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## Uncertainty in Natural Hazards, Modeling and Decision Support: An Introduction to This Volume

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### 1.1. INTRODUCTION

Modeling has been used to characterize and map natural hazards and hazard susceptibility for decades. Uncertainties are pervasive in natural hazards analysis, including a limited ability to predict where and when extreme events will occur, with what consequences, and driven by what contributing factors. Modeling efforts are challenged by the intrinsic variability of natural and human systems, missing or erroneous data, parametric uncertainty, model-based or structural uncertainty, and knowledge gaps, among other factors. Further, scientists and engineers must translate these uncertainties to inform policy decision making, which entails its own set of uncertainties regarding valuation, understanding limitations, societal preferences, and cost-benefit analysis. Thus, it is crucial to develop robust and meaningful approaches to characterize and communicate uncertainties.

Only recently have researchers begun to systematically characterize and quantify uncertainty in the modeling of natural hazards. Many factors drive the emergence of these capabilities, such as technological advances through increased computational power and conceptual development of the nature and complexity of uncertainty. These advances, along with increased sophistication in uncertainty analysis and modeling, are currently enabling the use of probabilistic simulation modeling, new methods that use observational data to constrain the modeling

approaches used, and other quantitative techniques in the subdisciplines of natural hazards. In turn, these advances are allowing assessments of uncertainty that may not have been possible in the past.

Given the expanding vulnerability of human populations and natural systems, management professionals are ever more frequently called upon to apply natural hazard modeling in decision support. When scientists enter into predictive services, they share professional, moral, legal, and ethical responsibilities to account for the uncertainties inherent in predictions. Where hazard predictions are flawed, limited resources may be unjustifiably spent in the wrong locations, property may be lost, already stressed ecosystems may be critically damaged, and potentially avoidable loss of human life may occur. These essential concerns for reliable decision support compel thorough characterization of the uncertainties inherent in predictive models.

### 1.2. ORIGINS AND OBJECTIVES OF THIS VOLUME

This volume is an outcome of the 2013 American Geophysical Union (AGU) Fall Meeting session entitled “Uncertainty in Natural Hazard Assessment: Volcanoes, Earthquakes, Wildfires, and Weather Phenomena,” which was a combination of two AGU Focus Group Sections: Natural Hazards and Volcanology/Geochemistry/Petrology. The session was inspired in part by the AGU SWIRL program, which encourages interdisciplinary research. In 2013, the SWIRL program offered a theme “Characterizing Uncertainty.” In the session, researchers from volcanology, wildfire, landslide analysis, and other fields were brought together to compare results in characterizing uncertainties and developing methods for spatial and temporal understanding of event probability.

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This monograph focuses largely on the work presented at this AGU session, as well as other presentations from across the 2013 AGU fall meeting that had a focus associated with the AGU SWIRL theme, “Characterizing Uncertainty.”

The principal objectives of this monograph are to provide breadth in terms of the types of natural hazards analyzed, to provide depth of analysis for each type of natural hazard in terms of varying disciplinary perspectives, and to examine emerging techniques in detail. As a result, the volume is largely application focused and targeted, with an emphasis on assorted tools and techniques to address various sources of uncertainty. An additional emphasis area includes analyzing the impacts of climate change on natural hazard processes and outcomes. We chose studies from various continents to highlight the global relevance of this work in mitigating hazards to human life and other natural and socioeconomic values at risk. In assembling studies across types of natural hazards, we illuminate methodologies that currently cross subdisciplines, and identify possibilities for novel applications of current methodologies in new disciplines.

To our knowledge, this volume is unique in that it brings together scientists from across the full breadth of the AGU scientific community, including those in real-time analysis of natural hazards and those in the natural science research community. Taken together, the chapters provide documentation of the common themes that cross these disciplines, allowing members of the AGU and broader natural hazards communities to learn from each other and build a more connected network.

We hope this will be a useful resource for those interested in current work on uncertainty classification and quantification and that it will encourage information exchange regarding characterization of uncertainty across disciplines in the natural and social sciences and will generally benefit the wider scientific community. While the work does not exhaustively address every possible type of hazard or analysis method, it provides a survey of emerging techniques in assessment of uncertainty in natural hazard modeling, and is a starting point for application of novel techniques across disciplines.

### 1.3. STRUCTURE

The remainder of this chapter introduces the contents of each part and chapter, and then distills emergent themes for techniques and perspectives that span the range of natural hazards studied. The monograph is composed of three main parts: (1) Uncertainty, Communication, and Decision Support (4 chapters); (2) Geological Hazards (7 chapters); and (3) Biophysical and Climatic Hazards (10 chapters). Specific types of natural hazards analyzed include volcanoes, earthquakes,

landslides, wildfires, storms, and nested disturbance events such as postfire debris flows.

#### 1.3.1. Part I: Uncertainty, Communication, and Decision Support

Here we provide a broad, cross-disciplinary overview of issues relating to uncertainty characterization, uncertainty communication, and decision support. Whereas most chapters in the subsequent two sections address specific quantitative analysis and modeling techniques, we begin with more qualitative concerns. We address questions related to various facets of uncertainty, introduce some basic tenets of uncertainty analysis, discuss challenges of clear communication across disciplines, and contemplate the role of uncertainty assessment in decision processes as well as at the science-policy interface.

In Chapter 2, Thompson and Warmink provide an overarching framework for identifying and classifying uncertainties. While they focus on uncertainty analysis in the context of modeling, the basic framework can be expanded to consider sources of uncertainty across the stages of decision making and risk management. While other typologies and frameworks exist and may be more suitable to a specific domain, the main point is the importance of beginning with the transparent and systematic identification of uncertainties to guide subsequent modeling and decision processes.

In Chapter 3, Rauser and Geppert focus on the problem of communicating uncertainty between disciplines. The authors bring to bear perspectives from the Earth system science community, leveraging insights from a series of workshops and conferences focused on understanding and interpreting uncertainty. Like natural hazards analysis, the field of Earth system science integrates a wide range of scientific disciplines, and so lessons on developing a common language of uncertainty across disciplines are highly relevant. As with *Thompson and Warmink* [Chapter 2, this volume], the authors stress the importance of being clear and explicit regarding the types and characteristics of uncertainties faced.

Last, *Thompson et al.* [Chapter 4, this volume] and *Webley* [Chapter 5, this volume] provide examples of operational decision support systems that incorporate uncertainty and probability. Thompson and coauthors focus on the context of wildfire incident management, and discuss the use of stochastic fire simulation to generate probabilistic information on possible fire spread, how this information can facilitate strategic and tactical decision making, and future directions for risk-based wildfire decision support. Webley focuses on the context of volcanic-ash cloud dispersal, and discusses the different types of uncertainties that play a role in assessing volcanic-ash hazard, and how the research community is working with operational

volcanic-ash advisory groups to improve decision making and the application of probabilistic modeling in the real-time hazard assessment and development of ash advisories for the aviation community.

In summary, this opening section introduces a framework for identifying and classifying uncertainty, presents insights on communicating uncertainty across disciplines, and illustrates two current examples of operational decision support systems that incorporate uncertainty and probability. Consider using this section as a lens through which to view subsequent sections: for example, examine the types of uncertainties the authors address, how the authors characterize the uncertainties, how they describe and communicate the uncertainties, how they tailor their analysis to match the uncertainties faced, and the types of decisions the analyses might support.

### 1.3.2. Part II: Geological Hazards

The type, size, and magnitude of hazards from geological processes are highly variable. Therefore, operational organizations as well as research scientists need to be able to classify the uncertainty and quantify the potential range of possible scenarios for hazard magnitude and timing. Being able to quantify the uncertainty can then lead to increasing confidence in the assessment of hazards and reducing the risk of exposure to hazards. The chapters in this section cover work currently occurring in uncertainty quantification of volcanic, earthquake, and landslide processes. Assessment of geological hazards is further complicated by the fact that they are sometimes nested. For example, a volcanic eruption may spawn lahars. Chapters in this section address topics regarding natural hazard patterns in both space and time, the role of physical and probabilistic analyses for forecasting and risk assessment, and novel methods for event early warning and response.

*Webley et al.* [Chapter 6, this volume] focus on developing a volcanic-ash dispersion modeling framework that accounts for uncertainties in the initial source parameters and variability in the numerical weather prediction (NWP) data used for the ash dispersal. The authors illustrate that in building a probabilistic approach, where a one-dimensional plume model is coupled to a Lagrangian ash-dispersion model, the uncertainty in the downwind ash concentrations can be quantified. Outputs include estimates of the mean ash concentrations, column mass loading, and ash fallout, along with the probability of mass loading or concentration exceeding a defined threshold. Comparison of their probabilistic modeling with observational data further constrains the uncertainties. The authors identify the need for new research projects to work with the end users to ensure that products are developed for transition to the operational environment.

*Gong et al.* [Chapter 7, this volume] highlight the uncertainties in estimating the magma source beneath volcanoes using spaceborne Interferometric Synthetic Aperture Radar (InSAR) measurements. The authors use InSAR data to estimate the volcanic source parameters, and subsequently illustrate how the accuracy in the inversion method is influenced by radar phase measurements. By using a Mogi source model approach, they discuss how different components of the InSAR deformation measurements, such as topography, orbital location, decorrelation, and tropospheric variability, can impact the estimation of the volcanic source parameter, such as magma storage depth and change in volume with time. When several parameters can be constrained, such as magma compressibility and topographical variability, the accuracy of estimates of magma depth and volume over time can be improved and increase our understanding of the volcanic system.

*Kristiansen et al.* [Chapter 8, this volume] focus on uncertainties that exist in volcanic emission clouds, including both ash and sulfur dioxide concentrations. Observational data are used to constrain the source terms using inversion modeling approaches, data assimilation, and ensemble modeling (consisting of inputs, numerical weather prediction [NWP], and multimodel ensemble approaches). One eruption, Grimsvötn volcano in 2011, is used as a case study to illustrate how an integrated approach that couples modeling with observations and compares multiple dispersion models can reduce uncertainties in the downwind volcanic emissions and increase confidence in forecasts for use in real-time hazard assessment.

*Tierz et al.* [Chapter 9, this volume] continue the focus on volcanoes, assessing the uncertainty in pyroclastic density currents (PDCs) through simulated modeling. A Monte Carlo modeling approach is applied to a study site on Mt. Vesuvius, Italy, to assess which parameters have the greatest influence on the simulated PDCs. The analysis specifies the different uncertainties that exist in modeling PDCs and quantifies their impact on the PDC simulations and predictability. Results demonstrate that the theoretical uncertainties in the Monte Carlo modeling outweigh, by up to a factor of 100, the uncertainties in the initial observations that drive the model.

*Kang and Kim* [Chapter 10, this volume] estimate losses from an earthquake using a site classification map, and demonstrate how improved knowledge of local site conditions can reduce uncertainty in predicting losses from future earthquakes. The authors present a new earthquake hazard classification map for different regions in South Korea, which enables them to better constrain the impacts of the underlying soil and ground structure to local buildings, thus producing improved estimates of potential loss from different earthquake scenarios. Impact to infrastructure ranging from residential buildings to

essential facilities such as hospitals, schools, and fire stations is estimated. The authors discuss how the improved site classification map could be used in decision making and provide more reliable estimates of earthquake loss in developing emergency plans.

*Anderson et al.* [Chapter 11, this volume] assess how different preprocessing techniques applied to digital elevation models (DEMs) could influence the delineation of debris flow inundation hazard zones. Results show that use of globally applicable DEMs and specific preprocessing techniques can impact the accuracy of the extent of the debris flows and reinforces need for DEMs with higher spatial resolution. Errors in the processed global DEMs propagate into the lahar modeling, leading to inaccurate debris flow maps, and thus reduce confidence in the modeling needed for critical decision making. The authors propose that continued conversations with the end users of the modeling are needed so end users can better understand the limitations of the modeling and potential errors in the debris flow maps.

The final chapter in the section comes from *Caballero et al.* [Chapter 12, this volume] who focus on evaluating lahar simulation flow modeling for two active volcanoes in Mexico. The authors analyze the impact of input parameter selection on the model's capability to match the observations of a real world lahar. While the results illustrate that the approach is an excellent tool for lahar modeling, several inputs (such as input hydrograph and rheologic coefficients) can have a significant impact on the spatial and temporal accuracy of the simulations as well as the predicted magnitude of the lahar. Retrospective analysis of well-studied volcanoes can be used to constrain the uncertainties in these input parameters, but there is a need to specifically improve the rheologic coefficient measurements or at least better understand how the variability impacts the modeling results.

In summary, the chapters in this section focus on prediction of volcanic ash clouds, using deformation to estimate changing volcanic magma sources, earthquake loss estimations, modeling of pyroclastic density currents, lahars, and debris flows. Each chapter highlights the uncertainties that can impact modeling of these geologic hazards and the need for observational data to both constrain the uncertainties and potentially be used with inversion methods to initialize future simulations.

### 1.3.3. Part III: Biophysical and Climatic Hazards

This part focuses on advancements in uncertainty and risk assessment for natural hazards driven by biological, physical, and climatic factors. Similar to the previous section, chapters address a variety of topical issues related to understanding and forecasting hazards across spatiotemporal scales, germane to both research and

management communities. Methods range from ensemble forecasting to scenario analysis to formal quantification of parameter uncertainty, among others. A key theme in this section is the consideration of future climatic conditions and their relationship to natural hazard processes.

In the first chapter, *Riley and Thompson* [Chapter 13, this volume] systematically identify and classify model-based uncertainties in current wildfire modeling approaches, in order to contribute to understanding, evaluation, and effective decision-making support. For each source of uncertainty identified, their analysis characterizes the nature (limited knowledge or variability), where it manifests in the modeling process, and level on a scale from total determinism to total ignorance. Uncertainty compounds and magnifies as the time frame of the modeling effort increases from the incident level to the 10 yr planning period to a 50 yr period, during which climate change must be incorporated into analyses.

*Ichoku et al.* [Chapter 14, this volume] evaluate the implications of measuring emissions from fires using satellite imagery of different resolutions from various remote sensing platforms. Their methodology includes a literature review and meta-analysis of the uncertainty ranges of various fire and smoke variables derived from satellite imagery, including area burned, flaming versus smoldering combustion, and smoke constituents. Findings indicate that as satellite resolution decreases, uncertainty increases. The authors note that most of the variables are observed at suboptimal spatial and temporal resolutions, since the majority of fires are smaller than the spatial resolution of the satellites, resulting in inaccuracy in estimation of burned area and fire radiative power. Discrepancies are smaller where satellite observations are more complete. As a result of this study, the authors recommend further research that combines ground-based, airborne, and satellite measurements with modeling in order to reduce uncertainty.

*Kennedy and McKenzie* [Chapter 15, this volume] couple a regional GIS-based hydroecologic simulation system with a new fire model, at a level of aggregation and process detail commensurate with the inputs. The new fire model (WMFire\_beta) expands the exogenously constrained dynamic percolation (ECDF) model by varying the probability of fire spread from a burning cell to each of its orthogonal neighbors based on vegetation, weather, and topographic parameters. The authors utilize fractal dimension (complexity of the fire perimeter) and lacunarity (measure of unburned space within the fire perimeter) to assess which combinations of the model parameters produced a run with similar characteristics to the Tripod Fire in Washington state. Findings indicate that the model is not sensitive to fuel moisture, meaning that the equation for assigning it was not sufficient to capture the role of fuel moisture. This methodology

enables the authors to falsify or verify components of model structure, and suggests development of a new representation that would improve the model and reduce uncertainty.

*Terando et al.* [Chapter 16, this volume] project changes in the frequency of extreme monthly area burned by wildfires for a study area in coastal Georgia at the end of the 21st century. A statistical model based on aggregated monthly area burned from 1966 to 2010 is used to predict the number of months with extreme area burned under future climate conditions. Uncertainty in future climate is addressed by the use of ensemble datasets, which weight the contribution of each general circulation model (GCM) based on performance during the recent historic period. Sources of uncertainty include variation in outputs from GCMs, the effects of different methods for weighting GCM outputs in ensemble models, sparse observations of months with extreme area burned, possible future changes in fuel characteristics over time, and changes in fire suppression actions. By the end of the 21st century, the model indicates increased probability of more frequent months with extreme area burned, likely due to longer and hotter wildfire seasons. However, 95% projection intervals for the three emissions scenarios all span zero. The authors conclude that while there is large uncertainty in these projections, the results give a more informative depiction of the current state of knowledge, and suggest that the increase in the projection of number of months with extreme area burned indicates the need for future large damages to be considered in risk assessments.

*Bachelet et al.* [Chapter 17, this volume] utilize the dynamic global vegetation model MC2 with fire enabled in order to simulate vegetation distribution and carbon storage under a suite of climate futures from the Coupled Model Intercomparison Project 5 (CMIP5), including two greenhouse gas concentration trajectories and the outputs of 20 general circulation models. All models predict a warmer future (although the magnitude varies), but large differences exist in magnitude and seasonality of precipitation. Large shifts in vegetation toward warmer types are predicted by the results (e.g., temperate to subtropical forest), with the shifts sometimes being rapid because they are driven by fire. Some results are not intuitive, for example, area burned was episodically larger under the lower greenhouse gas emission trajectory (RCP 4.5 versus 8.5) because the milder climate promotes fuel buildup under lower drought stress, leading to subsequently larger area burned. Uncertainties in projected area burned and areal extent of vegetation type are large across general circulation models and greenhouse gas trajectories (for example, change in areal extent of deciduous forest ranged from -95% to 1453% from the time periods 1972–2000 to 2071–2100).

*Le Page* [Chapter 18, this volume] examines the sensitivity of fires to climate, vegetation, and anthropogenic variables in the Human-Earth System FIRE (HESFIRE) model, a global fire model, which runs at 1 degree grid resolution. Because HESFIRE includes a suite of variables including climate (e.g., ignition probability from lightning, relative humidity) and human variables (e.g., ignition probability from land use, fragmentation), it has the potential to project fire activity under future climate or societal scenarios. In this study, a set of model parameters were varied in order to evaluate model sensitivity. In addition, the study evaluates the sensitivity of the model outputs to alternative input data (two land cover datasets and two climate datasets). Results indicate that the model is most sensitive to fuel limitation in arid and semiarid ecosystems, with sensitivity to landscape fragmentation being dominant in most grasslands and savannahs. Use of alternative climate and land cover datasets produces changes in projected area burned as large as 2.1 times. *Le Page* concludes that model evaluations should include sensitivity analyses, as well as investigations of how models represent fundamental aspects of fire ecology, in order to characterize model performance and uncertainties.

*Hyde et al.* [Chapter 19, this volume] review the current status of debris flow prediction following wildfires, and present a conceptual model of the general sequence of conditions and processes leading to these hazardous events. Six components constitute the postfire debris-flow hazard cascade: biophysical setting, fire processes, fire effects, rainfall, debris flow, and values at risk. Current knowledge and predictive capabilities vary between these components, and no single model or prediction approach exists with capacity to link the sequence of events in the postfire debris-flow hazard cascade. Defining and quantifying uncertainties in predicting postfire debris flows requires addressing knowledge gaps, resolving process contradictions, and conducting new research to develop a comprehensive prediction system.

*Haas et al.* [Chapter 20, this volume] couple two wildland fire models with a debris flow prediction model to assess which watersheds on a landscape in New Mexico, USA, are most susceptible to a combination of moderate-to-high severity fire followed by debris flows. The methodology allows for prefire estimation of the probability of a postfire debris flow based on a storm of a set of certain recurrence intervals and a set of simulated fire events. A primary innovation of the approach is an improved ability to capture variability surrounding the size, shape, and location of fire perimeters with respect to watershed boundaries. The authors note that identifying watersheds with highest probability and volume of postfire debris flows could assist land managers in evaluating potential mitigation measures such as fuel reduction treatments or retention dams.

*Nikolopoulos et al.* (Chapter 21) investigate implications of using thresholds in storm intensity and duration recorded at rain gauges to predict debris flows, which often occur at remote locations away from the sparse network of rain gauges. The study utilizes radar data of 10 storms in northern Italy that spawned 82 debris flows. Several different spatial interpolation methods were used to estimate rainfall at remote debris flow locations. All methods underpredict rainfall at debris flow locations, due in part to the localized nature of the rainfall, and in part to statistical properties of interpolation methods. In this study, uncertainty results largely from sparse data, and the authors suggest that uncertainty in predicting debris flows might be reduced by using radar data to refine models that predict debris flow occurrence.

*Markuzon et al.* [Chapter 22, this volume] address the limitations of using precipitation measurements to predict landslides and test the effect of using a combination of precipitation and longer-term atmospheric conditions (i.e., temperature, atmospheric pressure, and winds) on landslide predictions. Current methods rely on often limited and faulty precipitation data and coarse-scale precipitation estimates, such as those derived from general circulation models, that result in smoothed rainfall estimates and underprediction of landslide events. The need to forecast landslide probability under different climate change scenarios requires new methods to overcome the effects of uncertainty in precipitation measurements and estimations on the accuracy of landslide predictions. The authors demonstrate that a combination of antecedent and concurrent weather conditions effectively detects and predicts landslide activity and therefore can be used to estimate changes in landslide activity relative to changing climate patterns.

In summary, the chapters in this section address an assortment of biophysical and climatic hazards, ranging from wildfire to precipitation-induced landslides to coupled hazards such as postfire debris flows. Chapters acknowledge uncertainty present in natural hazard prediction for the current time period, often due to sparse data, with uncertainty compounding as climate change is expected to produce alterations in vegetation and disturbance regimes. The capability to assess uncertainty varies across different disciplines based on the current state of knowledge. Collectively, this section reveals knowledge gaps in modeling of biophysical and climatic hazards.

#### **1.4. A SYNTHESIS: LEARNING FROM THIS MONOGRAPH**

This overview of the chapters illustrates how natural hazard sciences and modeling efforts vary across multiple dimensions in terms of data availability, sufficiency, and spatiotemporal scale, the relative amount and cumulative expertise of scientists working in each field, and the state of the science in quantitative uncertainty assessment.

Chapters vary widely in content and focus, as well as how each set of authors characterizes, quantifies, and assesses uncertainty. The intended applications of individual chapters also vary, ranging from informing future research [e.g., *Ichoku et al.*, Chapter 14, this volume] to informing decision making and land management [e.g., *Haas et al.*, Chapter 20, this volume] among others. These observations speak as strongly as anything to the state of uncertainty science: assessment of uncertainty is robust in some areas and arguably nascent or even nonexistent in others. As *Hyde et al.* [Chapter 19, this volume] offered in their assessment of postfire debris flow hazards, where information and methods are not consistent, there can be no comprehensive assessment of uncertainty. Synthesis of these similarities and differences in scope and state of the science across chapters in this monograph highlights important synergies and opportunities for cross-hazard collaboration and learning. See Tables 1.1 and 1.2 for summaries of themes, techniques, and methods.

In compiling this volume, we learned that systematic identification of sources of uncertainty is a research endeavor in its own right; we present a framework that can be used in natural hazards [*Thompson and Warmink*, Chapter 2, this volume], and give an example for wildfire modeling [*Riley and Thompson*, Chapter 13, this volume]. Because of the resources required to perform systematic identification of uncertainty, the effort to do so can be prohibitive to researchers in the natural hazards, since limited resources are often available to produce natural hazard prediction models and outputs. In addition, once sources of uncertainty have been identified, quantifying each often requires further research. Because quantification of many sources of uncertainty has not been undertaken in many disciplines, it's challenging at this point for researchers to assess how the combination of multiple uncertainties might affect their model projections. As the body of knowledge on uncertainty grows, this task should become easier. We hope this monograph is a step toward accomplishing that goal.

Uncertainty can be broadly classified into two natures: knowledge and variability. Knowledge uncertainty can be reduced by further research, for example, by improving input data [e.g., *Webley et al.*, Chapter 6, this volume and *Kristiansen et al.*, Chapter 8, this volume]. Variability uncertainty is based on inherent variability in a system, and can't be eliminated, with weather and future climate being a recurring example [e.g., *Bachelet et al.*, Chapter 17, this volume]. Uncertainty manifests at different locations in the modeling process, for example in inputs or model structure. Understanding the nature and location of uncertainty can help researchers choose methods for addressing uncertainty.

We observe that the language used to describe uncertainty is still nascent. The term "uncertainty" itself is often used somewhat generically, without an attempt to define or classify it. Throughout the monograph, the use of terms (for example "structural uncertainty," which appears in both

**Table 1.1** Emergent Themes Based on Synthesis of This Volume

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**Uncertainty is often due to sparse data**, for example, due to sparse rain gauge locations [Nikolopoulos et al., Chapter 21, this volume], fire records from documentary or satellite sources [Terando et al., Chapter 16, this volume; Ichoku et al., Chapter 14, this volume], or DEMs [Anderson et al., Chapter 11, this volume]

**When predicting a phenomenon, uncertainty can often be fairly well constrained in some aspects but not in others, due to gaps in data and knowledge**, as in post-wildfire debris flow prediction [Hyde et al., Chapter 19, this volume]

**Uncertainty can stem from future events**, for example, climate change effects on vegetation and fire [Le Page, Chapter 18, this volume; Bachelet et al., Chapter 17, this volume], climate change effects on area burned [Terando et al., Chapter 16, this volume], post-fire debris flows on a pre-fire landscape [Haas et al., Chapter 20, this volume], uncertainty in fire extent for a given incident due to upcoming weather [Thompson et al., Chapter 4, this volume]

**Uncertainty is often driven by a combination of factors, necessitating broad uncertainty analysis of a phenomenon as a first step**. Several chapters focused on such broad assessments, including fire modeling [Riley and Thompson, Chapter 13, this volume], post-fire debris flows [Hyde et al., Chapter 19, this volume], and volcanic ash clouds [Webley et al., Chapter 6, this volume; Kristiansen et al., Chapter 8, this volume].

**Assessing model complexity is important; when linking models, complexity should be proportional to other models**. Uncertainty should be possible to assess, which is more difficult with complex models [Kennedy and McKenzie, Chapter 15, this volume].

**Uncertainty can derive from scale of measurement relative to temporal and spatial scale of phenomena**, for example in satellite measurements of fire extent and emissions [Ichoku et al., Chapter 14, this volume] and DEM spatial resolution for debris flow prediction [Anderson et al., Chapter 11, this volume].

**Uncertainty is often introduced by input data, and it's important to address the sensitivity of the model to uncertainty in inputs**. Many chapters mentioned this, and some addressed it quantitatively [Terando et al., Chapter 16, this volume; Le Page, Chapter 18, this volume; Webley et al., Chapter 6, this volume; Anderson et al., Chapter 11, this volume].

**Uncertainty can also exist in the model structure**, which can be tested by field validation as in Kennedy and McKenzie [Chapter 15, this volume] or by varying model coefficients, as in Le Page [Chapter 18, this volume].

**Observations can be used to constrain uncertainties, and to initialize future modeling**, as in Webley et al. [Chapter 6, this volume] and Kristiansen et al. [Chapter 8, this volume].

**Assessment of uncertainty in natural hazards is applicable across spatiotemporal scales**. Spatial extents of chapters ranged from study areas in specific locales, such as Terando et al. [Chapter 16, this volume] in coastal Georgia, USA, up to global scale, as in Le Page [Chapter 18, this volume]. Temporal extents also varied widely, from that of a single natural hazard, such as a single wildfire incident as in Thompson et al. [Chapter 4, this volume], up to the expected effects of climate change, as in Bachelet et al.'s [Chapter 17, this volume] examination of vegetation and wildfire regimes.

**Uncertainty compounds as spatial and temporal scales expand**, as in wildfire modeling [Riley and Thompson, Chapter 13, this volume].

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**Table 1.2** Selected Techniques and Methods for Handling Uncertainty in the Natural Hazards

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**Statistical models**, e.g. Terando et al. [Chapter 16, this volume]

**Monte Carlo simulation**, e.g. Gong et al. [Chapter 7, this volume], Tierz et al. [Chapter 9, this volume]

**Process models and dynamic global vegetation models**, e.g. Bachelet et al. [Chapter 17, this volume]

**Spatial techniques**

Hazard propagation from cell to cell, e.g. Kennedy and McKenzie [Chapter 15, this volume] and Haas et al. [Chapter 20, this volume]

Interpolation, e.g. Nikolopoulos et al. [Chapter 21, this volume]

**Use of remotely sensed data**

Satellite imagery, e.g. Ichoku et al. [Chapter 14, this volume]

Radar data, e.g. Nikolopoulos et al. [Chapter 21, this volume]

**Sensitivity testing** as a means to quantify uncertainty, especially where uncertainty is high due to large spatiotemporal scales, e.g. Le Page [Chapter 18, this volume], Kang and Kim [Chapter 10, this volume], and Anderson et al. [Chapter 11, this volume]

**Probabilistic outputs** as a way to convey uncertainty, as in fire models in Haas et al. [Chapter 20, this volume] and Thompson et al. [Chapter 4, this volume], and volcanic ash clouds as in Webley et al. [Chapter 6, this volume]. In fact, probabilistic outputs from fire models and volcanic ash cloud models were markedly similar, raising the question of whether similar techniques might be applicable in other disciplines where they are not yet used.

**Scenario planning** is a useful approach where uncertainty is high, as for precipitation delivery from storms [Haas et al., Chapter 20, this volume], future climate (e.g. Terando et al. [Chapter 16, this volume]), earthquakes (e.g. Kang and Kim [Chapter 10, this volume]), and topographic mapping for debris flow generation [Anderson et al., Chapter 11, this volume].

**Integrated approaches**, for example, comparison of statistical modeling and observational data, e.g. Webley et al. [Chapter 6, this volume], Gong et al. [Chapter 7, this volume], Kristiansen et al. [Chapter 8, this volume], and Anderson et al. [Chapter 11, this volume].

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*Terando et al.* [Chapter 16, this volume] and *Riley and Thompson* [Chapter 13, this volume], varies across chapters. We have not attempted to resolve the use of terms, but instead find that it emphasizes the current state of uncertainty sciences, and articulately argues for the need for defining a common terminology, as proposed by *Rausser and Geppert* [Chapter 3, this volume].

This monograph identifies the need for techniques to transition from the research domain to the operational domain for effective decision making, as well as the need to involve end users in developing probabilistic approaches [*Webley et al.*, Chapter 6, this volume]. There is also the need to open discussions between the research community and end users in order to foster understanding of the limitations of the methods used so the data can be applied to make more informed decisions [*Anderson et al.*, Chapter 11, this volume] and to ensure that new approaches can transition into operations. The objective of such collaborative efforts will be to improve confidence in the interpretation of final model simulations and the application of model results for improved decision support.

In closing, we recommend several directions for future work. Uncertainty assessment would benefit from increased attention to systematic identification, classification, and evaluation of uncertainties. In addition, need exists for increased emphasis on clear communication of uncertainties, their impact on modeling efforts, and their impact on decision processes. As natural hazard and modeling efforts become increasingly interdisciplinary, an emphasis on targeting common language and understanding across disciplines becomes necessary. With a number of techniques now available to researchers, uncertainty can be constrained and the confidence in modeling of natural hazards increased. The concept of value of information can be brought to bear to inform decisions across contexts, ranging from determining the merit of investing in long-term research and monitoring to postponing time-pressed decisions to gather more information. This process will entail linking the field of

uncertainty analysis with tools and concepts of decision analysis to characterize how and whether reduced uncertainty might influence decisions and outcomes. Last, and related to decision support, future work could consider involvement of end users for real-time hazard assessment during probabilistic workflow development, which will ensure end users can confidently apply new tools and understand derived products.

## 1.5. CONCLUSION

This volume arguably presents evidence that there is not yet a comprehensive recognition of the need for thorough uncertainty assessment nor consistent approaches to conduct these assessments. Yet, the need for uncertainty assessment has never been greater. Some natural hazards, such as wildfire, are on the rise, and the effect of others, such as landslides, is growing due to expanding human populations. The combined effect may strain already impaired natural resources. Inherent in the predictive services are professional, moral, legal, and ethical responsibilities to account for uncertainties inherent in predictions. The consequences of inaccurate predictions can be high: limited resources may be spent in the wrong locations, property may be lost, and human casualties can occur. We therefore advocate for a coordinated development of the science and practice of uncertainty assessment.

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