Estimating the benefits of early warning systems in reducing urban flood risk to people: a spatially explicit Bayesian model.

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Abstract: Flood risk assessment usually focuses on damages to material objects (indirect tangible costs) and downplays the broader socio-economic aspects of flood-prone systems. Such aspects are crucial for an accurate assessment of risk to human receptors and of the benefits of non-structural measures. For example, an early warning system (EWS) that reduces the amount of direct tangible costs only partially could: (i) save lives (direct intangible costs); (ii) help avoid long-lasting trauma (indirect intangible costs); (iii) prevent post-disaster evacuation costs (indirect tangible costs). We present a methodology to assess flood risk to people, which integrates people's vulnerability and ability to cushion hazards by coping and adapting. The study area covers the lower part of the Sihl valley (Switzerland) including the city of Zurich. Flood risk to people is modelled using a spatially explicit Bayesian network model calibrated on expert opinions (25 experts were involved). Risk to people is assessed in terms of: (1) likelihood of non-fatal physical injury; (2) likelihood of post-traumatic stress disorder; (3) likelihood of death. The model is used to estimate the benefits of improving an existing EWS, taking into account reliability, lead-time and scope. The proposed approach can: (1) improve flood cost estimation by extending its scope beyond direct and tangible damages; (2) complement quantitative and semi-quantitative data with subjective and local knowledge, improving the use of commonly available information; and (3) produce estimates of model uncertainty by providing probability distributions for all its outputs.

Keywords: flood risk, vulnerability, early warning system, Bayesian networks.

1. INTRODUCTION

River flooding is the most dangerous natural hazard in Europe in terms of economic losses (EEA, 2010).Integrated flood risk management is a priority for the European Union (e.g., EC, 2007; EFAS, 2010).

The definition and measurement of disaster risk are active research topics (Gain et al., 2012). The most widely adopted approach in Disaster Risk Reduction (DRR) is the calculation of expected damages as a function of hazard, physical and environmental vulnerability, and exposure (UNDRO, 1980; Crichton, 1999), where the first element (hazard) is characterized by specific return periods (an estimate of the likelihood of the event), and together with the second (vulnerability) it is usually expressed as a dimensionless index, while the latter (exposure) is expressed with the unit(s) of measurement of the elements at risk, which can be expressed in physical or monetary terms.

$$R = f (H, V, E) \tag{1}$$

Although disasters can impact social-ecological systems in multiple ways, this approach has been mainly used to assess damages to infrastructure. Ideally, a total cost assessment should include as cost elements:

1. damages to receptors that have a market value (direct tangible costs);
2. damages to people and the environment that have intrinsic value but no market value (direct intangible costs);
3. costs generated outside the time frame or the geographical location of the hazardous event (indirect costs).

Practically most of the times only direct tangible costs are assessed (Balbi et al., 2013) and this is considered to be sufficient to analyse and justify the decisions regarding structural risk reduction measures (e.g., dikes, embankments). Another difficulty with Equation 1 is that it misses the fact that the magnitude of the costs of disasters is influenced by the ability of human receptors to absorb or cushion against hazards (Rose, 2004). This is evident when considering the social dimension of vulnerability (Cutter, 1996), which has been progressively recognized as one of the main components of risk (UNISDR, 2005). This argument could have found traction during the 1990s, when disaster management was primarily focused on the response of governments, communities, and international organizations to deal with the consequences of disasters after they occurred. Currently, however, focus has been largely shifted to the role of knowledge and preparedness (UNISDR, 2005). The reason for this shift is twofold: (a) disaster occurrence is subject to intrinsic uncertainty, which will be exacerbated by climate change; and (b) the magnitude of a disaster increasingly depends on the behaviour of the affected people and their ability to adapt.

This study, aligned with the KULTURisk theoretical framework (Giupponi et al., 2014), presents methods to evaluate the benefits of risk prevention. Two main innovations are proposed with regards to the state of the art: (1) a measure of risk that goes beyond the direct tangible costs and (2) consideration of the social ability to reduce risk. The first is functional to the second, because the quantification of intangible and indirect costs is a prerequisite for assessing the benefits of both non- structural measures and preparedness. For example, an EWS might only partially reduce the amount of direct tangible costs but it can: (i) save human lives (direct intangible costs); (ii) change the behaviour of people by avoiding long-lasting trauma (indirect intangibles costs); (iii) prevent post-disaster evacuation costs (indirect tangible costs). Until now the KULTURisk framework has been implemented by means of deterministic risk assessment methods. In this paper we propose a probabilistic and spatially explicit implementation with Bayesian networks (BNs) built on elicited expert knowledge.

BNs are directed acyclic graph that allow a traceable and concise representation of the causal influence between the considered factors, expressed as nodes of the network. Parent nodes directly influence child nodes. Each node is a random variable defined by a probability distribution over a finite number of states or events. For input nodes this is termed the prior probability and for output nodes it is termed the conditional probability (i.e., the probability of its value conditional on a set of outcomes for its input nodes). The dispersion in the probability distributions of each outcome can be considered a proxy for data-related model uncertainty.

BNs have been applied to a wide variety of research problems across many disciplines, including natural resource management (McCann et al., 2006). Few examples are also available in the domain of natural hazards. Amendola et al. (2000) use BNs to consider the chain of indirect damages caused by natural hazards. Antonucci et al. (2003) assess debris flow hazards using credal nets. Straub (2005) illustrates the potential of BNs for rock-fall hazard ratings. However, only Gret-Regamey & Straub (2006) integrate the BNs and GIS to assess risk of avalanche in a spatially explicit mode. Main advantages of BNs are the ability to use different kind of knowledge (e.g. quantitative, semi-quantitative, data-based, opinion-based), to behave correctly with missing data, and to account for and help communicate uncertainty. In the case of flood risk it is common to have some background knowledge about expected impacts, among which some are subjective and some objective. Experts possess prior information about the prevalence of possible different conditions from previous events. At the same time decision-making cannot be based on purely statistical data of previous instances, since in each case the risk is unique in many aspects.

2. MATERIAL AND METHODS

2.1 Case Study

Our case study area is the lower part of the *Sihl* river valley in Switzerland, an area of 78 km^2 that includes

the city of Zurich with its 21 districts plus 5 municipalities (Adliswil, Kilchberg, Langnau am Albis, Rüschlikon, Thalwil). The residential areas cover 41.28 km^2, with approximately 289,000 inhabitants. About 10,000 properties are located in hazard zones. The *Sihl* flows beneath the main railway station of Zurich. It has been estimated that in case of a 300 to 500 year flood event, *direct tangible* costs can range from hundreds of millions to several billions of Swiss Francs (IG Zalo et al., 2008).

According to Zappa et al. (2010) an EWS has been in place in the region since 2006, and it is regarded as useful in significantly reducing flood risk although its benefits have never been quantified. For the purpose of this assessment, 4 experts from local authorities were surveyed about their perceived performance of the EWS regarding its *reliability* (the probability of a correct forecast), *scope* (the coverage of people reached by the warning), *lead time* (time in hours between the warning and the event occurrence). Expert knowledge was used to establish the baseline prior probabilities regarding the effectiveness of the EWS. In the following, we consider what the implications of an alternative scenario are when the EWS is improved to a maximum effectiveness of its performances.

2.2   Modelling framework

In accordance with Equation 1, our framework postulates that the magnitude of flood risk is directly related to the intensity of the hazard as well as to the *whole* (i.e. physical and social) vulnerability of the exposed social-ecological system.

Hazard is represented with maps of intensity of flood, provided by hydrological analysis and modelling, with reference to different return periods. For this study we used 3 hazard maps provided by the GIS- Centre of Zurich Canton describing the flood extension of *a 300 years event* in terms of *flood inundation depth*, *velocity of flooded water*, and *debris factor*. This can be considered a worst-case scenario for the study area. The Bayesian hazard module was developed mirroring the hazard rate function of DEFRA (2006).

Vulnerability maps result from the combination of both physical-environmental and social components. Input variables for the vulnerability model were broken down into 4 main groups of variables: *coping ability*, *susceptibility*, *risk governance* and *early warning effectiveness*. Coping ability is described by the percentage of people over 75, disabled people, and non-native speakers (e.g. newcomers, foreigners). Susceptibility is a function of age of the exposed buildings, percentage of single and two storeys buildings, and speed of onset, i.e. the time that the discharge takes to reach a location. Risk governance is articulated into societal risk awareness (derived from Maid and Buchecker (2013) - a survey of property owners) and per capita number of emergency personnel. EWS effectiveness was modelled as described above. The Bayesian vulnerability module developed by the authors was peer reviewed by the experts of the KULTURisk consortium. The selection of the vulnerability components was tailored to the application context taking into account hazard type, spatial scale and data availability. Where the data were not spatially explicit (i.e. distribute per raster cell or polygon), the available information was used to build the prior probabilities of the input nodes. All the data were discretized for use in BNs.

Exposure is the presence of people and assets in the modelled landscape. In this application we employ two scenarios: (1) we use the average residential population density per district to represent the event of an overnight flood; (2) we use data about hourly presence of people in selected public buildings of relevance (school, stations, shopping areas, etc.) during a working day to represent the event of a working hours flood hit. In the latter scenario, the data provided by the Civil Engineering Department of the City of Zurich cover only those districts of the study area where risks have been assessed as highest.
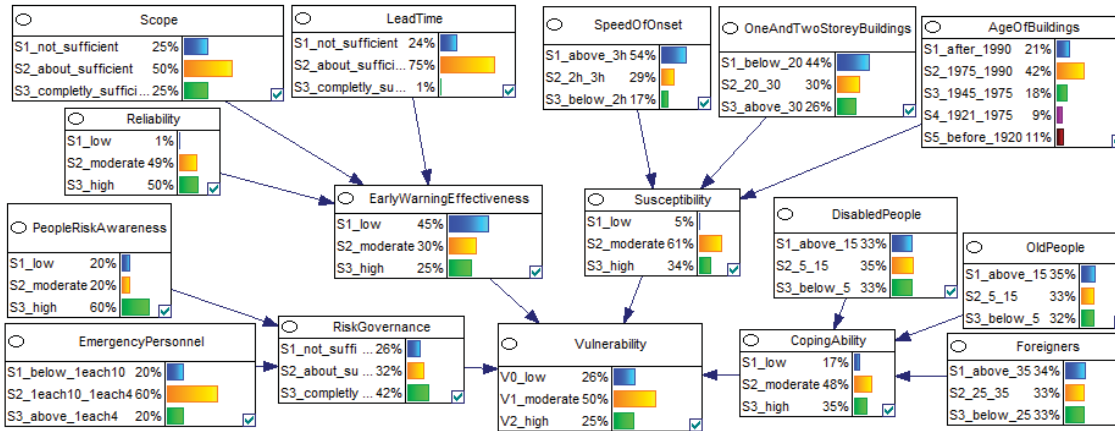
Figure 1. Vulnerability Bayesian diagram.

2.3   Elicited Knowledge

A panel of 25 experts was consulted through questionnaires in order to retrieve their opinions about expected consequences of given conditions of hazard and vulnerability within the case study. Among these experts, 20 had more than 5 years' experience on floods, 15 had been consulted by public bodies on flood risk, and 10 had direct knowledge about the case study. Experts were asked to rank the likely effect on an average individual for different scenarios of hazard and vulnerability using a numeric score between 0 and 100. Both hazard and vulnerability were described as discrete states (high, moderate or low) using a narrative format. For example, *moderate hazard* was described through the phrase "the flood depth is marginal (e.g. < 0.5m), but the water velocity is significant for an average person (e.g. > 2m/s) and there is some debris factor"; *moderate vulnerability* was described as "It's a residential area of individual houses with basement, where many retired people reside. There have been flash floods before but the EWS is not at the technological level to deal with those. However, the civil protection agency is physically located within the area".

The responses concerned the likelihood of: 1. *non-fatal physical injury*; 2. *post-traumatic stress disorder* (PTSD); and 3. *death*. In the questionnaire, experts were also asked to define the effect of exposure on risk. Although some experts recognized the existence of a non-linear relation, preliminary results were produced under the assumption that risk increases linearly with exposure.

The data provided by this panel of experts were used as evidence to train (Buntine, 1996) the BNs so that the contingent probabilities in the network approximate the causal structure in the evidence submitted. At the end of this training process we produced a comprehensive BN where the hazard and vulnerability modules interact to produce the 3 types of output. We then ran this BN in each cell of a rasterized landscape, producing different probabilities reflecting the spatially varying conditions of hazard and vulnerability. We finally multiplied these probabilities by the number of exposed receptors, provided by the exposure scenarios, to compute the actual number of people affected.

Spatially explicit environment and BN modelling are fully coupled in the simulation system used in this study (see Villa et al., 2014). Spatial contexts are defined as raster landscapes where both deterministic and probabilistic models can run at the grid cell level. For this application we used the GeNIe software (http://genie.sis.pitt.edu/) - directly supported in its native format - which is utilized as an external routine to run probabilistic models.

3.   RESULTS AND DISCUSSION

Results can be presented as a comparative analysis of the baseline (i.e. presence of the current EWS) with the alternative scenario representing the improvement of the EWS to a maximum theoretical effectiveness. The latter assumes that its reliability, scope and lead-time are completely effective based on the perception of experts. This method allows the quantification of the benefits of the EWS in terms of avoided injuries, PTSDs and fatalities. The summary of results, aggregated per district/municipality, is presented for the two exposure scenarios in Table 1 (day flood) and Table 2 (overnight flood). These data have been derived from the model output originally produced as GIS raster maps with a resolution of 50 m. Following we only present a

representative set of these maps (Figure 2).

For each cell in which the BN is applied the output is expressed as a probability distribution. To represent uncertainty we produced maps of the coefficient of variation (CV) calculated using the probability distribution along with maps of the mean values in each cell. For example, Figure 2b that describes the uncertainty of the number of injured people, shows higher uncertainty in cells with expected low impact. Results indicate the importance of EWS in reducing the risk to human life. An extremely effective EWS can avoid approximately 75% of fatalities with respect to the baseline both in the case of flood event during the day and overnight. The effect on injuries and PTSD is lower, around 20%.

Table 1. Affected human individuals per district – day flood

ID	District	INJU_BASE	INJU_IMP	%Benefit	PTSD_BASE	PTSD_IMP	%Benefit	DEAD_BASE	DEAD_IMP	%Benefit
2	Albisrieden	1	0	100.0%	1	0	100.0%	0	0	0.0%
3	Alt-Wiedikon	35	29	17.1%	31	26	16.1%	1	0	100.0%
4	Altstetten	2	1	50.0%	2	1	50.0%	0	0	0.0%
5	City	486	358	26.3%	428	337	21.3%	2	1	50.0%
7	Escher Wyss	0	0	0.0%	0	0	0.0%	0	0	0.0%
8	Friesenberg	13	10	23.1%	12	10	16.7%	0	0	0.0%
9	Gewerbeschule	0	0	0.0%	0	0	0.0%	0	0	0.0%
12	Höngg	0	0	0.0%	0	0	0.0%	0	0	0.0%
15	Langstrasse	25	20	20.0%	22	18	18.2%	1	0	100.0%
16	Leimbach	3	2	33.3%	3	2	33.3%	0	0	0.0%
17	Lindenhof	0	0	0.0%	0	0	0.0%	0	0	0.0%
21	Sihlfeld	12	9	25.0%	11	8	27.3%	0	0	0.0%
24	Werd	14	10	28.6%	13	10	23.1%	0	0	0.0%
25	Wipkingen	1	0	100.0%	1	1	0.0%	0	0	0.0%
26	Wollishofen	0	0	0.0%	0	0	0.0%	0	0	0.0%
	Total	**592**	**439**	**25.8%**	**524**	**413**	**21.2%**	**4**	**1**	**75.0%**

Table 2. Affected human individuals per district – overnight flood

ID	District	INJU_BASE	INJU_IMP	%Benefit	PTSD_BASE	PTSD_IMP	%Benefit	DEAD_BASE	DEAD_IMP	%Benefit
1	Adliswil	28	26	7.1%	25	23	8.0%	1	1	0.0%
2	Albisrieden	232	201	13.4%	201	174	13.4%	6	0	100.0%
3	Alt-Wiedikon	126	102	19.0%	115	90	21.7%	1	1	0.0%
4	Altstetten	171	149	12.9%	151	132	12.6%	4	1	75.0%
5	City	7	3	57.1%	6	3	50.0%	1	0	100.0%
6	Enge	2	1	50.0%	1	1	0.0%	0	0	0.0%
7	Escher Wyss	3	0	100.0%	0	0	0.0%	0	0	0.0%
8	Friesenberg	31	25	19.4%	28	23	17.9%	0	0	0.0%
9	Gewerbeschule	0	0	0.0%	0	0	0.0%	0	0	0.0%
10	Hard	0	0	0.0%	0	0	0.0%	0	0	0.0%
11	Hochschule	0	0	0.0%	0	0	0.0%	0	0	0.0%
12	Höngg	35	27	22.9%	30	24	20.0%	0	0	0.0%
13	Kilchberg	4	2	50.0%	4	2	50.0%	0	0	0.0%
14	Langnau am Albis	8	6	25.0%	7	5	28.6%	1	0	100.0%
15	Langstrasse	231	195	15.6%	201	172	14.4%	1	0	100.0%
16	Leimbach	12	9	25.0%	11	9	18.2%	0	0	0.0%
17	Lindenhof	12	2	83.3%	3	2	33.3%	0	0	0.0%
18	Oberstrass	5	4	20.0%	5	3	40.0%	0	0	0.0%
19	Rathaus	0	0	0.0%	0	0	0.0%	0	0	0.0%
20	Rüschlikon	2	1	50.0%	2	1	50.0%	0	0	0.0%
21	Sihlfeld	266	192	27.8%	231	173	25.1%	2	1	50.0%
22	Thalwil	35	30	14.3%	30	26	13.3%	1	0	100.0%
23	Unterstrass	0	0	0.0%	0	0	0.0%	0	0	0.0%
24	Werd	86	66	23.3%	76	63	17.1%	0	0	0.0%
25	Wipkingen	67	56	16.4%	59	50	15.3%	0	0	0.0%
26	Wollishofen	0	0	0.0%	0	0	0.0%	0	0	0.0%
	Total	**1363**	**1097**	**19.5%**	**1186**	**976**	**17.7%**	**18**	**4**	**77.8%**

The difference in absolute numbers and spatial distribution between day and night scenarios depends on the different exposure data. For example, while the City district could be the most at risk in case of day flood, it could be among the safest if the flood happens during the night. Alt-Wiedikon and Langstrasse appear to be at risk in both cases, while and Albisrieden, Altstetten and Sihlfeld are mainly at risk during an overnight flood. Thalwil and Adliswil are at risk during a night flood, but they are not covered by exposure data for the day scenario. Enge, Hard, Hochschule, Kilchberg, Langnau am Albis, Oberstrass, Rathaus, Rüschlikon and

Unterstrass are also not covered by day exposure data.

Note that the effect of the EWS improvement is different in every cell, and thus in every district/municipality, according to the different contribution to the reduction of vulnerability that it can achieve depending on the conditions of the other dimensions of vulnerability. For example vulnerability may remain high even with a very effective EWS because susceptibility is high (due to the speed of onset) and coping capacity is low (due to the presence of vulnerable human receptors). This is the case of Adliswil in particular.

a)   b)
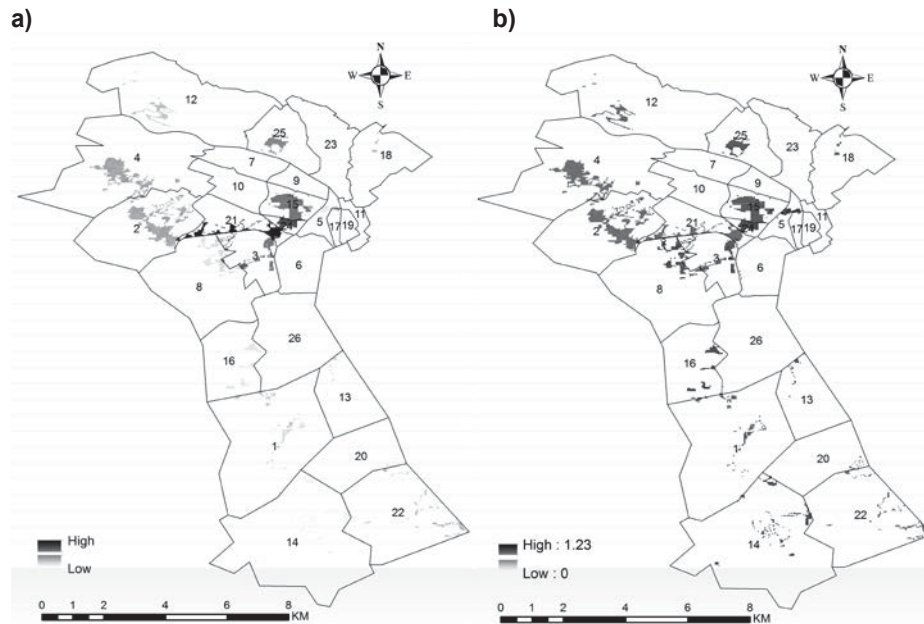
Figure 2. Spatial results for injuries in the baseline overnight flood scenario (a) and their uncertainty expressed as coefficient of variation (b). Numbering of districts refer to ID column in Table 2.

4.   CONCLUSIONS

This study demonstrates that scenario analysis focused on the potential benefits of EWS improvement and preparedness in flood risk management is possible by means of methodologies that employ quantitative data (flood modelling and GIS data), and semi-quantitative information integrating subjective (expert opinions) and local knowledge (risk perception and EWS baseline). In particular, the application of BNs allows us to produce probabilistic results and include an explicit visualization of model uncertainty. The results of our study can be of interest to policy makers who need to identify risk prone zones and tailor appropriate and cost-effective risk mitigation measures to the characteristics of each community at stake. Given our result, policy makers might need to shift their attention from structural defences to a combination of structural and non-structural defence measures.

As a mean of preliminary cross-validation we can anticipate that the results for baseline overnight flood scenario are dimensionally and spatially consistent with an equivalent GIS analysis (Olschewski, 2013) carried out during the KULTURisk project with a deterministic model and no expert involvement.

Two main future research directions are related to the hazard part of the model and to the presentation of results in economic terms. While this study has presented a static hazard scenario provided by exogenous hydrologic models, our modelling platform is on the way to integrate a flood module, which will be able to simulate different hazards linked to a weather generator module. This will sustain the ability to test different climate change scenarios, for example. Under a more traditional economic perspective, it is possible to envisage ways to compare monetary values by applying the method of disability adjusted life years (Murray et al., 2013) to injuries and PTSD results and to assess the loss of lives using the value of statistical life method (Jonkman et al., 2003).

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