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# Natural Hazard Modeling and Uncertainty Analysis

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*Essentially, all models are wrong, but some are useful.*

George E. P. Box

### ABSTRACT

Modeling can play a critical role in assessing and mitigating risks posed by natural hazards. These modeling efforts generally aim to characterize the occurrence, intensity, and potential consequences of natural hazards. Uncertainties surrounding the modeling process can have important implications for the development, application, evaluation, and interpretation of models. In this chapter, we focus on the analysis of model-based uncertainties faced in natural hazard modeling and decision support. Uncertainty analysis can help modelers and analysts select appropriate modeling techniques. Further, uncertainty analysis can ensure decision processes are informed and transparent, and can help decision makers define their confidence in model results and evaluate the utility of investing in reducing uncertainty, where feasible. We introduce a framework for identifying and classifying uncertainties, and then provide practical guidance for implementing that framework. We review terminology and offer examples of application to natural hazard modeling, culminating in an abbreviated illustration of uncertainty analysis in the context of wildfire and debris flow modeling. The objective of this brief review is to help readers understand the basics of applied uncertainty theory and its relation to natural hazard modeling and risk assessment.

### 2.1. INTRODUCTION

Natural hazards can have devastating consequences including the loss of human life and significant socio-economic and ecological costs. Natural hazards may be isolated events or they may be linked with cascading effects, for instance, debris flows after volcanic eruptions or wildfires. Although often destructive, these hazards are the result of natural processes with a range of potential environmental benefits as well (e.g., groundwater recharge after a flood). It is therefore important for society to be

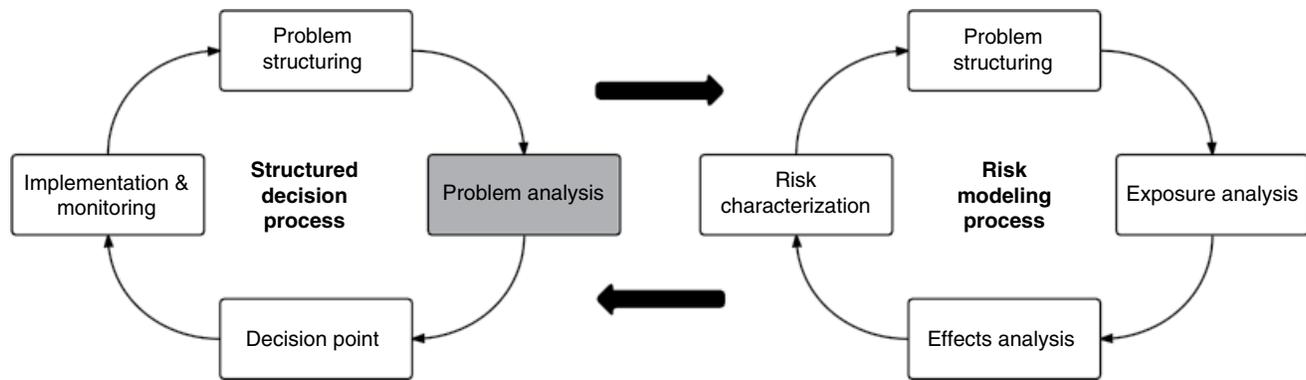
able to better understand, forecast, and balance the risks posed by natural hazards, in order to prepare for and mitigate those risks.

Broadly speaking, risk mitigation strategies can target either the natural hazard itself or the potential consequences. With respect to the former, reducing the likelihood or intensity of the hazard itself is only a feasible option in select cases, as in the case of wildfires, through preventing human-caused ignitions, manipulating fuel conditions, and increasing firefighting suppression capacity. With respect to the latter, reducing vulnerability is a more universally applicable mitigation strategy, which entails both reducing exposure through, for example, zoning to restrict development in hazard-prone areas and reducing susceptibility to loss through construction practices.

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**Figure 2.1** The four primary stages of a structured decision-making process and their relation to the four primary stages of a risk modeling process. Figure modified from *Marcot et al.* [2012], *Ascough II et al.* [2008], and *US Environmental Protection Agency* [1992].

The implementation of actions to manage risks from natural hazards begins with a decision process. The decision process may be formal or informal, and can span a range of decision makers from regulatory agencies to individual homeowners. Modeling can play a critical role in informing these decisions.

Figure 2.1 illustrates a generalized risk management process, and highlights the role of risk modeling in informing decision processes. The decision process has four primary stages: (1) problem structuring, (2) problem analysis, (3) decision point, and (4) implementation and monitoring [Marcot et al., 2012]. In the first stage, the problem context is framed, relevant natural hazards are identified, and objectives and evaluation criteria are defined. In the second stage, risk management options are defined and evaluated, key uncertainties are identified, and potential trade-offs analyzed. In the third stage, a decision for a particular course of action is reached, and, in the last stage, the decision is implemented and monitoring actions may be undertaken.

We highlight the problem analysis stage because it entails the principal natural hazard and risk modeling components and provides the informational basis for evaluating consequences and assessing trade-offs to support decisions. However, uncertainty arises in all stages of the risk management and modeling process and the presented tools are to a large extent also applicable across other stages.

The risk modeling process similarly has four primary stages: (1) problem structuring, (2) exposure analysis, (3) effects analysis, and (4) risk characterization [U.S. Environmental Protection Agency, 1992; Thompson et al., 2015]. In the first stage, the modeling objectives, scope of analysis, and assessment endpoints are identified, as are the salient characteristics of the natural hazards being analyzed. Exposure analysis, the second

stage, examines the likelihood, intensity, and potential interaction of natural hazards with values at risk. Effects analysis next examines potential consequences as a function of exposure levels, often depicted with dose-response curves. In the risk characterization stage, results are synthesized to provide useful information for the decision process. Implicit in the risk modeling process depicted in Figure 2.1 are the steps of collecting and processing data, developing the conceptual model(s), selecting and applying the model(s), and calibrating and validating results.

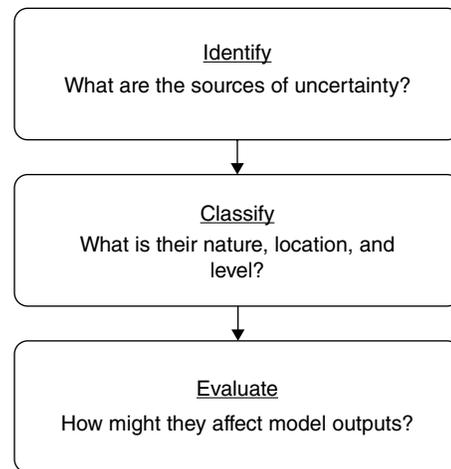
Natural hazard modeling efforts generally aim to characterize the occurrence, intensity, and potential consequences of natural hazards. The field is wide ranging and involves a multitude of disciplines including risk analysis, statistics, engineering, and the natural sciences. Part of the reason the field is so broad is that characteristics of natural hazards themselves are broad, in terms of the relevant spatial and temporal scales of analysis, the underlying natural and anthropogenic processes driving hazard dynamics, and the degree of control humans have over those processes. Key modeling questions often relate to the location, timing, duration, and magnitude of hazardous events, as well as their causal pathways, cascading effects, and potential feedbacks on future hazard and risk. A key feature of natural hazard modeling is the reliance on probabilistic and integrated environmental modeling techniques.

Regardless of their scope and complexity, models are still fundamentally an abstraction of reality. This abstraction can have important implications for how models are developed, applied, evaluated, and interpreted. Principal among these concerns are uncertainties surrounding model inputs, the modeling process, and model outputs. Unaddressed or overlooked uncertainties can ultimately lead to ill-informed and inefficient decisions, in the worst

case leading to increased hazard and/or vulnerability. Resultantly, an essential component of effective hazard and risk management is the analysis of uncertainties.

As we will describe in this chapter, there are a number of attributes with which uncertainty can be characterized. One important question is where uncertainties originate (i.e., from measurement error or knowledge gaps or modeling approximations or intrinsic system variability). A related question is whether the uncertainty is in some sense reducible through additional research and data collection; intrinsic system variability is considered irreducible [Rougier *et al.*, 2013]. Having a solid understanding of model-based uncertainties is important for a number of reasons. First, decision makers are able to define their level of confidence in model outputs and as a result decision processes are more informed and transparent. Second, decision makers can assess the degree to which uncertainty may affect choice of the best course of action and estimate the value of additional information. Third, decision makers can evaluate options for reducing uncertainty. Where the value of additional information is high, and where this information can be obtained (i.e., the uncertainty is reducible), then investing in additional research and monitoring or adopting an adaptive management approach may be warranted [Thompson *et al.*, 2013]. In turn, knowledge gained from monitoring may be used to update and inform modeling efforts, or could result in a reframing of how the problem is understood and a change in management strategy. Of course, not all forms of uncertainty are reducible, and attempting to reduce all forms of uncertainty may be an inefficient use of resources. It is therefore necessary to systematically assess model-based uncertainties.

In this chapter, we review concepts related to the identification, classification, and evaluation of uncertainties faced in natural hazard modeling and decision support. Our primary objectives are to introduce a formalized framework for analyzing uncertainties, and to provide practical guidance for implementing that framework. We introduce a typology to categorically describe sources of uncertainty along three dimensions, present an “uncertainty matrix” as a graphical tool to illustrate the essential features of the typology, and present a decision tree to facilitate proper application of the uncertainty matrix. We hope this chapter helps readers not just understand but also see how to actually apply uncertainty theory. Throughout our chapter, we build from the broader literature of environmental modeling and risk assessment, in particular from the work of Walker *et al.* [2003], Refsgaard *et al.* [2007], Ascough II *et al.* [2008], Maier *et al.* [2008], Kwakkel *et al.* [2010], Warmink *et al.* [2010], Skinner *et al.* [2014a], and Skinner *et al.* [2014b].



**Figure 2.2** Conceptual overview of a three-step process for uncertainty analysis.

## 2.2. IDENTIFYING AND CLASSIFYING UNCERTAINTIES

Figure 2.2 provides a generalized overview of the steps of uncertainty analysis. The development and evaluation of modeling approaches is iterative in nature and premised on transparently identifying, classifying, and evaluating how uncertainties may influence model results and ultimately decision processes. Uncertainty analysis begins with the identification of potential sources of uncertainty. Having a clear, systematic, and consistent approach to identifying uncertainties can help modelers and analysts identify salient uncertainties. By identifying up front the sources of uncertainties faced, modelers can identify approaches and techniques that might be most suited to the problem at hand. In turn, model evaluation can help identify uncertainties that may be introduced due to the structure and technical implementation of the particular model(s) chosen. Later in this chapter, we will return to the selection of appropriate techniques to evaluate uncertainty.

The identification and classification of uncertainties is often driven by the experience and best judgment of modelers and analysts. An uncertainty typology can be a particularly useful tool to help identify, define, and communicate the important features of uncertainties faced within the specific modeling context. Typologies can help modelers and analysts better understand and differentiate uncertainties faced in the modeling process, and do so in a systematic and consistent fashion. It is critical that typologies are complete and consistent to avoid generation of misleading hazard and risk assessments. Walker *et al.* [2003] classifies uncertainty along three dimensions: (1) the *nature* of the uncertainty (i.e., the underlying cause of how the uncertainty came to exist); (2) the *location* of

**Table 2.1** Definitions and Examples of the Nature Dimension of Uncertainty

Natures	Definitions	Examples
Linguistic	Ambiguity, vagueness, contextual dependency, evolving definitions	Definitions and conceptions of “sustainable” and “resilient”
Knowledge	Limitations of scientific understanding (reducible); also called epistemic	Knowledge gaps in understanding of the processes driving volcanic ash dispersal
Variability	Inherent variability of natural and human systems (irreducible); also called aleatory	Weather patterns driving fires and floods
Decision	Social cost-benefit analysis; unknown or inconsistent preferences	How to value a human life

Source: Modified from *Ascough et al.* [2008].

**Table 2.2** Definitions and Examples of the Location Dimension of Uncertainty

Locations	Definitions	Examples
Context	Assumptions and choices underlying the modeling process	Spatiotemporal scope of analysis
Input	Data to define or describe relevant characteristics for a specific model run	Measurement error
Model structure	Relationships between variables or model components and underlying system	Relying on an empirical rather than a process-based model
Model technical	Technical and numerical aspects related to algorithmic and software implementation	Trade-offs between resolution and processing time
Parameters	A priori determined values invariant within chosen context and algorithmic representation	Stress drop parameter in earthquake modeling

Source: Modified from *Warmink et al.* [2010].

uncertainty in the modeling or decision process; and (3) the *level* of the uncertainty, along the spectrum from total determinism to total ignorance. It is important to note that there could be multiple classification schemas for each dimension [*Skinner et al.*, 2014a], which may be more or less applicable depending upon the specific context.

To begin, we borrow from *Ascough et al.* [2008], who define four main natures of uncertainty: linguistic, knowledge, variability, and decision (Table 2.1). Linguistic uncertainty relates to ambiguity, vagueness, and contextual dependency of terminology. In fact, the field of uncertainty analysis itself has struggled with using a common lexicon for characterizing uncertainties across scientific disciplines [*Romanowicz and Macdonald*, 2005; *Rausser and Geppert*, Chapter 3, this volume]. Variability (or aleatory) uncertainty is an attribute of reality and refers to the inherent randomness of the natural system and by definition cannot be reduced. It is also referred to as objective uncertainty, external uncertainty, stochastic uncertainty, or random uncertainty [*van Asselt and Rotmans* 2002]. Climate change or weather predictions that drive natural hazards are examples of variability uncertainties. Knowledge (or epistemic) uncertainty refers to the limitation of our knowledge. It can be reduced by improved system understanding due to scientific research or acquiring more data. An example is the main process that is responsible for the dispersion of volcanic ash after an eruption. Scientific research may

answer this question, thereby reducing the uncertainty. Decision uncertainty enters the decision-making process after the estimation of risk has been generated. It deals with controversy about valuing social objectives, such as the value of a human life. Decision uncertainty can also refer to ambiguity or multiple equally valid frames of reference [*DeWulf et al.*, 2005], where no single truth exists.

How the location dimension is classified will very much depend on the scope of the uncertainty analysis. As described earlier, if the scope extends across the entire decision process then locations could include uncertainties related to how problems are defined and framed through to logistics of implementation and adaptive management. *Warmink et al.* [2010] define five main locations of model-based uncertainty: context, input, model structure, model technical, and parameters (Table 2.2). Context uncertainty refers to the underlying assumptions of the model, which are choices often made during the selection of a certain type of model. For example, using a two-dimensional or three-dimensional model or using a global circulation model or a regional model to predict weather patterns. Input uncertainties refer to the data that describe the modeling domain and time or space dependent driving forces (e.g., solar radiation). Uncertainties in these data may be caused by measurement errors. Model structure uncertainty refers to the processes in the model that describe the system relations. Using an empirical relation instead of a process-based description may cause model structure uncertainties. Model technical

**Table 2.3** Definitions and Examples of the Level Dimension of Uncertainty

Levels	Definitions	Examples
Statistical Scenario	Possible to characterize uncertainties probabilistically Possible to characterize uncertain outcomes but not their respective probabilities	Hazard occurrence probability Future global emissions and climate scenarios
Recognized ignorance	Impossible to outline different possibilities or their outcomes	No-analog vegetation shifts under climate change

Source: Modified from Walker et al. [2003] and Skinner et al. [2014a].

**Table 2.4** Stylized Uncertainty Matrix Illustrating How Sources of Uncertainty Can Be Analyzed According to Each Dimension: Nature, Location, Level

Source	Nature				Location					Level		
	L	K	V	D	C	I	MS	MT	P	St	Sc	RI
Definition of forest resiliency	X				X						X	
Frequency of natural and human-caused ignitions			X			X				X		
Equations predicting fire spread and intensity		X					X				X	
Role of ash in post-fire debris flow initiation		X			X							X
Discretized landscape		X						X			X	
Value of assets and resources impacted by debris flow				X		X				X		

Note: L = linguistic, K = knowledge, V = variability, D = decision, C = Context, I = Input, MS = Model structure, MT = Model technical, P = Parameter, St = Statistical, Sc = Scenario, RI = Recognized ignorance.

uncertainties arise in the technical and numerical implementation. Finally, parameter uncertainties refer to the constants in the model that can have a physical or empirical background. Uncertainty in parameters can be related to model calibration.

Last, the level dimension of uncertainty reflects the variety of distinct levels of knowledge, and is generally broken down according to degree of confidence in probabilities and outcomes. However, these concepts originate from broader risk analysis principles focused on hazardous events, and may be difficult to directly translate to specific analysis of a given source of uncertainty depending upon its nature and location. Thus, the level of any given uncertainty can be highly context dependent. Here we borrow from Walker et al. [2003] and Skinner et al. [2014a], who define three main levels of uncertainty: statistical, scenario, and recognized ignorance (Table 2.3). Determinism is omitted because there is no uncertainty; total ignorance is similarly omitted since it isn't possible to identify and classify what isn't known.

Table 2.4 provides an abbreviated uncertainty matrix wherein each identified source of uncertainty is classified according to the three dimensions. Our intent is not to comprehensively enumerate all potential sources of uncertainty or all potential combinations of nature/location/

level, but rather to illustrate how an uncertainty matrix can be developed. As an example we focus on modeling efforts that assess the potential for wildfires and the subsequent threat of postfire debris flows, the results of which can ultimately inform forest management and risk mitigation planning [e.g., Tillery et al., 2014; Haas et al., Chapter 20, this volume). Beginning with the top row, linguistic uncertainty regarding alternative definitions of forest resiliency could lead to different evaluation criteria and assumptions driving model selection (location = context). The second row indicates that the frequency of lightning-caused ignitions, an input to fire-prediction models, is subject to natural variability that can be characterized statistically. The third row indicates knowledge gaps in the structure of models that predict fire spread and intensity (level = scenario). There are similarly knowledge gaps regarding the role of ash in postfire debris flow initiation (fourth row), which is very poorly understood (level = recognized ignorance), and which likely influences model assumptions (location = context). Next, variability in how vegetation recovers between the fire and storm event can influence calculations of debris flow likelihood. Although these dynamics can be modeled directly, the rate of recovery can also be used as a parameter in longer-term modeling efforts [e.g., Jones et al., 2014] that may take on a range of values.

The next row identifies that discretized representations of the landscape can represent a form of knowledge uncertainty relating to technical model implementation, whose influence can often only be discerned through running the model with different configurations (level = scenario). Last, when quantifying the socioeconomic and ecological consequences of postfire debris flows, an input to risk assessment calculations, how assets and resources are valued is a source of decision uncertainty that can often be characterized statistically through econometric and related techniques. More detailed descriptions and classifications of uncertainties faced in fire and debris flow modeling are available in *Riley and Thompson* (Chapter 13, this volume) and *Hyde et al.* (Chapter 19, this volume).

Although the final outcome may appear simple, the actual population of such a table can be a complex and challenging endeavor. In practice, even experienced analysts and modelers may be unable to identify and classify the entire universe of possible uncertainties for any given context. Nevertheless the generation and evaluation of uncertainty matrices reflect best practices in modeling and uncertainty assessment.

### 2.3. GUIDANCE FOR IDENTIFYING AND CLASSIFYING UNCERTAINTIES

It is imperative to describe each uncertainty accurately so that it can be uniquely identified across all three dimensions. Ideally, the identification of uncertainties results in a list of unique and complementary uncertainties. Complementary implies that the uncertainties do not overlap, which may result in overestimating of the uncertainty. Unique implies that the uncertainties are comparable, which can be essential to decision making. *Warmink et al.* [2010] defined three decision trees to aid the population of the uncertainty matrix; we modified these decision trees to match our dimensions of uncertainty.

Figure 2.3 presents the decision trees to facilitate identification of the three dimensions of uncertainty. In uncertainty identification practice, the borders of the classes prove to be difficult leading to discussion about the exact classification of an uncertainty. The decision trees are based on strict definitions of the individual classes in the matrix and help to clarify the classification criteria. To identify an uncertainty, we start at the left (nature) tree and try to answer the questions. After following all three trees, the uncertainty has a nature, location, and level and can be uniquely classified.

Each uncertainty is well defined if it fits into a single class in the uncertainty matrix, so it belongs to only one nature, one location, and one dimension. For instance, an uncertainty should never be located in the context and in the model structure, in which case it is poorly defined. In

the decision trees, this implies that we need to be able to answer all questions. If we cannot answer a question, this means that the uncertainty is not well defined and needs to be specified by describing it more accurately. One possibility to better specify an uncertainty is to unravel it into two (or more) separate uncertainties, for example one uncertainty in the model structure and one uncertainty in the model context. Then for both uncertainties the identification starts again. This iterative process ultimately results in a list of unique and complementary uncertainties.

Ideally, the list of uncertainties is complete after the identification process. In practice it may not be possible reach this ideal situation, because we will never be able to cover all uncertainties that influence the model outcomes. Expert elicitation methods in combination with the decision trees, however, can likely increase the number of identified uncertainties. Comprehensive and thorough discussion of all possible sources of uncertainty can encourage experts to look beyond their first thoughts and more deeply consider model-based uncertainties including implicit assumptions and other contextual factors. A structured identification of uncertainties results in a better overview of uncertainties, which is an essential first step in uncertainty management.

### 2.4. TECHNIQUES FOR EVALUATING UNCERTAINTY

There is a rich set of modeling frameworks and uncertainty evaluation techniques that can be used throughout modeling and decision processes [*Matott et al.*, 2009; *Bastin et al.*, 2013]. These techniques can be used to assess potential uncertainty propagation and uncertainty in model outputs, and more generally to identify appropriate modeling approaches given the characteristics of uncertainties faced. *Refsgaard et al.* [2007] identify five groups of uncertainty analysis methodologies that differ according to purpose of use: (1) preliminary identification and characterization of sources of uncertainty, (2) assessment of levels of uncertainty, (3) analysis of uncertainty propagation through models, (4) ranking sources of uncertainty, and (5) reduction of uncertainty. A comprehensive review of all possible techniques along with a mapping to all possible combinations of three-dimensional uncertainty classifications is beyond the scope of this chapter. For instance, to assess the effect of an uncertainty due to model structure with a knowledge nature and scenario level, we can use the scenario analysis technique. However, sensitivity analysis [e.g., *Van der Perk*, 1997] or Monte-Carlo-based methods [e.g., *Pappenberger et al.*, 2006] are also applicable. Even expert elicitation might be used to quantify the uncertainty due to model structure error [*Warmink et al.*, 2011].

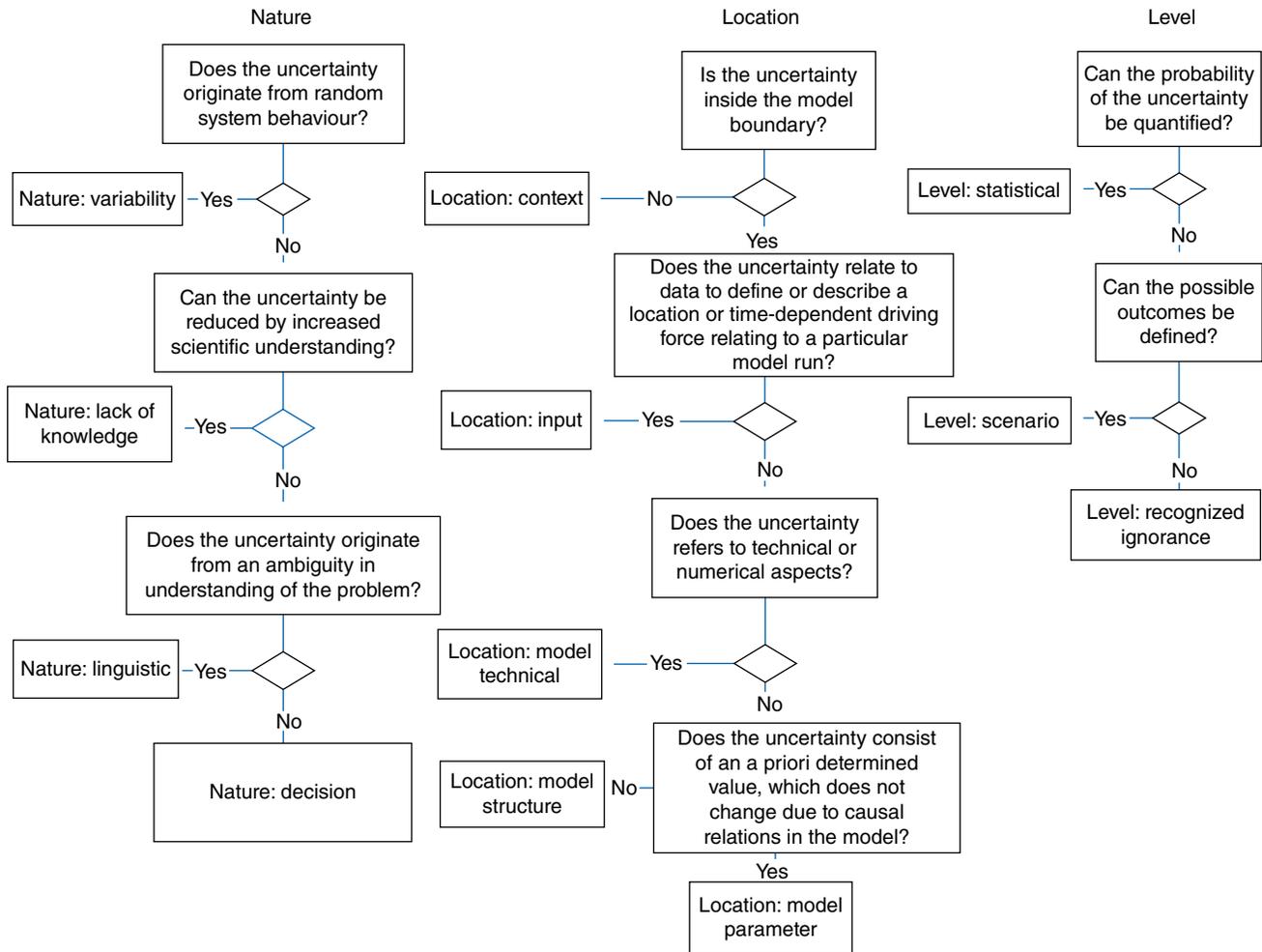


Figure 2.3 Three decision trees for classifying each dimension of uncertainty, modified from Warmink et al. [2010].

The advantages of using Monte-Carlo-based methods are that it is objective and uncertainties are quantified. Disadvantages are that the data acquisition and modeling process are time consuming and that only statistical uncertainties are considered. Expert elicitation on the other hand is relatively quick and provides a more comprehensive overview of the uncertainties, because it analyzes all levels and natures of uncertainty. However, its disadvantage is that it is more subjective. Another example is an uncertainty in the model context, where the decision of which input to use to predict a certain risk was not agreed upon. This uncertainty may have a decision nature and a level of (recognized) ignorance. Techniques to manage this uncertainty include scenario analysis [Refsgaard et al., 2007], multicriteria decision analysis, or approaches toward resolving conflicting views [Brugnach et al., 2008].

For each class in the uncertainty matrix, many techniques exist. In general terms, sensitivity analysis, scenario analysis, Monte Carlo simulation, fuzzy logic, expert

judgment elicitation, Bayesian belief networks, multicriteria decision analysis, and combinations thereof, are common approaches. The most suitable technique in the end depends on the amount of available data and the required level of detail. More information on these techniques and other approaches to evaluating uncertainty can be found in van der Sluijs et al. [2005], Refsgaard et al. [2007], Matott et al. [2009], Bastin et al. [2013], Thompson et al. [2013], and Skimmer et al. [2014a,b]. Here we focused on the identification and classification of uncertainties, using the uncertainty typology and uncertainty matrix as critical initial steps that can offer guidance for the appropriate evaluation and management of uncertainty. Starting with clarity in modeling context and objectives along with a firm understanding of uncertainties faced can go a long way toward selection of appropriate approaches. The selection of a specific uncertainty evaluation technique should link directly with the specific uncertainty, and should incorporate all three dimensions of that uncertainty.

## 2.5. DISCUSSION

In this chapter, we focused on the application of uncertainty analysis methods and tools to the context of natural hazard modeling. In particular, we introduced three key tools, the uncertainty typology (the three dimensions of uncertainty), the uncertainty matrix (a graphical overview of the essential features of uncertainty), and decision trees (guidance for populating the typology and matrix) and described their relation to identification, classification, and evaluation of uncertainties. We mentioned some of the more common techniques and gave direction as to how to select one to use in the development as well as evaluation of natural hazard modeling.

It is important to recognize that model-based uncertainties are not necessarily the most salient or significant impediment to efficient hazard and risk mitigation. Technical assessments of uncertainty, although necessary, may be insufficient when considering the broader context in which decisions are made [Brown, 2010]. That is, uncertainties can influence all stages of the decision process, and, depending upon the context it may be important to comprehensively analyze their characteristics and potential consequences. Uncertainty analyses that focus on the entire decision-making process will necessarily entail a broader set of uncertainties related to human communication, perceptions, and preferences, and may entail a different set of approaches to addressing the respective uncertainties [Maier et al., 2008].

Uncertainty analysis aids in development of a common understanding of modeling efforts, can serve as a starting point for modeling processes, and can clarify the role of modeling in broader decision processes. The frameworks we introduced here for the three dimensions of uncertainty are not intended to be universal, and every context will need to be evaluated in its own right. Identifying and classifying uncertainties facilitates communication between stakeholders, scientists/analysts, and decision makers, and helps prioritize effective ways of managing uncertainties [Gabbert et al., 2010]. Clear communication can become even more important when modeling efforts are interdisciplinary [Rausser and Geppert, Chapter 3, this volume], and span modeling domains from hazard likelihood and intensity to consequences and mitigation opportunities.

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