Decision Analysis for Management of Natural Hazards

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Abstract

Losses from natural hazards, including geophysical and hydro-climatic hazards, have been increasing worldwide. Thanks to improved monitoring, observations and modelling, it is now becoming possible to assess risks and forecast natural hazards more accurately. The focus of this review article is the process by which scientific evidence about natural hazards is applied to support decision making. Decision analysis typically involves estimating the future probability of extreme events, assessing the potential impacts of those events from a variety of perspectives, and evaluating options to plan for, mitigate or react to events. Application of formal decision analysis methodologies across natural hazard contexts has so far been uneven, but there are many valuable approaches available, and potential to learn across hazard types and timescales of response. We provide a summary and evaluation of existing applications, concluding that more thoughtful and widespread application of decision analysis will help to ensure that new scientific understanding yields the greatest possible benefits in terms of risk reduction.

1. Introduction

Mankind has always had to live with natural hazards. Civilisations have had to adapt to the inevitable arrival of natural hazards, or risk collapse. The development of civilisation has also hugely increased vulnerability to natural hazards. Indeed some aspects of civilisation (such as the need for energy and water, and the benefits of trade) have tended to concentrate development in particularly vulnerable locations: on the lower reaches of rivers, and on exposed coasts. The prosperity of society demonstrates some skill at managing these risks and trade-offs. Societies have built protection systems; the Twentieth Century saw the development of scientific forecasting and warning systems for hydro-meteorological and some geophysical hazards; huge resources have been mobilised for emergency assistance and recovery. It seems therefore that modern civilisation has adapted to natural hazards, as other societies have done in the past. Yet the escalating scale of losses from natural hazards (Munich Re, 2015), the global concern about these losses (UNISDR, 2015), and the apparent lack of attention to preparedness (when compared with the huge sums spent on response and reconstruction; Kellet and Caravani (2013) suggests that this adaptation is far from optimal. Decisions are being made, but apparently they are not always the right ones – expecting that they might be would be unrealistic, given the scope and severity of uncertainty in natural hazards decisions and the inevitability of trade-offs between different objective and actors. Improvement in decision making can be expected to contribute to reducing risk, allocating resources more efficiently, avoiding undesirable impacts and accessing co-benefits. Our proposition in this review paper is that, on balance, humankind would be better at managing natural hazards if more extensive use were made of formal decision analysis.

Decision analysis (Kleindorfer et al., 1993) encompasses normative theory of how decision-makers *should* make choices, alongside descriptive analysis of human decision making in practice. Empirical study of how people make choices under uncertainty has demolished notions that human beings behave as rational agents. Kahneman and Tversky (1979)'s prospect theory has been widely applied to understand risk assessment decisions, appearing to resonate well with actual behaviour (Greenberg et al., 2012). Wilson et al. (2011) showed that wildfire managers' decision making was influenced by risk-based biases, including a preference to minimise short-term over long-term risk due to the belief that future risk could be controlled. However, despite its ability to explain individuals' behaviour, Kahneman (2011) has argued that prospect theory should not be used for normative decision making, suggesting that decision-makers use his findings to become more aware of their decision framing. Here our emphasis is upon the prescriptive aspects of decision analysis, with a view to improving decision making about natural hazards. Normative decision analysis seeks to provide better framing and selection of alternatives than intuitive response (Keefer et al., 2004) by structuring problems in a way that improves understanding; makes assumptions clear, or clearer; and ensures that the decision flows logically from its framing and assumptions.

This paper will explore characteristics of natural hazards decisions, and evaluate current use of decision analysis across a range of natural hazards. We focus upon: (i) the role of uncertainty in natural hazards decision making; (ii) the multiple values, attributes and objectives that are typically brought to bear on natural hazards decisions and how these are handled in theory and practice; (iii) the multiple actors that are involved in natural hazards decisions and (iv) the ways in which good decision making processes might be constructed to reflect learning about these various challenging characteristics. Section 2 will set up the context and challenges associated with natural hazard decisions. The remainder of the paper will review decision analysis methodologies as potential solutions for formalising decision problems: first examining approaches for dealing with uncertainty (section 3), before moving onto methodologies for sequential decisions (section 4), and decisions with multiple objectives (section 5), and actors (section 6). In section 7 we consider how decision analysis might contribute towards decision making processes. Section 8 makes conclusions and recommendations for further research and practice. We hope to introduce insights from decision analysis to areas of natural hazard management where it has seen limited application, and promote learning across different classes of hazard, including geo-physical and hydro-meteorological, which are researched by different communities.

Conscious of the wide scope of the fields of 'decision analysis' and 'natural hazards', we limit ourselves to the presentation of decision analysis methodologies in terms of their capacities and shortcomings rather than providing guidance on their implementation and interpretation; and, given the limitations of space, we have selected illustrative examples rather than attempting comprehensive coverage of all decisions made for natural hazards. We focus predominantly on geological and meteorological/hydro-meteorological events and some directly associated hazards (wildfires, tsunami, avalanches and landslides).

2. The challenge posed by natural hazards for decision-makers

Natural hazards have been associated with "messy" (Ackoff, 1974), "wicked" (Rittel and Webber, 1973), and "post-normal science" (Funtowicz and Ravetz, 1990) problems, without clear or straightforward solutions (Frame, 2008). There are often complex interdependencies, large uncertainties, and pressing decisions with important implications for many stakeholder groups with potentially conflicting values. In this section we explore these challenging contexts, including how they differ between natural hazard decisions operating on different temporal and spatial scales. Characteristics of natural hazard decision problems are identified as a first step towards the selection of appropriate decision analysis methodologies, which will be described in the following sections.

Timescales of decision making

Decision making regarding natural hazards can be divided into: (i) long term planning or risk mitigation, (ii) early warning and preparation, (iii) during event response, and (iv) recovery (World Economic Forum, 2011, Rougier et al., 2013), The first three of these are the focus of this review. Each phase may involve different actors, institutions, and different requirements for decision analysis (Tacnet et al., 2012, Rougier et al., 2013). Planning and preparedness decisions lead to anticipatory actions designed to reduce the risk from natural hazards. Assuming that the triggering physical phenomenon (extreme rainfall, an earthquake) cannot be modified by human action, planning and preparedness focusses upon steps to reduce exposure and vulnerability, for example through land zoning, building protection (dams, dykes and earthquake resistant buildings), and contingency planning (Tacnet et al., 2012). Planning and preparedness decisions mostly deal with the allocation of resources or the regulation of activities. The latter may not have direct resource implications but often involves forgone development opportunities. The mandate and resources to incorporate risk of natural hazards into long term planning varies markedly between countries (World Economic Forum, 2011).

For many natural hazard events there is also the opportunity to make decisions during times of imminent threat, for example if a volcano becomes active; a cyclone is observed offshore; recent weather observations demonstrate conditions which might lead to flooding, landslides, or wildfires; or weather forecasts signal potential hazards (Rougier et al., 2013). These decisions are characterised by urgency, the possibility of (averting) major losses and the possibility of the undesirable consequences of false warnings and badly prioritised actions. On these timescales decision making revolves around early warning systems and emergency planning, for example cancelling leave, clearing roads, and evacuations. As the event unfolds these activities need to be reviewed as conditions change, for example as flood levels rise or fall. There may also be risks of secondary hazards.

The ability to respond ahead of and during an event depends on the temporal dynamics of the hazard, and its predictability. Distinction is made in the disaster risk reduction community between (Figure 1): i) slow onset events, such as drought and extended periods of cold weather; ii) the majority of natural hazard types which can be identified with lead times between several hours and several days, and iii) instantaneous events with little or no prior warning such as earthquakes and avalanches. Hazard prediction may rely on individual hazard events moving in a predictable manner (cyclones and rain storms), having known precursors (volcanic eruptions and tsunami), or there may be a gradual build-up of antecedent conditions (wildfires, groundwater flooding or landslides). Scientific and technological advances are changing the predictability of some natural hazards, with seasonal forecasts now demonstrating some skill in tropical regions (e.g. Tall et al., 2012).

Recovery and reconstruction decisions occur after the emergency response and deal with the allocation of resources for relief, rehabilitation, and reconstruction, and increasingly 'Build Back Better' (UNISDR, 2015).

Predictability across timescales and the resulting uncertainty varies markedly between hazards. Cyclones can be forecast days ahead of time with relative skill in estimating their magnitude and path, but estimating their long term trends under climate change is challenging due to the difficulty of representing them in current climate models (Collins et al., 2013). Heat waves, in contrast, show a clearer increase in occurrence probability under current predictions (Fischer and Knutti, 2015). For geological hazards, probability depends on tectonic properties which change on much longer timescales due to changes in stress and formation of new volcanic vents or fault lines (Vecchia, 2001).

Spatial scales of impacts

The spatial scale of hazards ranges from site specific events such as avalanches to continental phenomena such as heat waves (Figure 2). Precision in the prediction of future event locations is dependent on the hazard type, with those strongly dependent on local conditions such as volcanic eruptions more straightforward to locate than meteorological hazards such as rainstorms (Vecchia, 2001). The most spatially extensive natural hazards may hit several countries (e.g. Løvholt et al., 2014), and require co-ordination between multiple states or external international assistance. The impacts of natural hazards can spill over natural boundaries through disruption of supply chains (Haraguchi and Lall, 2015) and impacts on financial markets (especially insurance, reinsurance and catastrophe bonds). The most severe natural hazards can result in international, as well as internal, relocation of displaced persons (IDMC, 2015).

Uncertainty

Natural hazards decisions are suffused with uncertainty: concerning the nature, timing, severity and location of the hazard; the vulnerability of exposed populations and assets; and the costs and benefits of potential risk management actions. Uncertainty stems from limited data availability, challenges in modelling, difficulty in quantifying probabilities, and non-stationarity.

Natural hazards are complex phenomena, and the circumstances surrounding any particular event are never repeated, meaning data availability is almost always a problem, and statistical analysis of events needs to be undertaken very carefully (Hall and Anderson, 2002). The most extreme events are by definition rare, so there is limited empirical evidence of their occurrence or impact (Blazkova and Beven, 2009). Data collected for the most extreme hazards may be subject to significant uncertainties (e.g. Westerberg et al., 2011, McMillan et al., 2012), partly because disruption of infrastructure can prevent monitoring during the event itself (Rougier et al., 2013). Databases can be biased, for instance landslides only tend to be recorded when they damage infrastructure (Corominas et al., 2014) or human populations (Ibsen and Brunsden, 1996), with small slips rarely recorded (Lumb, 1975). It is challenging to obtain data for rapid onset events: extreme precipitation events may be too localised or intense to be captured by conventional rainfall monitoring. Data gaps in developing countries are an additional challenge, both for understanding hazard and vulnerability. New technologies provide opportunities for real time monitoring (e.g. David et al., 2009).

Given the scarcity and unreliability of empirical evidence about natural hazards, there is increasing use of simulation models to understand natural hazards, often in combination with, or calibrated by, statistical analysis. Environmental modelling has its own set of uncertainties which have been discussed at length elsewhere (Beven, 2009). Understanding one hazard event and its potential consequences may require a multitude of models, each with uncertainties; for example in predicting volcanic activity different models are needed for gas emissions, tephra fallout, debris avalanches, and lahars (Vecchia, 2001, Mackie and Watson, 2014) The ability to simulate hazards, and the resources required to run the models, varies between hazard types and will influence the kind of risk and decision analysis that is appropriate: for example high resolution climate modelling can be very computationally expensive, prohibiting the ability to represent statistics of extreme events using supercomputers (Allen, 2003), and leading some authors to emphasise representation of uncertainty which does not rely on complex models (Dessai et al., 2009, Blazkova and Beven, 2009, Brown et al., 2011b).

Even for those hazards which may be modelled, probabilities can be difficult to quantify. Natural hazards are characterised by higher moment properties such as variance and skewness and may be subject to propagating uncertainties. Hazard losses may be nonlinear functions of hazard magnitude (Rougier et al., 2013).

Uncertainties are complicated by changing drivers of risk. For hydro-meteorological hazards, the probability of occurrence is non-stationary due to natural variability (e.g. El Niño–Southern Oscillation events) and anthropogenic climate change (IPCC, 2012). Economic growth and population change, particularly expansion around coastal areas (Parker et al., 2007), generate non-stationarity in vulnerability as well as hazard (World Economic Forum, 2011), which is particularly evident in developing countries, which are likely to experience unpredictable socio-economic changes in the coming decades (Lempert and Kalra, 2014).

The uncertainty and risk analysis literature has conventionally identified two categories of uncertainty (Rougier et al., 2013, Parry, 1996, Ferson and Ginzburg, 1996, Winkler, 1996):

1. Aleatory uncertainty due to the apparently random nature of environmental hazards;
2. Epistemic uncertainty due to imperfect knowledge of relevant phenomena.

Though much debated (Rougier et al., 2013, Parry, 1996, Ferson and Ginzburg, 1996, Winkler, 1996), this distinction is often helpful in risk and decision analysis of natural hazards, where the frequency and severity of the hazard is characterised as a random process. Integrating the hazard with a function to describe damage generates an estimate of risk (Hall, 2013) which provides a direct route into decision making, as we shall see later in this paper. Layered onto this conventional probabilistic risk analysis are sources of epistemic uncertainty, because of scarcity and limited reliability of observations, because of the limitations of physical models and because of the uncertainties in the choices that determine the consequences of natural disasters.

Human agency and group decisions

Decisions regarding natural hazards cannot be evaluated without attention to the role of human agency and processes (Eiser et al., 2012, Mileti, 1999). One of the few good news stories from the 2004 Asian tsunami was the relatively small number of casualties among the aboriginal Onge tribes of the Andaman Islands - a people who had long developed oral traditions for hazard identification (Gupta and Sharma, 2006). Modern practice of decision making incorporates the role of stakeholders in virtually every aspect of decision making, from setting the decision scope, objectives, and criteria for success, to providing expert advice on the likelihood and consequences. Still more actors are involved in mediating the outcomes of natural hazards and efforts to reduce impacts. Decision analysis must evaluate the role of human livelihoods and the limits they place on the management options available (Tanner et al., 2015), as well as to the collective perception of outcomes given varied social norms, groupings, and lifestyles (Ozdemir and Saaty, 2006, Morrow, 2009).

With many actors involved, any decision regarding natural hazards must reconcile diverse perceptions and capabilities – differences that exist within a region, as well as between regions. Despite the difficulties in dealing with such complexity, public participation in natural hazard decisions has been shown to generate efficient outcomes (Gamper, 2008) and increase community resilience (Berkes, 2007).

Multiple and conflicting objectives

Natural hazard decisions are rarely determined by one objective. There are many criteria against which to evaluate policy options (Morgan et al., 1990). Natural hazard management typically involves weighing up economic costs and benefits against risks to people and sometimes also the environment. Politicians and other public servants may also be motivated by the reputational implications of making the wrong choice. In the worst cases, societal disruption and unrest can arise from natural catastrophes.

3. Decision–making under uncertainty for natural hazards

Uncertainty is possibly the foremost challenge in natural hazards decisions. There are three categories of approach to responding to these uncertainties in practice:

1. Deterministic methods which suppress explicit representation of uncertainty, or condense it to simple 'factors of safety'.
2. Probabilistic methods which quantify uncertainty in probabilistic terms.
3. "Deep uncertainty" methods that deliberately avoid probabilistic representation of uncertainty (or hybridise).

These categories correspond to the categories of decision making under certainty, risk and uncertainty identified by Knight (1921). Our review of approaches is summarised in Table 1 and elaborated in the remainder of this section.

Deterministic approaches

The simplest approach to dealing with uncertainty is to not deal with it explicitly at all. Decision makers who use deterministic approaches are typically all too aware of sources of uncertainty, but for a variety of reasons uncertainty is not formally brought into the decision analysis. A deterministic analysis identifies the desired alternative from a set of possible alternatives by identifying outcomes associated with each alternative and the cost and benefits of these outcomes. In the context of natural hazards, the decisions may involve building an avalanche barrier, issuing a severe weather warning or mobilising an evacuation team.

Though potentially challenging in a number of respects such as multiple objectives and actors, deterministic methodologies are straightforward in their (lack of) characterisation of uncertainty. They are also almost always a significant simplification of reality and do not communicate the confidence associated with decision making.

In natural hazards, the majority of decisions have historically been made in a deterministic framework, and many deterministic metrics for assessing natural hazards remain in practice and legislation. Although progress to probabilistic decision making seems inevitable, deterministic decision making has historic precedence, is well understood by operational users, and remains the standard upon which probabilistic decision analysis should improve, especially in situations where decision makers seek a 'best estimate' outcome.

Several strategies exist to mitigate the shortcomings of deterministic models. Firstly, the 'conservative' approach in engineering design allows hazard mitigation infrastructure to be designed in response to poorly defined upper boundaries of hazard magnitude. Infrastructure is designed to mitigate events to a standard at or above the highest perceived plausible hazard. In the past, this strategy was applied in earthquake engineering, with a model of the largest plausible seismic event at the closest potential point to the designed building used to inform construction (National Research Council, 1988). A related strategy is the 'design event', in which an event of a pre-specified magnitude is used to inform construction, widely used historically in design of flood protection (NERC, 1975) and still quite prevalent worldwide. The former approach can be extremely costly due to the required resilience of construction, and has sometimes fallen prey to actual events, whereas the latter involves a tacit understanding that there are plausible scenarios under which the infrastructure will fail. A third strategy is the 'safety factor' (Vrijling et al., 2011) in which an identified margin is added to specifications, in order to account for unquantified uncertainties introduced throughout the design process. Such factors are introduced as 'headroom' in water planning, with water providers designing drought resilience infrastructure to provide a percentage of water above that estimated to be required during droughts. Safety factors may be derived from quantiles of probabilistic distributions used in probabilistic approaches, which is the approach adopted in Level 1 reliability methods (Melchers, 1999)

Probabilistic approaches

Probabilistic concepts have been widely applied to quantify uncertainty in natural hazard decisions. Applications range from real-time flood forecasting (Todini, 2004, Young et al., 2014), flood warnings (Krzysztofowicz, 1993), flood risk planning (Dawson et al., 2005, Hall et al., 2003); earthquake hazards (Anbazhagan et al., 2009, Tseng and Chen, 2012, Sadeghi et al., 2015), climate change adaptation (Hall et al., 2012b, New et al., 2007, Borgomeo et al., 2014) and disaster risk (Kull et al., 2013, Michel-Kerjan et al., 2013, Hochrainer-Stigler et al., 2015, Woo, 2010).

In probabilistic decision making, the range of possible circumstances (states of nature) that might materialise in future are identified. Uncertainty as to which of these states will pertain is represented by a probability distribution over the possible states. The expected outcome is the probability weighted sum of the values of the possible outcomes in each future state. The risk-based decision problem compares a set of alternative acts (A_0, A_1, A_2,…, A_n), including the base case A_0, in which no intervention is chosen ("do nothing"), with corresponding expected losses (risks), R_0, R_1, R_2,…, R_n), and costs C_0, C_1, C_2,…, C_n, where by definition C_0=0. The benefit of alternative A_i is R_0-R_i, i.e. the baseline (do nothing risk) minus the residual risk for the given alternative. The net benefit for A_i is R_0-R_i-C_i. The optimal decision is the act which maximises the net benefit. In conditions of scarce resources (which is almost always the case) the option that maximises the benefit-cost ratio (R_0-R_i)/C_i will be preferred as the decision criterion in economic terms.

Costs and benefits will typically be distributed through time, in which case it is conventional to discount future streams and costs of benefits to Present Value, though the choice of discount rate is controversial (Gollier and Hammitt, 2014).

A further elaboration is the incorporation of decision makers' attitudes to risk. Taking decisions based on expected risk and cost will be the approach adopted by a risk-neutral decision maker. A risk-averse decision maker will weight low-probability high-consequence events more heavily, which can be achieved by using a concave utility function (Lindley, 1985).

The probabilities characterizing the uncertainty of different states of nature can be derived from empirical data, mathematical/statistical models, eliciting expert knowledge or any combination of these – often in a Bayesian framework (e.g. Medina-Cetina and Nadim, 2008, Rougier et al., 2013, Hall et al., 2011) . Expert elicitation methods have been adopted to estimate probabilities in the absence of statistical evidence (Cooke, 1991, O'Hagan et al., 2006). The choice of method will depend on the type and quality of data available, on the type of natural hazard in question and on the decision. Of interest is the probability of exceedances of a threshold (e.g., exceedance of a wave height) over a pre-defined period of time. For instance, probabilistic landslide assessments aim to predict exceedance probabilities of a landslide of a particular size in a particular location (Guzzetti et al., 2005).

A typical probabilistic decision analysis would: (i) estimate probabilities of occurrence for the variables in question (e.g., wind speed; wave height; ground motion level) that characterise the hazard; (ii) relate these probabilities to the consequences of the hazard (e.g. dike overtopping during a flood event; building collapse during an earthquake; water shortage occurrence during a drought) (iii) estimate the damage caused by the hazard occurrence of a given severity, and (iv) compare the capacities of alternative decisions to reduce the expected risk and associated costs. Results of steps (ii) and (iii) are summarised in the loss/consequence component of the risk definition (Hall and Solomatine, 2008). Step (iv) is based on net present value or benefit cost ratio calculations, which establish the preference ordering between different options based on their risk reduction and cost.

Estimating probabilities and consequences of natural hazards can result in a chain of causal reasoning, which can be structured in fault trees, event trees and decision trees (Benjamin and Cornell, 1970). Fault trees estimate the probability of a failure event by estimating the probabilities of the logical conditions that might lead to failure. Event trees are more naturally applicable to analysis of natural hazards, as they start with the hazard event and step through the causal chain of consequences that might lead to harmful outcomes. Sayers et al. (2002) used event tree analysis to analyse the risk of damage to coastal settlements from storm surges. A similar process of structuring causal influences is adopted in influence diagrams (Castillo-Rodríguez et al., 2014) which can be quantified in the form of Bayesian networks (Pearl, 1988, Smith, 2010). The latter method is useful for the incorporation of unknowns within a decision problem for the purpose of assessing whether more information is required to support good decisions (Ozdemir and Saaty, 2006), which moves towards the area of the non-probabilistic approaches covered in the subsequent section. Sensitivity analyses (either deterministic or probabilistic) can be used to determine if more refined information about the distribution and range of data might have a substantial effect on potential decision alternatives (Pianosi et al., in Review)

Probabilistic methods have been applied to inform natural hazard management decisions. For instance, dealing with floods has transitioned from an approach based on deterministic design standards to an explicitly risk-based approach (Hall et al., 2003, Sayers et al., 2002). This risk analysis problem is conventionally structured according to a source-pathway-receptor model (Sayers et al., 2002), which begins by characterisation of the flood hazard, then analyses flood inundation and the reliability of flood defence systems, before combining these with characterisation of the vulnerability of exposed people and properties. Elaborations have dealt with the joint probability of multiple hazard variables (e.g. wave height and water level, (Hawkes et al., 2002) and the spatial and temporal dependence structure of variables such as rainfall and river flows (Heffernan and Tawn, 2004, Keef et al., 2009). Beven and colleagues have played particular attention to the uncertainties in rainfall-runoff modelling and the implications for flood risk mapping (Beven et al., 2015).

Krzysztofowicz (1993) used probabilistic decision theory to develop a framework for issuing flood warnings. A Bayesian flood forecasting system was constructed to estimate the probability of flood occurrence. A loss function that quantified losses from false alarms and missed events was then used to optimally issue flood warnings. Martina et al. (2006) also used decision theory to optimally estimate rainfall thresholds for use in flood warnings at given river sections. Mylne (2002) discusses the evaluation of weather forecasts based on a simple binary model of user utility (loss). Expected losses are used to evaluate the forecasts, as opposed to evaluating them solely on forecast skill.

Probabilistic approaches have also been widely applied to seismic hazard analysis (Paté-Cornell, 1996, Smyth et al., 2004, Petersen et al., 2004, Bommer and Abrahamson, 2006). For instance, Sadeghi et al. (2015) derive a hazard probability curve for ground motion from past earthquake occurrence records, combine this with a loss calculation model to estimate the probability of structural losses based on different building types, and use this to evaluate alternative structural strengthening strategies in a cost-benefit analysis framework. The probability of volcanic eruptions can also be estimated, using conditional probability distributions with a combination of physically- and empirically-based simulation models (Hill et al., 2009). This is challenging given the non-stationarity of eruptions, with the probability of an eruption falling dramatically during long periods of dormancy.

Bayraktarli and Faber (2011) applied Bayesian probabilistic networks to support decision making for earthquakes. Bayesian networks were found to have two major advantages over alternative methods. First, they can integrate all aspects affecting structural damage including side-effects, structural response, direct and indirect consequences. Second, they are able to incorporate new information into uncertainty estimates relatively quickly, providing updated risk assessments to decision-makers allowing consideration of the changes to the decision situation that eventuate during and after earthquakes. Such a methodology is generally applicable to any such natural hazards that require real-time forecasting e.g. hurricanes, storm events, and volcanic eruptions. Aspinall and Woo (2014) used Bayesian Belief Networks to provide a rapid analysis of eruption risks in the popular holiday location in Santorini and concluded that with just three or four basic indicators, it was not feasible, or defensible, to attempt to judge mentally the implications of signs of tectonic unrest. They demonstrated that a structured probabilistic procedure using Bayes' Rule was a more rational approach for evaluating the strength of various sources of evidence.

Probability has been and still is the main tool used by decision-makers to measure or quantify uncertainty (Winkler, 1996) because it provides access to the full richness of statistics for data analysis. Furthermore, probabilistic and risk analysis approaches are attractive because they can be incorporated in traditional decision making frameworks and can be used as a mechanism to provide 'objective' justification for uncertain or difficult to negotiate public policy decisions (Rayner, 2007, Pidgeon and Butler, 2009). Although widely applied as a tool for characterizing uncertainty, probabilistic concepts can have limitations including: (i) biases and heuristics which affect decision-makers when defining probabilities, (ii) difficulty of reaching stakeholder agreement on probability distributions, and (iii) over-confidence or insufficiency in presenting all the uncertainties involved in a decision (Ozdemir and Saaty, 2006). Probabilistic representation of uncertainty to problems which are not well constrained and where values are contested may lead to bad decisions (Hall, 2007, Dessai et al., 2009). This emphasises the importance of extensive sensitivity analysis in all applications of probabilistic methods, to test assumptions and the implications of limitations in empirical evidence. Decision makers may nonetheless be confronted by situations where uncertainties are so hard to quantify that the notion of a probabilistic representation becomes untenable. It is these circumstances that methods for decision making under so-called 'deep uncertainty' or 'severe uncertainty' have been proposed.

Decision methodologies for deep uncertainty

In recent years there has been an increasing focus on 'deep uncertainty' (Lempert et al., 2003a, Lempert and Collins, 2007, Spiegelhalter and Riesch, 2011) , 'severe uncertainty' (Ben-Haim, 2006), 'info-gaps' (Ben-Haim, 2006), and 'black swans' (Popper, 1959, Taleb, 2007). Anthropogenic climate change has also been a particular trigger for analysis of deep uncertainty (Kalra et al., 2014, Wilby and Dessai, 2010, Huntjens et al., 2012, Hallegatte, 2009). The influence of climate change on extreme weather is often the greatest concern, making the work also of great relevance to decision making about natural hazards. Deep uncertainty does not only refer to an inability to quantify hazard probabilities, but also extends to valuing the consequences of decisions (Stirling, 2010) and incorporating multiple perspectives on uncertainty (Jones et al., 2014).

The naïve approach to epistemic ignorance is to resort to Laplace's principle of insufficient reason and apply a uniform distribution across the possible outcomes. There are good theoretical reasons why a uniform distribution is not a valid way of representing ignorance (Ben-Haim, 2006). Other probabilistic theorists have suggested that under conditions of severe uncertainty, everything must be done to obtain probability distributions, if necessary through expert elicitation exercises (O'Hagan et al., 2006). Alternatively the situation can be recognised as Knight (1921)'s problem of "decision making under uncertainty", in which no probability distribution is available over the future states of nature. The latter approach has a long tradition in decision analysis, and there is a range of different decision criteria that might be applied e.g. maxi-min, least regret and Hurwicz's criterion. Unfortunately, all of these strategies violate some criterion for rationality, so there is no normative approach to making a decision under these circumstances (Lindley, 1985, French et al., 2009)

Writers on decision making under deep uncertainty emphasise that 'optimal decisions', which are obtained by maximising expected utility in the ways described in the previous section, can be vulnerable to misspecification of probability distributions or incomplete valuation of possible outcomes. They therefore emphasise 'satisficing' (Simon, 1956), rather than optimising: the identification of options that perform acceptably well, rather than those that achieve the best score against the decision criteria (Hallegatte, 2009, Bankes, 2002). Ben-Haim (2006) in particular advocates 'robust satisficing': finding solutions that perform acceptably well over a wide range of possible conditions. Robustness (i.e. relative lack of sensitivity to assumptions or uncertainties) is proposed as a decision criterion (Lempert et al., 2006, Groves and Lempert, 2007). Robust strategies are particularly valuable when the consequences of taking a wrong decision are high.

The 'deep uncertainty' literature also emphasises the order in which decisions are explored, critiquing a "top down" approach to uncertainty assessment and calling for 'decision first' or 'policy-first' approaches which start by exploring the sensitivity of policy options to uncertain conditions. This helps to focus decision analysis on the uncertainties that matter. Methods have been developed for analysing and visualising the combinations of conditions that might lead to undesirable outcomes, including Robust Decision Making (Lempert et al., 2006, Lempert et al., 2003b) and decision scaling (Brown et al., 2012) methodologies. Borgomeo et al. (2015) used such a method in exploring the sensitivity of drought management options to unprecedented drought.

Robust Decision Making (RDM) uses multiple views of the future to identify conditions under which a decision would fail to meet its objectives (Lempert et al., 2006, Groves and Lempert, 2007, Lempert et al., 2013b). The RDM process includes scoping, simulation to identify a policy or decision for evaluation, scenario discovery to identify vulnerabilities of a policy, the identification of hedging actions and the visualisation of results to facilitate the selection of a robust decision (Lempert et al., 2006, Lempert et al., 2003b).

RDM has been applied to inform long-term planning for natural hazards, especially around water management (Groves et al., 2012, Groves and Lempert, 2007, Kalra et al., 2015), flood risk management

(Fischbach, 2010, Lempert et al., 2013a) and coastal flooding and storm surges (Groves et al., 2014). Figure 3 shows an example from RDM analysis, for water resources planning in Southern California (Lempert and Groves, 2010). The cost of the water utility's master plan is evaluated over 200 alternative future states of the world, to identify which scenarios would cause the plan to fail. Statistical analysis based on scenario discovery algorithms is then applied to understand which factors lead the plan to fail in these conditions. This information can inform decisions about whether and when the water utility should change its master plan.

Decision scaling focuses on stakeholder-defined thresholds that determine acceptable system performance and the conditions under which these thresholds are exceeded (Brown et al., 2011a, Brown et al., 2012). Decision scaling was applied to improve management of the Great Lakes in the United States (Brown et al., 2012), to assess flood risk (Steinschneider et al., 2015) and to trade-off ecological and water engineering performance indicators (Poff et al., 2015, Singh et al., 2014).

Info-gap decision theory was introduced by Ben-Haim (2006) to support decisions made where there is a mismatch between the information known on the decision variables of interest and the information needed to make a decision. In the context of natural hazards, these decision variables may describe the magnitude or frequency of occurrence of the hazard (e.g., the return period of a flood or the magnitude of an earthquake), the shape of the loss functions associated with the hazards, or even a set of utility functions associated with different materializations of the hazard. The best estimate of this uncertain variable is denoted $\tilde{u}$, and the departure from this estimate is parameterized by α: $\alpha \geq 0$. As α increases and we move away from this best estimate, the value of the variable u will become more and more uncertain as described in the uncertainty model $U(\alpha, \tilde{u})$. Using this uncertainty model, info-gap decision theory compares alternative decisions based on their robustness, defined as the maximum uncertainty horizon α over which a specific decision achieves a pre-specified performance, and 'opportuneness', which measures the minimum level of uncertainty α required to achieve a 'windfall' gain or reward to the decision-maker (Ben-Haim, 2006, Hall et al., 2012a).

Applications of info-gap decision theory to natural hazards range from analyses of the impact flood inundation models and flood frequency analysis uncertainties on flood management decisions (Hine and Hall, 2010), to water resources decision making under climate and socio-economic change (Korteling et al., 2013, Matrosov et al., 2013) and earthquake resilient design (Takewaki, 2013, Tang et al., 2015).

The deep uncertainty literature underscores the benefits of flexibility and adaptability in dealing with uncertainty. Successful strategies typically need to be adaptive as more information will become available in the future. Flexibility means that decisions can be reversed or modified as the uncertain future materialises. A flexible strategy may be one focussed on the short-term without long-term implications or a strategy that can be readily amended or updated in a cost effective manner through time (Wilby and Dessai, 2010, Huntjens et al., 2012, Wilby et al., 2009, Hallegatte, 2009). A flexible strategy will have a lower likelihood of experiencing negative 'lock-in' (Payo et al., 2015), that involves an irreversible destruction of capabilities. This then focusses attention on the sequences of decisions rather than single decisions, which we deal with next.

4. Sequential decisions

Management of natural hazards seldom involves one single decision. This is particularly true in real-time management of hazard events, which involves sequences of decisions as the event and its consequences materialise. It also however applies to longer-term risk management problems, where the nature of the hazard, exposure and vulnerability is evolving through time, so management actions need to evolve in response.

A particularly interesting question in sequential decision analysis is whether it is worth investing now to keep options open for the future. This is the question that is dealt with in real options analysis (Dixit and

Pindyck, 1994). Woodward et al. (2014) have applied real options analysis to the design of flood defence systems and Hino and Hall (in Review) extend the analysis to deal with land use zoning decisions in areas at risk of flooding.

Decision trees (French, 1986, Lindley, 1985) provide a structured way of dealing with sequential decision problems. The tree contains event nodes with uncertain outcomes (in the same way as probabilistic risk analysis) and decision nodes which characterise the choices available to a decision maker in given circumstances. Integration over the choices and events identifies the preferred course of action. Decision trees and real options analysis rely on probabilistic characterisation of uncertainties, whilst the proponents of 'adaptation pathways' (Haasnoot et al., 2012, Ranger et al., 2010) have emphasised sequential decisions as a means with dealing with deep uncertainty. The approach aims to build flexibility into a decision or strategy by sequencing the implementation of actions over time so that the system adapts to changing social, environmental and economic conditions and options are available to respond to a range of plausible future conditions. A pathway provides a visual representation of the sequencing of decision points and potential adaptive actions that may be implemented in the future. Monitoring of decision-relevant variables is an important component of implementing a pathways approach (Yohe and Leichenko, 2010). This establishes a linkage between risk assessment and adaptation action that is absent in many adaptation interventions.

An adaptation pathways approach was first applied as part of the Thames Estuary tidal flood risk management project in London (Ranger et al., 2010). Adaptation pathways have been used in a range of contexts including delta flood and water management in the Rhine-Meuse delta in the Netherlands (Haasnoot et al., 2012); strategic regional planning on the Eyre Peninsula, Australia (Siebentritt et al., 2014); coastal planning in Lakes Entrance, Australia (Barnett et al., 2014); urban adaptation in New York to hurricane and storm surge risk (Rosenzweig and Solecki, 2014); and flood risk management in the Hutt River, New Zealand (Lawrence et al., 2013). In each case, the approach was uniquely interpreted to respond to the local priorities and decision contexts.

5. Decisions with multiple objectives

Decision making regarding natural hazards typically involves multiple categories of impacts and costs. Reducing risk to life is a central objective for disaster risk reduction. Deciding what and how much to do to reduce risk to life leads, implicitly or explicitly, to the need to trade off the costs of risk reduction with the benefits of avoided loss of life. Natural hazard decision problems also bring in considerations of environmental impact, public confidence and reputational risk, all of which are also problematic to value in consistent ways.

Faced with this challenge, there are two routes that are adopted in the literature to dealing with multiple attribute in decision problems. The first seeks to monetize all of the different possible outcomes from a decision problem, so reducing it to a single attribute problem. Alternatively, the problem can be dealt with formally as a multi-attribute decision. Information on preferences can be included as weightings to each decision variable, using a compensatory approach in which strong performance in one criterion can compensate for poor performance in others; or as minimum or maximum values for one or more criteria, in a non-compensatory approach. Where non-compensatory approaches are used, multi-criteria decisions can be made as attribute-based or alternative based decisions. In an attribute-based approach, decision variables are considered in a pre-determined sequence, with alternatives not meeting each criterion in sequence rejected. In alternative-based non-compensatory decisions the search process stops when the first alternative matching or exceeding a criteria set is identified. This is typically performed where a large number of options are available or the process time for the decision is significant (French et al., 2009).

Linear weightings imply a constant marginal rate of substitution between different attributes, which seldom reflects the concerns that decision makers have about the system attributes that they value, least of all with different degrees of relative scarcity (Bommier and Villneuve, 2012). A wide range of multi-criteria decision making methods have thus developed to deal with the range of problem contexts, features of the information used, weighting requirements, number of actors and types of criteria used including deterministic, stochastic and fuzzy data types (Triantaphyllou, 2013). A comparison of alternative methods have shown that evaluation outcome depends heavily on both choice of the utility function and its parameters (Podvezko and Podviezko, 2010). Multi-attribute utility theory with non-additive utility functions provides a flexible version of the multi-attribute decision problem (Keeney and Raiffa, 1993). However, this comes with a high penalty of having to construct complex utility functions, which is an elicitation problem with which most decision makers struggle.

6. Group decisions

In theoretical terms, there is no acceptable solution to the problem of how competing values and objectives should be reconciled in formal decision problems (Arrow, 1951). Given this awkward fact, emphasis has to shift from formal methods to the practice of dealing with multiple actors in decision making settings. A variety of group decision making (GDM) methods have been developed to facilitate the convergence of decision maker opinions (Zhang et al., 2015).

Such GDMs face two major hurdles, namely dealing with the complexity of the heterogeneous information from a large number of decision makers, and providing acceptable solutions based on the unification of this information. Early GDMs employed voting rules to order relative preferences, with more recent GDMs attempting to better represent differences between actual evaluated values (Lee et al., 2015). Success appears most likely when actors from community groups, business, industry, and all levels of government and non-governmental organisations are involved in the decision making process from the very beginning (IPCC, 2014).

Such an involved process can be greatly facilitated through the development of a decision support system (Mejía-Navarro and Garcia, 1996) into which actors have considerable input and through which they are able to explore the implications of alternative portfolios of proposed risk reduction projects and disaster scenarios (IPCC, 2014). One unfortunate caveat to such progress is the evidence that the effectiveness of such decision support systems can be reduced over time through gamesmanship by various actors (Madani and Lund, 2011).

7. Good decision making processes

Our discussion of decision making for natural hazard management has so far focussed upon the formal structure of decision problems (treatment of uncertainty, sequential decisions, decisions with multiple attributes and actors). Decision theory emphasises the *process* of making decisions as being just as important as the formal structure adopted.

To address the ingredients for good decision making for natural hazards management, we might first consider what makes a good decision. The question has been considered widely in decision theory, risk governance, ethical reasoning, and related fields. There is no universal criterion for a good decision (Jones et al., 2014), it is difficult to evaluate decisions after they have been made and there is a notable lack of historical analysis of performance of decisions. Chance dictates that bad decisions can be associated with good outcomes and vice versa (Hammond et al., 1998). This is perhaps especially true for natural hazards: it is difficult to evaluate plans for high consequence events with poorly understood probabilities. Yet there is some agreement on what makes good decision making. Good decisions will likely emerge from processes in which: parties are explicit about their goals, agreed criteria, rules and norms are followed, the best available science is used, and alternative options and trade-offs are considered from a wide range of viewpoints (Jones et al., 2014). These principles emphasise the importance of good decision making processes, but also imply the importance of sound logic and rules, which is where decision analysis can contribute.

Morgan et al. (1990) present guidance for good decision analysis. Several, such as documenting the analysis clearly, and presenting the results for peer review, concern the quality of the output, which can nonetheless be challenging to uphold given the time pressures associated with policy relevant research, particularly for natural hazards. The other rules give more substantive direction in the recommended approach for decision analysis. Morgan et al. (1990) highlight the importance of letting the problem drive the analysis, which is echoed by others who emphasise the centrality of user needs (Jones et al., 2014): the decision analysis should not be separated entirely from the decision-makers. The importance of iterative analysis has also been highlighted, in order to incorporate new information about emerging risks. This may be particularly important during phases of imminent threat, or for long term planning under climate change, as climate change signals strengthen and emerge from natural variability (Ranger et al., 2010). Another key component of good decision analysis is to consider a wide range of views, but still keep the analysis as simple as possible, so that it can be widely understood, and is more likely to be seen as legitimate (Government Office for Science, 2011). Given inevitable simplifications it is important to be explicit about assumptions and uncertainty.

Good decision making is typically characterised as a cyclic process, encompassing (i) scoping/framing/problem identification (ii) analytical (iii) implementation and (iv) monitoring/evaluation/review phases (**Error! Reference source not found.**). This cycle should be tailored to the nature of the problem in hand, so that the complexity of the problem influences the design of the process (Jones et al., 2014). If risk is simple, well-bounded with clear cause and effect, a focus on numerical analysis might be appropriate; but if risk is complex, with conflicting values, large uncertainties, and unclear solutions, many stakeholders and contrast between calculated and perceived risk, then iterative, adaptive, process-driven stakeholder co-production is advised (Harris, 2007) .

8. Conclusions

Decision analysis allows the many disparate but connected management and mitigation challenges presented by natural hazards to be formalised. The range of natural hazards contexts is broad and it is not possible to formulate universally applicable solutions to natural hazards problems, but methodologies for their framing can be appropriated from theory and from successful application in other hazard contexts.

Application of formal decision analysis methods to natural hazard problems is still relatively immature. This is surprising because in many respects natural hazard management problems lend themselves to decision analysis – they involve explicit weighing up of costs and benefits under conditions of uncertainty. Acting against this has been the severe uncertainty that often characterizes natural hazards problems and the often urgent need to address these problems – which favours expediency over rigour.

In this paper we have identified generic characteristics of decision analysis problems for natural hazards. We have identified the following cross-cutting aspects:

1. The characterisation of uncertainty: deterministic (no uncertainty), probabilistic, or deep uncertainty (no probabilities)
2. Single step or sequential decision problems
3. Single or multi-attribute decision problems
4. Single or multi-actor decision problems

Applied decision analysis remains uneven and limited in its ability to develop by the importance of the decisions that are made, with natural hazard decisions often controversial, pre-existing decision frameworks legally mandated and limited capacity within decision making organisations. As opportunities to implement better decision methodologies emerge, communication between decision makers in different fields of the advantages, disadvantages and suitability of specific methods is essential for new theoretical work and practical experience to be appropriately dispersed. Decision analysis provides a means of justifying investment in data acquisition and research to explore uncertainties. Uncertainties are significant in natural hazard decisions, because of the potential for preference orderings to change, depending on what uncertain future materialises.

Decision analysis becomes ever-more relevant with the advent of new methods of data acquisition, from pervasive sensors to Earth observation. These new data streams provide the potential to generate better informed uncertainty estimates. Increased use of decision theory in natural hazard science will enable decision making to be better informed by new advances in scientific knowledge, thereby increasing society's ability to cope with such hazards.

Given the growing risk from natural hazards, and the potential for major policy interventions to reduce losses from natural hazards, there is a strong case for improving methodology. As risks, and commitments to risk management, grow, there will be increasing scrutiny applied to how natural hazard management decisions are being made. Decision analysis provides formal and repeatable frameworks for structuring decisions. However, the models which are used in decision analysis are reliant on assumptions which will introduce deep uncertainties, which must be explicitly examined as part of a good decision analytic process. Progress in the theory of decision analysis must be matched by progress in the application of state-of-the-art decision methodologies to natural hazards decision making, and monitoring and evaluation of successes and failures of decisions made for the short and long term. Exchanges between academia and operational hazard management will allow better understanding of real-world cases by academics and support operational decision making. Better integration between those managing separate hazard phases – planning, forecasting, response and recovery - will enable implementation of end-to-end risk-based approaches and shared expertise on formal decision analysis.

In this paper we have identified quite extensive but often rather isolated use of decision analysis in the management of natural hazards. We have identified the characteristics of natural hazard management problems that map onto different aspects of decision theory. By making this connection we hope to promote further uptake of applied decision analysis.

References

ACKOFF, R. L. 1974. *Redesigning the future: a systems approach to societal problems,* New York, Wiley.

ALLEN, M. 2003. Liability for climate change. *Nature,* 421**,** 891-892.

ANBAZHAGAN, P., VINOD, J. S. & SITHARAM, T. G. 2009. Probabilistic seismic hazard analysis for Bangalore. *Natural Hazards,* 48**,** 145-166.

ARROW, K. J. 1951. *Social Choice and Individual Values* Yale University Press.

ASPINALL, W. & WOO, G. 2014. Santorini unrest 2011–2012: an immediate Bayesian belief network analysis of eruption scenario probabilities for urgent decision support under uncertainty. *Journal of Applied Volcanology,* 3.

BANKES, S. C. 2002. Tools and techniques for developing policies for complex and uncertain systems. *Proceedings of the National Academy of Sciences,* 99**,** 7263-7266.

BARNETT, J., GRAHAM, S., MORTREUX, C., FINCHER, R., WATERS, E. & HURLIMANN, A. 2014. A local coastal adaptation pathway. *Nature Clim. Change,* 4**,** 1103-1108.

BAYRAKTARLI, Y. Y. & FABER, M. H. 2011. Bayesian probabilistic network approach for managing earthquake risks of cities. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards,* 5**,** 2-24.

BEN-HAIM, Y. 2006. *Info-Gap Decision Theory: Decisions under Severe Uncertainty,* London, Academic Press.

BENJAMIN, J. R. & CORNELL, C. A. 1970. *Probability, statistics, and decision for civil engineers,* New York ; London, McGraw-Hill Book Co.

BERKES, F. 2007. Understanding uncertainty and reducing vulnerability: lessons from resilience thinking. *Natural Hazards,* 41**,** 283-295.

BEVEN, K., LAMB, R., LEEDAL, D. & HUNTER, N. 2015. Communicating uncertainty in flood inundation mapping: a case study. *International Journal of River Basin Management,* 13**,** 285-295.

BEVEN, K. J. 2009. *Environmental modelling: an uncertain future? : an introduction to techniques for uncertainty estimation in environmental prediction,* London, Routledge.

BLAZKOVA, S. & BEVEN, K. 2009. A limits of acceptability approach to model evaluation and uncertainty estimation in flood frequency estimation by continuous simulation: Skalka catchment, Czech Republic. *Water Resources Research,* 45**,** n/a-n/a.

BOMMER, J. & ABRAHAMSON, A. 2006. Why do modern probabilistic seismic-hazard analyses often lead to increased hazard estimates? *Bulletin of the Seismological Society of America,* 96**,** 1967–1977.

BOMMIER, A. & VILLNEUVE, B. 2012. Risk Aversion and the Value of Risk to Life. *Journal of Risk and Insurance,* 79**,** 77-104.

BORGOMEO, E., HALL, J. W., FUNG, F., WATTS, G., COLQUHOUN, K. & LAMBERT, C. 2014. Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties. *Water Resources Research,* 50**,** 6850-6873.

BORGOMEO, E., PFLUG, G., HALL, J. W. & HOCHRAINER-STIGLER, S. 2015. Assessing water resource system vulnerability to unprecedented hydrological drought using copulas to characterize drought duration and deficit. *Water Resources Research,* 51**,** 8927-8948.

BROWN, A., GAWITH, M., LONSDALE, K. & PRINGLE, P. 2011a. Managing adaptation: linking theory and practice. Oxford. UK.: UK Climate Impacts Programme

BROWN, C., GHILE, Y., LAVERTY, M. & LI, K. 2012. Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. *Water Resources Research,* 48.

BROWN, C., WERICK, W., LEGER, W. & FAY, D. 2011b. A Decision-Analytic Approach to Managing Climate Risks: Application to the Upper Great Lakes. *JAWRA Journal of the American Water Resources Association,* 47**,** 524-534.

CASTILLO-RODRÍGUEZ, J. T., ESCUDER-BUENO, I., ALTAREJOS-GARCÍA, L. & SERRANO-LOMBILLO, A. 2014. The value of integrating information from multiple hazards for flood risk analysis and management. *Nat. Hazards Earth Syst. Sci.,* 14**,** 379-400.

COLLINS, M., KNUTTI, R., ARBLASTER, J., DUFRESNE, J., FICHEFET, T., FRIEDLINGSTEIN, P., GAO, X., GUTOWSKI, W., JOHNS, T., KRINNER, G., SHONGWE, M., TEBALDI, C., WEAVER, A. & WEHNER, M. 2013. Long-term Climate Change: Projections, Commitments and Irreversibility. *In:* STOCKER, T., QIN, D., PLATTNER, G., TIGNOR, M., ALLEN, S., BOSCHUNG, J., NAUELS, A., XIA, Y., BEX, V. & MIDGLEY, P. (eds.) *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge: Cambridge University Press.

COOKE, R. M. 1991. *Experts in Uncertainty: Opinion and Subjective Probability in Science,* New York, Oxford University Press.

COROMINAS, J., VAN WESTEN, C., FRATTINI, P., CASCINI, L., MALET, J. P., FOTOPOULOU, S., CATANI, F., VAN DEN EECKHAUT, M., MAVROULI, O., AGLIARDI, F., PITILAKIS, K., WINTER, M. G., PASTOR, M., FERLISI, S., TOFANI, V., HERVÁS, J. & SMITH, J. T. 2014. Recommendations for the quantitative analysis of landslide risk. *Bulletin of Engineering Geology and the Environment,* 73**,** 209-263.

DAVID, N., ALPERT, P. & MESSER, H. 2009. Technical Note: Novel method for water vapour monitoring using wireless communication networks measurements. *Atmos. Chem. Phys.,* 9**,** 2413-2418.

DAWSON, R. J., HALL, J. W., BATES, P. D. & NICHOLLS, R. J. 2005. Quantified Analysis of the Probability of Flooding in the Thames Estuary under Imaginable Worst-case Sea Level Rise Scenarios. *International Journal of Water Resources Development,* 21**,** 577-591.

DESSAI, S., HULME, M., LEMPERT, R. & PIELKE, R. 2009. Climate prediction: a limit to adaptation? *In:* ADGER, W. N., LORENZONI, I. & O'BRIEN, K. L. (eds.) *Adapting to climate change : thresholds, values, governance.* Cambridge: Cambridge University Press.

DIXIT, A. K. & PINDYCK, R. S. 1994. *Investment under uncertainty,* Princeton, N.J., Princeton University Press.

EISER, J., BOSTROM, A., BURTON, I., JOHNSTON, D. M., MCCLURE, J., PATON, D., VAN DER PLIGT, J. & WHITE, M. P. 2012. Risk interpretation and action: A conceptual framework for responses to natural hazards. *International Journal of Disaster Risk Reduction,* 1**,** 5-16.

FERSON, S. & GINZBURG, L. R. 1996. Different methods are needed to propagate ignorance and variability. *Reliability Engineering & System Safety,* 54**,** 133-144.

FISCHBACH, J. R. 2010. *Managing New Orleans Flood Risk in an Uncertain Future Using Non-Structural Risk Mitigation.* Doctoral Degree PhD thesis, Pardee RAND Graduate School.
FISCHER, E. M. & KNUTTI, R. 2015. Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nature Clim. Change,* 5**,** 560-564.
FRAME, B. 2008. 'Wicked', 'Messy', and 'Clumsy': Long-Term Frameworks for Sustainability. *Environment and Planning C: Government and Policy,* 26**,** 1113-1128.
FRENCH, S. 1986. *Decision theory : an introduction to the mathematics of rationality,* Chichester, Ellis Horwood.
FRENCH, S., MAULE, J. & PAPAMICHAIL, N. 2009. *Decision behaviour, analysis and support,* Cambridge, Cambridge University Press.
FUNTOWICZ, S. O. & RAVETZ, J. R. 1990. *Uncertainty and quality in science for policy*, Kluwer.
GAMPER, C. D. 2008. The political economy of public participation in natural hazard decisions – a theoretical review and an exemplary case of the decision framework of Austrian hazard zone mapping. *Nat. Hazards Earth Syst. Sci.,* 8**,** 233-241.
GOLLIER, C. & HAMMITT, J. K. 2014. The Long-Run Discount Rate Controversy. *Annual Review of Resource Economics,* 6**,** 273-295.
GOVERNMENT OFFICE FOR SCIENCE 2011. Code of Practice for Scientific Advisory Committees. London: Department for Business, Innovation and Skills.
GREENBERG, M., HAAS, C., COX, A., LOWRIE, K., MCCOMAS, K. & NORTH, W. 2012. Ten most important accomplishments in Risk Analysis, 1980-2010. *Risk Analysis,* 32**,** 771.
GROVES, D., FISCHBACH, J., KNOPMAN, D., JOHNSON, D. & GIGLIO, K. 2014. Strengthening Coastal Planning: How Coastal Regions Could Benefit from Louisiana's Planning and Analysis Framework. . Santa Monica, CA: RAND Corporation.
GROVES, D. G., FISCHBACH, J. R., BLOOM, E., KNOPMAN, D. & KEEFE, R. 2012. Adapting to a Changing Colorado River: Making Future Water Deliveries More Reliable Through Robust Management Strategies. . Santa Monica, CA: RAND corporation.
GROVES, D. G. & LEMPERT, R. J. 2007. A new analytic method for finding policy-relevant scenarios. *Global Environmental Change-Human and Policy Dimensions,* 17**,** 73-85.
GUPTA, M. & SHARMA, A. 2006. Compounded loss: the post tsunami recovery experience of Indian island communities. *Disaster Prevention and Management: An International Journal,* 15**,** 67-78.
GUZZETTI, F., REICHENBACH, P., CARDINALI, M., GALLI, M. & ARDIZZONE, F. 2005. Probabilistic landslide hazard assessment at the basin scale. *Geomorphology,* 72**,** 272-299.
HAASNOOT, M., MIDDELKOOP, H., OFFERMANS, A., BEEK, E. & DEURSEN, W. 2012. Exploring pathways for sustainable water management in river deltas in a changing environment. *Climatic Change,* 115**,** 795-819.
HALL, J. 2007. Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions. *Hydrological Processes,* 21**,** 1127-1129.
HALL, J. 2013. Flood Risk Management: Decision Making Under Uncertainty *In:* BEVEN, K. & HALL, J. (eds.) *Uncertainty in Flood Risk Management.* London: Imperial College Press.
HALL, J. & ANDERSON, M. 2002. Handling uncertainty in extreme or unrepeatable hydrological processes—the need for an alternative paradigm. *Hydrological Processes,* 16**,** 1867-1870.
HALL, J. & SOLOMATINE, D. 2008. A framework for uncertainty analysis in flood risk management decisions. *International Journal of River Basin Management,* 6**,** 85-98.
HALL, J. W., EVANS, E. P., PENNING-ROWSELL, E. C., SAYERS, P. B., THORNE, C. R. & SAUL, A. J. 2003. Quantified scenarios analysis of drivers and impacts of changing flood risk in England and Wales: 2030–2100. *Global Environmental Change Part B: Environmental Hazards,* 5**,** 51-65.
HALL, J. W., LEMPERT, R. J., KELLER, K., HACKBARTH, A., MIJERE, C. & MCINERNEY, D. J. 2012a. Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods. *Risk Analysis: An International Journal,* 32**,** 1657-1672.
HALL, J. W., MANNING, L. J. & HANKIN, R. K. S. 2011. Bayesian calibration of a flood inundation model using spatial data. *Water Resources Research,* 47**,** n/a-n/a.

HALL, J. W., WATTS, G., KEIL, M., DE VIAL, L., STREET, R., CONLAN, K., O'CONNELL, P. E., BEVEN, K. J. & KILSBY, C. G. 2012b. Towards risk-based water resources planning in England and Wales under a changing climate. *Water and Environment Journal,* 26**,** 118-129.

HALLEGATTE, S. 2009. Strategies to adapt to an uncertain climate change. *Global Environmental Change-Human and Policy Dimensions,* 19**,** 240-247.

HAMMOND, J. S., KEENEY, R. L. & RAIFFA, H. 1998. *Smart choices : a practical guide to making better decisions,* Boston, Mass., Harvard Business School ; London : McGraw-Hill.

HARAGUCHI, M. & LALL, U. 2015. Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction,* 14, Part 3**,** 256-272.

HARRIS, G. P. 2007. *Seeking sustainability in an age of complexity,* Cambridge, Cambridge University Press.

HAWKES, P. J., GOULDBY, B. P., TAWN, J. A. & OWEN, M. W. 2002. The joint probability of waves and water levels in coastal engineering design. *Journal of Hydraulic Research,* 40**,** 241-251.

HEFFERNAN, J. E. & TAWN, J. A. 2004. A conditional approach for multivariate extreme values (with discussion). *Journal of the Royal Statistical Society: Series B (Statistical Methodology),* 66**,** 497-546.

HILL, B., ASPINALL, W., CONNOR, C., KOMOROWSKI, J. & NAKADA, S. 2009. Recommendations for assessing volcanic hazards at sites of nuclear installations. *In:* CONNOR, C. B., CHAPMAN, N. A. & CONNOR, L. J. (eds.) *Volcanic and tectonic hazard assessment for nuclear facilities.* Cambridge: Cambridge University Press.

HINE, D. & HALL, J. W. 2010. Information gap analysis of flood model uncertainties and regional frequency analysis. *Water Resources Research,* 46**,** n/a-n/a.

HINO, M. & HALL, J. in Review. Real Options Analysis of Adaptation to Changing Flood Risk: Analysis of Structural and Non-Structural Measures. *Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*.

HOCHRAINER-STIGLER, S., MECHLER, R. & MOCHIZUKI, J. 2015. A risk management tool for tackling country-wide contingent disasters: A case study on Madagascar. *Environmental Modelling & Software,* 72**,** 44-55.

HUNTJENS, P., LEBEL, L., PAHL-WOSTL, C., CAMKIN, J., SCHULZE, R. & KRANZ, N. 2012. Institutional design propositions for the governance of adaptation to climate change in the water sector. *Global Environmental Change-Human and Policy Dimensions,* 22**,** 67-81.

IBSEN, M.-L. & BRUNSDEN, D. 1996. The nature, use and problems of historical archives for the temporal occurrence of landslides, with specific reference to the south coast of Britain, Ventnor, Isle of Wight. *Geomorphology,* 15**,** 241-258.

IDMC 2015. Global Estimates 2015: People Displaced by Disasters. Geneva: Norwegian Refugee Council.

IPCC 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge.

IPCC 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge.

JONES, R., PATWARDHAN, A., COHEN, S., DESSAI, S., LAMMEL, A., LEMPERT, R., MIRZA, M. & VON STORCH, H. 2014. Foundations for Decision Making. *In:* FIELD, C., BARROS, V., DOKKEN, D., MACH, K., MASTRANDREA, M., BILIR, T., CHATTERJEE, M., EBI, K., ESTRADA, Y., GENOVA, R., GIRMA, B., KISSEL, E., LEVY, A., MACCRACKEN, S., MASTRANDREA, P. & WHITE, L. (eds.) *Climate Change 2014: Impacts, Adaptation, and Vulnerability Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge: Cambridge University Press.

KAHNEMAN, D. 2011. *Thinking, Fast and Slow,* New York, Farrar, Straus, and Giroux.

KAHNEMAN, D. & TVERSKY, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47.

KALRA, N., HALLEGATTE, S., LEMPERT, R., BROWN, C., FOZZARD, A., GILL, S. & SHAH, A. 2014. Agreeing on robust decisions : new processes for decision making under deep uncertainty. Washington, DC: The World Bank.

KALRA, N. R., GROVES, D. G., BONZANIGO, L., PEREZ, E. M., RAMOS, C., CARTER, B. E. & RODRIGUEZ CABANILLAS, I. 2015. Robust decision-making in the water sector: a strategy for implementing Lima's long-term water resources master plan. Washington, D.C.: World Bank Group.

KEEF, C., TAWN, J. & SVENSSON, C. 2009. Spatial risk assessment for extreme river flows. *Journal of the Royal Statistical Society: Series C (Applied Statistics),* 58**,** 601-618.

KEEFER, D. L., KIRKWOOD, C. W. & CORNER, J. L. 2004. Perspective on Decision Analysis Applications, 1990–2001. *Decision Analysis,* 1**,** 4-22.

KEENEY, R. L. & RAIFFA, H. 1993. *Decisions with multiple objectives-preferences and value tradeoffs,* Cambridge & New York, Cambridge University Press.

KELLET, J. & CARAVANI, A. 2013. Financing Disaster Risk Reduction. Overseas Development Institute and Global Facility for Disaster Reduction and Recovery.

KLEINDORFER, P. R., KUNREUTHER, H. G. & SCHOEMAKER, P. J. H. 1993. *Decision Sciences: An Integrative Perspective,* Cambridge, Cambridge University Press.

KNIGHT, F. 1921. *Risk, Uncertainty and Profit,* Boston, Houghton-Mifflin Co.

KORTELING, B., DESSAI, S. & KAPELAN, Z. 2013. Using Information-Gap Decision Theory for Water Resources Planning Under Severe Uncertainty. *Water Resources Management,* 27**,** 1149-1172.

KRZYSZTOFOWICZ, R. 1993. A theory of flood warning systems. *Water Resources Research,* 29**,** 3981-3994.

KULL, D., MECHLER, R. & HOCHRAINER-STIGLER, S. 2013. Probabilistic cost-benefit analysis of disaster risk management in a development context. *Disasters,* 37**,** 374-400.

LAWRENCE, J., REISINGER, A., MULLAN, B. & JACKSON, B. 2013. Exploring climate change uncertainties to support adaptive management of changing flood-risk. *Environmental Science & Policy,* 33**,** 133-142.

LEE, G., JUN, K. S. & CHUNG, E. S. 2015. Group decision-making approach for flood vulnerability identification using the fuzzy VIKOR method. *Nat. Hazards Earth Syst. Sci.,* 15**,** 863-874.

LEMPERT, R. & GROVES, D. 2010. Identifying and Evaluating Robust Adaptive Policy Responses to Climate Change for Water Management Agencies in the American West. *Technological Forecasting & Social Change,* 77**,** 960-974.

LEMPERT, R. & KALRA, N. 2014. Managing Climate Risks in Developing Countries with Robust Decision Making. *World Resources Report Uncertainty Series.*

LEMPERT, R., KALRA, N., PEYRAUD, S., MAO, Z., TAN, S. B., CIRA, D. & LOTSCH, A. 2013a. Ensuring robust flood risk management in Ho Chi Minh City. The World Bank.

LEMPERT, R., POPPER, S. & BANKES, S. 2003a. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. Santa Monica: RAND Corporation.

LEMPERT, R. J. & COLLINS, M. T. 2007. Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches. *Risk Analysis,* 27**,** 1009-1026.

LEMPERT, R. J., GROVES, D. G., POPPER, S. W. & BANKES, S. C. 2006. A general, analytic method for generating robust strategies and narrative scenarios. *Management Science,* 52**,** 514-528.

LEMPERT, R. J., POPPER, S. W. & BANKES, S. C. 2003b. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. Santa Monica, CA: RAND.

LEMPERT, R. J., POPPER, S. W., GROVES, D. G., KALRA, N., FISCHBACH, J. R., BANKES, S. C., BRYANT, B. P., COLLINS, M. T., KELLER, K., HACKBARTH, A., DIXON, L., LATOURRETTE, T., REVILLE, R. T., HALL, J. W., MIJERE, C. & MCINERNEY, D. J. 2013b. Making Good Decisions Without Predictions: Robust Decision Making for Planning Under Deep Uncertainty. RAND Corporation.

LINDLEY, D. V. 1985. *Making decisions,* London, Wiley.

LØVHOLT, F., SETIADI, N. J., BIRKMANN, J., HARBITZ, C. B., BACH, C., FERNANDO, N., KAISER, G. & NADIM, F. 2014. Tsunami risk reduction – are we better prepared today than in 2004? *International Journal of Disaster Risk Reduction,* 10, Part A**,** 127-142.

LUMB, P. 1975. Slope failures in Hong Kong. *Quarterly Journal of Engineering Geology and Hydrogeology,* 8**,** 31-65.

MACKIE, S. & WATSON, M. 2014. Probabilistic detection of volcanic ash using a Bayesian approach. *Journal of Geophysical Research: Atmospheres,* 119**,** 2409-2428.

MADANI, K. & LUND, J. R. 2011. A Monte-Carlo game theoretic approach for Multi-Criteria Decision Making under uncertainty. *Advances in Water Resources,* 34**,** 607-616.

MARTINA, M. L. V., TODINI, E. & LIBRALON, A. 2006. A Bayesian decision approach to rainfall thresholds based flood warning. *Hydrol. Earth Syst. Sci.,* 10**,** 413-426.
MATROSOV, E. S., WOODS, A. M. & HAROU, J. J. 2013. Robust Decision Making and Info-Gap Decision Theory for water resource system planning. *Journal of Hydrology,* 494**,** 43-58.
MCMILLAN, H., KRUEGER, T. & FREER, J. 2012. Benchmarking observational uncertainties for hydrology: rainfall, river discharge and water quality. *Hydrological Processes,* 26**,** 4078-4111.
MEDINA-CETINA, Z. & NADIM, F. 2008. Stochastic design of an early warning system. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards,* 2**,** 223-236.
MEJÍA-NAVARRO, M. & GARCIA, L. A. 1996. Natural Hazard and Risk Assessment Using Decision Support Systems, Application: Glenwood Springs, Colorado. *Environmental & Engineering Geoscience,* II**,** 299-324.
MELCHERS, R. E. 1999. *Structural reliability : analysis and prediction,* Chichester, John Wiley.
MICHEL-KERJAN, E., HOCHRAINER-STIGLER, S., KUNREUTHER, H., LINNEROOTH-BAYER, J., MECHLER, R., MUIR-WOOD, R., RANGER, N., VAZIRI, P. & YOUNG, M. 2013. Catastrophe Risk Models for Evaluating Disaster Risk Reduction Investments in Developing Countries. *Risk Analysis,* 33**,** 984-999.
MILETI, D. S. 1999. *Disasters by design : a reassessment of natural hazards in the United States,* Washington, D.C., Joseph Henry Press.
MORGAN, M. G., HENRION, M. & SMALL, M. 1990. *Uncertainty : a guide to dealing with uncertainty in quantitative risk and policy analysis,* Cambridge, Cambridge University Press.
MORROW, B. 2009. Risk Behavior and Risk Communication: Synthesis and Expert Interviews. Miami: Soc Research.
MUNICH RE 2015. Natural catastrophes 2014: Analyses, assessments, positions. *In:* TWEST, S. (ed.) *Topics Geo.* Munich.
MYLNE, K. R. 2002. Decision-making from probability forecasts based on forecast value. *Meteorological Applications,* 9**,** 307-315.
NATIONAL RESEARCH COUNCIL 1988. *Probabilistic Seismic Hazard Analysis,* Washington D.C., National Academy Press.
NERC 1975. Flood Studies Report. Swindon: Natural Environment Research Council.
NEW, M., LOPEZ, A., DESSAI, S. & WILBY, R. 2007. Challenges in using probabilistic climate change information for impact assessments: an example from the water sector. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* 365**,** 2117-2131.
O'HAGAN, A., DANESHKHAH, A., EISER, R., GARTHWAITE, P., JENKINSON, D., OAKLEY, J. & RAKOW, T. 2006. *Uncertain Judgements: Eliciting Experts' Probabilities*, Wiley.
OZDEMIR, M. S. & SAATY, T. L. 2006. The unknown in decision making: What to do about it. *European Journal of Operational Research,* 174**,** 349-359.
PARKER, R., LITTLE, K. & HAUSER, S. 2007. Development Actions and the Rising Incidence of Disasters. Washington DC: Independent Evaluation Group (World Bank).
PARRY, G. W. 1996. The characterization of uncertainty in Probabilistic Risk Assessments of complex systems. *Reliability Engineering & System Safety,* 54**,** 119-126.
PATÉ-CORNELL, M. E. 1996. Uncertainties in risk analysis: Six levels of treatment. *Reliability Engineering & System Safety,* 54**,** 95-111.
PAYO, A., BECKER, P., OTTO, A., VERVOORT, J. & KINGSBOROUGH, A. 2015. Experiential Lock-In: Characterizing Avoidable Maladaptation in Infrastructure Systems. *Journal of Infrastructure Systems***,** 02515001.
PEARL, J. 1988. *Probabilistic reasoning in intelligent systems : networks of plausible inference,* San Mateo, Calif., Morgan Kaufmann Publishers.
PETERSEN, M. D., DEWEY, J., HARTZELL, S., MUELLER, C., HARMSEN, S., FRANKEL, A. & RUKSTALES, K. 2004. Probabilistic seismic hazard analysis for Sumatra, Indonesia and across the Southern Malaysian Peninsula. *Tectonophysics,* 390**,** 141-158.
PIANOSI, F., WAGENER, T., BEVEN, K., FREER, J., HALL, J., ROUGIER, J. & STEPHENSON, D. B. in Review. Sensitivity Analysis of environmental models: a systematic review with practical workflow. . *Environmental Modelling & Software*.
PIDGEON, N. & BUTLER, C. 2009. Risk analysis and climate change. *Environmental Politics,* 18**,** 670-688.

PODVEZKO, V. & PODVIEZKO, A. 2010. Dependence of multi-criteria evaluation result on choice of preference functions and their parameters. *Ukio Technologinis ir Ekonominis Vystymas,* 16**,** 143-158.
POFF, N. L., BROWN, C. M., GRANTHAM, T. E., MATTHEWS, J. H., PALMER, M. A., SPENCE, C. M., WILBY, R. L., HAASNOOT, M., MENDOZA, G. F., DOMINIQUE, K. C. & BAEZA, A. 2015. Sustainable water management under future uncertainty with eco-engineering decision scaling. *Nature Clim. Change,* advance online publication.
POPPER, K. R. 1959. *[Logik der Forschung.] The Logic of Scientific Discovery. (Translation prepared by the author.),* London, Hutchinson.
RANGER, N., MILLNER, A., DIETZ, S., FANKHAUSER, S., LOPEZ, A. & RUTA, G. 2010. Adaptation in the UK: a decision-making process. London: Grantham Institute for Climate Change.
RAYNER, S. 2007. The Rise of Risk and the Decline of Politics. *Environmental Hazards,* 7**,** 165-172.
RITTEL, H. J. & WEBBER, M. 1973. Dilemmas in a general theory of planning. *Policy Sciences,* 4**,** 155-169.
ROSENZWEIG, C. & SOLECKI, W. 2014. Hurricane Sandy and adaptation pathways in New York: Lessons from a first-responder city. *Global Environmental Change,* 28**,** 395-408.
ROUGIER, J., SPARKS, S. & HILL, L. J. 2013. *Risk and Uncertainty Assessment for Natural Hazards*, Cambridge University Press.
SADEGHI, M., HOCHRAINER-STIGLER, S. & GHAFORY-ASHTIANY, M. 2015. Evaluation of earthquake mitigation measures to reduce economic and human losses: a case study to residential property owners in the metropolitan area of Shiraz, Iran. *Natural Hazards,* 78**,** 1811-1826.
SAYERS, P., HALL, J. & MEADOWCROFT, I. 2002. Towards risk-based flood hazard management in the UK. *Proceedings of ICE,* 150**,** 36–42.
SIEBENTRITT, M., HALSEY, N. & STAFFORD-SMITH, M. 2014. Regional Climate Change Adaptation Plan for the Eyre Peninsula. . Prepared for the Eyre Peninsula Integrated Climate Change Agreement Committee.
SIMON, H. 1956. Rational Choice and the Structure of the Environment. *Psychological Review,* 63**,** 129-138.
SINGH, R., WAGENER, T., CRANE, R., MANN, M. E. & NING, L. 2014. A vulnerability driven approach to identify adverse climate and land use change combinations for critical hydrologic indicator thresholds: Application to a watershed in Pennsylvania, USA. *Water Resources Research,* 50**,** 3409-3427.
SMITH, J. Q. 2010. *Bayesian decision analysis : principles and practice,* Cambridge, Cambridge University Press.
SMYTH, A. W., ALTAY, G., DEODATIS, G., ERDIK, M., FRANCO, G., GULKAN, P., KUNREUTHER, H., LUS¸, H., METE, E. & SEEBER, N. 2004. Probabilistic Benefit-Cost Analysis for Earthquake Damage Mitigation: Evaluating Measures for Apartment Houses in Turkey. *Earthquake Spectra,* 20**,** 171-203.
SPIEGELHALTER, D. J. & RIESCH, H. 2011. Don't know, can't know: embracing deeper uncertainties when analysing risks. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* 369**,** 4730-4750.
STEINSCHNEIDER, S., WI, S. & BROWN, C. 2015. The integrated effects of climate and hydrologic uncertainty on future flood risk assessments. *Hydrological Processes,* 29**,** 2823-2839.
STIRLING, A. 2010. Keep it complex. *Nature,* 468**,** 1029-1031.
TACNET, J., BATTON-HUBERT, M., DEZERT, J. & RICHARD, D. 2012. Decision Support for Natural Hazard Management under Uncertainty. *12th Congress Interpraevent.* Grenoble.
TAKEWAKI, I. 2013. Toward greater building earthquake resilience using concept of critical excitation: A review. *Sustainable Cities and Society,* 9**,** 39-53.
TALEB, N. N. 2007. *The black swan : the impact of the highly improbable,* New York, Random House.
TALL, A., MASON, S. J., VAN AALST, M., SUAREZ, P., AIT-CHELLOUCHE, Y., DIALLO, A. A. & BRAMAN, L. 2012. Using Seasonal Climate Forecasts to Guide Disaster Management: The Red Cross Experience during the 2008 West Africa Floods. *International Journal of Geophysics,* 2012**,** 12.
TANG, H., FAN, D., LI, D. & XUE, S. 2015. Info-gap decision for the robust seismic design optimization of structures. *Journal of Hunan University Natural Sciences,* 42**,** 21-28.
TANNER, T., LEWIS, D., WRATHALL, D., BRONEN, R., CRADOCK-HENRY, N., HUQ, S., LAWLESS, C., NAWROTZKI, R., PRASAD, V., RAHMAN, M. A., ALANIZ, R., KING, K., MCNAMARA, K.,

NADIRUZZAMAN, M., HENLY-SHEPARD, S. & THOMALLA, F. 2015. Livelihood resilience in the face of climate change. *Nature Clim. Change,* 5**,** 23-26.
TODINI, E. 2004. Role and treatment of uncertainty in real-time flood forecasting. *Hydrological Processes,* 18**,** 2743-2746.
TRIANTAPHYLLOU, E. 2013. *Multi-criteria Decision Making Methods: A Comparative Study,* Berlin, Springer.
TSENG, C.-P. & CHEN, C.-W. 2012. Natural disaster management mechanisms for probabilistic earthquake loss. *Natural Hazards,* 60**,** 1055-1063.
UNISDR 2015. Sendai Framework for Disaster Risk Reduction 2015 - 2030. Geneva.
VECCHIA, A. 2001. A unified approach to probabilistic risk assessments for earthquakes, floods, landslides and volcanoes. *U.S. Geological Survey Urban Hazards Initiative Multidisciplinary Workshop.* Golden.
VRIJLING , J., SCHWECKENDIEK, T. & KANNING, W. Safety Standards of Flood Defenses *In:* VOGT , N., SCHUPPENER , B. & BRAU, G., eds. 3rd Int. Symposium on Geotech, Safety and Risk, 2011 Munich.
WESTERBERG, I., GUERRERO, J. L., SEIBERT, J., BEVEN, K. J. & HALLDIN, S. 2011. Stage-discharge uncertainty derived with a non-stationary rating curve in the Choluteca River, Honduras. *Hydrological Processes,* 25**,** 603-613.
WILBY, R., TRONI, J., BIOT, Y., TEDD, L., HEWITSON, B., SMITH, D. & SUTTON, R. 2009. A review of climate risk information for adaptation and development planning. *International Journal of Climatology,* 29**,** 1193-1215.
WILBY, R. L. & DESSAI, S. 2010. Robust adaptation to climate change. *Weather,* 65**,** 180-185.
WILSON, R., WINTER, P., MAGUIRE, L. & ASCHER, T. 2011. Managing wildfire events: Risk-based decision making among a group of federal fire managers. *Risk Analysis,* 31**,** 805.
WINKLER, R. L. 1996. Uncertainty in probabilistic risk assessment. *Reliability Engineering & System Safety,* 54**,** 127-132.
WOO, G. 2010. Operational Earthquake Forecasting and Risk Management. *Seismological Research Letters,* 81**,** 778-782.
WOODWARD, M., KAPELAN, Z. & GOULDBY, B. 2014. Adaptive Flood Risk Management Under Climate Change Uncertainty Using Real Options and Optimization. *Risk Analysis,* 34**,** 75-92.
WORLD ECONOMIC FORUM 2011. A vision for managing natural disaster risk. Geneva.
WORLD HEALTH ORGANISATION 2011. Useful Definitions and Early Warning Information for Natural Hazards. *Disaster Risk Management for Health Fact Sheets.*
YOHE, G. & LEICHENKO, R. 2010. Adopting a risk-based approach. *Climate Change Adaptation in New York City: Building a Risk Management Response,* 1196**,** 29-40.
YOUNG, P., ROMANOWICZ, R. & BEVEN, K. 2014. A Data-Based Mechanistic Modelling Approach to Real-Time Flood Forecasting. *In:* BEVEN, K. & HALL, J. (eds.) *Applied Uncertainty Analysis for Flood Risk Management.* London: Imperial College Press.
ZHANG, F., IGNATIUS, J., ZHAO, Y., LIM, C. P., GHASEMI, M. & NG, P. S. 2015. An improved consensus-based group decision making model with heterogeneous information. *Applied Soft Computing,* 35**,** 850-863.

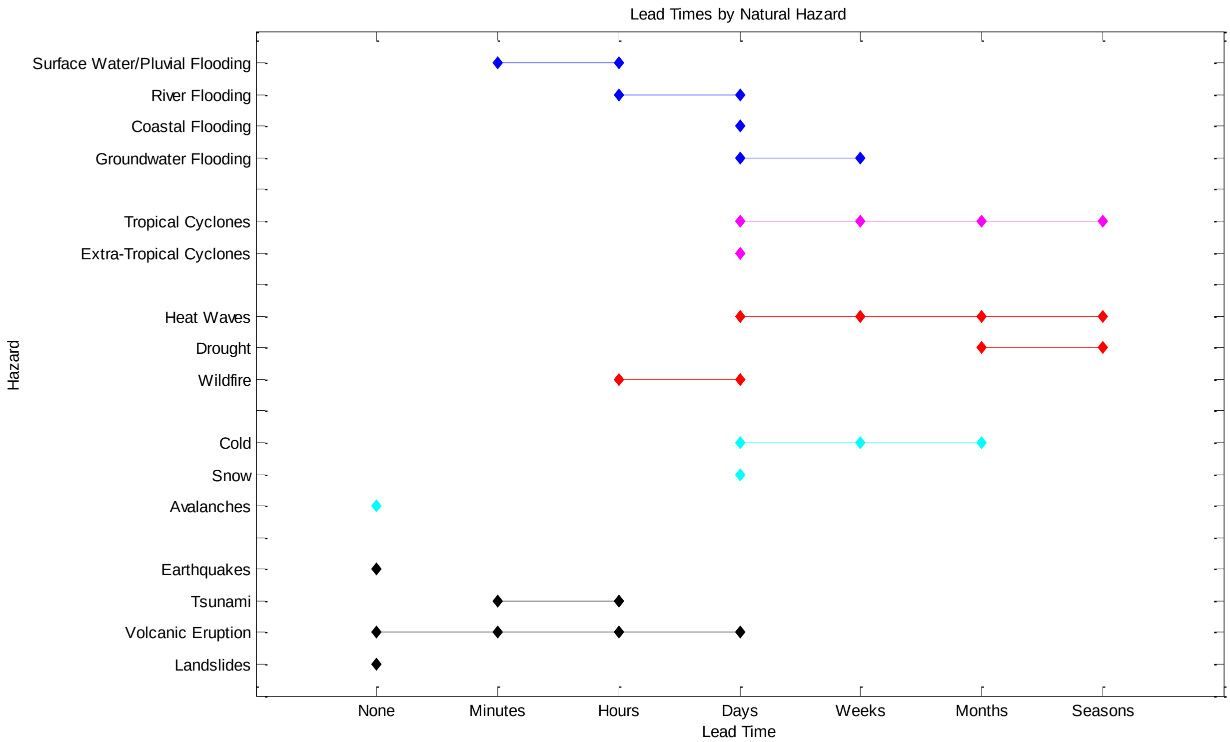

Figure 1. The range of lead-times of natural hazards (data from World Health Organisation (2011))

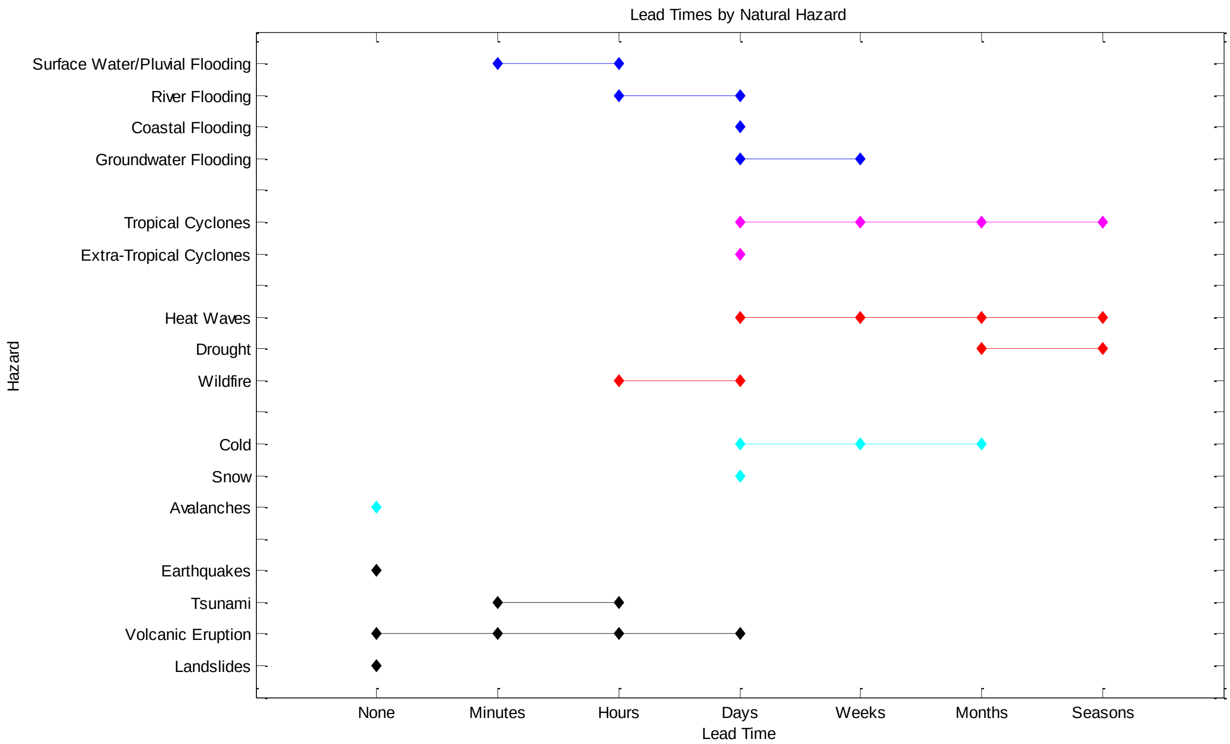

Figure 2. The spatial scales of natural hazards

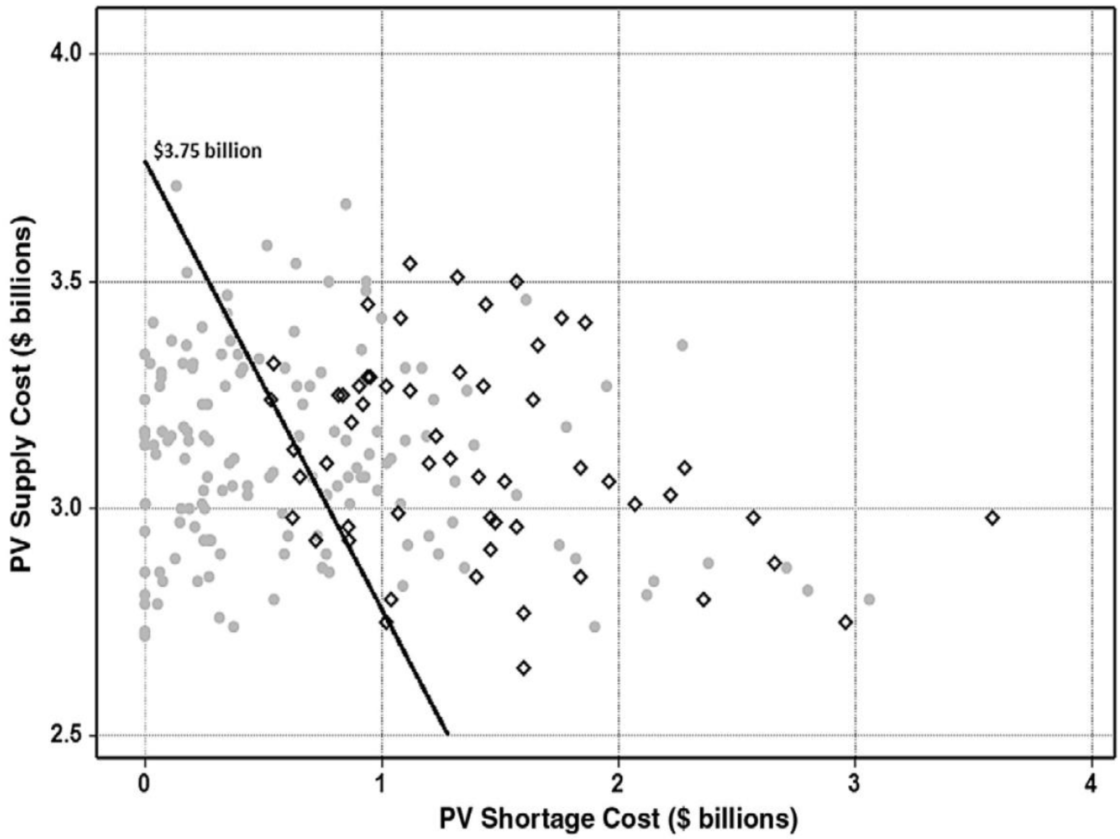

Figure 3. Projected present value (PV) shortage costs and supply costs for a water utility's master plan for 200 alternative states of the world, reflecting different combinations of uncertain climate sequences, water demands, groundwater response, future costs and impact of climate change on imported supplies. The diagonal line shows the satisficing criterion and the diamonds show the states of the world where the combination of uncertain factors (decline in precipitation, reduction in imported supplies and changes in groundwater response) leads to poor performance (from Lempert and Groves, 2010).

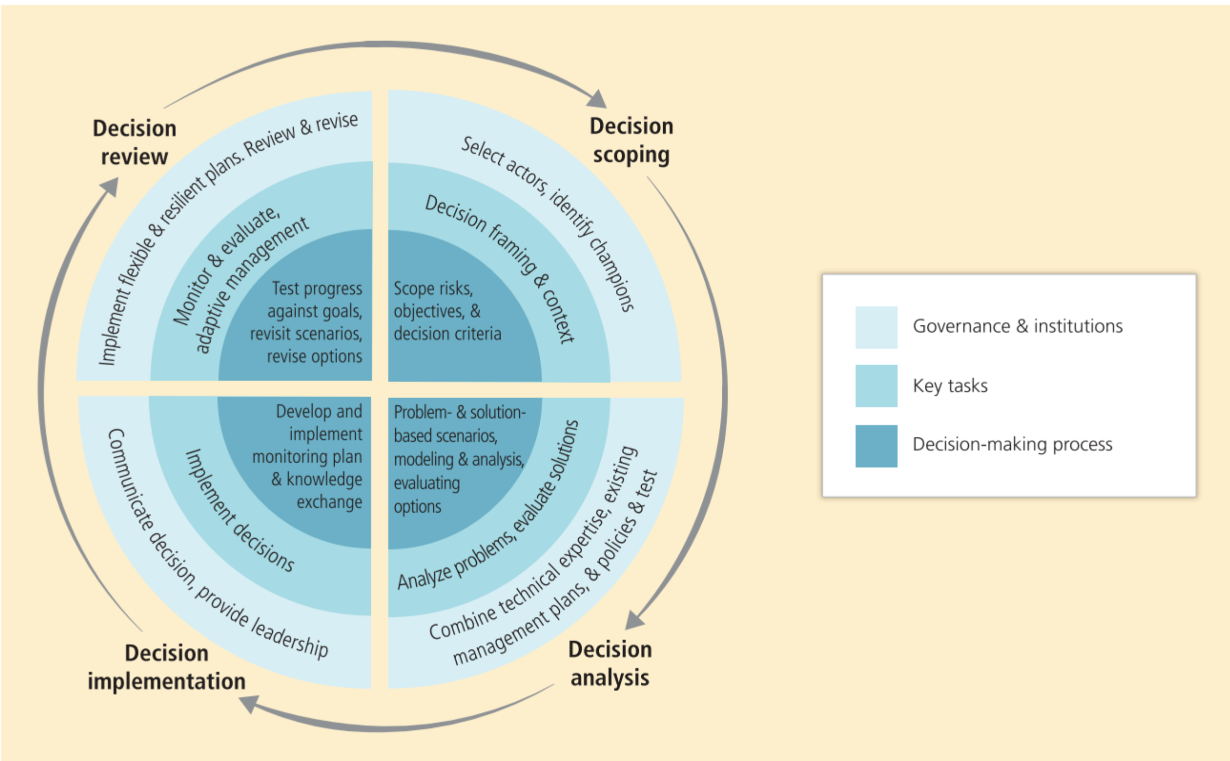

Figure 4 The decision analysis cycle (from Jones et al., 2014).

Approach to uncertainty	Methodology	Key principles	Examples of application to natural hazards
Deterministic	Conservative Engineering	Design to highest plausible hazard	Historically for Earthquake Engineering (National Research Council, 1988)
	Design Event	Nominal Hazard	Flood Risk (NERC, 1975)
	Safety Factor	Added Margin	Flood Risk (Vrijling et al., 2011), Drought (Hall et al., 2012b)
Probabilistic	Decision Trees	Mapping probabilistic decisions	Tornado Warnings (Durage et al., 2016) Typhoon Management (Cheng et al., 2007)
	Influence Diagrams	Can frame complex decisions and supporting information	Flood Risk (Castillo-Rodríguez et al., 2014)
	Bayesian Decision Networks/Bayesian Belief Networks	Bayes' Rule Conditional independence	Volcanology (Aspinall and Woo 2014), Earthquake Risk (Bayraktarli and Faber (2011)
	Sensitivity Analysis	Tests for information uncertainty	Earthquake Risk (Rohmer, 2014)
Deep Uncertainty	Adaptation Pathways	Postponement of a sequence of decisions to await new information on uncertainties	Flood and Drought Management (Haasnoot et al., 2013), Hurricanes (Rosenzweig and Solecki, 2014)
	RDM	Bottom-up maximin approach	Water Resources (Kalra et al., 2015), Flood Risk (Lempert et al., 2013a), Coastal Flooding (Groves et al., 2014)
	Info-gap	Compares alternative decisions based on their robustness and opportuneness	Flooding (Hine and Hall, 2010), Drought (Matrosov et al., 2013), Earthquake Resilient Design (Tang et al., 2015)
	Decision Scaling	Uses stakeholder-defined thresholds, finds conditions under which these thresholds are exceeded	Drought and Climate studies (Brown et al., 2012) and Flood Risk (Steinschneider et al., 2015)

Table 1 Methodologies for decision making under uncertainty