Institutional alarmism and the damage it provokes in case of hydrogeological disasters: a simulative estimation

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***Abstract*— It is common practice for local authorities to create weather alerts even when there is no need, in order to protect themselves legally. However, this has a strong negative effect on the population, involving in a first phase fear and alarmism, and subsequently a drastic decrease of trust in the authority and therefore in what it reports. The catastrophic result is that in the long-term periods the alert itself loses its value, so the population will not respond effectively when it is time to do so.**

The purpose of this work is to provide an idea of the possible damage caused by this practice. Therefore, we realized a simulative scenario, in which a population faces a series of events over time, with the risk of a critical one, while the authority decides whether to communicate its forecast as it is or to overestimate it. Trust acts as glue in the close relationship between authorities and citizens, and then we start analyzing it and then showing how its decrease, due to the alarmism, increases the damage that the population suffers, providing also a quantitative evaluation.

***Keywords*— trust; social simulation; cognitive agents.**

I. INTRODUCTION

The interest in critical hydrogeological phenomena such as floods has always been high, because of the enormous damage they cause, both in terms of lives and in economic loss. Cunado & Ferreira [4] 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.
This phenomenon is strongly influenced by urbanization: cities act as social hubs, attracting more and more people from rural areas. Suffice it to say that in 2016 54.5% of the population lived in urban settlements[1] with more than 29,000 citizens per km^2 and these numbers are destined to increase.
So, people tend to create areas with a high concentration of inhabitants and structures. When these areas are affected by cataclysms, the damage suffered is enormous: it arises the need to identify strategies minimize this problem.
In particular, it has been realized how critical the role of the authorities is in order to reduce damage, therefore not only in the interventional phase, but also in the preventive one, leading the population towards the appropriate behavior.
The aim of the authority should therefore be to produce the most reliable prediction it can, communicating it to the population so that they make a correct decision.
However, even if the quality of weather forecasting has improved over the years, using increasingly effective models, we are still dealing with forecasts and as such they may be wrong.
In particular, as Stewart [22] underlines "actions that are based on predictions lead to two kinds of errors. One is when an event that is predicted does not occur, i.e., a false alarm. The second is when an event occurs but is not predicted, i.e., a surprise. There is an inevitable tradeoff between the two kinds of errors; steps taken to reduce one will increase the other."
This reasoning is now contextualized in the domain of alluvial disasters. When an event that has not been predicted occurs, the damage it entails is enormous.
Since it is the duty of the local authorities to inform the population promptly and correctly about what will happen, the population will consider the local authority responsible for the damage that occurred, with consequent legal repercussions.

All this naturally turns the authority away from what is its main task, resulting in the necessity to secure itself. The strategy that is implemented is to launch an alert even when there is no real need. This is how the tendency to false alarms arises, i.e. the choice to overestimate the actual risk. The point is that while a false negative involves enormous damage, this does not happen with the false positive: if the critical event that had been foreseen does not occur, there will be no obvious damage; there are no destructive consequences, nor direct repercussions.

[1] http://www.un.org/en/development/desa/population/publications/pdf/urbanization/the_worlds_cities_in_2016_data_booklet.pdf

However, even this phenomenon has negative effects on long periods. If the authority always launches false alerts, in the long run the population will no longer trust this and the value of the alert itself loses its value. In the presence of a true alert, the population will not respond appropriately and it will suffer a very high amount of damage.

In this article, we are interested in estimating the quantitative effects of the damage caused by false alerts in the population. Through a simulative approach, we will analyze the behavior of a population [10] in this context and the long-term effect of false alarms.

We will focus in particular on tangible and direct damages, as they are more immediately perceivable and economically quantifiable. Instead, we will not deal with indirect damage, which have an intangible impact and cannot be monetary quantified, such as loss of life or psychological trauma.

II. State of the Art

The literature has focused on assessing, as accurately as possible, the impact that the weather phenomena have or could have on the affected areas.

The first point to clarify is which part of the damage produced by an event we want to estimate, thus providing a classification of the various types of damage that are present. However, the literature does not converge on a homogeneous classification. In this paper, we take into consideration the classification proposed by Gentle [8]. Here the damage due to natural disasters is divided into 4 types. The main distinction occurs between tangible, monetarily quantifiable, and intangible damage, which is more difficult to quantify (such as loss of life, psychological traumas, etc.). In turn, these are classified into direct, that is the damage caused directly by the event (damage to roads, buildings, houses...), and indirect, i.e. the secondary damage that the event causes, such as the closure of companies, the decline in tourism, etc. In general, researchers estimate flood damage mainly focusing on tangible direct damage, since this is the most practical dimension to estimate economically.

In order to compute flood damage, it is first necessary to estimate the magnitude of the event and the value of the structures affected. The magnitude is influenced by many variables, however only the most important are taken into consideration, such as the flood water level or the duration of the event [9].

In general, researchers estimate the damages that an event can cause by the means of the simulative approach [20]. For instance, in [13] the authors propose a model simulating critical scenarios and evaluating the expected economic loss. Here the flood water level is considered as the factor indicating the event magnitude.

Olivieri and Santoro [16] express the damage as a product of a) the average value per unit of a zone, b) the actual extension of the territory affected by the disaster and c) the percentage of damages suffered. Although they provide a detailed estimation of the parameters they use in their calculations, they then use the average economic value of buildings to determine the value of the area affected by the event. This is an oversimplification, as cities are often heterogeneous from this point of view, especially if we consider very large areas.

The authors of [25] propose a much more accurate approach. They want to realize a simulator able to compute flood damage on St Maarten Island, one of five island areas of the Netherlands Antilles.

Thanks to a GIS software, they estimated the value of each area as the sum of the building that it contains. They consider many characteristics of the buildings, such as their dimension and the number of floors. Moreover, they classify buildings according to their use in residential, commercial and industrial. Then the authors define 7 damage curves to estimate the direct damage to the buildings.

They also try to estimate tangible indirect damage, calculated as a fixed percentage of the direct damage, and the intangible damages, such as anxiety - computed as a function of flood depth and land use - and loss of productivity – computed as a function of anxiety and income.

Although these tools are very accurate, they require an excellent knowledge of the territory and anyway the measurements are subject to large variability [15].

However, all these works limit their focus on estimating the damage that the event produces. These tools can be very helpful, allowing for the individuation of urban solutions that can reduce the flood damage. However, although direct intervention by the authorities is important to prevent damage, it can have very high costs and take a very long time. On the contrary, interventions by individuals are quicker and it seems that the citizens' choices can help to reduce the flood damage by up to 80%. What we want to do is precisely to link the damage suffered by citizens with their choices, which are in turn strongly influenced by authority.

Our model allows us to study the complex relationship between the reaction of citizens with what the authority reports, and thanks to this approach we can study the effects of the authority's communications on the damages that occur.

III. The Trust Model

The trust model used is this work is that of [19], which is an adaptation of the cognitive model of trust of Castelfranchi and Falcone [3]. Trust seems in fact an excellent way to deal with information sources [1][2][14][17][24].

This model makes use of the Bayesian theory, one of the most used approaches in trust evaluation [18][26], so information is represented as a probability density function (PDF).

Each information source S is represented by a trust degree called *TrustOnSource* [5][7], with 0 ≤*TrustOnSource* ≤1, plus a Bayesian PDF that represents the information reported by S. The *TrustOnSource* parameter is used to smooth the information referred by S: the more I trust the source, the more I consider the PDF; the less I trust it, the more the PDF is flattened. Once an agent gets the contribution from all its sources, it aggregates the information to produce the global evidence (GPDF), estimating the probability that each event is going to happen.

A. Feedback On Trust

Trust is a dynamic value, changing with time depending on the situation. In this model, starting from a neutral trust level (that does not imply trust or distrust) the agents will try to understand each information source's reliability (*TrustOnSource)*, by the means of direct experience for trust evaluations [21][23]. Using the weighted mean, the will perform the feedback on trust. Given the two parameters α and β, the new trust value is computed as:

$$newTrustOnSource=\alpha*TrustOnSource+\beta*performanceEvaluation \quad (1)$$

$$\alpha+\beta=1$$

TrustOnSource is the previous trust degree and *performanceEvaluation* is the objective evaluation of the source performance. This last value is obtained comparing what the source said with what actually happened.

The values of α and β have an impact on the trust evaluations. With high values of α/β, agents will need more time to get a precise evaluation, but a low value (below 1) will lead to an unstable evaluation, as it would depend too much on the last performance. We do not investigate these two parameters in this work, using respectively the values 0.9 and 0.1. In order to have good evaluations, we let agents make a lot of experience with their information sources.

IV. THE FRAMEWORK

The simulations were realized using NetLogo [27], an agent-based framework. A population of citizens, modeled through cognitive agents and randomly distributed over a wide area, has to face the risk of a critical event. The citizens have the necessity to identify the future weather event on the basis of their information sources and of the trustworthiness they attribute to them. They possess an initial capital to administer, making the correct investments; thus, they need to understand which is the most convenient choice, according to the costs and damages related to each decision. The authority informs promptly the citizens about the weather phenomena, providing them with its own forecasts. Notice that, being just forecasts, it is not certain that what it reports is really going to happen. This depends on the authority's reliability, its ability to make predictions. However, the authority can decide to overestimate its forecast, raising an alarm when it is not necessary.

The citizens can also evaluate the situation on their own, but they cannot be as good as the authority in making predictions, since they do not possess the appropriate means.

Then, according to the trust model proposed in Section 3, 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. After that, they will reason about this information and they will decide if to invest or not.

The critical phenomena occur with a 10% probability; when they do, citizens will suffer 10 units of damage if they did not invest, and 2.5 units of damage if they invested. In the other 90% of cases nothing happens, so that the citizens who have invested have wasted their money.

After the event, the citizens adjust the trust values of their sources, on the basis of the corresponding performances. We repeat this phase 100 times, enough for them to properly evaluate the sources. After that, each citizen possesses a final capital and it has suffered a given amount of damage. These two dimensions are heavily influenced by the authority strategy on reporting information.

A. Information sources

In order to take a decision and to maximize the utility of their investments, the citizens need to gather information about what is going to happen[6]. In particular, the citizens can consult two different information sources, reporting some evidence about the incoming meteorological phenomenon:

1. The *authority*, which distributes into the world weather forecast, trying to prepare citizens to what is going to happen. This is the most competent source, as it has the means to produce a correct evaluation of the phenomena, but it is not sure that the authority will faithfully report the forecast.
2. Citizens' *personal judgment*, or self-evaluation, based on the direct observation and evaluation of the phenomena. The point is that, usually, the citizens do not have the means to produce a proper forecast.

B. 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 3.1). Each citizen is also characterized by its ability to see and to read the phenomena. We modeled this associating to the citizens a *probability of success,* used to produce the forecast for the meteorological events. In the simulation, we used the value 50%. Given that there are just two possible choices, it is the equivalent of a random choice.

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 the possible damage in case of an event. If it does not, it exposes itself to the risk of a possible high damage.

C. The authority

The authority's duty is to inform promptly 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. As for the citizens, its forecasts are produced using the *probability of success*, which may assume the values 50%, 75% or 100%: the authority is at least as reliable as the citizens, but it could even produce perfect forecasts.

The point is that, as already said, it is not given that its goal coincides with its duty. In order to protect itself legally, the authority could decide to overestimate a forecast, raising an alarm of critical event when it is not necessary. We characterized it with a *probability of overestimation*, determining if it is going to report the truth or not. In the simulation, it will assume the values 0%, 25%, 50%, 75% and 100%.

D. How the citizens decide

Once the citizens gathered information from their sources, the processed through trust values and then aggregated it, they are able to estimate with what probability there will be a critical event. Then they need to understand which choice is more convenient: to invest or not to invest.

Each choice has a fixed cost, the investment, and a variable part, the damage, which depends on the event. The investment is equal to 1 unit, but they can decide not to invest (0 unit). In case of critical event, the damage is equal to 10 if they did not invest and to 2.5 if they invested, while it is 0 if there is no event.

Table 1 and Table 2 report the cost and damage linked to each decision respectively when there is no event and when there is a critical event.

Table 1: cost and damage linked to each decision in case of no event

	To ignore the problem	To take measures
Cost	0	1
Damage	0	0

Table 2: cost and damage linked to each decision in case of critical event

	To ignore the problem	To take measures
Cost	0	1
Damage	10	2.5

The citizens compute the probabilistic cost of each choice and they will make the decision that minimizes the cost:

CostOfInvestment = Investment + (MaxDamage/4)*P(event) (1)
CostOfNotToInvest = 0 + MaxDamage*P(event) (2)

Notice that if we consider the a priori decision, without any information about what is going to happen, the choice of making an investment has a cost equal to 1.25 (Equation 3), while the choice of not investing is 1 (Equation 4).

CostOfInvestment = 1 * 1 + 2.5 * 0.1 = 1.25 (3)
CostOfNotToInvest = 0 * 1 + 10 * 0.1 = 1 (4)

From Equations (3) and (4), we deduce that without information the best choice is not to invest. The citizens need to use their information to maximize the utility of their choice.

E. Platform inputs

The first thing that can be customized is the **number of citizens** and their **probability of success**, i.e. their ability in making predictions, and their initial **monetary capital**. Then, one can set the value of the two parameters **α and β**, used for updating the sources' trust evaluation.

Concerning the authority, it is possible to change its reliability, **probability of success**, and its **probability of overestimation**. One can also set the **critical event's probability**.

V. THE SIMULATION

The purpose of this simulation is to quantify the damage that the authority's overestimation effect of events produces in citizens.

Therefore, in the experiment we change the correctness of the authority in making forecasts and its probability to overestimate the risk.

Each simulation has a fixed duration of 100 events, in which the citizens make experience with their information source and calibrate the parameters of the model, i.e. the trust that they place in their sources of information.

At the end of these 100 events, we measure the damage the citizens suffered and we test their ability to make the correct choice.

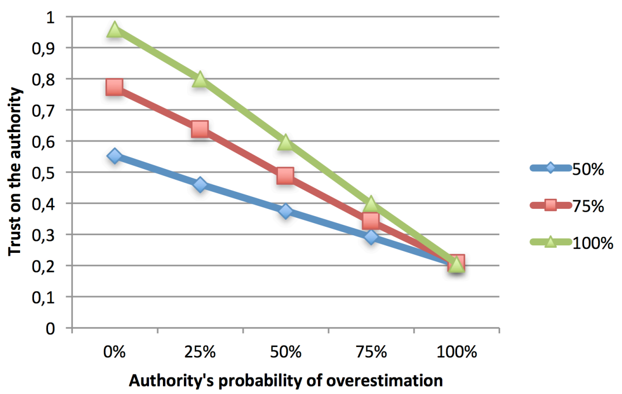

Fig. 1. The citizens' trust on the authority, depending on the authority's *probability of success* and *probability of overestimation.*

The most immediate consequence of alarmism is the diminution of trust in authority (Figure 1), at least for this kind of tasks. When the authority does not overestimate its forecasts, the trust values are very similar to the authority's *probability of success*. When the *probability of overestimation* increases, the trust values decrease: the citizens will ignore what the authority says, since they consider it an unreliable source

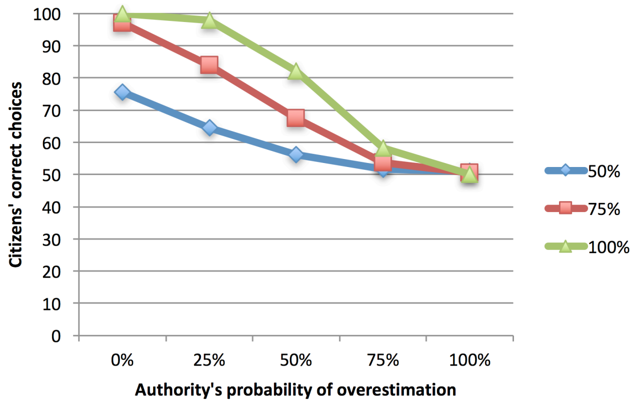

Fig. 2. Percentage of citizens' correct decisions, depending on the authority's *probability of success* and *probability of overestimation.*

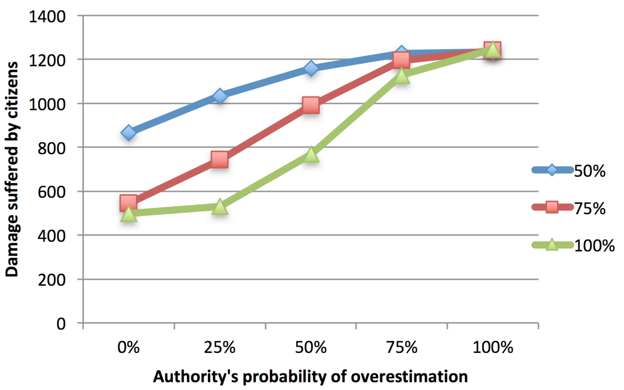

Fig. 3. Quantification of the damage the citizens suffer in the simulation, depending on the authority's *probability of success* and *probability of overestimation.*

Figure 2 shows the percentage of citizens' correct decisions, depending on the authority's *probability of success* and *probability of overestimation*. The *probability of success* assumes the values 50%, 75% and 100%, represented respectively in blue, red and green. The *probability of overestimation* assumes the value 0%, 25%, 50%, 75%, 100%, represented in the axis of the abscissas.

As expected, a more skilled authority allows citizens to get a better performance. The ideal case is when we have a very skilled authority (*probability of* success=100%) that faithfully reports its forecast (*probability of overestimation* = 0%). However it is an impossible case in the real world: even assuming that the authority faithfully reports its prediction, every prediction always carries with a degree of uncertainty.

Increasing the effect of overestimation, the citizens' performance decreases to the lower value, which is 50% since the other source (*personal judgment*) has 50% reliability, equal to a random choice.

Figure 3 represents the quantification of the damage the citizens suffer in the simulation, again depending on the authority's *probability of success* and *probability of overestimation*.

The best performance, i.e. the one that guarantees lower levels of damage, is obtained when the authority is 100% correct. Increasing the *probability of overestimation*, the quantity of damage increases: it can even reach 2 and a half times the value of the ideal case.

This huge difference is indicative of the impact of the authority's communication in preventing damage to the population.

VI. CONCLUSIONS

The purpose of this article is to provide a quantitative estimation of the alarmism effects on the population, in case of hydrogeological risk.

Although it is now common practice for local authorities to overestimate events to protect themselves on a legal aspect, it is also true that this practice has many negative effects on the population.

The *first effect* is that of a decrease of trust in the authority (at least in this context): since this always reports untrustworthy information, the population will not trust anymore what it says, so when there really will be a critical event, the population will underestimate the alarm.

This therefore leads to the *second effect*: the decrease in the performance of citizens. Unable to rely on a reliable source, their performance inevitably decreases.

The third effect concerns the quantification of the damage. In fact, agents suffer losses related to their wrong decisions. The more they are wrong and the higher the damage will be. As we have seen, the damage could even become 2 and a half times with respect to the ideal case (100% reliable authority, with 0% *probability of overestimation*).

In short, although not alarming in case of a critical event may have immediate catastrophic effects, even the alarmism should not be underestimated: even if its damage cannot be immediately estimate, it can be dangerous for the population in the future through secondary effects. This phenomenon should be studied more in depth, in order to identifying solutions that stop it from arising, allowing local authorities to focus on more important goals.

The results of this study do not want to be exhaustive, but they provide quantitative estimates that highlight the critical nature of the phenomenon and the need for further studies in this regard.

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