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## 4.5 Social Impacts: Integrating dynamic social vulnerability in impact-based weather forecasting

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### 4.5.1 Drivers of social impacts from extreme weather events

#### ***What is the role of human exposure and vulnerability in weather-related disasters?***

Direct exposure of human beings to changing weather patterns or to their indirect effects such as changes in water, food, livelihoods and infrastructures can cause major social impacts in terms of death, disability and suffering. According to the United Nations Intergovernmental Panel on Climate Change (IPCC, 2012), extreme *weather hazards* become *weather disasters* when threatening the normal functioning of a community or a society '*due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response*'. The last 20 years, unexpected or unusual severe weather has been associated with more than 12,000 extreme weather events leading to catastrophic natural disasters such as storms, floods and heatwaves worldwide (Eckstein et al., 2020). In their latest report – the 15th edition of the Germanwatch Global Climate Risk Index -, Eckstein et al. (2020) estimate about 500,000 deaths as a direct result of those weather hazards between 1999 and 2018. If social impacts refer to a broad spectrum of disruptions, damages, and human health issues, this chapter will specifically deal with direct adverse human consequences which are the main reason for developing forecasting capabilities and early warning systems. In the present chapter, the terms human risk or human impacts may be used interchangeably, with a focus on the likelihood of loss of life during weather crisis. In particular, we address social impacts from extreme weather types discussed in Chapter 2 by Nikolopoulos and Astitha (ref to this book) (e.g., heavy rainfall), not mentioning impacts from slow-onset weather and climate processes such as rising temperatures, ice melting and sea-level rise that have been largely associated with important disruptions on ecosystems, transformations in biodiversity and agriculture, and degradation of coastal environments.

Both climate variability and anthropogenic climate change linked to greenhouse gas emissions are supposed to enhance the potentiality for severe weather phenomena in populated areas since they are expected to increasingly affect the frequency and extent of heavy rainfall at local and regional level (1.5°C IPCC, Hoegh-Guldberg et al., 2018). Though, the observed rise in health and economic impacts from extreme floods and storms is mainly attributed to socioeconomic and demographic drivers, e.g., the increase of exposure and vulnerability of people and assets. In fact, after reviewing several scientific studies on impacts from major extreme weather types in different countries, Bouwer (2019) draws the conclusion that there is no clear trend of increase in the historic losses after the records have been normalised for increasing exposure.

Future exposure is expected to increase with population growth and urban sprawl leading to higher risks for human life and settlements, livelihoods and economies. However, we cannot assume such an increasing trend in the overall social vulnerability. As disaster risk reduction and adaptation endeavours develop worldwide, risk awareness and the capability of people to cope with hazardous events might step up. This assumption fits mostly to wealthier societies than the developing ones, which may lack the economic strength to invest in disaster preparedness and mitigation actions, or in emergency aid. In both cases, however, the increasing exposure to more frequently occurring extreme weather events can form important experiences that, depending on the circumstances, might favour the know-how of individuals and communities to react to a future hazard. Lately, the National Oceanic and Atmospheric Administration (NOAA) noted that from 2015 to 2019 the number of reported weather hazardous events has increased

17% while for the same period the number of human injuries and losses decreased 49% and 19%, respectively<sup>1</sup>.

Following the purpose of the Sendai Framework for ‘*substantial reduction of disaster risk and losses in lives, livelihoods and health and in the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countries*’ (UNISDR, 2015), the last national or international initiatives set as a focal point the establishment of risk culture; the culture of persons, communities and countries of living with natural hazards. In the 4<sup>th</sup> World Landslide Forum (WLF4) held in Slovenia, forum participants addressed the importance of informed risk education tools and awareness messages on ‘*changing behaviour of governments, communities and all people at risk*’, recognizing vulnerability as the ‘*real cause of disasters*’ (Alcántara-Ayala et al., 2017). In this direction, current efforts in disaster risk reduction like the European Floods Directive 2007/60, are driven by a conceptual shift to holistic approaches that integrate hazard monitoring and vulnerability assessment with the ultimate goal to analyse the human-environmental conditions and interactions within socio-ecological systems threatened and impacted by weather stressors.

### ***How is social vulnerability defined and measured?***

The concept of vulnerability describes both the social processes driving the potential for harm and the characteristics of individuals or groups of people that make them susceptible to be harmed. Vulnerability has taken various definitions depending on the research objective and the author’s background (Adger, 2006; Birkmann, 2006). The majority of definitions tends to view vulnerability either i) as a pre-existing state of the social system defined independently of the hazard occurrence, or ii) as a potential for losses caused by the system’s exposure to a particular hazard and its sensitivity to specific impacts. The former idea is mainly supported by purely social-oriented scientists representing vulnerability through a set of selected socio-economic characteristics that reveal the inherent fragility of the system (Sarewitz et al., 2003). The second definition is promoted by climate change community which links vulnerability with the likelihood of impact occurrence considering the specificity of the hazard under study. The Intergovernmental Panel on Climate Change (IPCC) describes vulnerability with the following statement:

*‘The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity.’ (IPCC, 2007, p.20)*

McCarthy et al. (2001) defined sensitivity as ‘*the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli. The effect may be direct (e.g., a change in crop yield in response to a change in the mean of temperature) or indirect (e.g., damages caused by an increase in the frequency of coastal flooding due to sea level rise)*’. Thus, sensitivity is a term that explains the degree to which a system is modified or affected by hazards. Adaptive capacity is ‘*the ability of a system to evolve in order to accommodate environmental hazards or policy change and to expand the range of variability with which it can cope*’ (Adger, 2006).

In the frame of the socially oriented studies where vulnerability is considered as an internal (pre-existing) property of the society, Cutter et al. (2009) highlighted some broad indicators that appear frequently in the literature using different proxies to measure vulnerability: the socioeconomic status (e.g., wealth or poverty); the age; the special needs populations (e.g., people in hospitals); the gender; and the race and/or the ethnicity are some of the most commonly used characteristics. These indicators summarize social dependencies and economic disadvantages of the population through indexes assigned to geographic

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<sup>1</sup> Weather-related facts available at <https://injuryfacts.nsc.org/home-and-community/safety-topics/weather-related-deaths-and-injuries/>.

units varying from block groups to states (Cutter et al., 2000; Cutter, 2003). Especially, the eleven social vulnerability indicators that compose the Social Vulnerability Index (SoVI) proposed by Cutter et al. (2003) have largely been used in later studies (Azar & Rain, 2007; Rygel et al., 2006).

***The space-time scales of human exposure: an intersection of the weather and vulnerability driving forces?***

Given the multifaceted nature of vulnerability to different hazards, adopting indicators that may be available through the literature is not the best practice. In the words of Brooks et al. (2005), '*vulnerability depends critically on context, and the factors that make a system vulnerable to a hazard will depend on the nature of the system and the type of hazard in question*'. For example, flood insurance may indicate the existence of preparedness measures specifically reducing vulnerability to flood but not to other hazards (e.g., wind). Flood insurance cannot directly reduce vulnerability during flooding but may facilitate the recovery process after a flood disaster (Tunstall, 2009; Zhong et al., 2013). In addition to that, such flood prevention measures may be relevant for some countries and type of economies but not for others (e.g., economic differences between developed and developing countries, differences in insurance policy between Europe and U.S.). Rufat et al. (2015) reviewed 67 flood-hazard case studies (1997-2013) to present the main factors considered when assessing social vulnerability to floods. Their results showed that the demographic and socio-economic characteristics, and health and coping capacity issues are the most frequently used ones in the quantification of social vulnerability. Though, the frequency varies depending on the flood type (e.g., riverine or flash flood), disaster phase (e.g., response or recovery) and place of application (e.g., developed or developing country) (Rufat et al., 2015). Indeed, Doocy et al. (2013) presented a historical review of flood fatalities (1080-2009) worldwide showing that in contrary to the developing countries, greater proportions of males compared to female fatalities are observed in most of the developed countries.

Flooding is the most common and widespread weather disaster. Among them, flash floods are specially dangerous ones because of their suddenness, their violence, and their low predictability challenging the efficacy of early warning systems (Gruntfest & Handmer, 2001). It happens that a terrain goes from dry and to fully-covered by rushing flash flood water in seconds, just after a few hours or even minutes of heavy rainfall. In August 2014, an open area known for its wine production in the Veneto Region (Italy) was converted into a raging river in less than 30 minutes of a heavy thunderstorm that hit the upstream section of Lierza catchment (Borga et al, 2019). About one hundred persons were surprised while enjoying the summer festival, turning the celebration to a deathly scene (4 people died and 20 were injured as waters carried away participants, stands and vehicles). Events of this type are occurring with an alarming frequency in Europe and elsewhere and they are characterized by the highest average mortality, when compared with other types of floods.

For different types of flood, there may be also differences in the drivers of human vulnerability and the subsequent impacts depending on the way that the phenomena intervene social processes, and whether it creates opportunities for anticipation or not. When scrutinizing the socio-demographic variables in flash flood-related human losses, for example, it becomes obvious that they reflect the space-time distribution of everyday life activities (e.g., commuting to work in a vehicle), revealing both the dynamics of exposure and the difficulty to adapt patterned movements to fast-changing and potentially dangerous conditions. Whereas the elderly comprised the largest share of casualties in historic weather events such as heat waves and large-scale fluvial flooding, it has been shown that in fact it is young motorists who are most likely to be killed in flash flooding of small catchments (Ruin et al., 2008). In the analysis of 1,075 flash flood-specific human losses reported from 1996 to 2014 in the U.S., Terti et al. (2017) found that the median age of victims was about 40 years for past vehicle-related circumstances, confirming that the generic concept of elderly people being the most vulnerable to natural hazards is not categorically supported in the flash flood context. It was found that older people are more likely to die inside inundated buildings most commonly associated with longer duration flash flood events, and especially in twilight and darkness hours when rescue or evacuation operations are hindered. On the other hand, younger and middle-aged people (and especially males) are more likely to get trapped by very fast responding flash flood events while

participating in daytime outdoor activities. As a consequence, generic vulnerability factors addressing the overall fragility of populations with poor biophysical, social, and/or financial capital fail to capture the variability of the situations in which people become vulnerable and perish in flash flooding conditions. In this perspective, studying social vulnerability to a specific temporal and spatial context of the flood hazard is a key step to identify relevant and measurable indicators (Fekete, 2009). It also helps to explain the causative processes avoiding generalizations and simplifications in vulnerability assessment and mapping.

### ***How the concept of dynamic social vulnerability can support weather impacts prediction?***

To address such particularities in vulnerability to specific situational settings, social scientists have a long history in documenting disasters and the associated response of people through the collection of post-event data (Drabek, 1999; Grunfest, 1977; Kellens et al., 2013; Quarantelli, 1997, 2003; Walker et al., 2012). In rapidly evolving events like flash floods, post-event investigations show that the amount of time available to detect the threat and respond to it is so limited that protective actions often require dealing with contingent situations triggered by the rapid onset of dangerous circumstances amidst the ongoing rolling-on of normal routines and daily life (Ruin et al., 2008, 2009; Terti et al., 2015). Understanding how people actually detect potentially dangerous circumstances and manage to adapt their routine in time to cope with the speed of the hazard evolution remains a challenge. In a series of papers, a group of authors (Creutin et al., 2013; Lutoff et al., 2016; Ruin et al., 2014) presented an interdisciplinary methodology to collect information needed for understanding individual human behavioural responses in their social and hydrological contexts. The main objective was to understand how floods interfere with the completion of a daily schedule and under what conditions people abandon their daily priorities to cope with risky changes in environmental circumstances.

Much of this knowledge is captured in the conceptual framework for dynamic social vulnerability presented by Terti et al. (2015) (Figure 1). The authors used the term “coupled place-activity” to point out that the nature and dynamics of the individuals’ reactions will differ according to the location and activity they were performing when they felt the need for action, and their capability to connect with their relatives or to have social interactions allowing a group response (Lindell & Perry, 2012; Mileti, 1995; Ruin et al., 2014). This concept evolves out of time geography that describes the sequential path (also called life path) of personal human events (with time and place as dimensions) that marks the history of a person (Gamow, 1970) within a situational context (Hägerstrand, 1970). Hägerstrand (1970) stated that *‘life paths become captured within a net of constraints, some of which are imposed by physiological and physical necessities and some imposed by private and common decisions’*. When faced with a life-threatening event, cognitive processes mediate to form the choices in human behaviour. Risk perception impacts each individual’s subjective judgment about the severity of the flood risk. For example, a person who has previous flooding experience might perceive the danger differently than someone who has never faced such an event. Thus, the experienced people might have a better chance to notice, understand and interpret the actual circumstances according to the mental model (cognitive map) that organizes their stored knowledge and beliefs. A direct perception (through the 5 senses) can then be translated into the final sense of a situation to give (or not) an alert signal referring to higher or lower sense of danger. In fact, cognitive mapping (i.e., mental maps or schemes that organize the information on different subjects in everyone’s brain) is a factor that not only contributes to the understanding of the situation but also to the behavioural response. Among the stored information, spatial attributes or relationships between places are important elements that will partly drive people’s spatial behaviour and the way they will react to perturbations. For instance, when a perturbation is faced on daily routes, the familiarity with the place may help to find an alternative and safer route (Ruin et al., 2007). Nevertheless, when on the way home other emotional concerns like attachment to the place may intervene by lowering the perceived distance and/or difficulty to use this usual route, even when submerged, to get home (Maples & Tiefenbacher, 2009).

Those contextual natural and social factors result from long-term “Land Use” factors (i.e., the decisions taken at the national or community level concerning land use planning and management), “Risk Governance” factors (i.e., the risk prevention policy), and “Individuals’ Status” characteristics related to the individual’s position in life, attitudes, values and worldviews (for more details see Table 1 in Terti et al.,

2015). Over the long-term, societies shape their surroundings by making strategic choices that drive individual's decisions in terms of residential mobility related to the job market, for instance. Those 'slow-evolving processes' are characterized by rates of change ranging from months to years, and condition the 'fast-evolving processes' namely the daily routine of individuals and the way they deal with the range of perturbations that may affect their daily project or tasks when they meet unusual hydro-meteorological circumstances (e.g., notable water depths, flow velocities).

By considering such a process-oriented flash flood and impact-specific conceptual model, the aim is to link social vulnerability conceptualizations with realistic forecasts of prominent impacts from short-fuse flood hazards. The authors argue that social vulnerability, and the human impacts caused from short-fuse weather disasters, is not a constant estimation but an evolving outcome that depends on the interaction of physical and social dynamics at specified spatial and temporal units. In the next pages, we discuss the need to take into account the dynamic vulnerability of individuals, activities, and communities towards impact-specific predictions and warnings. We also provide examples of interdisciplinary methodological advances towards integrated human-hazard modelling to support decision makers and emergency planning for disaster risk reduction in the case of fast evolving and short-duration extreme weather (here flash floods).

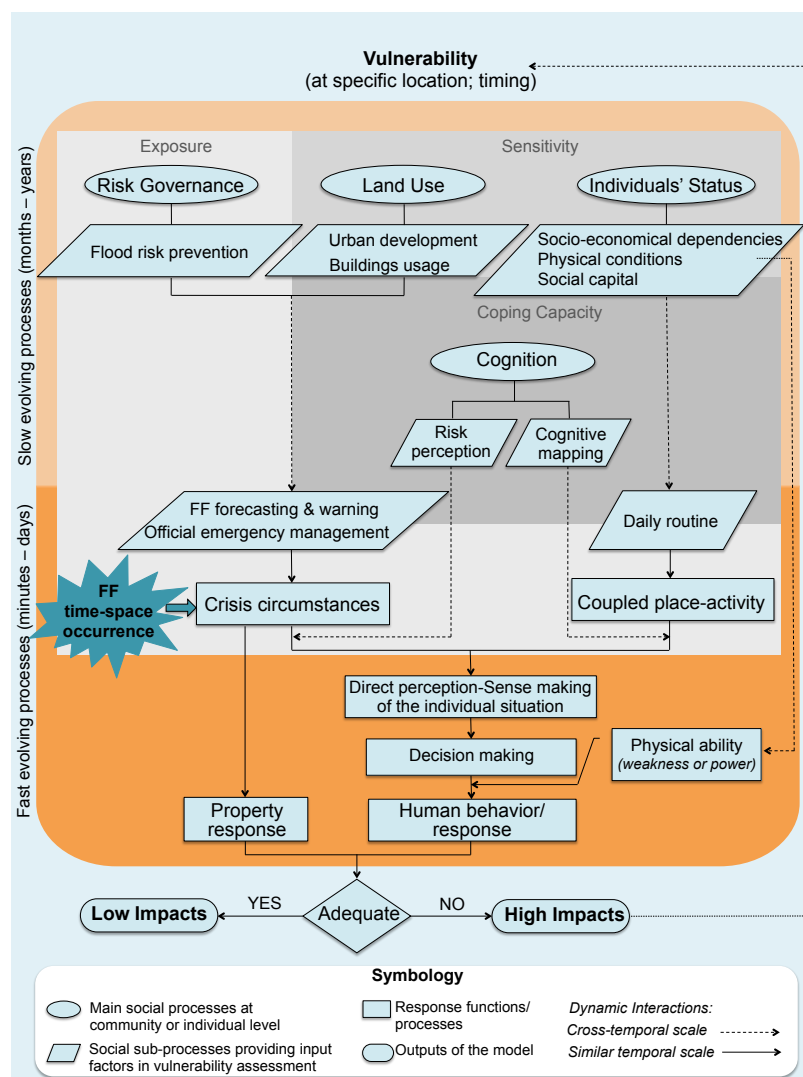


Figure 1 Conceptual model of dynamic vulnerability drivers leading to flash flood impacts. Source: Terzi et al. (2015).

#### 4.5.2 The need for integrated forecasting tools to anticipate social impacts

##### *Are hazard forecasts sufficient to improve early warning systems?*

If impacts arise from the interplay of multiple, natural and social factors, then an early warning system should address all of these factors relevant to the particular risk. In contrary to other weather hazards, there is still an increasing number of people dying in particular extremes linked to floods and heatwaves around the world. It is apparent that modern technological improvements, including increases in accuracy and lead time of the hydro-meteorological forecasts alone, do not guarantee reduction of fatalities and economic disruption (Petrucci et al., 2018; Terti et al., 2017).

Effective disaster risk management relies not only on the accuracy and precision of official hazard predictions but also on how those are communicated to and interpreted by end users to support informed decision-making on allocating human and material resources before and during the crisis (Kox et al., 2018). Social studies show that warning response is an iterative process starting with the detection of a threat and ending with the adoption of a protective response. In the example of Tropical Cyclone Fitow that caused significant flooding in the Chinese mainland in October 2013, the Shanghai Meteorological Service issued accurate warnings according to standard operating procedures and protocols. Indeed, they increased the severity from blue to red as the situation worsened and alerted over 18 million people when the appropriate meteorological thresholds were exceeded. More than 1.2 million people were finally affected since this highest level of warning was issued “too late” in the midst of the morning rush hour just after a Chinese national holiday. As indicated in the WMO 2015 Guidelines (WMO, 2015), this is one example of many national warning systems that, solely based on hydrometeorological products, can provide messages restricted to generalized advice, ignoring local vulnerabilities and social dynamics. Such warning system could unintentionally play an important role in the progression of the crisis.

When a severe rainfall threatens flood prone areas, governmental forecasting offices combine rainfall observations with hydro-meteorological models output to inform emergency services and other user groups for the imminent risk to life and property in the area of their responsibility. This information may be in the format of text messages or visual warnings and are transmitted to emergency managers in the control centres (e.g., known as Emergency Operation Centres – EOC in Europe) and are further disseminated to other public authorities (e.g. local fire stations) or voluntary organizations to prepare for action (Figure 2). Before deciding on any emergency action, emergency managers examine the forecast information and deal with uncertainties seeking the most concrete indications for both the weather event and its potential impacts. Without supportive impact quantifications, their decision-making is often based on their own experiences and subjective perceptions. National Meteorological and Hydrological Services, research institutes, and international organizations that participate in the consortium of the World Meteorological Organisation (WMO) recognize that both the authorities responsible for emergency management and the public need specific information on ‘what the weather might do’ on people’s lives and properties in order to take appropriate actions. It is highlighted that it is no longer adequate to provide an accurate and timely forecast or warning of only ‘what the weather will be’ (WMO, 2015). In addition, the Sendai Framework for Disaster Risk Reduction (2015–2030) calls for a multi-hazard approach (i.e. takes into account the interaction of natural and man-made hazards), people-centred (i.e. takes into account the needs and rights of the affected persons) and preventive (i.e. aims to completely avoid the potential adverse impacts of a disaster through action taken in advance) (Müller et al., 2017).

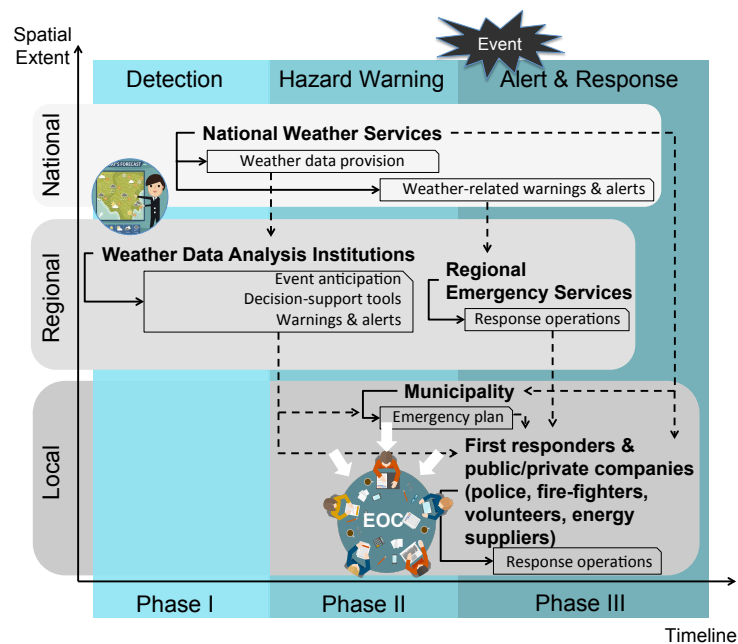


Figure 2 Conceptual framework of the Weather-related Warning Systems (applied primarily in a European context). National, regional or local actors are framed within light, medium or dark grey rectangles, respectively. According to the warning/response phase in which they mainly operate, actor actors and their warning or emergency actions/decisions (snip single corner rectangles) are presented inside the light (detection), medium (hazard warning) or dark green boxes (emergency response). The dashed arrows illustrate the flow of information among national, regional and local actors. Source: Terti et al. (2019).

### How to shift from hazard forecasts to impact-based forecasts?

In this direction, recent decision-support tools promote the elaboration of impact-based or risk-based forecasts that translate meteorological and hydrological hazards and related cascading effects into sector- and location-specific impact estimations to improve understanding and coping capacity for better responses to those risks (Luther et al., 2017). In late 2020, the World Meteorological Organization will publish the updated “2015 Guidelines on Multi-Hazard Impact-Based Forecast and Warning Services (IBFWS)”<sup>2</sup> to further support National Meteorological and Hydrological Services (NMHSs) and disaster reduction and civil protection agencies (DRCPAs) to progress from weather forecasts to impact forecast and warning services. Although there are several NMHSs that seek to issue impact-based weather warnings in the last decade, these efforts are still based on subjective assessments, highly depended on the meteorologist expertise and experience of past high-impact weather events. An operational example is the risk matrix used since 2011 by the UK Met Office, that combines the level of impacts the weather may cause and the likelihood of those impacts occurring to define a warning level (Met Office, 2017). Tackling the shift to modelled impact-based forecasts requires a multidisciplinary and highly integrated focus on the dynamic conjunction of the specific hazard and social vulnerability. This integration challenges both NMHSs and DRCPAs to incorporate data and knowledge not previously used in the weather forecasting-warning chain (e.g., demographic data, behavioural data, Geographical Information Systems (GISs), crowd-sourcing techniques). Obviously, weather and vulnerability experts need to work very closely to establish relevant methods to link hydrometeorological information with factors related to social and behavioural vulnerability processes to capture the complex and dynamic circumstances leading to social impacts from extreme weather. Building substantial collaborations between researchers and practitioners from different

<sup>2</sup> The 2nd edition of the guidelines will be published in late 2020 and will include six new chapters, based on recommendations from the symposium of service providers, users and funders hosted by the UK’s Met Office in December 2019. Announcement published at <https://public.wmo.int/en/media/news/wmo-updates-guidelines-multi-hazard-impact-based-forecast-and-warning-services>.



disciplines is a long process though, in which common understanding and communication are to be established.

Up to today, weather scientists and vulnerability scientists work quite apart from each other, developing their own techniques at different scales and resolutions. From one side, hydro-meteorologists work in priority on the challenging issue of modelling physical processes associated with the occurrence and magnitude of extreme weather events. In the example of short-fuse rainfall-flooding, a suite of hydrometeorological products operating at high spatiotemporal resolutions has been developed to support operational forecasters when issuing flash flood warnings (e.g., Borga et al., 2011; Gourley et al., 2016). Like most of the hydrometeorological services, current flash flood monitoring and forecasting systems generally aim to produce flood magnitudes (e.g., water discharges or return periods) using rainfall radar measurements and distributed rainfall-runoff models. The coupling with advanced 2D hydraulic models producing flood depth or flood extension maps is further proposed to assess the hazard severity in highly impacted areas (e.g., urban areas). It thus enhances the “usual” flood forecasting chain in modern Early Warning Systems (EWSs) (Papaioannou et al., 2019; Scorzini et al., 2018; Silvestro et al., 2016). Although the integration of impact-based services in EWS is largely discussed in the weather enterprise, the establishment of impact models is at a very preliminary stage. In majority, recent efforts comprise of either i) impact severity classifications in which each impact category is often associated with pre-defined hazard thresholds through qualitative evaluations (e.g., after interviews or focus groups with forecasters and stakeholders) (Sai et al., 2018; Schroeder et al., 2016) or ii) quantitative estimations of direct damages through modelled stage-damage curves and damage functions (Scorzini et al., 2018; F. Silvestro et al., 2019). In the first case, impacts are usually expressed in terms of general damages to land (e.g., corps damages), critical infrastructure (e.g., school closure, inundated or closed roads, inundated households), and services (e.g., electricity outages, lack of drinking water) and are defined at the event-scale. In the second group, damages refer to economic losses at the building scale (most often to residential buildings) and only a few do estimations of affected people (Cole et al., 2016; Silvestro et al., 2016).

Impact or risk assessment in the multi-model forecasting-warning chain is approached into two subsequent steps: i) the estimation of hazard scenarios (e.g., flood extent or flood depth maps) and, ii) the damage estimation associated with each of the previously analysed hazard scenarios. This approach lacks a holistic integrative method from hazard detection to impact prediction. Such methodology might be suitable for static assessments of potentially impacted infrastructures under pre-defined hazard conditions, especially serving as auxiliary tools for emergency planning, but cannot address impacts on dynamic social features like mobile people and activities. This is why, in the very few works including human impacts, impacted people are mainly estimated as the number of exposed people in buildings. Although, when assessing economic damages vulnerability of buildings is described through multiple variables (e.g., number of floors, basement volume, building usage, type, and material), affected population is calculated only based on their distribution in potentially inundated buildings (Cole et al., 2016) or in hazard zones where conditions favour instability of individuals (threshold values estimated as product of the water level and speed in the zone) (Cox et al., 2010; Jonkman et al., 2009; Silvestro et al., 2019). More inputs from social vulnerability science are required to complete the forecasting chain with social impacts forecasts such as the likelihood of rainfall impact on road users during rush hour, using vulnerability and exposure datasets along with meteorological and hydrological information.

### ***How vulnerability metrics can complement hydrologic forecasts towards impact estimation?***

Currently, social vulnerability modelling research is still separated from the weather enterprise and is dominated by the construction of indexes summarizing social dependencies and economic disadvantages of the population in geographic units varying from block groups to states (Clark et al., 1998; Cutter, 2003; Cutter et al., 2000; Tapsell et al., 2002). While there is a lot of research on analysing flood impacts and understanding the underlying causes of social vulnerability to flood hazards (Ashley & Ashley, 2008; Diakakis & Deligiannakis, 2013; Doocy et al., 2013; Jonkman & Kelman, 2005; Sharif et al., 2012, 2014; Terti et al., 2017), establishing specific vulnerability metrics remains rare. Being strongly influenced by pioneering studies (Clark et al., 1998; Cutter et al., 2000), social vulnerability quantification in cases of natural hazards

like flooding relies on either data-reduction techniques such as factor analysis (Rygel et al., 2006) or arithmetic methods such as standardization scores (Chakraborty et al., 2005; Wilhelmi & Morss, 2013; Wu & Li, 2006) to compose indicator-based aggregated social vulnerability measures and maps. With these approaches, social vulnerability is treated separately and is then merged with the hazard information (provided through flood hazard maps or scores) only as a final step to provide a static map of integrated socio-economical risk (Koks et al., 2015; Wilhelmi & Morss, 2013). Depending on the statistical method used, the classification of the estimated social vulnerability varies leading very different interpretations even about the vulnerability of the same population group (Willis & Fitton, 2016).

Indicators are chosen based on theoretical knowledge (deductive approach) or data-driven analysis (inductive approach) whereas links with impact-related observations are rarely considered (Fekete, 2009; Zahran et al., 2008). Zahran et al. (2008) analysed 832 flood events in Texas from 1997-2001 to explore the intersection of population vulnerability characteristics and aggregated flood casualties at the county level. Adopting a multiple regression analysis their study revealed that flood casualties are dependent on certain social vulnerability patterns. It was found that flood deaths and injuries in Texas are positively correlated with socially vulnerable populations, whereas they are reduced with the increase of structural and non-structural flood mitigation strategies in the exposed communities. Here, social vulnerability is still described in a static way in terms of racial minorities and economic status, inviting further research on the integration of more hazard and circumstance-specific vulnerability predictors. Terti et al. (2017) analysed 19 years of flash flood fatality reports in the United States to investigate differences in vulnerable situations as they emerge from the socio-spatiotemporal conditions in various death circumstances (e.g., in vehicles, inside buildings, recreational areas). They found that circumstances associated with fatalities in short-fuse flooding have specific characteristics related to the time at which the event happens, the duration of the flood, and tend to be associated with specific age and gender groups, inviting a situational approach when evaluating vulnerability and the subsequent risk of people to flash flooding. Driven from this analysis and the literature review on social vulnerability to flooding and natural hazards in general, Terti (2017) proposed an exhaustive list of indicators to represent flash flood-specific vulnerability of individuals in each of the identified death circumstances. Each indicator was selected based on its relevance to i) the temporal phase of the event (i.e., emergency phase versus preparation to or recovery from the hazard), ii) the circumstance of the life-threatening incident (e.g., vehicle-related incidents versus indoor loss of life), and iii) the interaction between the social and flood dynamics (e.g., flow of commuters at the time of peak runoff versus night-time population distribution). In parallel, the author investigated nationwide available data sets in the U.S. to serve as measurable proxy variables of those indicators describing the exposure, sensitivity, and coping capacity of people during flash floods, as presented by Terti et al. (2015).

Using an integrative and interdisciplinary approach (Figure 3), Terti et al. (2017) proposed to combine knowledge and data from meteorology, hydrology and human geography in an effort to predict combinations of physical and social characteristics and processes favourable for the outbreak of impacts (e.g., fatalities, injuries) within a flash flood, or other fast-evolving weather event. Especially, Terti et al. (2017) applied a “supervised” machine learning technique on historic fatal events to assess the likelihood of fatality occurrence for a given circumstance as a function of representative indicators. Their first application was limited in predicting events with lethal vehicle-related accidents in which most of the flash flood fatalities happen (Ashley & Ashley, 2008; Diakakis & Deligiannakis, 2013; Fitzgerald et al., 2010; Terti et al., 2017). This study built on the social vulnerability and risk analysis research with two main contributions: (i) human vulnerability aspects were integrated, for the first time, with hydrological forecasts to account for the evolution of human risk to flash flood hazard in time and space, and (ii) historic losses were involved in the modelling procedure to link vulnerability conceptualizations with human impact observations.

With a view to take into account the temporal and spatial evolution of risk to populations, section 4.5.3 details two modelling examples that share a common objective: being able to simulate life-threatening situations during the “event” phase of flash floods, when the majority of deaths occur (Ruin et al., 2008; Sharif et al., 2012). These efforts focus on the quantification of one of the main causes of mortality during these events, i.e. the daily mobility of exposed populations. While both models attempt to take into

account the critical interactions between vulnerability dynamics and hydro-meteorological dynamics at the sub-daily scale, they differ in the methods and data used. The first model is a probabilistic predictive model based on automatic machine learning techniques using random forests deployed by Terti et al. (2017) in the U.S.. The second model, called MobRISK is a discrete-event micro-simulation model using Bayesian networks developed by (Shabou et al., 2017) in France.

The development of such models for predicting human impacts raises the question of the use of this type of information for crisis management. Do these probabilistic predictions help decision-makers to better prioritise protection actions or to better target safety messages to the most vulnerable ones? In an attempt to answer these questions, the last part of this chapter describes the development of a participatory tool designed as a serious game to measure the impact of different types of information on the decision-making process in crisis conditions.

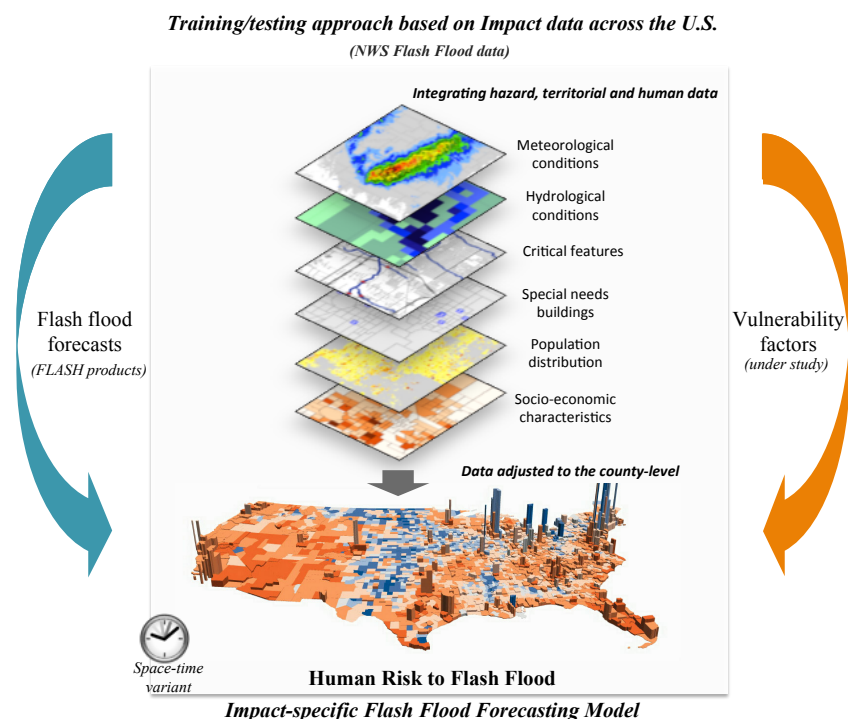


Figure 3 General concept of the interdisciplinary approach toward flash flood human impacts prediction. In Terti 2017.

#### 4.5.3 Insights of methodological advances in modelling the coupled socio-hydrometeorological system in high-impact weather events

##### **Examples of two aggregated and individual-based micro-scale interdisciplinary approaches**

- *Simulation of motorists' exposure to road flooding: The MobRISK simulation model*

MobRISK is a model for assessing and simulating road users' exposure to road flooding due to extreme flash flood events by combining travel-activity simulations following an activity-based approach with hydrometeorological data. The model's architecture includes three modules simulating:

1. **The dynamics of the road flooding:** Probability of submersion is assigned to every road cut by combining the flooding susceptibility level at each road-river intersection (Naulin et al., 2013) and the return period of stream discharge simulated by the CVN distributed hydrological model (Branger et al., 2010; Vannier et al., 2016; Viallet et al., 2006) at an hourly time step.

2. **The individual's daily mobility:** daily schedules (informing on the time and purpose of travels) are based on travel-activity data provided by the French National Transport and Travel Survey (ENTD). A pre-processing step is necessary to:
  - i. identify the sociodemographic characteristics of individuals and households corresponding to the study area,
  - ii. assign daily schedules, based on the effects of sociodemographic variables on schedules dissimilarities, to every individual of the study area (Shabou et al., 2019),
  - iii. locate the areas where they are likely to conduct their activities based on localized tax datasets and land use information.

The resulting travel patterns are then distributed on the road network using the classical Dijkstra algorithm – a single source shortest path algorithm (Dijkstra, 1959).

3. **The individual's protective response decision-making processes** allowing exposed people to take decisions when confronted to hydro-meteorological disruptions. A Bayesian network approach is used to link variables related to the individual's evaluation of danger and flexibility of the next scheduled activity with the following four protective decisions options:
  - i. continue without adaptation,
  - ii. stop and wait in front of a submerged road-river intersection,
  - iii. delay the next activity,
  - iv. return home.

In addition, user input data, issued from national census and geographical data providers, are stored in a spatial relational database management system.

A discrete event simulator (DES) runs the main temporal loop of the simulations (Shabou et al., 2017). The pending event set is organized as a priority queue, sorted by event time and handled in chronological order (Fujimoto, 2016; Robinson, 2004). Six types of changes in conditions or events are considered: the submersion of roads, the movement of individuals, the crossing of cut-off points, the end of activity (which marks the initiation of a move to the location of the next activity in the schedule), the perception of environmental signs (change in precipitation levels for example), weather warning or vigilance information.

MobRISK simulations provide a measure of motorists' exposure to road submersion based on the probability to encounter one or several flooded road cuts on their route during the simulated event period. Since individuals are likely to cross several road cuts with different probabilities of submersion, total exposure is computed by calculating the joint probability of submersion of all the crossed road cuts.

A first application of the model to the 39 municipalities of the Gard region, that were strongly affected by the September 8–9, 2002 flash flooding in France, allowed to quantify the exposure of 110,000 individuals based on the simulation of their movements and behavioural response to this dramatic event. The simulation showed that the exposure index varied significantly according to occupational status, activity, age and gender, with men at a prime age being the most exposed. This study also enables to locate the most dangerous road/river intersections in space and time because of the number of individuals likely to cross them when submerged. For this event, the temporal analysis of the model outputs indicated that the risk of flooding was highest during the night from Sunday to Monday when traffic was expected to be the lowest. The simulation combining the risk of road flooding and the daily mobility expected for these weekdays confirmed a reasonable temporal difference between the peak of cuts and the peak of mobility in this sector (Figure 4). Finally, on the basis of behavioural scenarios, the approach tested the combined effect of different standard attitudes to risk, risk assessment methods, and decision-making choices on individual exposure at the event level. For instance, decisions to stop and wait in front of a submerged road or to shift trips by re-planning daily activities tends to reduce the percentage of people exposed and to a lesser extent their level of exposure compared to the decision to return home.

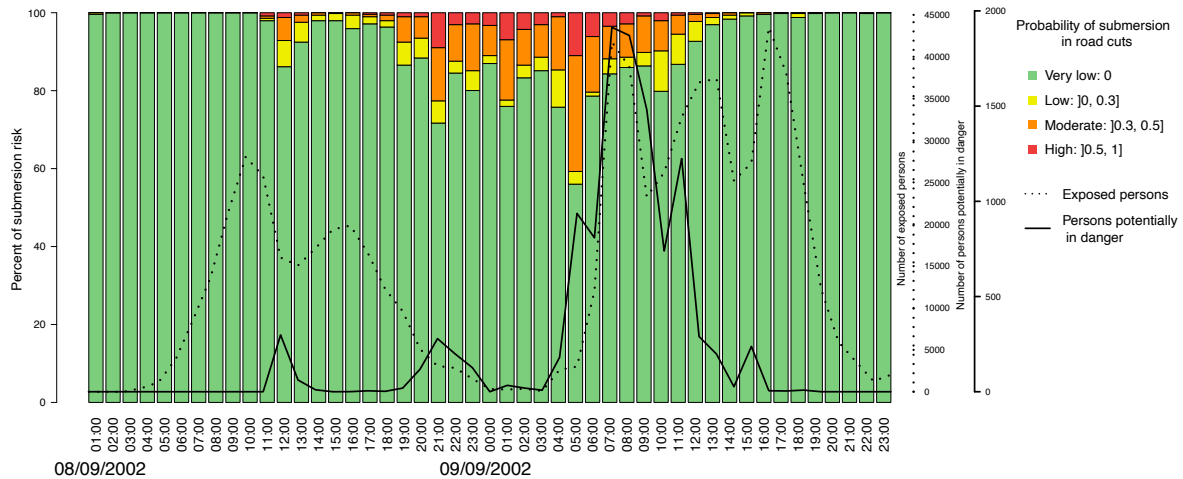


Figure 4 Time lag between the temporal distribution of the probability of submersion (colored bars) and the traffic load at road cuts (line). The dotted line represents the temporal distribution of the risk index referring to the number of persons potentially in danger (resulting from the combination of both the probabilities of submersion and traffic load). Results obtained by the simulation of the MobRISK model for the 8–9 September 2002 flash flood event in the study area (Gard, France). Source: Shabou et al., 2017.

- Machine-learning predictions of flash flood human risk related to vehicles

Terti et al. (2017) adopted an empirically guided, predictive approach to estimate the likelihood of one or more vehicle-related fatality incidents to occur in a specific flash flood event given the conjunction of supplemented characteristics about the hydrometeorology of the event and the infrastructure and demography of the exposed county. The input “impact data” in the data-driven modelling approach were compiled from a list of 38,106 flash flood events with and without human losses, reported in the *U.S. Storm Data*<sup>3</sup> from 2001 to 2011 in the contiguous U.S. This allowed for a binary classified dataset of flash flood events to formulate the target variable to understand or predict when assessing the occurrence of human losses from flash flooding in the vehicle-related circumstance. To address the lack of a comprehensive dataset to build the target-predictor scheme, the authors compiled extra thirteen different databases, which provided about 400 proxy variables explaining the hydrological and meteorological responses, the geomorphological characteristics, the information about the available official emergency response, and other spatial and socio-demographic attributes (Terti, 2017). The variety of the origin of the data (e.g., hydrological, meteorological, spatial, demographic, loss) in the analysis suggests the divergence of spatial and temporal resolutions. Therefore, the main challenge here was to find a compromise between addressing vulnerability factors related to individual behaviours and hydro-meteorological dynamics at very small scales while using readily available data at the national scale (usually defined by coarser resolution such as the county units) for replicable research at the scale of the entire United States.

Random forest (RF), a well-known decision-tree based ensemble machine-learning algorithm for classification and regression, was adopted for this analysis (Breiman, 2001). This method provides for the

<sup>3</sup> *Storm Data* is the most extensive nationwide database in the U.S., recording four types of impacts (i.e., fatalities, injuries, and property and crop damages) for forty-eight weather related events (e.g., Hail, Heat, Hurricane, Flood, Flash Flood, Tornado, Tsunami, Wildfire etc.). Documentation of the Storm Data is available online at <http://www.ncdc.noaa.gov/stormevents/details.jsp?type=eventtype>.

identification of the variables that best represent the interplay between the natural hazard and human vulnerability processes for commuters during flash flooding events. It was shown that peak unit discharge played the most important role in partitioning the flash flood events in events with and without vehicle-related fatalities. The unit peak discharge (i.e., discharge normalized by the cell's upstream drainage area in  $\text{m}^3\text{s}^{-1}\text{km}^{-2}$ ) was computed by running the Coupled Routing and Excess Storage (CREST) distributed hydrologic model (at  $0.01 \times 0.01$  degree resolution over the conterminous United States) (Wang et al., 2011). Being dynamic, this variable and the maximum precipitation both describe the magnitude of the natural hazard. Especially, it is because these dynamic variables were determined in much higher spatial and temporal resolutions than the county-level demographics, that they probably can inherently capture some local conditions crucial for the occurrence of life-threatening scenes. Variables that describe the social aspects (e.g., median age of commuters, household size) were considered as weaker predictors in the model. However, when these variables were excluded from the predictors set, the ability of the model to predict the probability of flash flood events with vehicle-related fatalities in the validation set was reduced. There is a plausible signal that considering all possible interactions between the probably weak predictors leads to a better predictive model. The internal predictive performance evaluation of the model was significant ( $0.5 < \text{AUC} = 0.7 < 1.0$ )<sup>4</sup> (Mason & Graham, 2002), especially if one considers the coarse resolution of the predictors used.

The authors applied the machine-learning model to the catastrophic flash flood events of May 2015 in the conterminous U.S. Especially, daily risk maps from May 16 to May 29 were constructed with a focus on the 254 counties in Texas and 77 counties in Oklahoma, where 34 people lost their life. For illustration purposes, the estimated probabilities were equally distributed in four categories: i) low likelihood:  $\leq 0.25$ , ii) moderate likelihood:  $(0.25 - 0.50]$ , iii) high likelihood:  $(0.50 - 0.75]$ , and iv) very high likelihood:  $> 0.75$  (Figure 5a). The mapped predictions were visually compared with i) the counties with vehicle-related victims, as reported in the *Storm Data* (highlighted with red boundaries), and ii) the Local Storm Reports (LSRs) that represent flash flood emergency issues such as road flooding, closures, and rescues issued in near real-time by the local National Weather Services (NWS) (red dots) (Figure 5a). The model predicts fairly well the high probabilities of larger events extending over the entire county. On the other hand, vehicle risk tends to be overestimated for very localized events, which may depend largely on local sensitivities that are difficult to capture with the current limitations on the spatial resolution of the model. It is quite interesting that hourly predictions for the most catastrophic day of May 26 in Harris County (Texas), estimate the highest probabilities mainly from 03:00 a.m. to 09:00 a.m. and reduce throughout the day, revealing the conjunction of commuters and flood dynamics during morning commuting hours (Figure 5b). These results are encouraging in identifying the spatio-temporal evolution of the risk to daily travels during periods of rapid flooding.

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<sup>4</sup> The optimal model was selected to maximize the area under the receiver-operating characteristic (ROC) curve (AUC) across the resamples. An AUC value of 0.5 corresponds to random guessing and a value of less than 0.5 indicates discrimination worse than random chance.

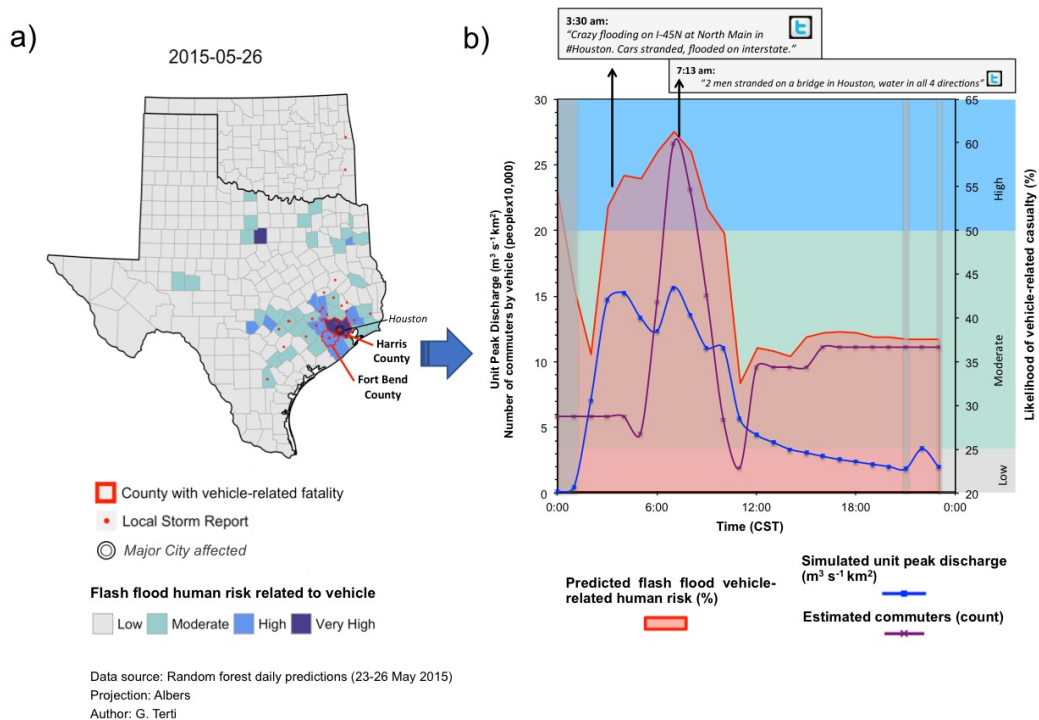


Figure 5 a) Spatial distribution of the county-level daily forecast of vehicle-related human risk for the day of May 26, 2015 in Texas and Oklahoma States, and b) Estimated hourly predictors, and vehicle-related risk predictions by local time (Central Standard Time), for flash flooding in Harris County (Texas) on May 26, 2015. Source: Terzi (2017).

### Methodological comparison: Strengths and weaknesses of the interdisciplinary modelling

The two models presented above have the advantage of taking into account the dangerous coincidences between social dynamics (daily mobility, specific vulnerabilities) and hydro-meteorological dynamics (rain, runoff and river rise) over large territories (from a French administrative region to the whole United States) and at relevant spatial and temporal resolutions (from meters to the U.S. County geographic unit, and from minute to hour).

The MobRISK model establishes a risk index based on the probability of motorists crossing flooded sections of roadways on their way to their daily activities. The high temporal and spatial resolution of the model allows exploring the impact of flash floods on daily mobility and individual adaptation behaviours triggered in response to the individuals' perception of danger. This simulation tool, therefore, enables the identification of the most exposed socio-demographic profiles (working people, from the middle age classes and mostly males).

The MobRISK model has the advantage of being efficient in terms of calculation time, taking into account a large number of agents (e.g., more than 100,000) and, therefore, it can potentially accommodate a large or densely populated territory. Its drawbacks relate to the highly demanding data pre-processing phase and the high level of computer expertise required to modify the C++ code that models the spatial and temporal dynamics. Compared to the capabilities of other micro-scaling approaches like the multi-agent models (Adam et al., 2015; Beck et al., 2014; Watts et al., 2019), MobRISK represents a simplified version of interactions between agents. That means that it does not take into account the cognitive influence that agents can exert on each other when making decisions. Thus, agents located in the same place at the same time are not "aware" of the presence of other agents and act according to their own perception of the environment and assessment of the danger.

The choice of a discrete event model from the authors is explained by their focus on road risk and the identification of road-river intersections as dangerous zones where hydrological hazards and human issues meet. Therefore, all of their reasoning and calculations are based on the assumption that the main danger is related to the use of cars at specific points where the roads are flooded. The human risk associated with pedestrian movements or the flooding of buildings is not taken into account in the current model. This advancement would require the integration of additional data representing the temporal evolution of the extension of the floods and the associated water heights as well as the height of the buildings. These hydrological data are currently difficult to obtain, especially in urban and peri-urban contexts, which require high spatial resolution modelling to simulate the channel runoff. Nevertheless, taking into account individual daily timetables, MobRISK makes it possible to locate people at any time of the day or night depending on their activities and thus, to assess the exposure of population by taking into account their mobility trajectories and the time they spend in buildings that are potentially exposed.

The choice of the modelling methodology depends not only on the type of data available, but also on the study area and the intended objective. In an effort to meet more operational needs, automatic predictions of road deaths risk during flash flood occurrences produced by the machine-learning model described above, is a reasonable choice. In the machine-learning model, uncertainty in quantification of human risk related to vehicles is accounted for by treating the occurrence of flash flood fatalities in a probabilistic way. Compared to previous studies, vulnerability is illustrated as an evolving likelihood of vehicle-related incidents overcoming the one-sided static generalization of social vulnerability from county to county. The machine-learning algorithm is much simpler in use and faster than the MobRISK configuration, producing impact forecasts in just a few minutes. However, its resolution is lower to the one provided by MobRISK. Overall, the two approaches are complementary since new knowledge on the individual vulnerabilities that arises from the Bayesian framework used in MobRISK could further inform and update the machine-learning procedure.

The main constraints in the data-driven approaches arise from the need for large number of observations to construct an adequate statistical sample for the machine-learning algorithm. This necessitates the consideration of many years of flash flood event observations within a large geographic area (i.e., whole U.S.). Therefore, regional differences and local specificity that may convert an initially moderate risk flash flood event to a catastrophic event are not considered in the modelling of (Terti et al., 2019). At the time of their analysis the county was the most reliable spatial reference for the reported impacts in *Storm Data*. The county level was used in the predictive modelling to avoid spatial vagueness and inconsistencies between *Storm Data* files, and to maximize the number of available records. The fact that reports on flash flood fatalities are not spatially explicit complicates the supplementation with other extra datasets available at higher resolution than the county. Local and sometimes dynamic information defined on the order of a few kilometres and/or with high temporal resolution (e.g., population density, unit discharge) were aggregated, losing details that might contribute to the occurrence of a lethal scene. When the accuracy of the bounding polygons currently adopted by the NWS to report impacted areas in flash flood events allow for it, it would be interesting to bring all the data in finer resolution. Furthermore, the reported bounding polygons could be cross-checked with the extent of the hydrologic forecast to delineate even more specific exposed areas. This would provide for the collection of more spatially precise predictors to be used as input in the machine-learning model training. Consideration of other types of human impacts such as injuries or rescues could also contribute to a larger sample of impactful flash flood events with vehicle-related incidents. This is a limitation in the study since systematic classification of nonlethal circumstances is not available at the U.S. scale, yet.

Despite unavoidable biases and scale issues, this work represents a first attempt to provide a (pre-) operational prediction system that supports emergency preparedness and response to flash flood disasters. Based on readily available data sets across the United States, the adopted modelling approach could support a nationwide prediction effort for forecasters and emergency managers to target their warnings on anticipated human impacts, forcing the model with real-time hydrologic forecasts.



Validation of the developed models is not a straightforward exercise. Rare events such as flash floods with casualties are difficult to predict. Casualties depend on many parameters such as personal strengths and last-minute decisions. The same conjunction of socio-hydrological conditions identified as lethal in past flash flood events may not result in fatalities during a future event due to differing circumstances at a very local level that cannot be taken into account on the basis of the currently available data. To assess the performance of these models in more detail, a large amount of accurately geo-located and time-stamped impact data would be required. Therefore, we recommend that the disaster science community and practitioners conduct data collection with more details and at finer resolutions to better capture local temporal and spatial complexities associated with human losses from fast-evolving weather events. The collection of such data from i) online behavioural surveys and/or the elaboration of citizens' calls to the emergency services (Papagiannaki et al., 2017), ii) post-event surveys such like the SHAVE experiment in the U.S. (Calianno et al., 2013), and iii) information extracted from social media (Morss et al., 2017), seems an interesting avenue to explore for the evaluation of social impact models. Expert engagement is also a necessity to compensate the scarcity of large and suitable data at the scale of the short-term flood disasters. Participatory approaches, involving forecasters and emergency managers, are a strong recommendation not only to fit the model objectives and outputs to their needs, but also to get feedback on potential adjustments and improvements of the modelling itself based on experts' knowledge and experience in the area of their responsibility.

#### **4.5.4 Toward operational decision-making in high-impact weather events: Insights from a participatory role-playing experiment**

Validation and verification are important processes before new forecasting tools join the forecasting-warning chain operationally. However, impact-based advancements cannot be evaluated with the verification metrics used for traditional hydro-meteorological models (e.g., contingency tables, false alarm ratios). At least not at this early stage that the systematic impact data collection for social impacts is still a far-away expectation for both developing and developed countries. As mentioned in the 2015 Shanghai Workshop on 'Implementing Multi-Hazard Impact-based Forecast and Warning Services', *'here the emphasis is on the utility of the forecast, not just the accuracy of the underlying meteorological or hydrological prediction'* (GFDRR, 2016).

The utility of services and impact-based developments is based on the ability of end-users to exploit the information and take effective action. When it comes to the implementation of impact forecast and warning services, the WMO roadmap sets as an important step to create a group of users and to *'establish feedback protocols and quality assurance with the user group so that during trials the partnership can evaluate and verify the usefulness and relevance of new services'* (WMO, 2015). Therefore, designing of interactive communication approaches among developers and stakeholders should be viewed as a central part to investigate the contribution of site-specific and impact-based information in weather-related crisis decision making in both the designing and the implementation phases.

Participatory approaches, involving forecasters and emergency managers, is key methodology to i) understand the decision-making challenges in warning services and crisis management, and ii) get feedback on potential adjustments and improvements of the developed decision-support tools based on experts' knowledge and experience in the area of their responsibility. In the U.S., the HMT- Hydro Experiment has been organized annually from 2015 in the National Weather Centre (NWC) in Oklahoma (U.S.) with the aim to allow operational forecasters to assess emerging products and techniques designed to improve the prediction and warning of flash flooding. During the experiment, National Weather Service (NWS) forecasters work with research scientists to test -among others- i) the application of user-defined probabilistic forecasts in experimental flash flood watches and warnings, and, ii) the utility of the Hazard Services interface with flash flood recommenders in real-time experimental warning operations. In the 2015 HMT-Hydro held at the NWC from 6 July to 24 July, 2015, Terti (2017) discussed their conceptualisation for the predictive modelling of vehicle-related flash flood casualties presented in section 4.5.3. Ad hoc feedback

from forecasters recognized the need for a tool to synthesize information about the exposed population and the surrounding environment, and the importance of quantifying their relationship with the hydrologic forecasts, in order to have on hands an auxiliary metric (probabilistic or not) to use in a warning decision support role.

Another type of participatory experiments that gains space in the hydrological forecasting community is the one of serious game experiments in the form of role-play. Role-playing games (RPGs) are the virtual simulation of real-world events especially designed to educate, to inform and to train the players for the purpose of solving a specific problem (Bowman, 2010; Drachen et al., 2009; Susi et al., 2007). A series of role-playing games were developed the last years to investigate how seasonal forecasts are actually used by decision makers in water resources management (Arnal et al., 2016; Crochemore et al., 2016; Ramos et al., 2013). These experiments especially focus on the utility of probabilistic forecasts for improving decision-making on water management issues, but they do not test yet impact-based forecast information (Ramos et al., 2013).

In an effort to explore "if" and "how" improved multi-model outputs, including information on impact-based vulnerability data, can support the decision chain towards better responses in European warning-response systems, Terti et al. (2019) proposed ANYWHERE Crisis and Risk Experiment (ANYCaRE)<sup>5</sup>. ANYCaRE was developed in the frame of ANYWHERE European Project as a communication tool that engages participants in the decision-making process at different levels of the weather-related emergency system (from hazard detection to citizen response) (see Figure 1). The focus of the experiment is a tabletop or pen-and- paper role-playing game (PnP) for adults in which participants act their role through speech while sitting in a comfortable setting (Cover, 2005). The PnP game is structured in progressive simulations in which modern multi-model outputs, including information on i) impact assessments and maps and ii) live data on exposure and vulnerability derived from social media and crowdsourcing (named as "impact-based vulnerability information"), are presented as new decision-support tools to the players who represent an Emergency Operation Centre (EOC). Through (semi-) realistic "what if" scenarios in two subsequent trials the players assess different information that describe an imminent risk situation and decide collectively what protective and communication actions, if any, are needed in every playing round (Figure 6). The players are guided through the simulations to experiment the outcomes of their decisions and learn from their playing experience (Dieleman & Huisingsh, 2006; Huyakorn et al., 2012). In the debriefing phase after the simulations, participants are invited to comment on either positive remarks or suggestions for improvements related to the game itself but also to the modern products provided as input data to support decision-making in the simulations. Short textual annotations on post-it notes are gathered and classified into themes after qualitative analysis (Rebolledo-Mendez et al., 2009). The methodology includes also the analysis of responses from short pre- and post-experiment questionnaires that may be delivered to the participants (Huyakorn et al., 2012).

The experiment includes tabletop gaming simulations of i) flooding and flash flooding, and ii) strong winds and thunderstorms. An alternative version of the game, S-ANYCaRE, was further developed based on the flood scenario to simulate and test how public information from social media is used in emergency operations centres to make decisions on risk protection and communication (Weyrich et al, 2021). An additional extension of ANYCaRE includes a more complex scenario describing cross-cutting and cross-sectoral cooperation needs to respond to CBRN (Chemical, Biological, Radiological and Nuclear) hazards and hybrid threats. This version was played by 80 delegates from the EU Countries participating in the Finland's Presidency of the European Union in 2019. In total, about 200 players played the different versions

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<sup>5</sup> The acronym includes the name of "EnhANCing emergency management and response to extreme WeatHER and climate Events" (ANYWHERE) European Project (EC-HORIZON2020-PR700099-ANYWHERE) in which the experiment was developed. ANYWHERE project is an innovating action that aims at developing and implementing a pan-European decision-support platform integrating cutting-edge forecasting technology. More information about the project is available online at <http://anywhere-h2020.eu>.

of ANYCaRe from September 2017 to November 2019. ANYCaRE experiments took place in different settings (e.g., European workshops, trainings, university classes). Depending on the purpose of the experiment, participants ranged from students and young researchers to developers, expert hydro-meteorologists, operational forecasters and other stakeholders.

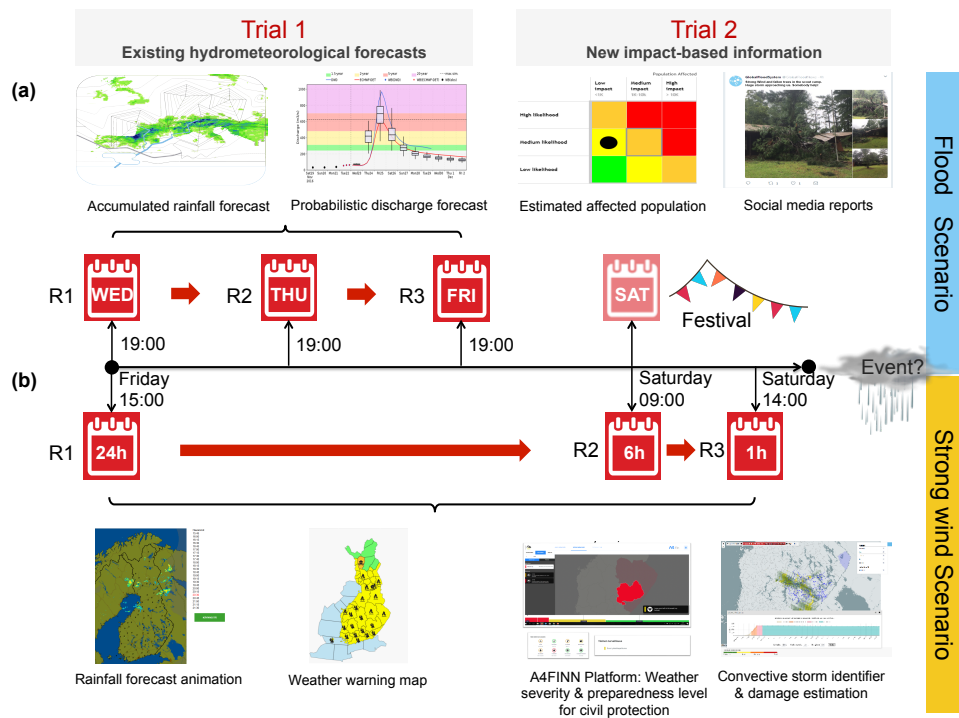


Figure 6 Schematic illustration of the gaming timeline (rounds 1 to 3) and the information provided to the players of ANYCaRE for the: (a) Flood scenario and (b) Strong wind scenario. In the second trial of each round, the players receive additional decision-support tools including high-resolution forecasts and impact-based vulnerability inputs. Source: Terti et al. (2019)

The games aroused the interest and enthusiasm of participants and offered to the players a protected environment to try-out emergency actions without facing true risk for human life. Terti et al. (2019) found that the role-playing approach facilitates interdisciplinary cooperation and argumentation on emergency response in a fun and interactive manner. Their results indicate that multi-model developments and crowdsourcing tools increase the level of confidence in the decision-making under pressure. In terms of the perception of the challenges faced by crisis decision-makers, the players highlighted the difficulty to manage the multitude of data, the prioritization of actions in order to better anticipate and choose the optimal decisions without being overwhelmed. ANYCaRE experiment was proposed, therefore, as a valuable learning tool to enhance participants' understanding of the complexities and challenges met by various actors in weather-related emergency management.

With certain modifications, an experimental framework like the one proposed in ANYCaRE can be extended to other tabletop exercises or to be digitalized to offer a modern multi-task and multi-role structure for deeper understanding of various decision-making aspects in weather crisis and for the introduction of impact-based decision-support prototypes. Given the scarcity of chances to actually experience demands for decision-making on weather emergencies, playing the simulation-based game is a simple but essential mean for participants to nourish their recognition of the emergency management difficulties and beneficial tactics. Also, "playing" may provide an excellent opportunity for current or future decision-makers to get familiar with pre-operational impact models and explore the potentialities of an impact-oriented weather forecasting chain before the real crisis strikes.

### 4.5.3 Conclusion

Extreme weather and climate events challenge weather forecasting and emergency response operations and are often related to dramatic social impacts. Despite the latest advances in weather forecasting technologies, the question remains open: How to anticipate the "unexpected" responses to extreme weather in order to intervene at the right time and places to avoid unmanageable situations?

This chapter highlights the need to integrate modern forecasting-warning chains with dynamic human vulnerability models describing fluctuations in the activities, behaviours, and personal and situational constraints of the exposed people. The authors argue that since people and their activities are rarely static but move across space at different times, the dominant vulnerability factors also change correspondingly. For example, the lives of active people (e.g., workers, students) are often threatened when a weather hazard interrupts daytime commutes. On the other hand, the sudden exposure of people during night-time rest hours, challenges the most vulnerable ones such as kids and elderly, especially when incapable to evacuate. The paper introduces such long-term and short-term socio-ecological dynamics related to human response to weather hazards with a special focus on sudden, fast evolving and short-duration weather events like flash-floods. This knowledge is a prerequisite in the emergency phase of the event when advisory (public warning messages, impact information) and emergency interventions (rescues, evacuations) are at stake.

This is a new area for weather services and requires an extensive knowledge of how meteorology and hydrology affect day-to-day activities, the vulnerability of exposed people and infrastructures, and the choice of protective responses during the crisis. Traditional weather forecast and warning services have been focused on the modelling of the hydrometeorological events (e.g., the magnitude, the spatial extent and the duration of the physical phenomenon). Impacts modelling is an emerging topic for researchers and practitioners to further provide quantified information about the imminent risk of these events to the exposed society. The term "impact modelling" is, however, not commonly understood in the disaster community. For example, secondary hazards derived from meteorological events (e.g., flooding) are often considered by weather experts as the 'weather impact' to forecast. This does not provide any information on the effect of flooding on people, which requires insights from local vulnerability and exposure data. Obviously, the more the message refers to specific expected impacts, the more people would imagine what to prepare for and how to cope with it, as suggested by the difference in the following message examples: i) a "hazard warning" (e.g., *'Rainfall accumulations of 200 to 300 mm are expected to cause severe flooding'*), ii) an "impact-based warning" (e.g., *'Rainfall accumulations more than 200 mm are expected tomorrow, expect road closures and rerouting of traffic to avoid flood prone areas'*), and iii) an "impact warning" (e.g., *'Based on the risk of flooding along your normal commute from workplace to home tomorrow, follow the alternative route... flexible time will be implemented - Based on your usual work schedule, leave work at least 1 hour earlier than normal to avoid significant delays'*) (GFDRR, 2016).

This shift goes beyond the expertise of forecasters who are called now to translate hazard forecasts into impact forecasts and warnings facing new sources of uncertainty. The WMO launches specific programs to assist NMHSs and their partner agencies to build their understanding of the consequences of the hazards to their societies, and based on this understanding, to develop relevant impact-based decision support tools (WMO, 2015). It is still under question though, if the NMHSs or the DRCPAs alone can be responsible for this transition. It is recognized that successful implementation of impact-based services implies for a change in the working practices of both operational forecasters and those responsible for civil protection. Co-working with expert geographers and social vulnerability scientists is a hint towards the development of more localized, geographically- and timely-specific warnings that target certain people and their activities.

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