{x,i})_{x\in \underline{X}}$ takes the following values : (1,1,1,1), (2,2,2,2), (3,3,3,3), (4,4,4,4) and (5,5,5,5). $c = 0.00035299$, $or_1 = 1.036665763$, $or_2 = 2,231593606$, $or_3 = 1,204434523$ and $or_4 = 1,799138048$.

From this figure we decide, as a first approximation, to consider that

$$\rho := \frac{1}{N}\sum_{i=1}^{N} P((a_{x,i})_{x\in X}))$$

is a linear function of the mean $\frac{1}{N}\sum_{i=1}^{N} a_{5,i}$ of $a_{5,i}$ over the population, where we recall that for each individual i, $a_{5,i}$ may take all the integer values between 1 and 5. Hence if we introduce for the sake of readability the notations:

$$\rho_1 := \frac{1}{N}\sum_{i=1}^{N} P((a_{x,i})_{x\in \underline{X}}), a_{5,i} = 1)$$

which ranges from $\rho_{1,min} := P((1)^4, 1)$ to $\rho_{1,max} := P((5)^4, 1)$, we obtain

$$\rho \approx \rho_1 + \left(\frac{1}{N} \sum_{i=1}^{N} (a_{5,i} - 1)/4 \right) A\rho_1 \tag{F.3}$$

with

$$A = \frac{P((5)^4, 5) - P((5)^4, 1)}{P((5)^4, 1)} \tag{F.4}$$

to ensure that when all attributes in the population equal 5, $\rho = P((5)^5) = P((5)^4, 5)$.

For each individual i, $a_{5,i}$ ranges from 1, when no neighbour of i has implemented the protection measure, to 5, when all the neighbours of i have implemented the protection measure. As we assumed that the individuals having implemented the protection measure are uniformly distributed on the graph, we deduce that $(\sum_{i=1}^{N} a_{5,i})/N$ is a linear function of α, which equals 1 when $\alpha = 0$ and 5 when $\alpha = 1$. Thus $(\sum_{i=1}^{N} a_{5,i})/N = 1 + 4\alpha$. Inserting this expression into Equation (F.3) yields

$$\begin{aligned} \rho &\approx \rho_1 + \alpha A \rho_1 \\ &= (1 + \alpha A)\rho_1 \end{aligned} \tag{F.5}$$

and we approximate equation (F.2) by

$$\alpha'(t) = \frac{1}{M\Delta T} (\rho_1 (1 + A\alpha(t))(1 - \alpha(t)) - Q\alpha(t)) \ . \tag{F.6}$$

When an information campaign u occurs, the attributes of the proportion β_u of individuals who are reached by the campaign are modified by function f_u. Hence an information campaign causes a jump of ρ_1 and the mean value of ρ_1 just after the campaign u and denoted by $\overline{\rho_{1,u}}$ equals:

$$\begin{aligned} \overline{\rho_{1,u}} &= \tfrac{1}{Card(V)^{4N}} \textstyle\sum_{(a_{x,i})_{x \in \underline{X}} \in V^{4N}} \tfrac{1}{N} \sum_{i=1}^{N} \left(\beta_u P(f_u((a_{x,i})_{x \in \underline{X}})), 1) + (1 - \beta_u) P((a_{x,i})_{x \in \underline{X}}, 1) \right) \\ &= \tfrac{1}{Card(V)^4} \textstyle\sum_{(a_x)_{x \in \underline{X}} \in V^4} \left(\beta_u P(f_u((a_x)_{x \in \underline{X}}), 1) + (1 - \beta_u) P((a_x)_{x \in \underline{X}}, 1) \right) \end{aligned} \tag{F.7}$$

Next, the influence of the campaign decreases with time due to the attribute level decrease described by function g. Actually, at each time step a proportion β_g of the population undergoes this attribute level decrease and the mean value of the subsequent decrease of ρ_1 denoted by $\overline{\Delta\rho_{1,g}}$ equals :

$$\begin{aligned}\overline{\Delta\rho_{1,g}} &= \tfrac{1}{Card(V)^{4N}} \sum_{((a_{x,i})_{x\in\underline{X}})\in V^{4N}} \tfrac{1}{N} \sum_{i=1}^{N} \left(\beta_g(P((a_{x,i})_{x\in\underline{X}},1) - P(g((a_{x,i})_{x\in\underline{X}} \tfrac{1}{Card(V)^4}),1)\right) \\ &= \tfrac{\beta_g}{Card(V)^4} \sum_{(a_x)_{x\in\underline{X}}\in V^4} (P((a_x)_{x\in\underline{X}},1) - P(g((a_x)_{x\in\underline{X}}),1))\end{aligned} \tag{F.8}$$

Hence, the mean consequence of campaign u at time 0 is described by the values of ρ_1 which decrease with time :

$$\rho_1(t) = \max(\overline{\rho_{1,u}} - \overline{\Delta\rho_{1,g}}t, \rho_{1,min}) \tag{F.9}$$

and then the area between this curve and a the constant value $\rho_{1,min}$ equals $\frac{(\overline{\rho_{1,u}}-\rho_{1,min})^2}{2\overline{\Delta\rho_{1,g}}}$.

So, if the cost of campaign u is C_u, the infinitesimal cost c according to its impact on ρ_1 denoted by c equals:

$$c = \frac{C_u}{\frac{(\overline{\rho_{1,u}}-\rho_{1,min})^2}{2\overline{\Delta\rho_{1,g}}}} \tag{F.10}$$

Now we have to define u_{max}, the maximal instantaneous campaign intensity. We choose it such as making a maximal campaign during one unit time has the same cost as a campaign at one time of the discrete model, C_u.

Hence $u_{max} = \frac{(\overline{\rho_{1,u}}-\rho_{1,min})^2}{2\overline{\Delta\rho_{1,g}}}$.

Finally, if we enlarge the campaign possibilities to consider control functions $u(t) \in [0, u_{max}]$, we can describe the dynamics by:

$$\alpha'(t) = \frac{1}{M\Delta T}((u(t) + \rho_{1,min})(1 + A\alpha(t))(1 - \alpha(t)) - Q\alpha(t)) \tag{F.11}$$

When a flood v occurs, the attributes of the proportion β_v of individuals who are reached by the flood are modified by function f_v. Hence a flood causes a jump of ρ_1 and the mean value of this jump compared to the difference between ρ_1 and its maximal value $\rho_{1,max}$ denoted by $\overline{\Delta\rho_{1,v}}$ equals:

$$\begin{aligned}\overline{\Delta\rho_{1,v}} &= \tfrac{1}{Card(V)^{4N}} \sum_{((a_{x,i})_{x\in\underline{X}})\in V^{4N}} \tfrac{1}{N} \sum_{i=1}^{N} \left(\beta_v \tfrac{P(f_v((a_{x,i})_{x\in\underline{X}}),1)-P((a_{x,i})_{x\in\underline{X}},1)}{\rho_{1,max}-P((a_{x,i})_{x\in\underline{X}},1)}\right) \\ &= \tfrac{\beta_v}{Card(V)^4} \sum_{(a_x)_{x\in\underline{X}}\in V^4} \left(\tfrac{P(f_v((a_x)_{x\in\underline{X}}),1)-P((a_x)_{x\in\underline{X}},1)}{\rho_{1,max}-P((a_x)_{x\in\underline{X}},1)}\right)\end{aligned} \tag{F.12}$$

Hence just after flood v, the value of ρ_1 can be approximated by $\rho_1+\overline{\Delta\rho_{1,v}}(\rho_{1,max}-\rho_1)$, and this value decreases with time due to function g as described above, so the mean consequence of flood v at time 0 is described by the values of ρ_1 which decrease with time :

$$\rho_1(t) = \max(\rho_1 + \overline{\Delta\rho_{1,v}}(\rho_{1,max} - \rho_1) - \overline{\Delta\rho_{1,g}}t, \rho_{1,min}) \tag{F.13}$$

Consequently, from (F.6), the evolution of α after a flood in absence of other flood or information campaign is described by :

$$\alpha'(t) = \frac{1}{M\Delta T}(\max(\rho_1+\overline{\Delta\rho_{1,v}}(\rho_{1,max}-\rho_1)-\overline{\Delta\rho_{1,g}}t, \rho_{1,min})(1+A\alpha(t))(1-\alpha(t))-Q\alpha(t)) \tag{F.14}$$

We note that $\max\{t \geq 0 | \rho_1(t) > \rho_{1,min}\} \leq \frac{(\rho_{1,max}-\rho_{1,min})}{\overline{\Delta\rho_{1,g}}} := T$ and we choose to approximate these dynamics on interval $[0;T]$ by:

$$\begin{cases} \alpha(0) & = \alpha_0 + \Delta_v\alpha_0 \\ \alpha'(t) & = -\frac{1}{M\Delta T}(Q + x_v(\alpha_0))\alpha(t)) \end{cases} \tag{F.15}$$

with a jump of α_0 proportional to the one of ρ_1:

$$\Delta_v\alpha_0 := \overline{\Delta\rho_{1,v}}(1 - \alpha_0) \tag{F.16}$$

and with the constraint that if the system governed by (F.6) is at equilibrium before the flood, that means that the value of ρ_1 denoted by $\rho_{1,0}$ equals

$$\rho_{1,0} = \frac{Q\alpha_0}{(1 + A\alpha_0)(1 - \alpha_0)} \tag{F.17}$$

then both systems (F.15) and

$$\begin{cases} \alpha(0) & = \alpha_0 \\ \alpha'(t) & = \frac{1}{M\Delta T}(\max(\rho_{1,0} + \overline{\Delta\rho_{1,v}}(\rho_{1,max} - \rho_{1,0}) - \overline{\Delta\rho_{1,g}}t, 0)(1 + A\alpha(t))(1 - \alpha(t)) - Q\alpha(t)) \end{cases} \tag{F.18}$$

have the same value at time T.
Let us denote by $\tilde{\alpha_0}$ the solution of (F.18), we then want that :

$$\tilde{\alpha_0}(T) = (\alpha_0 + \Delta\alpha_0)e^{-\frac{1}{M\Delta T}(Q+x_v(\alpha_0))T} \tag{F.19}$$

that is

$$x_v(\alpha_0) = -\frac{M\Delta T}{T}ln(\frac{\tilde{\alpha_0}(T)}{\alpha_0 + \Delta\alpha_0}) - Q \tag{F.20}$$

We then define $\overline{x}$ the mean value of $x(\alpha_0)$ over α_0 which equals:

$$\overline{x}_v = \int_{\alpha_0=0}^{1} -\frac{M\Delta T}{T} ln(\frac{\tilde{\alpha_0}(T)}{\alpha_0 + \Delta\alpha_0}) - Qd\alpha_0 \tag{F.21}$$

and choose to approximate (F.18) over $[0;T]$ when a flood v occurs at $t = 0$ and without any information campaign by

$$\begin{cases} \alpha(0) & = \alpha_0 + \Delta_v \alpha_0 \\ \alpha'(t) & = -\frac{1}{M\Delta T}(Q + \overline{x}_v)\alpha(t)) \end{cases} \tag{F.22}$$

We finally have to define the maximal value V_{max} of the variable $v(t)$ which will range over all possible floods and extrapolate from the individual based model which can provide triplets $(v, \Delta\rho_{1,v}, \overline{x}_v)$ functions from v to $(\Delta\rho_{1,v}, \overline{x}_v)$, we denote by $\Delta\rho_1(v)$ and $\overline{x}(v)$. And then, combining (F.11) and (F.22), we obtain the dynamics description including flood $v(t)$ and information campaign $u(t)$ possibilities:

$$\begin{cases} \alpha(t^+) & = \alpha(t^-) + \Delta\rho_1(v)(1-\alpha) \text{ if } v(t) > 0 \\ \alpha'(t) & = \frac{1}{M\Delta T}((u(t) + \rho_{1,min} 1_{\tau(t)\leq T})(1 + A\alpha(t))(1-\alpha(t)) - (Q + \overline{x}_v 1_{\tau(t)\geq T})\alpha(t)) \\ \tau(t^+) & = 0 \text{ if } v(t) > 0 \\ \tau'(t) & = 1 \\ u(t) & \in [0; \rho_{1,max} - \rho_{1,min}] \\ v(t) & \in [0; V_{max}] \end{cases} \tag{F.23}$$

The second aggregated variable we consider is the average wealth $w := \frac{1}{N} w_R + \sum_{i=1}^{N} w_i$ with the discrete dynamics from Eq. (E.4) and (E.5) when a campaign u is carried out and a flood $v(t)$ occurs at t:

$$w(t + \Delta T) = w(t) + \frac{\sum_{i=1}^{N} B_i}{N} - C_u - \frac{\sum_{i=1}^{N} D(i, v(t), b_i)}{N}$$

With the assumption of homogeneous distribution of protected individuals, $\frac{\sum_{i=1}^{N} D(i,v,b_i)}{N}$ can be approximated by:

$$\begin{aligned} \frac{\sum_{i=1}^{N} D(i,v,b_i)}{N} &\approx \frac{\sum_{i=1}^{N} \alpha D(i,v,1) + (1-\alpha)D(i,v,0)}{N} \\ &= \overline{D(v,1)}\alpha + \overline{D(v,0)}(1-\alpha) \end{aligned}$$

with $\overline{D(v,b)} := \frac{\sum_{i=1}^{N} D(i,v,b)}{N}$.

For the information campaign, we have derived the instantaneous cost c from (F.10).

Hence, the dynamics of w can be described by an hybrid system:

$$\begin{array}{ll} w(t^+) & = w(t^-) - (\overline{D(v(t),1)}\alpha(t) + \overline{D(v(t),0)}(1-\alpha(t))) \text{ if } v(t) > 0 \\ w'(t) & = \frac{1}{\Delta_T}(\overline{B} - cu(t)) \\ u(t) & \in [0; \rho_{1,max}] \\ v(t) & \in [0; V_{max}] \end{array} \tag{F.24}$$

with $u(t)$ the intensity of campaign u at time t.

This model is then based on three state variables: the proportion α of the population who has adopted protection measures, an indicator of populations' aggregate wealth, w, and the time period duration since last flood, τ. It also takes into account a one-dimensional control variable, u, which corresponds to the communication effort, and a certain number of flood events that are characterized by their water height v. From (F.23) and (F.24), the dynamics are given by the hybrid system:

$$\left\{ \begin{array}{ll} \alpha(t^+) & = \alpha(t^-) + \Delta\rho_1(v)(1-\alpha) \text{ if } v(t) > 0 \\ \alpha'(t) & = \frac{1}{M\Delta T}((u(t) + \rho_{1,min})(1 + A\alpha(t))(1-\alpha(t)) - (Q + \overline{x}_v 1_{\tau(t) \leq T})\alpha(t)) \\ \tau(t^+) & = 0 \text{ if } v(t) > 0 \\ \tau'(t) & = 1 \\ w(t^+) & = w(t^-) - (\overline{D(v(t),1)}\alpha(t) + \overline{D(v(t),0)}(1-\alpha(t))) \text{ if } v(t) > 0 \\ w'(t) & = \frac{1}{\Delta_T}(\overline{B} - cu(t)) \\ u(t) & \in [0; \overline{\rho_{1,u}} - \rho_{1,min}] \\ v(t) & \in [0; V_{max}] \end{array} \right. \tag{F.25}$$

with

$$\overline{D(v,1)} = D(v,1)/3 + D(v-50,1)/3 + D(v-100,1)/3$$

and

$$\overline{D(v,0)} = D(v,0)/3 + D(v-50,0)/3 + D(v-100,0)/3.$$

We can simplify the equation writing by setting :

- $B := \frac{1}{\Delta_T}\overline{B}$
- $C := \frac{1}{\Delta_T}c$
- $U_{max} := \overline{\rho_{1,u}} - \rho_{1,min}$

- $damage(\alpha, v) := \overline{D(v(t), 1)}\alpha(t) + \overline{D(v(t), 0)}(1 - \alpha(t))$
- $A_1 := \frac{1}{M\Delta T}$
- $T_m := \frac{ln(2)M\Delta T}{Q}$
- $T_a := T_m - \frac{ln(2)M\Delta T}{Q+\overline{x}_v}$

Then Eq. F.25 becomes :

$$\begin{cases} \alpha(t^+) & = \alpha(t^-) + \Delta\rho_1(v)(1-\alpha) \text{ if } v(t) > 0 \\ \alpha'(t) & = -\frac{log(2)}{T_m - T_a 1_{\tau(t)\leq T}}\alpha(t) + A_1(u(t) + \rho_{1,min})(1 + A\alpha(t))(1-\alpha(t)) \\ \tau(t^+) & = 0 \text{ if } v(t) > 0 \\ \tau'(t) & = 1 \\ w(t^+) & = w(t^-) - damage(\alpha, v) \text{ if } v(t) > 0 \\ w'(t) & = B - Cu(t)) \\ u(t) & \in [0; U_{max}] \\ v(t) & \in [0; V_{max}] \end{cases} \tag{F.26}$$