Community Dynamics in case of Critical Hydrogeological Phenomena: Some Simulated Scenarios

Rino Falcone and Alessandro Sapienza[1]

Institute of Cognitive Science and Technology -
National Research Council of Italy(ISTC-CNR), 00185 Rome, Italy
rino.falcone@istc.cnr.it, alessandro.sapienza@istc.cnr.it,

Abstract. The problem of critical floods has raised a lot of interest in the last few years, due to the significant losses they can cause, both in economic terms and especially in terms of injuries and human lives. In this work we provide some useful insights about critical weather phenomena, focusing on the strict relationship between citizens and the authority. We realized a simulative agent-based platform in which the citizens (modeled through cognitive agents) need to identify -on the basis of their information sources and of the trustworthiness attributed to them- the risks to which they are exposed and act accordingly. The main results of this work are: 1) the identification of the most significant indexes to evaluate the citizens' performance; 2) a detailed analysis of some possible strategies for the citizens and for the authority; 3) the identification of what we call "dissonance between evaluation and action", i.e. the fact that in a risky situation I could trust my sources and what they report, but still acting differently from what they suggest.

Keywords: trust, social simulation, multi-agent systems

1 Introduction

Every year the whole world is subjected to enormous inconvenience due to critical weather phenomena and in particular floods. The most important issue is the serious loss in terms of lives. This is the primary reason why governments should seriously care about floods (their prevention, but also their management and monitoring). Moreover, hydrogeological disasters often produce a huge economic loss [13]. Cuñado & Ferreira [7] report that floods represented 40% of all natural disasters between 1985-2009. Guha-Sapir et al. [11] state that in 2013 hydrogeological disasters took the largest share in natural disaster occurrence (48.2%) and that the most expensive hydrogeological disaster ever registered happened in Thailand in 2011, causing US$ 41.4 billion of damages. The point is that the whole damage is not so easy to estimate. The direct damages, produced to buildings, infrastructures, houses, streets and farming, are easier to detect. Actually, these natural disasters can also cause a series of secondary and indirect damages, much more difficult to quantify. Let's just think to psychological traumas [14], or other kind of disease [12] that a critical event can provoke, maybe due to the risk of dying, to the loss of material goods or even loved ones.
Grothmann & Reusswig [10] report that "self-protective behavior by residents of flood-prone urban areas can reduce monetary flood damage by 80%, and reduce the need for

public risk management". Then, while floods represent a very serious threat both to the authorities and the population, the adoption of self-protective behavior by citizens can substantially reduce the problem of direct and indirect damages.

The local authorities are crucial in this situation. Their role is not just helping people after a disaster, but they should instead stimulate preventive behaviors, which can in turn minimize the future risks. The damage a population suffers strictly depends on the strong relationship with authority. Both the citizens and the authority have their own goals. In particular, each citizen wants to protect its own interests, while the authority has to protect and safeguard the collective interest. In general their interests should converge, but this is not always true; it is essential to study their behavior in order to understand how they relate to each other and what is the outcome of their interaction.
In this work we propose a multi-agent system approach, in which the citizens and the authority are modeled through cognitive agents. We intend to provide a useful tool to analyze the problem both from the authority's and from the citizens' point of view.

2 State of the art

Identifying and measuring risks and vulnerabilities before a disaster occurs is essential to reduce the impact of the disaster itself. The current literature proposes a lot of studies on natural risks, even if just a few of them focuses on the human behavior [1][21]. Moreover, the risk attitude is domain specific [24], so it is not possible to take into account results concerning different natural phenomena, applying them to floods.
The classical approach to the problem is that of survey [3][15]. After defining a psychological model for the population, this method aims to exploit surveys to identify the correlations among the psychological variables introduced in the model.
In [10] the authors state that the monetary damage can be reduce by the 80% just thanks to the citizens' adaptation measures. They propose a socio-psychological model explaining why some people adopt precautionary measures while others do not, showing the correlations between the model parameters and the citizens' actions.
Another way to deal with this topic is to take into account the historical evolution of the phenomena happened in a given geographical area: the way they happened, their intensity, frequency etc. For instance [2] analyzed all the historical natural events occurred in a mountain area in the Central Italian Alps, producing a georeferenced database. The authors show how making use of this historical information is fundamental to identify hypothetical critical scenarios and to evaluate the territorial threats and then to handle future emergencies.
The simulative approach is normally used to estimate the damage that an event can cause [13][18]. For instance, in [13] the authors propose a model simulating critical scenarios and evaluating the expected economic loss.
Alternatively, social simulations can be used to model citizens' decision in the case of critical weather phenomena. In [20], the authors create a computerized simulation model for capturing human behavior during flood emergency evacuation. The idea is that of producing a useful tool for assisting the decisions of emergency managers. Their complex model, which can be summarized in the four phases of *concern*, *danger recognition*, *acceptance* and *evacuation decision*, is very focused on the citizen, but underes-

timates the relationship with the sources reporting the information to it.
Another critical point is the performance evaluation. Usually, the platforms simulating human response consider the number of citizens successfully evacuated or alive after the event. This is truly the most important dimension: we want our citizens to be safe. But this dimension becomes important in a short time window. In a longer period view, it is necessary to consider other indexes. In our work, we want to provide a novel approach to deal with this topic, exploiting trust and multi-agent systems. We investigate the citizens decision to take precautionary actions or not, thus we consider a medium/long term window. In our approach we use social simulations and a multi-agent system to study the problem, modeling both the citizens and their sources as cognitive agents and also focusing on their interaction, mediated by trust. This way to analyze the problem allows showing some interesting outcomes, as we have the possibility to put into the same world a huge number of agents interacting with each other and we can infer what social phenomena emerge. Moreover, this approach allows us to study the role and the influence of the individual actions on the general context, changing the parameters referred to the individuals and observing the results on the society.

3 The framework

The simulations were realized using NetLogo [25], an agent-based framework, while the trust model was implemented in Java and imported as a plug-in into NetLogo.
Given a population distributed over a wide area, some weather phenomena happen over time in the world with a variable level of criticality. Our classification of the events is based on [2], except that, as we are not interested in the difference between low and no damages events, we considered them to be the same event. Consequently, we implemented in the framework three possible events: event 1 (light or no event), event 2 (medium event) and event 3 (critical event). Moreover [2] provides the frequency with which these events occur: 77,91 *light event*; 17,44% *medium event*; 4,65% *critical event*. Each of these events can cause damage to citizens' personal capital and to the authority's social capital. The events happen in a time window covering a long period (months); we are not analyzing short-term situations.

The population is modeled through cognitive agents (citizens), randomly distributed and having the necessity to identify the future weather event on the basis of their information sources and of the trustworthiness they attribute to these different sources:

1. Citizens' *personal judgment*, based on the direct observation and evaluation of the phenomena.
2. *The authority*, which distributes into the world weather forecast, trying to prepare citizens to what is going to happen.
3. Observation of the *others' behavior* (other agents in the radius of 3 NetLogo patches): agents are in some way influenced by community logics, tending to partially or totally emulate their neighbors' behavior. According to this source, the probability of each event is directly proportional to the number of neighbors making the related decision.

They possess an initial capital to administer, making the correct investments; thus they need to understand which is the most convenient choice for them, according to the costs and damages related to each decision. Here we focus on direct damages, we are not considering indirect damages, due to the difficulties to compute them. Other works tried to model them as a percentage of direct damages [23]; we believe it is a much more complex issue.

The authority informs promptly the citizens about the weather phenomena. Notice that, being just forecasts, it is not certain that what it reports is really going to happen. The probability that a forecast is correct is linked to the standard deviation of the source. Furthermore, the citizens can evaluate the situation on their own and can also exploit the evaluations produced by their neighbors (seeing the effect of their decisions). The social source is the result of the agents' decisions aggregation in the neighborhood: if a neighbor has not decided, it is not considered. Then they estimate the probability that each event occurs, considering all the information they can access and aggregating each single contribute according to the corresponding trust value. When the event ends, the citizens adjust the trust values of their sources, on the basis of the corresponding performances. We repeat this phase 100 times, enough to properly evaluate the sources. After that, each citizen possesses a final capital and it has avoided a given amount of damage; the same applies to the authority. The best strategy will maximize these two dimensions, but it is not sure that the strategy maximizing the performance of the citizens maximizes also the authority's performance.

3.1 Managing information through trust

According to [5], trusting an information source *s* means to use a cognitive model based on the dimensions of competence and reliability/motivation of the source, which in turn may arise for different reasons: *direct experience* with the source on that specific kind of information content; *recommendations* of other individuals about *s* or *reputation* (the shared general opinion of others about s) on that specific information content [6][16][17][26]; the *categorization* of *s* (it is assumed that a source can be categorized and that its category is known), exploiting inference and reasoning (analogy, inheritance, etc.)[4][8][9].

The trust model used in this work exploit the trust definition defined in [5] and mainly relies on direct experience to produce evaluations. Actually, we also use the categorization analysis for distinguishing the sources on the basis of their different nature.

This model is composed by a set of citizens C, sources S, and information I. Each citizen c_k evaluates the performance of its information sources, in order to understand how trustworthy they are, concerning a specific kind of informative task. They will use the function $trustOnS : S$ x $I \rightarrow T$,where T is a real value defined in the range $[0, 1]$, producing a different evaluation for each source according to their direct experience.

Initially, there is no evidence about the sources' performance, and then these values are set to 0.5 (a situation of uncertainty between trust and distrust). Each source s possesses the information i, represented with a probability density function (PDF), divided into 3 segments (seg_1, seg_2 and seg_3), as there are the 3 possible outcomes (light, medium and critical event). The citizens can access the PDF through the function $getInfo : S$ x $T \rightarrow I$. Here the trust value is fundamental. In fact, the information obtained with getInfo is not exactly the one reported by the source, but it is properly manipulated according to trust: the citizens will use it as a weight to smooth the PDF.

The idea is that we trust on what the source says proportionally to how much we trust the source itself. The individual segments of the PDF are smoothed as in Equation 1. The Equation 2 has the purpose of normalizing the PDF (in order to be a PDF, its area needs to be equal to 1). Once estimated the PDF for each information source, they are aggregated through $aggr : I$ x $I \rightarrow I$. Each agent initially possesses a global distribution (global evidence or ge) with no evidence/information. Then it will add the information coming from each source. Here (equation 3) we use the classical Bayesian logic, recursively on each source:

$$newSeg1_j = (1 + (seg_j - 1) * trustOnS(s, i)) \tag{1}$$

$$newSeg2_j = \frac{newSeg1_j * N}{\sum_{j=1}^{N} newSeg1_j} \tag{2}$$

$$newGe = aggr(ge, i) = \frac{ge * i}{NF} \tag{3}$$

Here N is the number of segments and it is equal to 3; the index j goes from 1 to N. The output $newSeg1_j$ of Equation 1 is the new value of the segment, but it still needs to be normalized. This is done in Equation 2, which in fact takes as input $newSeg2_j$ to produce $newSeg2_j$. NF is a normalization factor that, as for i, ensures ge is still a probability density function. In other words $newGe$, that is the global evidence that an agent has, is computed as the product of the old ge and the new contribute reported by the source. The probability that each event will happen is obtained by integrating information i in the segment representing the specific event. The citizens will reason about these probabilities to make their decisions.

3.2 Updating trust

Our citizens need to adapt to their world, which in this framework means to produce a trust evaluation [19][22] of their information sources, understanding how reliable they are. As mentioned above, at the beginning they possess a neutral trust value (the initial trust is 0.5), which is the starting point for feedback on trust. The new trust value ($newT_s$: trust on the source s) is computed as the weighted mean of the old evaluation t_s and the new performance $newPerformance_s$:

$$newT_s = \frac{\alpha * t_s + \beta * newPerformance_s}{\alpha + \beta} \tag{4}$$

$$\beta = |AvoidedDamage - IncurredCost| \tag{5}$$

$$\beta = |IncurredDamage - IncurredCost| \tag{6}$$

In Equation 4 $newPerformance_s$ is obtained comparing what the source said with what actually happened. We take into account just a portion of the reported PDF, i.e. the estimated probability of the actually occurred event.

Here α and β are respectively the weights of the old trust value and the newly-realized experience. In particular α has a fixed value equal to 10; on the contrary, β changes in the range $[0, 10]$ on the basis of the risk to which the agent is subjected, computed as the effective damage and the cost of my decision. In particular, if the source suggests to invest (*critical* and *medium events*) the agent will consider the damage it avoided thanks to the source as in Equation 5 (or that it would have avoided if it had listened to it), while for *light events'* forecasts it will consider the incurred damage, as in Equation 6. In both cases the agent will take into account the decision-making cost.

3.3 Citizens' description

One of the parameters characterizing the citizens is the *trust they have in their information sources*. This is a dynamic value, changing because of direct experience (see Section 3.2). Each citizen is also characterized by its ability to see and to read the phenomena. For representing these abilities, we associated with the citizens' evaluations a value of *standard deviation* related to the meteorological events. In the simulations we used the value 0.7, producing a correctness of 45% for agents' personal evaluations. This value seems to us to represent more realistically the citizen's ability to make predictions on his own.
Further, citizens possess an initial *monetary capital*; they want to save it, but it could decrease in time. Each citizen decides if to invest its capital to make security modifications to its own property, reducing or even deleting the possible damage in case of an event. If it does not, it exposes itself to the risk of a possible high damage.

3.4 The authority

The authority wants to inform citizens about what is going to happen and to stimulate them to invest in order to reduce possible damages. We suppose that it is able to inform all the citizens with a high level of correctness. Its forecasts are produced using a standard deviation of 0.5, meaning that it will have a correctness of 70%. As a choice, we made that the information coming from the authority has a greater correctness than that coming from personal evaluation. This is reasonable, as the authority possesses the tools to make a good prediction, while usually the individual citizens do not.
Even the authority has a capital, which can be used to stimulate citizens to take preventive measures for the incoming events. In particular, there are three possible strategies. A *punitive authority* fines citizens if it asks them to take measures and they do not do it. However, it will not discover all the guilty citizens, but just a percentage of them. The fine value is equal to the maximal investment and the fine probability is 20%. The fines increase the capital of the authority. An *encouraging authority* monetarily helps citizens to take measures; if the citizens make an investment, they will receive an incentive equal to the 50% of the investment. A *punitive and encouraging authority* fines citizens if they do not take measures and it helps them if they make the investment.

In addition to this, the authority suffers damage due to the wrong choices of citizens. In fact when the population is affected by a *medium* or *critical* event there will be the necessity to help it: the cost of hospitalization for the wounded, the cost of restructuring infrastructures and the cost of helping population, etc. The authority will have to act and that will consequently corrode its capital. In practice, it needs to understand if it is better to invest in the preventive phase or in the intervention phase, after the event.

3.5 How citizens decide

The citizens need to identify the most convenient decision in every situation, considering the information they have on the specific context in which they act. They can make the *maximal investment*: in this case the damage is reduced to zero for *light* and $medium$ events and it is minimal for $critical$ events. This is the most conservative choice. They can make the *medium investment*: even in this case there are no damages for $light$ and $medium$ events, but there is an important damage for $critical$ events. At last, they can decide *not to invest*: this decision allows saving money, but it exposes the citizens to high damages in case of $medium$ events and very high damages in case of $critical$ events.

From the global evidence ge described in Section 3.1, the citizens subjectively estimate the probability with which each event will occur: P(e1), P(e2) and P(e3). Their final decision depends on 1) the probability that each specific event occurs (based on the information coming from their information sources), 2) the fixed costs related to each decision, 3) the possible damage depending on the event that is going to happen. The computation of these costs is made using the formulas 7, 8 and 9.

$$PCMI = MI + \frac{MaxD}{4} * P(e3) - Inc \tag{7}$$

$$PCmI = \frac{MI}{2} + \frac{MaxD}{2} * P(e3) - \frac{Inc}{2} + \frac{F}{2} * P(F) \tag{8}$$

$$PCNoI = MaxD * P(e3) + \frac{MaxD}{2} * P(e2) + F * P(F) \tag{9}$$

Here $PCMI$, $PCmI$ and $PCNoI$ are respectively the probabilistic costs for the maximal, medium and no investment, $MI = 1$ is the maximal investment, $MaxD = 10$ is the maximal damage, $Inc = 0.5$ is the maximal incentive, $F = 1$ is the fine amount, $P(F) = 0.2$ is the fine probability.

In the Equations 7, 8 and 9 incentives and fines are considered (or not considered) according to the authority's profile. These formulas take as input the actual cost an agent has to pay taking a given choice and the potential damage that it could suffer, providing just a probabilistic estimation. What it will pay depends on its decision and on the event that will actually happen.

We define this kind of agents ESC (exploiting sources and costs). This is the most possible rational agent in this context, as it takes into account all the information it has. However, not all the citizens decide to use the same logic: someone could just focus on a part of these data. To model that, we introduced in the simulation five agent's type.
Random agents do not consider any information about the event, and then their decision is absolutely random. This is the most basic kind of agent.
A Priori agents (AP agents) consider the a priori probabilities of the events, which characterize the world, but do not refer to the specific situation. It acts considering the most probable event; therefore it will always make the same choice.
A Priori and Costs agents (APC agents) are able to evaluate both the a priori probabilities and the costs and damages corresponding to each decision. Although they produce a better evaluation than AP and random agents, their decisions are still context-independent, then they will always take the same choice.

Exploiting Sources agents (ES agents) estimate the events' probability using the available information sources. Then they will decide according to the most probable event, just following the sources and their trustworthiness.
Exploiting Source and Costs agents (ESC agents) are the most complete agents, exploiting all the available information.

It is worth noting that while the fourth kind of agent acts maximizing the probability to guess the event, the fifth type has the aim of minimizing the possible losses. These two different goals lead to different choices and performances.

3.6 Output's parameters

In order to evaluate the agents' performance in each scenario, it is necessary to identify the most representative dimensions. The most intuitive is the *final capital*. It provides a representation of how good is the citizen in saving money. This would be enough if the citizens' capital were not influenced by the authority. Given that, we need also to take into consideration the citizen's ability to avoid damages. This dimension is crucial, since we do not just want them to save money, but to be safe. The *final capital* and *the avoided damage* need to be considered together as they provide a partial view of the performance if taken individually: an agent performs properly if it saves enough capital and it avoids a high percentage of damage. These dimensions are available both for the citizens and the authority. Another dimension is the *percentage of successes* the citizens have in facing a given type of event with the adequate investment. Finally, we consider the *percentage of times the citizens follow what a specific source reports*. In particular, we will use it for the authority.

4 The simulation

In this scenario, we identify the performance of each agent's profile, starting from the simplest to the most sophisticated one. Experimental setting: number of citizens = 200; citizens' initial capital = 100 units; authority reliability = 0.5, which implies a correctness of 70%; authority's profile = punitive, encouraging, punitive and encouraging; authority's initial capital = 20000 units; maximal investment = 1 unit; medium investment = 0.5 units; maximal damage = 10 units; medium damage = 5 units; fine amount = 1 unit; fine probability = 20%.

Table 1a and Table 1b report the final capital and the avoided damage for all the kind of agent we analyzed. Table 2 provides instead in grayscale the sum of these two dimensions, which is a much more useful index. The first strategy is the *random* one. The agents adopting it do not exploit their information at all, randomly choosing. Clearly, they will identify the correct event just once in three, unnecessarily wasting their capital when there is no risk and exposing to a high risk without investing. Their final capital is very low, even below zero, and also the avoided damage is very low.

After random agents, *AP agents* evaluate the situation with a priori information, i.e. based on the event distribution in the world. They react to the most likely to happen

Table 1: (a)*Final capital* and (b)*avoided damage* of random, AP, APC, ES and ESC agents by type of authority

(a) *Final capital*

	punitive	encouraging	P&E
random	-8.49	19.07	17.07
AP	-38.34	-33.88	-38.91
APC	26.35	51.59	51.92
ES	47.31	59.57	59.46
ESC	36.92	54.67	54.9

(b) *Avoided damage*

	punitive	encouraging	P&E
random	77.64	77.75	77.22
AP	0	0	0
APC	110.56	110.89	110.11
ES	104.64	106.64	105.35
ESC	116.29	119.17	117.77

Table 2: *Final capital* plus *avoided damage* of random, AP, APC, ES and ESC agents by type of authority

	punitive	encouraging	P&E
random	69.15	96.82	94.29
AP	-38.34	-33.88	-38.91
APC	136.91	162.48	162.03
ES	151.95	166.21	164.81
ESC	153.21	173.84	172.67

event, which in this case is the light event: they will never make an investment, always suffering all the damages. Their performance is even worse than the random agent's one. Their capital assumes a very negative value, while their avoided damage is always equal to zero, as they do not make investments.

APC agents start making considerations about the costs and damages linked to their decisions. Their performance seems to be good enough. Even if they do not use their information sources, they know that each decision is associated with a cost, but also a risk, a possible damage. Thanks to this knowledge, they get a good performance.

Differently from APC, *ES agents* exploit just the information of their sources, but they ignore costs and damages. Their strategy aims to maximize the probability to guess the event. Thanks to that they obtain a high performance, both in terms of final capital and avoided damage.

At last, the *ESC* agents use all the available information, with the strategy of minimizing the risk: they want to suffer as less damage as possible. ES's and ESC's performances are very similar. The firsts have a higher final capital, while the seconds get a higher avoided damage. As we can see from Table 2, the performance of ES and ESC agents are very similar, but the ESC perform slightly better. Consider that, if at least one source was 100% reliable, the performance of ES agents would be the best: having always reliable information would allow them not to take risks. For instance, table 3 shows what happens when the authority has a 90% correctness. In this case the ES agents' performance exceeds that of the ESC.

Table 3: The sum of *final capital* and *avoided damage* for ES and ESC agents, by type of authority, when the authority has a 90% correctness

	punitive	encouraging	P&E
ES	182.93	191.06	191.2
ESC	176.49	188.02	187.67

Table 4: The sum of *final capital* and *avoided damage* for ES and ESC agents, by type of authority, when the authority has a 90% correctness and the damage is fivefold

	punitive	encouraging	P&E
ES	587.17	590.12	597.1
ESC	583.1	611.88	607.2

All this depends on the level of risk. Even if the sources are very reliable, in case of conspicuous damage it is still necessary to carry out probabilistic reasoning. Table 5 shows what happens when the authority has a 90% correctness, as in Table 3, but the damage is fivefold. Here the ESC performance returns to be the best. Resuming, when the source does not have a high level of accuracy or when there is a very precise sources but also a very high potential damage, reasoning further taking risks into account - as ESC agents - maximizes performance. In any case, using reliable sources leads to an improvement in terms of performance: the better the sources, the better the result. Given the agents' adaptability to the sources, it is sufficient that one of them is very reliable to allow the citizens to perform well.
Moreover, it is necessary to clarify that this analysis takes into account just direct damages, excluding those indirect or secondary. These last would further penalize ES's performance, as they are more exposed to critical events. A peculiarity of these agents concerns how they use their information sources. We expect them to follow the indications of the sources they consider most reliable, as the other agents do, but ESC agents reason differently: even if they trust a lot a source (here in particular we are interested in the institutional source), they could not follow its indications. Although this phenomenon could seem strange, it results natural if we think about the aim moving them and to their way to think. While ES agents want to maximize the probability to guess an event, and this lead them to use the most reliable sources, ESC agents want to minimize the risk, in order to reduce the possible damages. Thus, even if they trust a lot a source, they could take (and they actually take) different decisions from what the source said. In general it happens precisely because it allows to reduce the potential risks.

ES agents (Table 5) follow the authority instructions the 99% of the cases. This is because authority is the best source they have, communicating the most accurate information. ESC agents follow its indication just the 58% of the times if the authority is punitive and the 42% if it is encouraging or punitive&encouraging. This phenomenon is completely independent of trust values, which derive from the authority's estimated reliability. Its average value is about 70% and it is correctly identified in both cases. However, with the same level of trust, ES agents completely rely on the authority, as it allows them to maximize the results of their strategy, while the ESC agents go beyond

Table 5: Percentage of times in which ES (a) and (b) ESC agents follows the authority's indications

	punitive	encouraging	P&E
ES	99.26	99.28	99.07
ESC	57.62	42.15	42.19

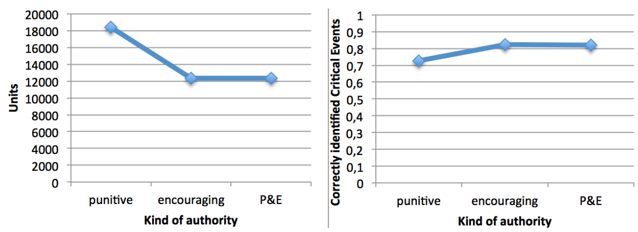

Fig. 1: (a) The authority's final capital and (b) the percentage of critical events correctly identified by ESC agents

what the source reports. Although ESC agents believe the authority reports correct information, they also take into account the possible risks linked to a wrong decision. In other words "I trust what you said, but I will not do that". This is why they act differently. We call this phenomenon *"dissonance between evaluation and action"*.
Concerning the authority, regardless of the chosen strategy, it has a heavy effect on ES agents, which completely follow its indications. For ESC agents it is a very different story. They follow the punitive authority the 58% of times and the 42% of times when it is encouraging or punitive&encouraging. These lower values have not to be interpreted as a bad result; what happens here is that, thanks to the available incentives, they can afford to avoid much more risk: they make an investment even if it is not strictly necessary. This allows them to increase the avoided critical event's percentage of 10% (the difference for the medium events is very low, as they already avoid the majority of them). On the contrary, the fines are almost unused, they do not have any effect on these agents since, for their very nature, they already tend to protect themselves. Moreover, Figure 1 shows how a punitive strategy preserves the authority's capital, but an encouraging one allows the citizens to block more critical events. We can then conclude that, to the purpose of maximizing citizens' safety, the best authority's profile is the encouraging one. Moreover, there are no substantial differences between the encouraging and the punitive&encouraging, because of the little weight the fines have in this context.

5 Conclusions

The simulative platform we presented wants to study the social behavior of a population in presence of hydrogeological phenomena of various criticality. In these situations, as we saw, the interests of the citizens and the authority do not necessarily correspond, as they pursuit partially different tasks. Thus we analyzed the best strategies on the various contexts.

Concerning citizens, we explored different profiles on the basis of the different quantity of information they take into account. Although the best performance is ensured by the use of all the available information, sometimes in a risky context it is not so easy to consider the complete knowledge. In this regard, we showed that taking into account the information sources already allows to get good performances, even ignoring the costs and the potential damages. This in itself is already useful information for authority. A higher level strategy would be in fact working not just on the information, but stressing the use of a specific information rather than another. For instance, if the population is not prone to a full rational choice (not necessarily its members are able to take in consideration all the useful parameters), it is better to stimulate it to take into account the information sources and not the information about costs and damages (see Table 2).
Concerning the ESC agents, we identified what we called *"dissonance between evaluation and action"*: they can trust a lot their information sources and believe them to be reliable, but in the end they take a different decision, as they reason at a different level of abstraction and they take into account the possible risks linked to a wrong decision. Since the forecasts are just probabilistic suggestions, it is necessary to take into account even the less probable events, which can have in fact a very high impact in case they happen.
As regards the authority, we analyzed three possible strategies. We showed how in general an encouraging authority has a greater impact than a punitive one. However, if the citizens' choices are strongly linked together link in the second experiment, the use of fines still has a positive effect, since it pushes them not to rely too much on their neighbors. In this case the authority has the best performance with a punitive&encouraging strategy.
These important results are useful considerations and a good point to start for the authorities as, besides identifying the best strategies in each situation, they allow to understand the effects and the links that emerge within the population.

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