Decision Analysis for Management of Natural Hazards

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Abstract

Losses from natural hazards, including geophysical and hydrometeorological hazards, have been increasing worldwide. This review focuses on the process by which scientific evidence about natural hazards is applied to support decision making. Decision analysis typically involves estimating the 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. We consider issues that affect decisions made across a range of natural hazards, summarize decision methodologies, and provide examples of applications of decision analysis to the management of natural hazards. We conclude that there is potential for further exchange of ideas and experience between natural hazard research communities on decision analysis approaches. Broader application of decision methodologies to natural hazard management and evaluation of existing decision approaches can potentially lead to more efficient allocation of scarce resources and more efficient risk management.

Contents

1. INTRODUCTION

Humankind has always had to live with natural hazards. Civilizations have had to adapt to the inevitable arrival of natural hazards, or risk collapse. The development of civilization has also hugely increased vulnerability to natural hazards. Indeed some aspects of civilization (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 hydrometeorological and some geophysical hazards; huge resources have been mobilized for emergency assistance and recovery. It seems therefore that modern civilization has adapted to natural hazards, as other societies have done in the past. However, the escalating scale of losses from natural hazards (1), the global concern about these losses (2), and the apparent lack of attention to preparedness [when compared with the huge sums spent on response and reconstruction (3)] 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 magnitude of uncertainty in natural hazard decisions and the inevitability of trade-offs between different objective and actors. Improved decision making can be expected to contribute to reducing risk, allocating resources more efficiently, avoiding undesirable impacts, and accessing co-benefits.

Decision analysis (4) encompasses normative theory of how decision makers should make choices, alongside descriptive analysis of how decisions are made in practice. Empirical study of how people make choices under uncertainty has demolished notions that human beings behave as rational agents. Kahneman & Tversky's (5) prospect theory has been widely applied to understand decision making under uncertainty and appears to resonate well with actual behavior (6). Wilson et al. (7) showed that wildfire managers' decision making was influenced by risk-based biases, including a preference to minimize short-term as opposed to long-term risk due to the belief that future risk could be controlled. However, despite its ability to explain individuals' behavior, Kahneman (8) has argued that prospect theory should not be used for normative decision making, suggesting that decision makers become more aware of their decision framing. Here we emphasize 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 (9) 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. Although we provide examples of decision analysis methodologies within hazard research communities, essentially we restrict in scope the review to an assessment of the benefits and shortcomings of decision analysis methodologies. The social, cultural, and psychological questions regarding how decisions are made in practice we set aside.

Normative decision making: analysis of how choices should be made, in contrast with descriptive decision analysis, which details how decisions are made (22)

This review explores characteristics of natural hazard decisions and evaluates current use of decision analysis across a range of natural hazards. We focus on the role of uncertainty in natural hazard decision making; the multiple values, attributes, and objectives that are typically brought to bear on natural hazard decisions and how these are handled in theory and practice; the multiple actors that are involved in natural hazard decisions; and the ways in which good decision-making processes might be constructed to reflect learning about these various challenging characteristics. Section 2 presents the context and challenges associated with natural hazard decisions. Section 3 reviews decision analysis methodologies as potential solutions for formalizing decision problems. Section 4 draws conclusions. We end with the Future Issues list, describing future challenges and goals pertaining to decision analysis for natural hazards. We summarize insights from contemporary decision analysis methodologies to areas of natural hazard management where they have been applied, to promote learning across different classes of hazard, including geophysical and hydrometeorological, 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. We provide illustrative examples rather than attempt comprehensive coverage of all decisions made for management of natural hazards. We focus predominantly on geological and hydrometeorological events and some directly associated hazards (wildfires, tsunamis, avalanches, and landslides).

2. THE CHALLENGE POSED BY NATURAL HAZARDS FOR DECISION MAKERS

Natural hazards have been associated with messy (10), wicked (11), and postnormal science (12) problems, without clear or straightforward solutions (13). 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. Characterizing natural hazard decision problems is a first step toward the selection of appropriate decision analysis methodologies, which we describe in the following sections.

2.1. Good Decision-Making Processes

Our discussion of decision making for natural hazard management focuses on the formal structure of decision problems (treatment of uncertainty, sequential decisions, decisions with multiple attributes and actors). Scholars of decision analysis emphasize the process of making decisions as being just as important as the formal structure adopted (4).

To address the ingredients for good decision making for natural hazard management, we first consider what makes a good decision. The question has been considered widely in decision theory, risk governance, ethical reasoning, and related fields. Good decisions are widely regarded as those that lead to the "right" answer, such as the identification of forecast methodologies that have the highest accuracy (14, 15). However, there is no universal criterion for a good decision (16), it is difficult to evaluate strategic 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 (17). This is perhaps especially true for natural hazards: It is difficult to evaluate plans for high-consequence events with poorly understood probabilities. However, 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, there are 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 (16). These principles not only emphasize 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. (18) present guidance for good decision analysis. Several of Morgan's guidelines, 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 guidelines give more substantive direction in the recommended approach for decision analysis. Morgan et al. (18) highlight the importance of letting the problem drive the analysis, which is echoed by others who emphasize the centrality of user needs (16): The importance of iterative analysis has also been highlighted, 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 (19). Another key component of good decision analysis is to consider a wide range of views, while keeping the analysis as simple as possible, so that it can be widely understood and is more likely to be seen as legitimate (20). Given inevitable simplifications, one must be explicit about assumptions and uncertainty.

Good decision making is typically characterized as a cyclic process, encompassing (*a*) scoping/framing/problem identification, (*b*) analysis, (*c*) implementation, and (*d*) monitoring/evaluation/review phases (**Figure 1**). 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 (16). If risk is simple and 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, unclear solutions, many stakeholders, and contrast between calculated and perceived risk, then iterative, adaptive, process-driven stakeholder coproduction is advised (21).

2.2. Comparing Formalized and Intuitive Decision Making

The fallibility of intuitively made decisions is well documented. French et al. (22) provide a review of intuitive decision making and the specific logical challenges that cause the intuitive decision maker to make choices that are irrational, illogical, or not supported by evidence. This may be in the context of choosing between options or, as is commonly relevant to the probabilistic decisions made in response to natural hazards, in assessing the uncertainty associated with such a choice. French et al. (22) cite Simon's (23) argument that intuitive decision making in the face of complex or uncertain problems relies on reducing the problem to a simple set of minimum standards and choosing the first available option that meets these criteria. In itself, this does

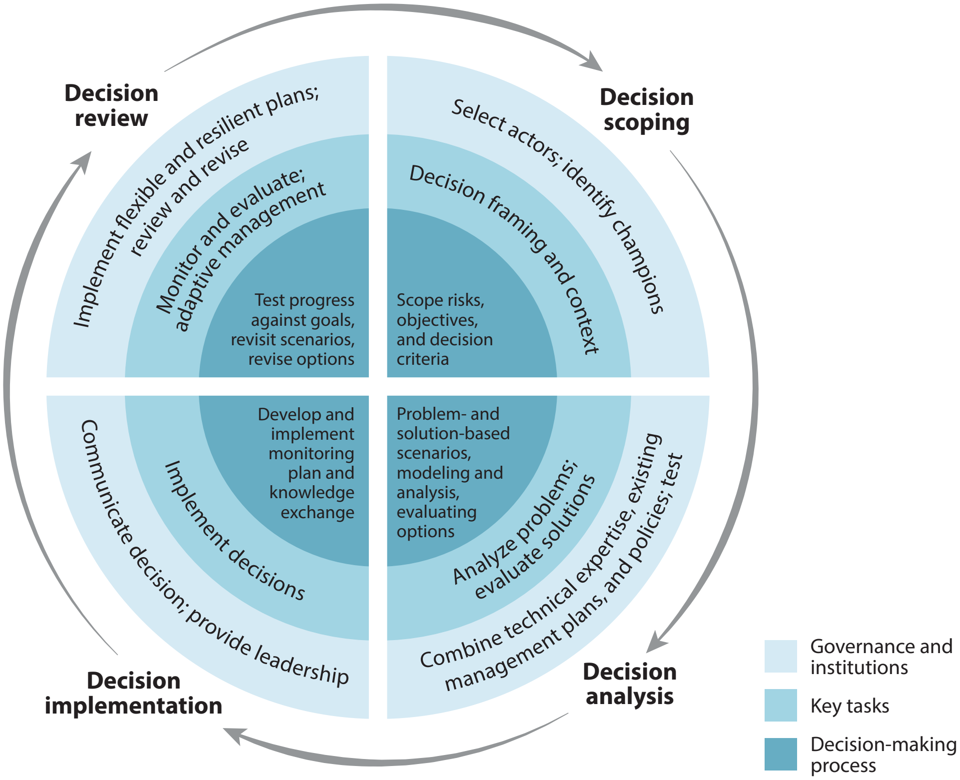

Figure 1

The decision analysis cycle. Reprinted from Reference 16, with permission.

not lead to bad decision making and can be a useful tool (23). However, this simplification has limitations when faced with specific types of complexity such as conditional probabilities (22), and intuitive preferences between sets of options may not be consistent under alternative framings of the decision in question (5). Critics of a formalized decision-making approach refer to a lack of uptake among decision makers, in particular under time-pressured situations (24). Responding rationally to other human agents is central to game theory (25), which has been applied to drought planning (26). However, the assumption in game theory that participants act rationally has been questioned (15). The need for decision analysis to extend a formal framework to problems involving irrational actors has resulted in the development of behavioral decision making and its application to fields such as economics in which irrational actors may be found (27).

The supporting evidence is strong for the merit of applying a formalized approach where suitable conditions exist. Grove et al. (28) conducted a meta-analysis of 136 medical studies in which expert/intuitive and formal/procedural predictive judgments could be compared directly. Although in many cases the intuitive judgment was approximately as good as the formalized prediction, in approximately half of the studies reviewed a formal approach was demonstrably more successful. Where there is scope to take decisions with time and in response to a set of options with stable values, the use of a formal decision analysis is preferable.

2.3. Timescales of Decision Making

Decision making regarding natural hazards can be divided into (*a*) long-term planning or risk mitigation, (*b*) early warning and preparation, (*c*) during event response, and (*d*) during recovery (29, 30). The first three of these are the focus of this review. Each phase may involve different actors, institutions, and requirements for decision analysis (30, 31). Planning and preparedness decisions lead to anticipatory actions designed to reduce the risk from natural hazards. Assuming that the triggering physical phenomenon (e.g., extreme rainfall, an earthquake) cannot be modified by human action, planning and preparedness focuses on steps to reduce exposure and vulnerability, for example through land zoning, building protection (dams, dykes, and earthquake-resistant buildings), and contingency planning (31). 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 vary markedly between countries (29).

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 that might lead to flooding, landslides, or wildfires; or weather forecasts signal potential hazards (30). These decisions are characterized by urgency, the possibility of (averting) major losses, and the possibility of the undesirable consequences of false warnings and badly prioritized actions. On these timescales, decision making revolves around early warning systems and emergency planning, for example, mobilizing staff and machinery, 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, as well as its predictability. **Figure 2** illustrates the distinction made in the disaster risk reduction community between (*a*) slow onset events, such as drought and extended periods of cold weather; (*b*) the majority of natural hazard types that can be identified with lead times between several hours and several days; and (*c*) instantaneous events with little or no prior warning such as earthquakes and avalanches. Hazard prediction may rely on individual hazard events developing in a predictable manner (cyclones and rain storms), having known precursors (volcanic eruptions and tsunamis), or a gradual buildup 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 (see, e.g., 32).

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 (34). Heat waves, in contrast, show a clearer increase in occurrence probability under climate change (35). For geological hazards, probability depends on tectonic movements that change on much longer timescales due to changes in stress and formation of new volcanic vents or fault lines (36).

Maier et al. (37) suggest that static approaches to decision making should be adopted when the decision horizon is short, when the decision is not flexible (cannot be rapidly changed or adapted), and when the implementation time is long relative to the rate of change of the system. For instance, decisions to respond to uncertain natural hazards with very short lead times and very fast rates of change in the system (e.g., eruptions, earthquakes, and tsunamis) are more likely to benefit from these approaches than long-term decisions responding to creeping natural hazards, such as droughts, where decision makers might wish to switch between decisions as the hazard's characteristics evolve. Under the latter circumstances, sequential decisions may be used to identify better solutions (see Section 3).

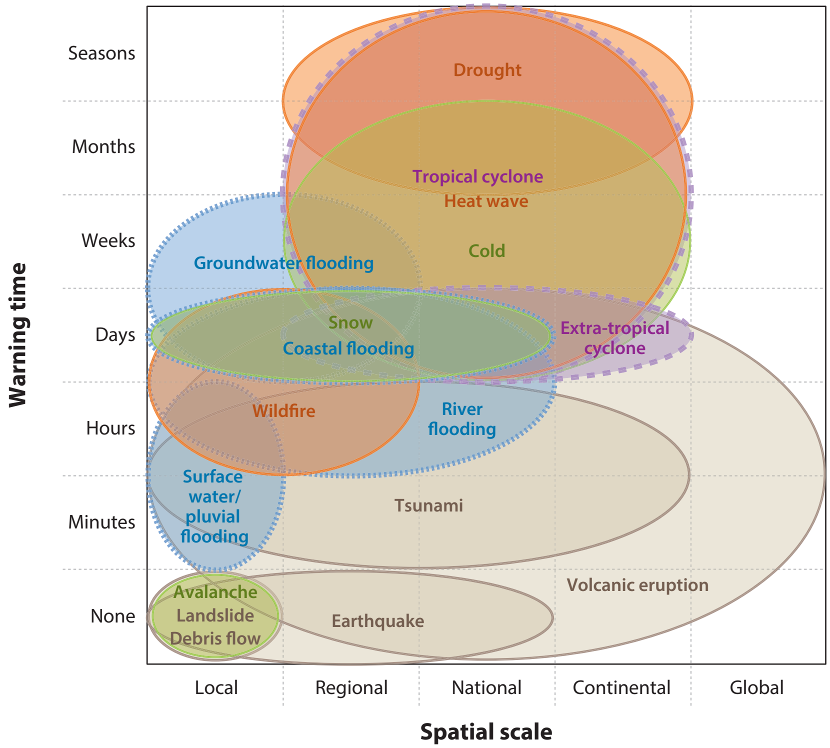

Figure 2

The range of warning times and spatial scales of natural hazards. Warning time is defined as the maximum possible time between detection of forthcoming hazard events and the hazard occurrence based on optimal current technologies. Where no forecasting system exists, it may be possible to provide warning of heightened likelihood of occurrence (e.g., of volcanic eruption) but this is not included in this figure. Related natural hazards are shown in the same color. Data are from Reference 33.

2.4. Spatial Scales of Impacts

The spatial scale of hazards ranges from site-specific events such as avalanches to continental phenomena such as heat waves or ash clouds (**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 hydro-meteorological hazards such as rainstorms (36). The most spatially extensive natural hazards may hit several countries (see, e.g., 38) and require coordination between multiple states or external international assistance. The impacts of natural hazards can spill over natural boundaries through disruption of supply chains (39) 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 (40).

2.5. Uncertainty

Natural hazard 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 modeling, difficulty in quantifying probabilities, and nonstationarity.

Nonstationarity: change in the statistics of a time series or, more formally, such changes that can specifically be attributed to deterministic processes (188)

Aleatory uncertainty: variability in system responses due to stochastic processes; essentially synonymous with risk, although the latter is ambiguous through its alternate association with hazard consequence (49)

Epistemic uncertainty: variability in system responses that cannot be attributed to stochastic processes; in principle, can be better understood and described following further observations and experiments, in contrast to aleatory uncertainty

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 (41). The most extreme events are by definition rare, so there is limited empirical evidence of their occurrence or impact (42). Data collected for the most extreme hazards may be subject to significant uncertainties (see, e.g., 43, 44), partly because disruption of infrastructure can prevent monitoring during the event itself (30). Databases can be biased, for instance landslides only tend to be recorded when they damage infrastructure (45) or human populations (46), with small slips rarely recorded (47). It is challenging to obtain data for rapid onset events: Extreme precipitation events may be too localized or intense to be captured by conventional rainfall monitoring. Data gaps in developing countries are an additional challenge, for understanding both hazard and vulnerability. New technologies provide opportunities for real-time monitoring (see, e.g., 48).

Given the scarcity and unreliability of empirical evidence about natural hazards, increasingly, simulation models are used to understand natural hazards, often in combination with, or calibrated by, statistical analysis. Environmental modeling has its own set of uncertainties, which have been discussed at length elsewhere (49). 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 (36, 50). The ability to simulate hazards, and the resources required to run the models, varies between hazard types and will influence the appropriate risk and decision analysis: For example, high-resolution climate modeling can be very computationally expensive, prohibiting the ability to represent statistics of extreme events using supercomputers (51) and leading some authors to advocate for representation of uncertainty that does not rely on complex models (42, 52, 53).

Even for those hazards that may be modeled, probabilities can be difficult to quantify. Natural hazards are associated with the extreme properties of probability distributions, for which observed data are scarce. Hazard losses may be nonlinear functions of hazard magnitude (30, 54).

The uncertainty and risk analysis literature has conventionally identified two categories of uncertainty (30, 55–57):

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

Although much debated (30, 55–57), this distinction is often helpful in risk and decision analysis of natural hazards, where the frequency and severity of the hazard is characterized as a random process. Integrating the hazard with a function to describe damage generates an estimate of risk (58), which provides a direct route to decision making, as we discuss later. 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.

2.6. Nonstationarity

Decision making on the basis of probabilities requires an understanding of how those probabilities may change over time (59). For hydrometeorological hazards, the probability of occurrence is nonstationary due to long-term trends in time series such as anthropogenic climate change (60). The accurate identification of probabilities is further complicated by periodic shifts in environmental conditions such as El Niño–Southern Oscillation events. Economic growth and population change, particularly expansion around coastal areas (61), generate nonstationarity in vulnerability as well as hazard (29), which is particularly evident in developing countries, which are likely to experience unpredictable socioeconomic changes in the coming decades (62).

Although hazard models have developed to simulate nonstationarities due to climate change (63), this approach does not include other sources of change, the influence of which may be detectable in the observation record (64). However, the short length of the observation records and the large return periods of events that models are intended to detect mean that such approaches also result in large uncertainties. The uncertainty in estimates of nonstationarity has contributed to the rise in popularity of deep uncertainty approaches (65, 66). Beyond natural hazard modeling, nonstationarity has implications for decision analysis through changes to the costs and values of decision consequences, though the possibility of these factors changing is not widely considered (63).

Deep uncertainty: a decision-making environment in which actions cannot be associated with consequences or probabilities of consequences, or in which such associations are disputed (153, 175); alternatively a lack of specific knowledge that cannot be reliably quantified (154)

Public confidence: level of belief held within a community that an organization or individual can make decisions with competence

2.7. 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. In the case of identifying areas at risk from natural hazards, vulnerability can be determined in terms of population and economic criteria (67), more broadly as social, physical, and systemic vulnerabilities (68), or purely in terms of factors likely to generate hazards (69). Where multiple intervention options for hazard mitigation are considered, 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 entail environmental impact and public confidence, which are also problematic to value in consistent ways. These may be qualitative, external to the people or areas protected by the evaluated option, and subject to changes in value over time (63). The inclusion of costs and benefits beyond the conventional financial cost/risk reduction trade-off has become widespread (70).

Faced with this challenge, there are two routes that are adopted in the literature to dealing with multiple attributes in decision problems. The first seeks to monetize all of the different possible outcomes from a decision problem, thus reducing it to a single attribute problem (see, e.g., 70). 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 noncompensatory approach (see, e.g., 71). Where noncompensatory approaches are used, multicriteria decisions can be made as attribute-based or alternative-based decisions. In an attribute-based approach, decision variables are considered in a predetermined sequence, with alternatives not meeting each criterion in sequence rejected. In alternative-based noncompensatory decisions the search process stops when the first alternative matching or exceeding a criteria set is identified. This is typically performed when several options are available or the process time for the decision is significant (22).

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 (72). A wide range of multicriteria 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 (73). A comparison of alternative methods has shown that evaluation outcome depends heavily on both choice of the utility function and its parameters (74). Multi-attribute utility theory with nonadditive utility functions provides a flexible version of the multi-attribute decision problem (75). However, this comes with the high penalty of having to construct complex utility functions, which is an elicitation problem with which most decision makers struggle.

2.8. Group Decisions

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 (76), as well as on the collective perception of outcomes given varied social norms, groupings, and lifestyles (77, 78).

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 (79) and increase community resilience (80).

In theoretical terms, there is no acceptable solution to the problem of how competing values and objectives should be reconciled in formal decision problems (81). 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 (82).

Such GDMs face two major hurdles, namely dealing with the complexity of the heterogeneous information from several 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 (83). Success appears most likely when actors from community groups, business, industry, and all levels of government and nongovernmental organizations are involved in the decision-making process from the very beginning (84).

Such processes can be facilitated through the development of a decision support system (85) 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 (84). One unfortunate caveat to such progress is the evidence that the effectiveness of such decision support systems can be reduced over time through gamesmanship (86).

3. DECISION MAKING UNDER UNCERTAINTY FOR NATURAL HAZARDS

Uncertainty is possibly the foremost challenge in natural hazard 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 hybridize)

These three approaches may be applied to single or sequential problems.

Natural hazard problems vary in their complexity, spatial range, and urgency, depending on both the characteristics of the hazard in question and on the stage of the hazard response. The application of new methodologies in hazard decisions research is in general driven by the relevant

Table 1 Examples of implementation of decision methodologies for natural hazards and their key principles

Approach to uncertainty	Methodology	Key principles	Examples of application to natural hazards
Deterministic	Conservative engineering	Design to highest plausible hazard	Historically for earthquake engineering (87)
	Design event	Nominal hazard	Flood risk (88)
	Safety factor	Added margin	Flood risk (89), drought (90)
Probabilistic	Decision trees	Mapping probabilistic decisions	Tornado warnings (91), typhoon management (92)
	Influence diagrams	Can frame complex decisions and supporting information	Flood risk (93)
	Bayesian belief networks	Bayes' rule, conditional probability	Volcanology (94), earthquake risk (95)
	Sensitivity analysis	Tests for information uncertainty	Earthquake risk (96)
Deep uncertainty	Robust decision making	Bottom-up maximin approach	Water resources (97), flood risk (98), coastal flooding (99)
	Info-gap	Compares alternative decisions based on their robustness and opportuneness	Flooding (100), drought (101), earthquake-resilient design (102)
	Decision scaling	Uses stakeholder-defined thresholds and finds conditions under which these thresholds are exceeded	Drought and climate studies (66), flood risk (103)
Sequential decisions	Decision trees	Mapping a sequence of probabilistic decisions	Water resources (104)
	Real options analysis	Valuation of flexibility	Flood risk (19, 105, 106)
	Adaptation pathways	Postponement of a sequence of decisions to await new information on uncertainties	Flood and drought management (107), hurricanes (108)

hazard community rather than the decision analysis community. As such, the use of decision analysis methodologies in practice has historically been segregated by hazard type, with slow transmission of ideas across fields. We provide a list of examples of the application of decision analysis to natural hazards in **Table 1**.

3.1. 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 mobilizing an evacuation team.

Although potentially challenging in numerous respects such as multiple objectives and actors, deterministic methodologies are straightforward in their (lack of) characterization of uncertainty. They are also almost always a significant simplification of reality. Deterministic models do not represent uncertainty, and therefore the communication of the confidence associated with modeled outcomes is not straightforward.

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 bounds 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 (87). A related strategy is the design event, in which an event of a prespecified magnitude is used to inform construction, widely used historically in design of flood protection (88) 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 (89) in which an identified margin is added to specifications, 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 (109).

The majority of formal decisions around natural hazards 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 on which probabilistic decision analysis should improve, especially in situations where decision makers seek a best-estimate outcome. Although efficient at quickly resolving decision problems with the minimum calculation required, deterministic information implicitly does not make full use of all available data and cannot communicate information from modeling, observation, or expert judgment as clearly as probabilistic information (110). The design event methodology is criticized, as it does not recognize the true complexity of the causes and impacts of flooding. Hazards have probabilities of joint occurrence, such as simultaneous coastal and fluvial flooding, and flood probabilities are spatially dynamic; for example, fluvial flood risk may change along a river. The addition of flood defenses change these probabilities in different ways and may even increase them (111). The conservative approach to deterministic decision making is used in calculating the quantity of available water or deployable output in water resource planning; however, this is criticized as the calculation of uncertainties is excluded from the decision process and becomes marginalized (90).

3.2. Probabilistic Approaches

Probabilistic concepts have been widely applied to quantify uncertainty in natural hazard decisions. Applications exist within real-time flood forecasting (112, 113), flood warnings (114), flood risk planning (115, 116), earthquake hazards (117–119), climate change adaptation (90, 120, 121), and disaster risk (122–125).

In probabilistic decision making, the range of possible circumstances (states of nature) that might materialize in the future are identified. Uncertainty as to which of these states will materialize 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 with corresponding expected losses and costs. The benefit of a given alternative is the baseline (do-nothing risk) minus the residual risk for the given alternative. The optimal decision is the act that maximizes the net benefit. In conditions of scarce resources (which is almost always the case) the option that maximizes the benefit-cost ratio 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, although the choice of discount rate is controversial (126).

The probabilities characterizing the uncertainty of different states of nature can be derived from empirical data and mathematical/statistical models, eliciting expert knowledge or any combination of these—often in a Bayesian framework (see, e.g., 30, 127, 128). Expert elicitation methods have been adopted to estimate probabilities in the absence of statistical evidence (129, 130). 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 predefined period of time. For instance, probabilistic landslide assessments aim to predict exceedance probabilities of a landslide of a particular size in a particular location (131).

A typical probabilistic decision analysis would (*a*) estimate probabilities of occurrence for the variables in question (e.g., wind speed, wave height, ground motion level) that characterize the hazard, (*b*) 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), (*c*) estimate the damage caused by the occurrence of a hazard of given severity, and (*d*) compare the capacities of alternative decisions to reduce the expected risk and associated costs. Results of steps *b* and *c* are summarized in the loss/consequence component of the risk definition (132). Step *d* is based on net present value or benefit–cost ratio calculations, which establish the preference ordering between different options given their risk reduction and cost.

Estimating probabilities and consequences of natural hazards can involve a chain of causal reasoning, which can be structured in fault trees, event trees, and decision trees (133). 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. (111) used event tree analysis to analyze the risk of damage to coastal settlements from storm surges. A similar process of structuring causal influences is adopted in influence diagrams (93), which can be quantified in the form of Bayesian networks (134, 135). 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 (77), which moves toward the area of the nonprobabilistic approaches covered Section 3.3. Sensitivity analyses (either deterministic or probabilistic) are used to determine if more refined information about the distribution and range of data might have a substantial effect on decision alternatives (136).

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 (111, 116). This risk analysis problem is conventionally structured according to a source-pathway-receptor model (111), which begins with characterization of the flood hazard, then analysis of flood inundation and the reliability of flood defense systems; finally, it combines these with characterization 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 (137)] and the spatial and temporal dependence structure of variables such as rainfall and river flows (138, 139). Beven et al. (140) have played particular attention to the uncertainties in rainfall-runoff modeling and the implications for flood risk mapping.

Krzysztofowicz (114) 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. (141) also used decision theory to optimally estimate rainfall thresholds for use in flood warnings at given river sections. Mylne (142) 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.

Severe uncertainty: decision-making environment in which evidence upon which to base a decision is "scarce and only of limited relevance to predicting what may happen in the future" (175)

Probabilistic approaches have also been widely applied to seismic hazard analysis (143–146). For instance, Sadeghi et al. (119) 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 benefit-cost 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 (147). This is challenging given the nonstationarity of eruptions, with the probability of an eruption falling dramatically during long periods of dormancy.

Bayraktarli & Faber (95) 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, and direct and indirect consequences. Second, they are able to incorporate new information into uncertainty estimates relatively quickly, providing updated risk assessments 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 & Woo (94) used Bayesian belief networks to provide a rapid analysis of eruption risks in the popular vacation destination 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 robust 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 (57), 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 normative decision-making frameworks and can be used as a mechanism to provide objective justification for uncertain or difficult-to-negotiate public policy decisions (148, 149). Although widely applied as tools for characterizing uncertainty, probabilistic concepts can have limitations, including (*a*) biases and heuristics that affect decision makers when defining probabilities, (*b*) difficulty of reaching stakeholder agreement on probability distributions, and (*c*) overconfidence or insufficiency in presenting all the uncertainties involved in a decision (77). Probabilistic representation of the uncertainty in problems that are not well constrained and where values are contested may lead to bad decisions (52, 150). This emphasizes 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.

3.3. Decision Methodologies for Deep Uncertainty

Probabilistic decision analysis may be confounded by an inability to characterize probabilities with reasonable confidence. Such conditions are common, and the associated uncertainty is known as deep uncertainty (151–153). A common example is anthropogenic climate change, in which the probabilities of given future scenarios of climate are difficult to quantify precisely (154–157). The influence of climate change on extreme weather is often the greatest concern, making the work also of great relevance to decision making for natural hazards. Deep uncertainty extends to valuing the consequences of decisions (158) and incorporating multiple perspectives on uncertainty (16). Although it is questioned whether rational decisions can be made in such circumstances (159), decisions incorporating this partial information must be made, and a range of methodologies for decision making under deep uncertainty has developed.

Extreme weather: atmospheric states from the upper or lower end of the distribution of observations, typically where these cause noticeable impacts [for a thorough list of such conditions, see Rougier et al. (30)]

Scenario discovery: identification of future states of the world that may challenge a set of performance goals; achieved via an automated search of input parameter space (168).

The naive approach to deep uncertainty 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 (160). Other probabilistic theorists have suggested that under conditions of deep uncertainty, everything must be done to obtain probability distributions, if necessary through expert elicitation exercises (130). Alternatively, the situation can be recognized as Knight's (161) 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.

Writers on decision making under deep uncertainty emphasize that optimal decisions, which are obtained by maximizing expected utility in the ways described in Section 3.2, can be vulnerable to misspecification of probability distributions or incomplete valuation of possible outcomes. They therefore emphasize satisficing (162), rather than optimizing, that is, the identification of options that perform acceptably well, rather than those that achieve the best score against the decision criteria (157, 163). Ben-Haim (160) advocates robust satisficing, that is, 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 (164, 165). Robust strategies are particularly valuable when the consequences of making a wrong decision are high.

The deep uncertainty literature also emphasizes the order in which decisions are explored, critiquing a top-down approach to uncertainty assessment and calling for decision-first or policy-first approaches that start by exploring the sensitivity of policy options to uncertain conditions rather than by trying to quantify uncertainty. This helps to focus decision analysis on the uncertainties that matter. Methods have been developed for analyzing and visualizing the combinations of conditions that might lead to undesirable outcomes, including robust decision making (RDM) (153, 164) and decision scaling (66) methodologies. Borgomeo et al. (166) used such a method in exploring the sensitivity of drought management options to unprecedented drought.

RDM uses multiple views of the future to identify conditions under which a decision would fail to meet its objectives (164, 165, 167). 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 visualization of results to facilitate the selection of a robust decision (153, 164). Scenario discovery (168, 169) uses statistical data-mining algorithms with a large ensemble of simulation model runs to identify the combinations of uncertainties, and respective ranges, that best predict cases of poor system performance in order to identify vulnerabilities of a policy.

RDM has been applied to inform long-term planning for natural hazards, especially around water management (97, 165, 170), flood risk management (98, 171), and coastal flooding and storm surges (99). **Figure 3** shows an example from RDM analysis, applied to a water resources planning decision in Southern California (169). In their study, 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 strategy (169).

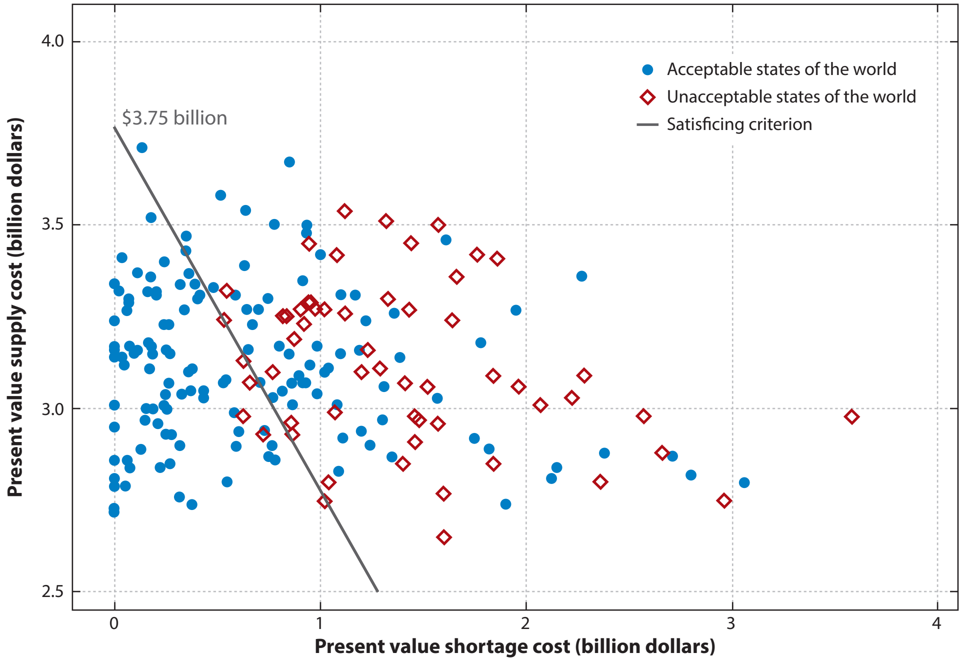

Figure 3

Projected present value 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, 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, and circles represent states of the world resulting in acceptable performance. Figure adapted from Reference 169 with permission.

Decision scaling focuses on stakeholder-defined thresholds that determine acceptable system performance and the conditions under which these thresholds are exceeded (66, 172). Decision scaling was applied to improve management of the Great Lakes in the United States (66), to assess flood risk (103), and to trade off ecological and water engineering performance indicators (173, 174). Applications of RDM and decision scaling show the potential for these methods to explore decisions' sensitivity to a wide range of futures; however, they also demonstrate the importance of judgments on the decisions to include in the analysis and the measures of acceptable performance (i.e., robustness metrics) in influencing the final ranking of decisions.

Ben-Haim (160) introduced the info-gap decision theory in support of decisions made when 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. Info-gap decision theory differs from the other deep uncertainty methods because rather than starting from a set of decisions, it starts by identifying a best estimate of the uncertain variables and then constructing an uncertainty model around it (160, 175). Furthermore, and unlike other methods, it explicitly differentiates between losses—when conditions are worse than expected—and gains—when conditions are better than expected. 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 (100), to water resources decision making under climate and socioeconomic change (101, 176) and earthquake-resilient design (102, 177).

Contrary to probability-based approaches, where uncertainty is characterized consistently with probability distributions, the approaches presented here characterize uncertainty in different ways and rank decisions based on different robustness criteria. As Herman et al. (178) and Giuliani & Castelletti (179) show, this has important implications for decision making, as the choice of robustness metrics is not unequivocal, and different metrics lead to different decisions. Methods for decision making under deep uncertainty require a series of judgments and assumptions that need to be tested and acknowledged (175). This limitation of deep uncertainty approaches underscores the importance of selecting multiple robustness definitions to evaluate alternative decisions and of considering a plurality of approaches (158).

3.4. Sequential Decisions

Although the approaches described above characterize uncertainty and robustness to uncertainty in different ways, they all share the common objective of identifying decisions whose performance is insensitive to future conditions. However, this insensitivity to future conditions is normally tested for a single decision and for a static point in the future. This implies that these approaches fail to address the dynamic and manifold nature of most decisions. Societal preferences and decision makers' attitudes change as outcomes materialize, and multiple decisions may need to be taken in sequence over a long time horizon to respond to natural hazards. Sequential decisions look at multiple decisions in a single framework to add flexibility to the decision-making process.

The importance of time-evolving preferences, the manifold nature of decisions, and the ability to switch between decisions underscores the benefits of flexibility and adaptability in dealing with uncertainty. Successful strategies typically need to be adaptive as more information becomes available in the future. Flexibility means that decisions can be reversed or modified as the uncertain future materializes. A flexible strategy may be one focused 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 (156, 180). An important benefit of considering both current and future decisions simultaneously is the ability to foresee decision outcomes that reduce future flexibility (181).

Sequential decisions can incorporate probabilistic and deep uncertainty decisions. Decision trees, explored earlier in this section, can be used to evaluate a sequence of decisions. Real options analysis—widely used in economics (182)—allows the value of options to be identified in financial terms (105). Both of these approaches are implemented under probabilistic conditions. The adaptation pathways methodology (19, 183) also uses sequential decisions but within a deep uncertainty context. These approaches aim 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 (184). This establishes a link between risk assessment and adaptation action that is absent in many adaptation interventions.

Woodward et al. (106) have applied real options analysis to the design of flood defense systems. An adaptation pathways approach was first applied as part of the Thames Estuary tidal flood risk management project in London (19). Adaptation pathways have been used in a range of contexts including delta flood and water management in the Netherlands (183); strategic regional planning on the Eyre Peninsula, Australia (185); coastal planning in Lakes Entrance, Australia (186); urban adaptation in New York to hurricane and storm surge risk (108); and flood risk management in the Hutt River, New Zealand (187). Ranger et al. (19) applied adaptation pathways approaches to flooding and to water resources planning.

4. CONCLUSIONS

Good decision making has huge potential to mitigate the negative impacts of natural hazards on economies and societies: an imperative that is increasingly important given rising exposure and vulnerability. Although there are no universal criteria for good decisions, research in other fields highlights the benefits of formalizing decision processes, not only to make them repeatable and justifiable, but also because formalized processes generate better outcomes empirically. Decision analysis is an important component of such a process and has been applied for the management of natural hazards, but not uniformly and with little comparison between the research communities that tend to work separately on different natural hazards. In this review, by examining the challenges and opportunities for decision analysis in a range of natural hazard contexts, we hope to stimulate further research and operational use of decision analysis methodologies, as well as promote learning across hazards and timescales.

Natural hazard decision contexts vary dramatically, including decisions on a range of timescales, from quiescence to imminent threat, emergency, and recovery. Generally, there has been little application of formal decision analysis for emergency response, and this represents an area for further development. Other variables that might influence the appropriate application of decision analysis include (*a*) the temporal dynamics and spatial extent of the hazard and (*b*) its stationarity, predictability, and the level of uncertainty resulting partly from data availability and model ability. For example, for slow onset hazards and planning decisions, such as increasing coastal surge from sea level rise, approaches that keep options open and facilitate future adaptation may be most appropriate.

Uncertainty is effectively universal in natural hazard decision problems, and its evaluation and treatment are critical in natural hazard decision making. There may be multiple sources of uncertainty arising from natural hazard modeling, including potentially multiple sources of hazard from one environmental or geological event. The impacts of hazards are uncertain, as are the effectiveness of options that may be adopted to reduce those impacts. The development of succinct information to aid decision making requires simplification of these uncertainties into a small number of metrics. However, sensitivity to error in uncertainty quantification may be high, and awareness of the overall picture of uncertainty is an important element of the decision process. Nonstationarity poses a real challenge to the quantification of hazard probabilities, especially in the case of hydrometeorological hazards and climate change.

The inclusion of multiple criteria for decisions is a further cross-cutting challenge. Weighting schemes are widely adopted but may be controversial, as they may involve quantification of nonfinancial losses such as human life or environmental damage in financial terms. Noncompensatory approaches may be used to identify a minimum standard in one or more criteria. Alternative-based approaches allow a rapid identification of a suitable option among many alternatives but are unlikely to find the optimal solution. More elaborate approaches are possible; however, these become more expensive to construct and less intuitive as complexity increases. Many strategic decisions involve the input of several participants, leading to a requirement for group decision-making processes. Although it is challenging to reconcile different views to give a single decision, an involved process of negotiation and scenario exploration can be helpful.

Deterministic decision making has a long history of successful application and works well in data-sparse environments but can result in overengineered solutions. Where more data are available, probabilistic decision approaches can effectively communicate uncertainties to decision makers and make the process of decision analysis more transparent, including the opportunity to compare risks directly, leading to the straightforward comparison of multiple risks. Decision-making methodologies for deep uncertainty are used to resolve problems where uncertainty is impossible to quantify, so the emphasis is to identify management options that are as far as possible robust to uncertainty. Sequential decisions allow an assessment of whether the decision may be better deferred and whether it is worth investing resources in keeping options open for the future.

Exchanges between research 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. 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.

SUMMARY POINTS

1. Natural hazards have historically led to extensive damage to human health and well-being. Climate change, population growth, and the focus of human development in vulnerable areas result in natural hazard impacts increasing with time.
2. Risk management and mitigation for natural hazards would be improved if formalized methodologies were adopted for decision making. Evidence from natural hazards and elsewhere shows that decisions based on data are better than intuitive responses. Where decisions are made that rely on the responses and actions of human beings, formal decision approaches may be less important than selection of the decision-making group.
3. Natural hazard decision making is confounded by the challenge in quantifying rare and complex events.
4. Historic attempts to formally manage natural hazard preparedness took deterministic approaches. These are now superseded by probabilistic methods that convey uncertainty more clearly.
5. Where probabilities are challenging to quantify, deep uncertainty approaches allow insight into systemic vulnerability to natural hazards.
6. Sequential decisions allow an assessment of whether a decision may be better deferred and whether it is beneficial to keep options open for the future.

FUTURE ISSUES

1. The general uptake of advanced decision theory is impeded by the complexity of techniques, which may require highly specialized analysts for their correct implementation. Knowledge exchange between research and operational communities must be developed and maintained.

2. Decision analysis is challenging to implement for emergency and short-term decision making. New methodologies integrating optimal decision making with contemporary understanding of how human decision making occurs may enable this process.
3. Experience and methodologies may remain siloed, with limited exchange between fields. Better transmission of experience across natural hazard fields is needed.
4. Natural hazard decision-making algorithms may lose credibility if not well informed or conditioned. Acquisition and integration of new data are important.
5. Even if well informed and conditioned, rational decisions can still have negative consequences (e.g., constructing a 1-in-200-year return period flood defense before a 1-in-201-year event), with decision-making algorithms vulnerable to perceived failure. Evaluation of decision algorithms on the basis of evidence and long-term performance is vital.
6. Strategic decisions for natural hazard planning are closely linked to interaction with other human decision makers making intuitive decisions. These must be better represented within a rational framework.
7. As stakeholder communities grow, a narrow view of natural hazard decision questions may not capture all requirements. Better understanding of GDM is important.
8. Extreme natural hazard events are by definition uncommon; accurate quantification of their probabilities and the identification of nonstationarities remain a challenge.

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Annual Review of Environment and Resources

Volume 41, 2016

Contents

V. Methods and Indicators

Indexes

Errata

An online log of corrections to *Annual Review of Environment and Resources* articles may be found at http://www.annualreviews.org/errata/environ