

Implicit Visualization as Usable Science
Visualizing Uncertainty as Decision Outcomes

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved December 2012 by the
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ARIZONA STATE UNIVERSITY

May 2013

ABSTRACT

Decision makers contend with uncertainty when working through complex decision problems. Yet uncertainty visualization, and tools for working with uncertainty in GIS, are not widely used or requested in decision support. This dissertation suggests a disjoint exists between practice and research that stems from differences in how visualization researchers conceptualize uncertainty and how decision makers frame uncertainty. To bridge this gap between practice and research, this dissertation explores uncertainty visualization as a means for reframing uncertainty in geographic information systems for use in policy decision support through three connected topics.

Initially, this research explores visualizing the relationship between uncertainty and policy outcomes as a means for incorporating policymakers' decision frames when visualizing uncertainty. Outcome spaces are presented as a method to represent the effect of uncertainty on policy outcomes. This method of uncertainty visualization acts as an uncertainty map, representing all possible outcomes for specific policy decisions. This conceptual model incorporates two variables, but implicit uncertainty can be extended to multivariate representations.

Subsequently, this work presented a new conceptualization of uncertainty, termed explicit and implicit, that integrates decision makers' framing of uncertainty into uncertainty visualization. Explicit uncertainty is seen as being separate from the policy outcomes, being described or displayed separately from the underlying data. In contrast, implicit uncertainty links uncertainty to decision outcomes, and while understood, it is not displayed separately from the data. The

distinction between explicit and implicit is illustrated through several examples of uncertainty visualization founded in decision science theory.

Lastly, the final topic assesses outcome spaces for communicating uncertainty through a human subject study. This study evaluates the effectiveness of the implicit uncertainty visualization method for communicating uncertainty for policy decision support. The results suggest that implicit uncertainty visualization successfully communicates uncertainty in results, even though uncertainty is not explicitly shown. Participants also found the implicit visualization effective for evaluating policy outcomes. Interestingly, participants also found the explicit uncertainty visualization to be effective for evaluating the policy outcomes, results that conflict with prior research.

DEDICATION

To my mom and dad, without you, I would not have made it here through
some very dark times

ACKNOWLEDGMENTS

There are many people whose support helped me make it through times I was not sure I would be able to be here. Dr. Elizabeth Wentz, my committee chair, encouraged me when I first started to follow my interests in applying research to practical problems, listening to my theories and pushing me to explain more and not make grand assumptions. Her willingness to read through so many drafts of ideas, and stick with me as they developed, helped make them much stronger. Dr. Rob Edsall, who encouraged me to enter the program, and provided the guidance and encouragement needed to find something about which I am passionate. Dr. Patricia Gober, who worked with me when I was going through a scary and challenging time in my life, but never treated me like I was anything but capable. She provided the spark for the direction of this work, and exemplifies the merging of science and practice. And finally, Dr. Michael Goodchild, whose comments and feedback during my graduate work, and whose research, helped to shape my own work.

During my time here, the School has been a source of support and sounding boards from so many people. Dr. Luc Anselin listened to my overly enthusiastic ideas about uncertainty when he arrived at ASU, and offered support and encouragement to me when I needed it most. Kathleen, Laura, Gloria, and Sue you were always there to help with scheduling and offer encouragement when things were overwhelming.

There are many graduate students who helped me along the way, being willing to take my surveys and read through drafts of this work. Naming everyone would be an impossible task, but I want to thank Melinda Shimizu who was there to talk through my ideas and share challenges of research directions that did not work out, and Elyssa Gutbrod and Stephen Gibson who suffered with me through so many writers block.

The following institutions provided financial aid for this research: The School of Geographical Sciences and Urban Planning, Decision Center for a Desert City (DCDC), and the Central Arizona Phoenix Long Term Ecological Research Project (CAP-LTER).

Finally, I want to thank my parents and friends for sticking through this with me, even when I was not sure I would be here to finish. The last five years have been the hardest of my life, and finishing this dissertation was one goal that kept me going. Instead of encouraging me to take a leave, you encouraged me to keep working, even when things were dark. Thank you for helping me find hope and giving me a reason to believe I would find my way here.

TABLE OF CONTENTS

	Page
LIST OF TABLES	xi
LIST OF FIGURES	xii
CHAPTER	
1. INTRODUCTION	1
1.1 Introduction.....	1
1.2 Literature Review	3
1.2.1 Decision Making Under Uncertainty	4
1.2.2 Uncertainty Visualization in Cartography and GIS	11
1.2.3 Summary	16
1.3 Research	16
1.3.1 Topic 1: Visualizing decision making under uncertainty as continuous outcome space.....	18
1.3.2 Topic 2: Conceptualizing explicit and implicit uncertainty.....	21
1.3.3 Topic 3: Evaluating the effectiveness of implicit uncertainty visualization for communicating uncertainty in decision support settings...	24
1.4 Dissertation Format.....	25
1.5 References.....	27
2. UNCERTAIN DECISIONS AND CONTINUOUS SPACES: VISUALIZING THE UNCERTAIN IMPACTS OF CLIMATE CHANGE FOR DECISION SUPPORT	39

CHAPTER	Page
2.1 Abstract.....	39
2.2 Introduction: Communicating Uncertain Science.....	40
2.3 Uncertainty in Climate Science Research.....	48
2.4 Framing Uncertain Science for Decisions Under Uncertainty	50
2.5 The Complexity of Uncertainty Communication	52
2.6 Uncertainty Visualization as an Outcome Space	58
2.7 Conclusions.....	63
2.8. References.....	64
3. USING DECISION THEORY MODELS TO CONEPTUALIZE AND DEVELOP UNCERTAINTY VISUALIZATION METHODS.....	72
3.1 Abstract.....	72
3.2 Introduction.....	74
3.3 Literature Review.....	76
3.3.1 Decision Making Under Uncertainty	76
3.3.1.1 Normative Decision Making Models.....	77
3.3.1.2 Descriptive Decision Making Models	79
3.3.1.3 Prescriptive Decision Making Models.....	83
3.3.2 Uncertainty Visualization in Cartography and GIS.....	85
3.4 Explicit and Implicit Uncertainty.....	89
3.5 Examples of implicit uncertainty visualization.....	96
3.5.1 Outcome spaces	96
3.5.2 Parallel Coordinate Plots.....	98

CHAPTER	Page
3.5.3 Goal plots	100
3.5.4 Youden plots	101
3.5.5 Linking and brushing	103
3.6 Conclusions	105
3.7 References	109
4. EVALUATING IMPLICIT VISUALIZATION OF GEOGRAPHIC UNCERTAINTY FOR PUBLIC POLICY DECISION SUPPORT	116
4.1 Abstract	116
4.2. Introduction	118
4.3. Visualizing Uncertainty	122
4.4. Methods	123
4.4.1 Scenario Overview	124
4.4.2 Visualizations	126
4.4.2.1 Implicit Uncertainty Decision Set	127
4.4.2.2 Explicit Uncertainty Decision Set	129
4.4.2.3 No Uncertainty Decision Set	129
4.4.3 Decision Set Questions	131
4.4.4 Survey Sample	134
4.4.5 Analysis	135
4.4.5.1 Policy Ranking Comparison	135
4.4.5.2 Do visualizations incorporate uncertain impacts of climate change?	136

CHAPTER	Page
4.4.5.3 Is the visualization effective for evaluating the impact of policy changes on groundwater?.....	136
4.4.5.4 Comparison of change in rankings and indication of whether they used the visualization in decisions.....	137
4.5. Results.....	138
4.5.1 Demographics	138
4.5.2 Policy Ranking Comparison	140
4.5.3 Do visualizations incorporate uncertain impacts of climate change?	141
4.5.4 Is the visualization effective for evaluating the impact of policy changes on groundwater?.....	143
4.5.5 Comparison of change in rankings and indication of whether they used the visualization in decisions	144
4.6. Discussion.....	145
4.7. Conclusion	151
4.8. References.....	152
5. CONCLUSIONS AND FUTURE WORK.....	155
5.1 Conclusions.....	155
5.2 Implications.....	161
5.3 Future Research and Challenges.....	162
REFERENCES	165

APPENDIX	Page
A. IRB APPROVAL AND SURVEY INSTRUMENT	180
B. STATEMENT OF PERMISSIONS.....	197

LIST OF TABLES

Table	Page
4.1. Survey participant age distribution	139
4.2. Survey participant education summary.....	139
4.3. Paired differences results of the ranking comparison	141
4.4. Results of the uncertainty comparison indicate that both the implicit and explicit visualizations were seen as including uncertainty, while those without uncertainty were not	142
4.5. Results of the effectiveness comparison indicate that all three visualizations were seen as effective for evaluating the policy decisions	143
4.6A. Implicit versus no uncertainty decision set use responses reflect a statistically significant difference in rankings for both the true group, but not the false groups	146
4.6B. Implicit versus explicit decision set use responses reflect a statistically significant difference in rankings for both the true and false groups.	147
4.6C. Explicit versus no uncertainty decision set use responses reflect a statistically significant difference in rankings for both the true and false groups.....	148

LIST OF FIGURES

Figure	Page
1.1 Intrinsic and Extrinsic Visualization Methods.....	14
1.2 Conceptual outcome space visualizing implicit uncertainty.....	19
2.1. Uncertainty shown through scaling the size of glyphs (a), varying glyph color (b), using color to represent uncertainty (c), and error bars (d) (Sanyal et al., 2009)	44
2.2. Lyme disease prediction uncertainty depicted as confidence (Luengo, 2008)	45
2.3. Implicit representation of uncertainty visualized as continuous values in an outcome space. Uncertain variables considered important to the decision problem are used as the axes. A model is run for the full range of uncertain values based on a set of policy decisions. The resulting outcomes for all model runs are shown as a continuous field in the outcome space.....	47
2.4. Conceptual outcome space showing change in ground water based on uncertain river flow.....	61
2.5. WaterSim outcome space (conceptual visualization environment). The values here represent a single policy decision implemented by the user run for all combinations of projected flows on the Salt/Verde River and Colorado River.....	62
3.1 Intrinsic and extrinsic symbology for visualizing uncertainty.....	87
3.2 Explicit uncertainty as a normative model of decision-making.....	91
3.3 Implicit uncertainty as a descriptive model of decision-making	92

Figure	Page
3.4 Explicit and implicit uncertainty.....	94
3.5 Conceptual representation of an outcome space.....	97
3.6 Parallel coordinate plot with specified geographies.....	98
3.7 Conceptual goal plot relating number of parcels that meet a given criteria based on the uncertain variable of interest.....	101
3.8 Adapted Youden plot relating uncertain variable of interest to outcome values by location.....	104
3.9 Uncertainty visualization and decision-making.....	108
4.1 Elements of Outcome Space.....	128
4.2 Implicit uncertainty visualization decision set.....	130
4.3 Explicit uncertainty visualization decision set.....	132
4.4 No uncertainty decision set.....	133

CHAPTER 1

INTRODUCTION

1.1 Introduction

Public policy decisions are often made in the face of future conditions that are inherently uncertain. Policies are statements by the government of what it intends to do (or not do) as a response to a problem that impacts the public (Birkland, 2001). Policy makers routinely rely on scientific results to identify alternatives and evaluate their potential impacts (Pielke et al., 2010; Dilling and Lemos, 2011). Policy makers contend with and manage uncertainty, while identifying the best alternatives for a given problem. Science has sought to provide tools and information to support policy decision making in the face of uncertainty for issues impacting society, including public health (Rychetnik et al., 2002), climate change (Gober et al., 2010; Gober et al., 2011; van Vuuren et al., 2011), water management and planning (Xu and Tung, 2008; Lee et al., 2010), transportation and land use planning (Geerlings and Stead, 2003; Litman, 2003; Arampatzis et al., 2004), housing policies (Horner and Murray, 2003; Natividade-Jesus et al., 2007) geology (Viard 2011), ecology (Ascough et al., 2008), and environmental management (Sigel, Klauer and Pahl-Wosti 2010; Verstegen et al. 2012). As an example, Rehr et al. (2012) developed and applied a decision support framework for coral reef protection and management in Florida. This framework focused on supporting complex and uncertain decision making by integrating science with the decision problem through two steps. The first translates scientific results into meaningful information for use in decision-making, by illustrating

potential outcomes (both intended or unintended) of different decision alternatives. The second clarifies the decision problem, objectives and goals of the decision makers in order to ensure relevant legal, social, and institutional constraints are considered. Their approach highlights uncertainties in the decision process enabling better-informed decisions. Nevertheless, the usability of uncertain scientific information remains limited in terms of providing decision support for complex, highly uncertain problems (Dilling and Lemos 2011; Dong and Hayes 2012).

Providing usable science for decision support considers whether decision makers perceive the information as useful, as well as whether they can integrate the information into their decision process (Pidgeon et al. 2003; Pielke, Sarewitz, and Dilling 2010; Dilling and Lemos 2011). As a means to make science more usable for decision support, researchers have focused on reframing information to make it relevant to policymakers (Couclelis 2003; Nisbet and Mooney 2007; Nisbet 2009). Reframing scientific results in this way shifts the focus from communicating technical complexities of research to providing information that supports policymaker's ability to manage the impacts of uncertainty on policy options. This dissertation explores uncertainty visualization as a means for reframing uncertainty in geographic information systems (GIS) for use in policy decision support through three major topics. The first topic explores visualizing the relationship between uncertainty and policy outcomes as a means for considering the decision frames of policymakers when presenting uncertainty through visualization in GIS (Chapter 2). The second topic takes reframing

further, discussing a new conceptualization of uncertainty, termed explicit and implicit, that integrates decision makers' framing of uncertainty and outcomes into uncertainty visualization (Chapter 3). The final topic evaluates the effectiveness of an implicit uncertainty visualization for communicating uncertainty for policy decision support (Chapter 4).

The remainder of this chapter discusses these topics in more detail including a literature review of relevant work in decision science, visual communication of science and uncertainty visualization. Further discussion of the three topics discussed above and research topics follow the literature review. The chapter concludes with a breakdown of the dissertation format.

1.2 Literature Review

This literature review supports the development of a new approach to uncertainty visualization for decision support meant to bridge the gap between researchers' and decision makers' conceptualization of uncertainty. This review is divided into two themes. The first is a review of decision science as it relates to decisions under uncertainty and decision frames. This theme provides the foundation for considering the user in uncertainty visualization methods. The second theme focuses on GIS and visualization research as it relates to uncertainty visualization, including existing approaches to developing uncertainty visualization and evaluations of existing methods. These themes relate to each of the three chapters that make up this dissertation. Each chapter has its own literature review that highlights the relevant work for that chapter. The inclusion of this review here is

to synthesize the ways in which these themes are connected and support the dissertation research.

1.2.1 Decision Making Under Uncertainty

Decisions represent often ill-structured problems in which the decision maker assesses two or more alternatives and then commits to one (Jonassen, 2012).

Decision-making is the process by which an individual's beliefs and desires are merged to choose between alternatives (courses of action) (Hastie 2001). When making decisions, individuals must evaluate the consequences of choices (alternatives or actions) through the assessment of alternatives in light of what the decision maker wants and expects (Hastie 2001). Some problems require only making a single decision, such as what computer to purchase, while other complex and inherently uncertain problems require iterative decision making where the selection of an alternative lays the foundation for evaluating the next decision. For example, a city's decision to restrict water usage would lead to additional decisions about how and when to implement restrictions.

Normative models of decision making, such as expected utility, define how decisions under uncertainty *ought* to be made. Decisions are broken down into four basic components: (1) alternatives, (2) possible future conditions of the world, (3) probabilities of the future conditions of the world, and (4) information about outcomes of the alternatives under differing future conditions (Jonassen, 2012). These models assume decision makers are rational, well able to work through complicated decisions, and fully informed, and that the uncertainties and

probabilities for given alternatives are agreed upon, knowable and known. The goal is not to explain or predict behavior, but to facilitate better decisions through structured analysis of decision alternatives and the probabilities associated with those alternatives (Schmoldt, 2001) to select the most optimal outcome.

Decision support tools meant to support evaluation of decisions under uncertainty are often normative in nature, focusing on identifying, quantifying, and explicitly representing probability and uncertainty (Manson et al., 2002; Sevcikova et al., 2007; Ascough et al., 2008). Sevcikova et al. (2007) developed probability methods for assessing uncertainty in UrbanSim, an urban simulation decision support model, with the goal of identifying and quantifying sources of uncertainty in land use and transportation policy. UrbanSim consists of nine individual models that integrate household location and mobility, economic location and mobility, employment location and mobility, land pricing, real estate development and transportation (accessibility). Researchers stated that significant sources of uncertainty in the system must be identified in order to carry out a probabilistic assessment, with the goal of quantifying as much of the uncertainty as possible.

While the normative approach is beneficial for decisions where uncertainty can be identified and quantified, and specific probability distributions of alternative are known, this poses a significant disadvantage for decisions under deep uncertainty where the information needed to identify the optimal solution cannot be agreed on or often does not exist (Polasky et al., 2011). *Deep uncertainty* exists in decisions where there is disagreement on the state of future

conditions and the probability distributions of alternatives and outcomes cannot be known or agreed upon (Lempert et al., 2003;Gober et al., 2010). This leads to challenges in developing probability based decision support tools for complex, deeply uncertainty problems. Van der pas et al. (2010) developed an exploratory multi-criteria decision analysis methodology to address deep uncertainty in intelligent speed adaption (ISA) devices that are meant to adjust driving speeds and reduce traffic accidents. Many aspects of the implementation of ISA devices are deeply uncertain, including how to model the traffic implications of using the devices, and whether or not the public would accept using the devices or believe their benefits. Under these deep uncertainties, developing a best estimate model is not a viable approach. In response, Van der pas et al. (2010) adapted a sensitivity analysis approach to evaluate the viability of ISA implementation.

Developing decision support tools for experienced decision-makers poses additional challenges, as normative, probabilistic approaches are not necessarily compatible with how experienced decisions makers solve problems (Cohen and Freeman, 1996). Descriptive models of decision making explore how people make decisions. In practice, decision makers rarely select alternatives based on purely rational choices, but instead base decisions on information about the decision alternatives combined with affective feelings and emotions about those alternatives (Slovic et al., 2004;Slovic et al., 2007). In domains where decision makers know a lot about decision problems, and have their own beliefs, biases and experiences with those problems, decisions problems become both context

and domain dependent (Cohen and Freeman, 1996;Rettinger and Hastie, 2001;Jonassen, 2012).

Any decision problem – defined by the alternatives and consequences involved with a particular decision, governed by the available data and the relative uncertainty of the data – is framed by the unconscious emotions, past experiences and expectations a decision maker associates with a particular course of action (Tversky and Kahneman 1981). Consequently, decision-making is context dependent, with people framing decisions in many ways (Jonassen, 2012). Different decision frames arise due to many factors, such as one person who has multiple or changing goals, or by many different decision makers, each having different perspectives, experiences, or conceptual understandings of the problem. Moreover, when faced with decisions under uncertainty, individuals often revert to heuristics, or abstract mental rules to determine a course of action. Individuals learn to apply heuristics that result in the most favorable outcomes, reducing the complexity of assessing the alternatives and potential outcomes in these frequently met problems (Patt and Zeckhauser 2000;Spiegelhalter, et al. 2011). Strategies for working through decisions often rely on the development of internal narratives (stories) about the problem, trying to minimize negative or maximize positive impacts (Jonassen, 2012). Decision support tools that integrate these psychological components of decision making into their methods may better support how people actually come to a decision.

Prescriptive decision models acknowledge that humans can be poor decision makers. These models are concerned with the development of tools to support and enhance the decision-making process, focusing on the development of tools that fulfill two goals. Tools must be both useful to decision makers, and decision makers must actually be able to use them. In effect the goal of prescriptive models is to prescribe how decision makers can approximate normative decision processes in practice. The result is a synthesis of normative and descriptive models (Brown and Vari, 1992).

Prescriptive theories have resulted in varied approaches to bridge decision-making theory and practice. Some approaches focus on a structured sequence of activities. For example, decision trees offer a means to graphically depict available decision alternatives, the uncertainty and probabilities associated with those alternatives, and evaluations/measures of how well each alternative meets the objectives for the decision problem (Kingsford and Salzberg, 2008). This approach assumes discrete alternatives with known or knowable probabilities. For decision making under deep uncertainty, these probabilities may not be known, and the identification of a discrete set of alternatives that perform well over variable future conditions may not be feasible.

Scenario planning offers a means to better handle evaluation of variable future conditions. Scenario planning offers methods that build on how people make decisions, offering a wide range of decision support functions (Bishop et al., 2007; Volkery and Ribeiro, 2009). Ideally, scenarios support thinking creatively about the future, allowing decision makers to be prepared for

conditions of deep uncertainty, by allowing them to evaluate policies over many plausible futures (Volkery and Ribeiro, 2009). Scenarios consist of the stories of these plausible futures, from the anticipated to the highly uncertain, that are meant to allow decision makers to make better sense of change, their perceptions of the problem, and related problem solving strategies. This approach allows better identification and management of conflicts between groups and competing social interests, helping to find common ground for decisions, a key element of policy making (Volkery and Ribeiro, 2009). Uncertainty can be accounted for in the range of plausible futures, as well as identification of strategies that perform at a required level even in worst-case scenarios.

For example, Klosterman (1999) developed “What if?”, a scenario based policy-planning tool for projecting future land use demands and identifying locations suitable for those land uses. The system allows users to create alternate scenarios related to development and policy, and to see the impact of those choices on projected future land use plans, as well as the impact of the projected land use on employment and population trends. While the system was shown to be easy to use, as the number of future states, policy alternatives and input parameters increase, users would have to run through more and more scenarios (individually) to see the full range of impacts. The sheer number of scenarios that could result would be incredibly challenging to evaluate (Lempert et al., 2003).

With many plausible scenarios for future conditions, developing static policies that perform well in many of these futures is unlikely (Walker et al., 2001;Lempert, 2002;Lempert et al., 2003). Addressing problems with deep

uncertainty requires policies that are robust across a range of plausible futures, instead of being optimized for a single best estimate of future conditions. Policies that involve *deep uncertainty* occur when not enough is known about future conditions to predict changes, and there is insufficient information, or lack of agreement among stakeholders, about the system model and its probabilities (Lempert et al., 2003;van der Pas et al., 2010). *Robust decision-making* focuses on identifying policies that are less sensitive to these unknowns (deep uncertainties) by representing multiple plausible futures. Rather than identify optimal policies that perform the “best” for a given future condition, the goal in robust decision-making is to identify policies that perform well over a number of possible futures. Decision makers can then evaluate these robust policies in detail (Lempert et al., 2003).

The evaluation of policy decisions over a range of possible future conditions serves as a dynamic and anticipatory approach to dealing with conditions of deep uncertainty. Instead of focusing on the most likely outcome, robust approaches stress the importance of planning for a range of future conditions. The result is a shift from producing and evaluating discrete solutions for a single future, to envisioning how decisions (policies) will perform over a range of possible future conditions (Coclelis, 2003;Lempert et al., 2003), resulting in a continuous range of outcomes. In robust decision-making, decision support tools that support the assessment of this range of outcomes over uncertain futures would be advantageous over those that provide discrete solutions and probability estimates of uncertainty. Visualization is well suited for

communicating this level of continuous data, as visualization can convey complex and dense information in a single view, that otherwise would not be easily communicated through individual images or the written word (Tufte, 1983; Cleveland, 1984a; Hedges, 1987).

1.2.2 Uncertainty Visualization in Cartography and GIS

Several efforts in cartography, visualization, and GIScience research have sought to incorporate uncertainty information in geographic visualization (Aerts et al., 2003a; Pham and Brown, 2003; Li and Zhang, 2006; Bostrom et al., 2007; Viard et al., 2011; Dong and Hayes, 2012). Researchers have sought the most appropriate and effective means of depicting uncertainty (Buttenfield, 1993; Goodchild et al., 1994; Leitner and Buttenfield, 2000), carrying out experiments comparing visualization techniques (Blenkinsop et al., 2000; Aerts et al., 2003a; Slocum et al., 2003; Keuper, 2004). For example, MacEachren et al. (1998) developed and tested a pair of intrinsic methods for depicting “reliability” of data on choropleth maps used in epidemiology.

A common approach is to begin with the adaptation of Bertin’s (1983) visual variables for the representation of uncertainty. These visual variables include size, shape, value, orientation, color, and texture. Along with these variables, additional graphic variables, such as transparency, saturation, and clarity have also been proposed (MacEachren, 1992; Slocum et al., 2004) specifically for uncertainty visualization.

Additionally, Gershon (1998) proposed two general categories of visualization strategy: intrinsic and extrinsic. Both categories rely on visualizing either quantitative or qualitative estimates of uncertainty. Intrinsic techniques integrate uncertainty in the display by varying an existing object's appearance to show associated uncertainty. Although the uncertainty and "object" are represented in unified representation, such as using fuzzy lines to represent vague boundaries, the uncertainty is still explicitly depicted as separate from the underlying data. Extrinsic techniques rely on the addition of geometric objects to highlight uncertain information. For example, model results might be qualitatively identified using a range of certain to uncertain using hatch marks of varying density (extrinsic), while surface heights offer a method for representing error quantitatively (intrinsic). These categories offer methods for representing uncertainty of specific features or objects as explicit uncertainty, but do not offer a means to integrate uncertainty, data, and decision outcomes (Figure 1.1).

The primary focus of many studies is to develop generalizable methods of uncertainty visualization that would be applicable to a wide range of uses. Studies meant to evaluate specific uncertainty visualization methods often focus on designing the visualization (Buttenfield, 1993;Fauerbach et al., 1996;Djurcilov et al., 2002;Bostrom et al., 2007;), evaluating whether users were able to identify specific uncertainty values (Blenkinsop et al., 2000) and assessing the impact of uncertainty visualization on perceptions and data identification (Hope and Hunter, 2007;Xiao et al., 2007). Newman and Lee (2004) evaluated both extrinsic and intrinsic techniques for the visualization of uncertainty in volumetric data

comparing glyph-based techniques, such as cylinders and cones, with color-mapping and transparency adjustments. They found that while each method was useful for identifying uncertainty in the scenario test, the glyph techniques were most beneficial. Leitner and Buttenfield (2000) focused on the alteration of the decision-making process by changing the representation, through systematically altering Bertin's visual variables, finding that inclusion of uncertainty clarified mapped information and reduced decision time.

Some researchers have also focused on the effectiveness of uncertainty visualization specifically for decision support environments, while still focusing on visualizing discrete uncertainty values (Cliburn et al., 2002; Aerts et al., 2003a; Slocum et al., 2003; Goovaerts, 2006). Aerts et al. (2003a) analyzed static representations and toggling as methods for visualizing uncertainty in a water balance model. Their study found that planners and decision makers found the inclusion of uncertainty information useful, preferring the static representations to toggling back and forth between the maps.

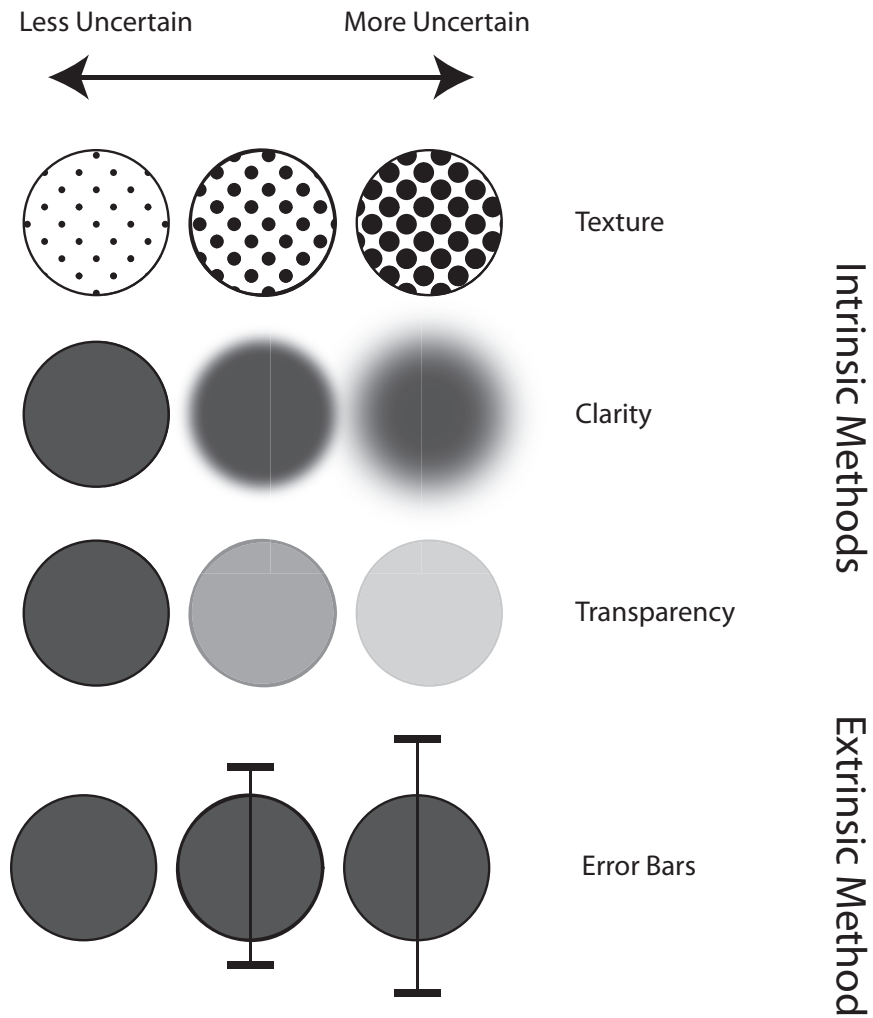


Figure 1.1 Intrinsic and Extrinsic Visualization Methods

Cliburn et al. (2002) developed a visualization environment to allow decision makers to visualize the results of a water-balance model. Their study focused on the effectiveness of explicit intrinsic and extrinsic methods for communicating explicit uncertain values for use in decision support. That study found that the complexity and density of the representation methods seemed to overwhelm novice decision makers, while experts were able to use the detail more readily in decision-making. They suggest that intrinsic methods provide a more general

representation of uncertainty data, which non-expert users may prefer over more-detailed visualizations. An additional approach to assessing the effectiveness of uncertainty visualization for decision support emphasizes identifying areas of commonality between alternatives instead of providing probability estimates or directly identifying uncertainty. Dong and Hayes (2012) tested an uncertainty visualization method that identified overlap in the range of possible values for two or more alternatives. This goal is to support identification of ambiguity in the alternatives. In tests of a decision support system, both with and without this uncertainty information, they found that participants did not distinguish between ambiguous and unambiguous alternatives when the uncertainty visualization was excluded. While the system still requires users to input information for each individual alternative or scenario, it is interesting to note, that uncertainty is represented as a range of values, and not as a single probability estimate.

While uncertainty visualization research has sought to develop and evaluate methods effective for visualizing uncertainty, the focus on representing specific uncertainty values is not effective for decisions under deep uncertainty. In context dependent decision support settings, such as public policy, visualizing discrete uncertainty values does not support the assessment of multiple alternatives over multiple futures. Conceptualizing uncertainty as the relationship between decision outcomes and differing future conditions offers a new approach to uncertainty visualization, integrating the ways in which policy decision makers frame decisions under uncertainty (Cohen and Freeman, 1996;Jonassen, 2012),

and where visualizing the full range of outcomes for all plausible future conditions represents the uncertainty in future conditions.

1.2.3 Summary

Decision science seeks to understand the ways in which people choose between alternatives in the face of uncertainty. Many models of decision making identify both how people should make decisions and the probabilities associated with given alternatives. However, when developing tools for decision support, understanding how people actually make decisions under uncertainty is beneficial. Decision makers frame decisions based on their emotions, biases, past experiences and prior knowledge, and some decision support models attempt to capitalize on these decision frames in order to develop better decision support tools. In practice, decision makers often view uncertainty as unavoidable, and potentially, as integral to the definition of a problem (Pahl et al. 2007;Brugnach et al. 2008). However, many decision makers consider existing methods for visualizing uncertainty as either irrelevant or detrimental for successful data communication and insight generation (Cliburn et al. 2002;Slocum et al. 2003; Brugnach et al. 2007).

1.3 Research

In decision support settings, technical and complex scientific visualizations and statistical estimation, like those tools currently being developed in GIS uncertainty research, may not be usable or easily understood by decision

makers. One explanation for this is that specific uncertainty estimates might be less important than an understanding of the impact of uncertainty on decision outcomes over a range of possible future conditions (Lempert, Popper, and Bankes 2003; Pawson, Wong and Owen 2011). This suggests a possible discrepancy (Goodchild, 2006) between GIS uncertainty research and the practical methods of addressing uncertainty in decision-making.

This dissertation suggests that this disconnect stems from a mismatch between the ways that GIS decision support research conceptualizes uncertainty and the ways in which decision makers' frame uncertainty in decision settings. To bridge this gap in understanding, this dissertation presents a new conceptualization of uncertainty, termed *explicit and implicit*, which integrates the ways in which decision makers consider both uncertainty and outcomes when making decisions under uncertainty. This conceptualization is presented and evaluated through three main research topics presented in three publishable manuscripts:

- Topic 1: Visualizing decision making under uncertainty as continuous outcome space
- Topic 2: Conceptualizing explicit and implicit uncertainty
- Topic 3: Evaluating the effectiveness of implicit uncertainty visualization for communicating uncertainty in decision support settings.

The remainder of this section presents these topics in detail.

1.3.1 Topic 1: Visualizing decision making under uncertainty as continuous outcome space

The first topic in this dissertation (Chapter 2) presents continuous outcome space as an approach to uncertainty visualization that integrates user decision frames. This research builds upon visualization methods presented by Lempert, Popper, and Bankes (2003) for mapping Landscapes of Plausible Futures (LPF) (Gober and Kirkwood, 2010). The landscapes provide decision makers with visualizations intended to aid in exploration of patterns and properties of large, multidimensional data sets produced as output to robust decision making scenarios. In these landscapes, the axes represent uncertainty variables identified as vital to the problem under consideration. Each point of intersection between values on the axes represents the outcome of a given scenario. The area within the landscape that represents all possible outcomes (defined in this research as the outcome space) can further be delineated into regions of no/mild/overwhelming regret. An adaptation of the LPF is introduced as a method to visualize uncertainty (Figure 1.2) by showing the outcomes of policy decisions for all possible future conditions under study.

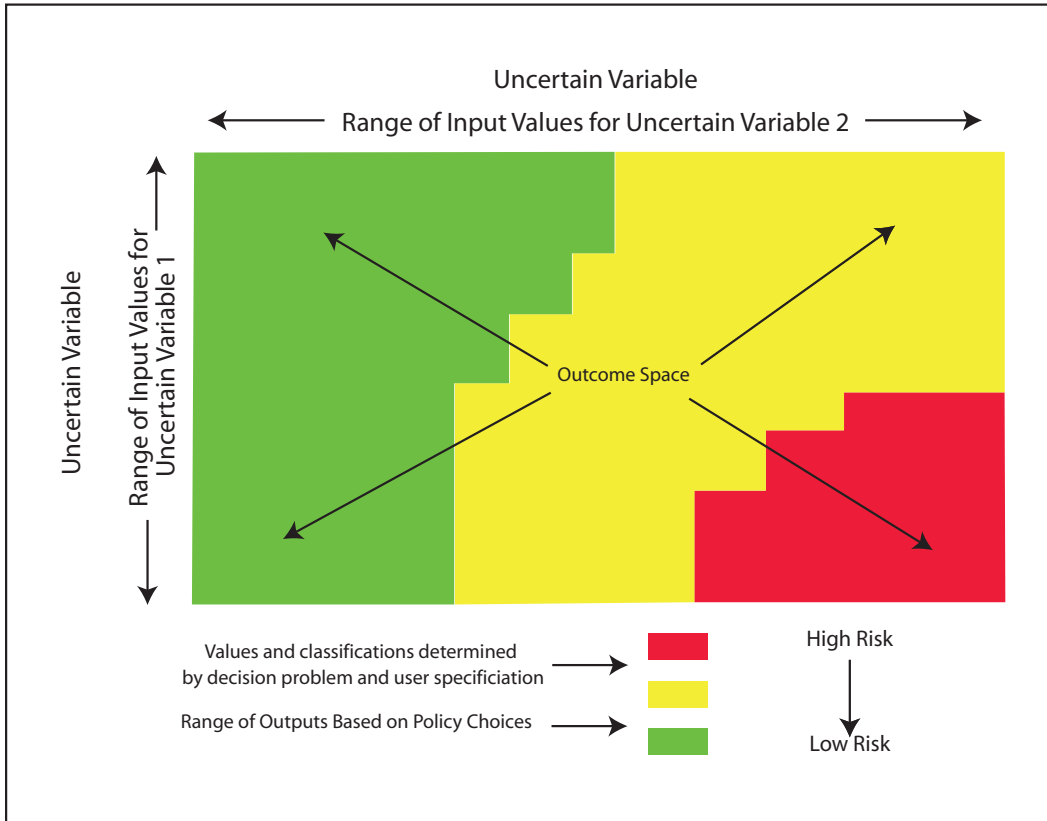


Figure 1.2 Conceptual outcome space visualizing implicit uncertainty

This approach conceptualizes uncertainty as the variability of decision outcomes over a range of uncertainty future conditions. The focus on alternatives aligns with policy maker decision frames of evaluating outcomes and offers advantages over identifying specific uncertainty values at specific locations. First, the LPF allows decision makers to identify the scenarios with the most favorable outcomes. After these scenarios are identified, more detailed exploration of outcomes could continue. Second, this approach views uncertainty as a function of relationship between the range of possible futures and decision outcomes. Lastly, this approach addresses a shortcoming of scenario planning, where there

may be multiple future scenarios that could be considered by decision makers. Often it is necessary to reduce the number of scenarios to make assessments by decision makers more manageable. This means multiple scenarios of future conditions may be eliminated prior to decision makers, the ones responsible for the decisions, becoming involved. Adapting LPF allows decision makers to identify policies robust over the largest range of future conditions. After these policies are identified, further analysis can be completed for each area under study.

The conceptual example of LPF in Chapter 2 focus on water management systems, which are traditionally operated under the assumption of stationarity—the idea that natural systems fluctuate within an envelope of variability that does not change (Milly et al., 2008;Gober et al., 2010). Climate change, however, poses a challenge to the stationarity assumption; as changes to the Earth’s climate are altering the rate of river discharge, mean precipitation, sea levels, and other aspects of the water cycle and water supply. Water planners express awareness and acceptance of the uncertain nature of the impacts climate change may have on this assumption, as well as the uncertainty inherent in the models used to predict these changes (Howard, 2008). In the conceptual example presented in Chapter 2, the outcome space represents the net cumulative change in groundwater based on policy decisions made by decision makers. As policy decisions are implemented, the values in the outcome space can change based on the model results. This conceptualization of uncertainty as a continuous outcome space offers an opportunity for decision makers to explore how climactic uncertainty (evidenced

by changes to the stationarity assumption) affects outcomes of policy decisions, supporting the assessment of the relationship between uncertainty, alternatives, and outcomes.

1.3.2 Topic 2: Conceptualizing explicit and implicit uncertainty

The second topic of this dissertation (Chapter 3) builds on the uncertainty visualization approach presented in Chapter 2, developing a conceptualization of uncertainty, termed *explicit and implicit*, as a way to approach uncertainty visualization that is prescriptive in nature, bringing tools to support evaluation of uncertainty in decisions in a manner useful and usable by decision makers.

Explicit uncertainty is linked more to normative models, theoretically defining what decision makers should know about data and model outcomes. Implicit uncertainty is linked to both descriptive and prescriptive models, integrating what decision makers actually do in practice into tools to support better decisions.

Explicit uncertainties are gaps, errors, and unknowns displayed or represented through quantitative values (e.g., error bars) or qualitative estimations (e.g., more or less uncertain). In explicit visualization, uncertainty is conceived of as specific values or measures, related to, but not the same as, the underlying data. GIS researchers use explicit uncertainty to evaluate uncertainty in data sources, models parameters, and results. Most current methods for visualizing uncertainty, as described above, are explicit.

Explicit approaches to uncertainty visualization for decision support share traits with the normative models of decision-making. Like normative models that build on how decision makers should make decisions, visualization features such as transparency or texture (MacEachren, 1992), focus on representing known uncertainties, assuming that better decisions result from evaluation these values. There is an inherent assumption that decision makers can use statistical estimates to evaluate policy options. For many of these methods, the probabilities of future conditions must be known or knowable, and the goal of using these methods is to improve decisions by identifying optimal solutions. For decision support settings, specific statistical estimates of uncertainty for discrete alternatives do not reflect how decision makers approach decision-making under uncertainty in practice.

Implicit uncertainty represents how, in practice, decision makers consider a range of alternative decisions due to different data sources, model parameters, models, and policy choices. As such, the definition, interpretation and, potentially, representation of uncertainty is informed by the users and the domain. Implicit uncertainty is conceived of as being related to policy outcomes, so that the overall range of potential outcomes is as important as the geographic variability of the outcomes. Few geographic visualization methods represent implicit uncertainty.

Implicit visualization builds on descriptive decision approaches, acknowledging the impact of decision makers experience, emotions and knowledge on how they frame decision problems, without assuming that the probability of future conditions are known or knowable. The goal of implicit visualizations is to develop tools that are both useful to, and usable by, decision

makers in order to support more informed decisions through exploration of the relationship between uncertainty and decision outcome. The relationship between uncertainty and decision outcomes becomes key to identifying policies that are robust against uncertainty. This focus on providing tools that assist decision makers in integrating uncertainty visualization in decision-making is prescriptive in nature.

The development of explicit and implicit uncertainty based on theories in decision science about how decision makers address uncertainty in practice addresses the first three components of usable science (Pielke et al., 2010; Dilling and Lemos, 2011). First, it relates the goals of this research to the specific “on the ground” problems of policy decision making under deep uncertainty. Second, the work engages with and strives to understand the needs of the policy decision makers through studies that engage decision makers and seek to understand how they integrate uncertainty into their decisions. And lastly, it brings the needs of the user into the science process with the consideration of decision frames.

Focusing on uncertainty as inherent to decision outcomes, instead of separate or ancillary, is a departure from prior approaches to uncertainty visualization. Representing decision outcomes and uncertainty as integrated information reflects the manner in which decision makers frame decisions under uncertainty. This reframing supports exploration of the relationship between decisions and uncertainty relative to its role in the decision process, focusing on uncertainty and decisions as a whole, and not as individual and separate information.

1.3.3 Topic 3: Evaluating the effectiveness of implicit uncertainty visualization for communicating uncertainty in decision support settings

The third topic of this dissertation (Chapter 4) focuses on evaluating the effectiveness of the implicit uncertainty visualization shown in Chapter 2 for communicating uncertainty in decision settings where the goal is to identify the most robust policy choice. Here robust indicates the scenario that produces the most favorable outcomes for the largest number of future conditions. This is done through a human subject study evaluating the impact of policy options on groundwater. The goal of this study is to evaluate whether users are able to both understand that implicit visualization includes uncertainty information, even if it is not explicitly shown, and use the information to evaluate policy choices. Responses were compared for policy decisions made using implicit and explicit visualization of uncertainty as well as no visualization of uncertainty. The human subject study specifically seeks to answer the following research questions:

1. Does implicit visualization of uncertainty result in policy decisions that differ from explicit/no uncertainty visualization?
2. Are implicit representations of uncertainty perceived as effective for evaluating the robustness of a policy decision?
3. Do users interpret implicit visualization as being uncertain?

The work in Chapter 4 poses an evaluation of effectiveness that differs from prior studies, focusing on the whether implicit representations produce different decisions from explicit methods, as well as whether users identify the representations as effective for evaluating the robustness of a policy choice for

future conditions. This differs from much of the prior research that defines effectiveness as correct responses, time to respond, or the ability to discover specific values. The reason for this change is that in decision making under uncertainty, there is often not a single correct response that works for all future conditions. This work suggests that for decision-making, effectiveness and usability do not always relate to the ability to extract specific uncertainty values, but should include support understanding of relationships between decisions and uncertainty.

1.4 Dissertation Format

There are five chapters in this dissertation, with three major chapters each being a separate first-authored manuscript. These were submitted as a book chapter (Chapter 2) and to peer-reviewed journals (Chapter 3 and Chapter 4) that frequently publish GIS and visualization articles. For each article, I was responsible for originating the research direction, questions, and/or objectives, as well as deciding on primary methodology, data collection, analysis, and discussion of results. This includes being the lead author, writing and formatting each manuscript for journal submission, as well as responding to referee and editorial comments during the peer-review process. Each chapter identifies the objectives of the paper, provides a literature review relevant to the theme of the paper, and when appropriate, discusses the methods for the research.

The first chapter (Chapter 1) provides an introduction to the research and the specific topic of each article. Some of the work in Chapter 1 is also contained

in the articles presented in Chapter 2 – Chapter 4. There is no intention of submitting Chapter 1 for publication outside of this dissertation.

Chapter 2 (Topic 1) presents a literature review and conceptualizes uncertainty as continuous outcome space, building upon visualization methods presented by Lempert, Popper, and Bankes (2003) for mapping Landscapes of Plausible Futures. The objectives of this chapter were to provide a foundation for the concept of continuous outcome spaces as a conceptualization of uncertainty for robust decision-making. This chapter was submitted as a chapter for *Understanding Different Geographies* (edited by K. Kriz et al) in 2010 and published as Chapter 10 in 2012.

Chapter 3 (Topic 2) synthesizes literature in both visualization and decision science, to present a new conceptualization of uncertainty, termed explicit and implicit uncertainty, as a way to bridge this gap in understanding between GIS researchers and decision makers. Additionally, implicit visualization methods including outcome spaces and parallel coordinate plots are discussed. This chapter was coauthored with Elizabeth A. Wentz. As first author, I was responsible for writing and formatting each manuscript for journal submission. I will be responding to referee and editorial comments during the peer-review process. This work will be submitted to the *Annals of the Association of American Geographers* in May 2013.

Chapter 4 (Topic 3) presents the results of the human subject study comparing implicit and explicit visualizations of uncertainty. The objectives of this chapter were to evaluate the effectiveness of implicit visualizations to

communicate uncertainty to decision makers, and support the evaluation of policies over a range of future conditions. This chapter was coauthored with Elizabeth A. Wentz, and submitted to Computers, Environment, and Urban Systems in November 2012. Review comments have been received, and I will be responding to the reviewer comments in May 2013.

A final concluding chapter (Chapter 5) summarizes the results and evaluates the contributions of the dissertation towards uncertainty visualization for decision support research. Some of the work in Chapter 5 is also contained in the articles presented in Chapter 2 – Chapter 4. There is no intention of submitting Chapter 5 for publication outside of this dissertation.

Lastly, Appendix A contains the survey instrument and Arizona State University Institutional Review Board exempt study letter and Appendix B contains a statement of permission for including the co-authored manuscript in Chapter 3 and Chapter 4 as a chapter for this dissertation.

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Chapter 2

UNCERTAIN DECISIONS AND CONTINUOUS SPACES: VISUALIZING THE UNCERTAIN IMPACTS OF CLIMATE CHANGE FOR DECISION SUPPORT

This chapter was originally published in *Understanding Different Geographies* (edited by K. Kriz et al) in 2010 and published as Chapter 10 in 2012. Changes made from the published work include minor editorial changes based on comments from the committee, including a new Figure 1, herein referred to as Figure 2.1, and a revision of Figure 5, herein referred to as Figure 2.5, to include explanatory labels. This work is not substantially changed, and will not be submitted to alternate publications.

2.1 Abstract

Scientific results serve as the foundation for public policy decisions in local and global society. Communicating these findings to policymakers poses an immense challenge, as information considered beneficial for evaluating a problem is very different for scientists and decision makers. This is especially true in decisions related to climate change mitigation and adaptation, where conflicting results and controversy leaves many decision makers questioning the veracity of results or waiting until uncertainty is reduced. This conflict does not support evaluation of policy alternatives meant to address causes and future effects of climate change. Robust decision-making offers a foundation for methods that include the context of uncertainty and decisions, by visualizing the relationship between uncertainty

and policy alternatives. This research presents outcome spaces as a method of implicit uncertainty visualization to represent the effect of uncertainty on policy outcomes. The uncertain impact of climate change on water policy serves as a case study for the visualization method presented here. Implementation of an outcome space in a water simulation model is presented here. Uncertain variables act as coordinates on x- and y-axes to produce a space of policy outcomes. This method of uncertainty visualization acts as an uncertainty map, representing all possible outcomes for specific policy decisions. This conceptual model incorporates two variables, but can be extended to multivariate representations.

Keywords: uncertainty visualization, outcome space, decision support, decision frames

2.2 Introduction: Communicating Uncertain Science

Understanding scientific results is critical as policies informed by scientific expertise and developments can have far reaching impacts on society. More and more, public policy decision makers, as well as the public, are expected to consume scientific information to inform their opinions (Nisbet and Mooney, 2007;Kahan et al., 2011). For many of these information consumers, knowledge of science comes through policy reports and recommendations, as well as science communications developed for non-science audiences. Often, there is little to no direct experiences with research activities or scientific journals (Corbett and Durfee, 2004;Smith, 2005). Individuals depend on these communications to

inform their decisions and expand their knowledge about the world beyond their experiences (Boykoff and Boykoff, 2007). Translating scientific knowledge into consumable information requires that often complex, sometimes contested or uncertain results, be distilled into easily digestible, seemingly certain facts and recommendations. Through this distillation of scientific knowledge, risk perceptions, attitudes, and actions are shaped, to some extent, by mediated scientific information (Carvalha and Burgess, 2005). This is especially true for issues that exist outside everyday experiences or that occur at a scale (either geographic or temporal) that seems “invisible” on an individual level, such as the impact of natural disasters, changes in the economy, outbreaks of disease, and climate change.

Science communication plays a central role in the climate change dialog between scientists, policymakers, and the public (Nisbet and Mooney, 2007;Kahan et al., 2011). This influences public perception and policy maker action (or inaction) in both climate change mitigation and adaptation. Mitigation is the reduction of environmental impacts and greenhouse gases in to the atmosphere to slow or stop anthropogenic contributions to climate change (Boykoff and Roberts, 2007). Adaptation is an adjustment in human systems in response to actual or anticipated climactic changes or their effects (Boykoff and Roberts, 2007). Communicating the science of climate change is important for encouraging policy actions in diverse policy areas including water conservation, alternative transportation, and environmental protection. However information such as explanations of risk, uncertainty, and the scientific process behind the

results (Carvalha and Burgess, 2005) are not easily incorporated by decision makers into their decision-making process. Moreover, the challenge of communicating uncertain science is complicated by competing and conflicting “scientific facts” that are often presented to decision makers through complex statistics and visualizations or bleak scenarios of future conditions. While these methods initially capture the attention of policymakers, they do little to help users incorporate scientific results into their understanding of the problem or the outcome of policy decisions. Furthermore, competing research reports and conflicting scientific findings often leave individuals questioning the veracity of results and whether it is better to wait in the hopes that uncertainty will be reduced (Council, 2007; O'Neill, 2008). However, holding out for more certainty does not guarantee that new methods or information will result in a reduction in uncertainty. Ultimately, these methods often fail to effect policy action (Abbasi, 2005). This research speaks to the challenge of overcoming this desire to wait for more certainty, through methods that incorporate uncertainty in a manner that resemble decision-making processes.

There are many sources of uncertainty in climate change science that end up part of policy decision making. Much of this often relates to what is unknown about the natural variability of climate systems and how changes in greenhouse gases and human behaviors affect these systems (Mearns, 2010). These uncertainties are often amplified in studies of future climate conditions, which rely on complex computer models meant to simulate the processes of global climate systems. These models must account for atmospheric, ocean, and land

surface processes. Although the development of these models has grown more sophisticated and robust, there are still many processes that remain unknown, difficult to represent or poorly understood. Moreover, when studies focus on climate at a larger scale, these climate models must be scaled down from a global to regional level. This process introduces new uncertainties, as scientists must translate global processes to local conditions. Scientists are often comfortable working with and interpreting these inherent uncertainties. Unfortunately, public policy decision makers tend to struggle to incorporate these uncertain conditions even though they often face uncertainty in other policy decisions (Pahl-Wostl et al., 2007;Brugnach et al., 2008). The key is to build on existing comfort with uncertainty in other decision settings by presenting current information and findings to policymakers in a manner that supports evaluating policy decisions and outcomes.

Scientists and policymakers acknowledge the importance of developing methods to communicate uncertainty about climate science in ways that avoid misunderstandings and misuse (C.C.S.P, 2003;Nisbet and Mooney, 2007;Kahan et al., 2011). Existing approaches often follow a “predict then act” framework, starting with climate science and characterizing the uncertainty of future climate change, then using this information to evaluate the desirability of policy decisions. This is often the method familiar to scientists. However, there are other approaches, such as robust decision-making, that frame uncertainty in a way more usable by characterizing uncertainty in the context of the decision task and outcomes. Robust decision-making includes three key concepts that differentiate

it from the predict than act approach. First, instead of using a single view of the future, multiple views of the future characterize uncertainty. Second, robust decision making uses the idea of robustness rather than optimality to assess alternate policies, often focusing on tradeoffs instead of strictly ranking alternatives from best to worst. Lastly, this method identifies the uncertainty most important to the decision-making task. Particular decisions provide the context to characterize the uncertainty (Lempert et al., 2004).

Most current methods for and research on visualizing uncertainty are explicit in nature (Davis and Keller, 1997a; Davis and Keller, 1997b; Cliburn et al., 2002; Zhang and Goodchild, 2002; Aerts et al., 2003b; Devillers and Jeansoulin, 2006b). Explicit uncertainty visualization directly identifies gaps, errors, and unknowns through quantitative values (including error bars or flows as shown in Figure 2.1) or qualitative estimations (as shown in Figure 2.2). Uncertainty is conceived of, and evaluated as, unique information, related to, but not the same as, the underlying data. Often, these values are not clearly or easily related to the decision task or the potential outcomes of policy decisions.

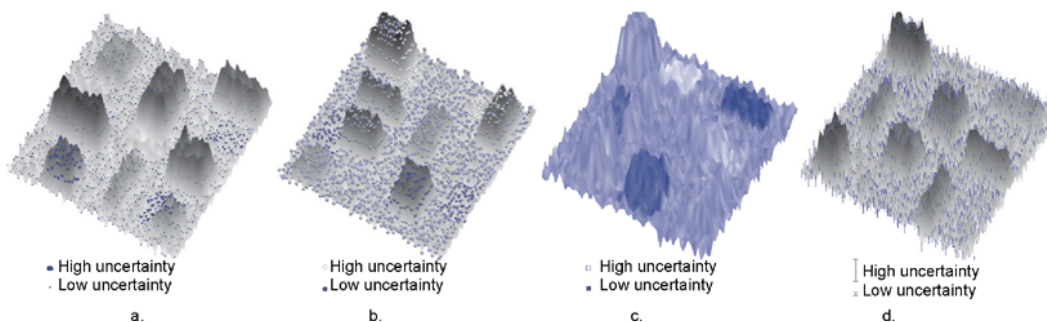


Figure 2.1. Uncertainty shown through scaling the size of glyphs (a), varying glyph color (b), using color to represent uncertainty (c), and error bars (d) (Sanyal et al., 2009)

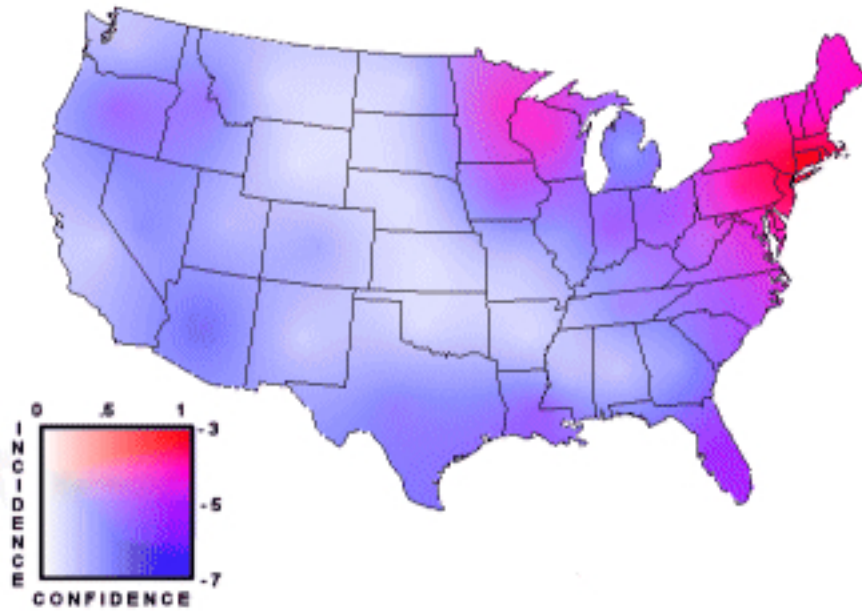


Figure 2.2. Lyme disease prediction uncertainty depicted as confidence (Luengo, 2008)

Implicit uncertainty visualization, by contrast, is context dependent. The specific decision task informs the definition, interpretation and, potentially, the representation of the uncertainty. Here, specific values of uncertainty are not quantified, but instead representations focus on showing the effect of uncertainty on policy decision outcomes. Uncertainty is treated as an inherent attribute of the data, and not as separate information. In this way, implicit uncertainty visualizations are similar to composite indicators in sensitivity analysis (Lilburne and Tarantola, 2009; Paruolo et al., 2012) aggregating uncertainty and decision outcomes, which support increased understanding of the relationship between uncertainty and decisions, provide a visual method to evaluate the robustness of a decision in the face of uncertainty, and enhance communication of uncertainty and outcomes between scientists and decision makers. Reframing uncertainty in

this way, it is possible to explicitly define uncertainty (such as providing probability for a projection), and then use implicit methods for visualizing that uncertainty (visualizing the range of probability values for several different projections).

Outcome spaces visualize outcomes and uncertain variables as a continuous variable space. For a given policy decision, possible outcomes are plotted for the full range of values for two or more uncertain variables considered significant to the decision problem. For example, in water simulation, future projections for river discharge might range from a decrease of 10 percent to an increase of 30 percent (this represents the uncertainty in the decision problem). In traditional approaches, if water managers wished to evaluate the impact of a policy on ground water, they would have to run the model several times for each potential discharge value, for a single policy scenario. Each model run would result in one discrete ground water value. Evaluation of the outcome of one or more policy decisions requires comparing these outputs. Outcome spaces in contrast, visualize the full range of possible outputs for one or more uncertain variables for a given policy scenario. This method represents outcomes of policy decisions for all possible values of the uncertain variable(s), providing a continuous range of outcomes. Classifications such as sustainable/unsustainable, favorable/unfavorable, high/moderate/low risk offer a means for decision makers to compare projected results for multiple policy scenarios. Figure 2.3 presents a schematic outcome space. With this approach, the policy decisions no longer produce single discrete outcomes, but a continuous field of possibilities.

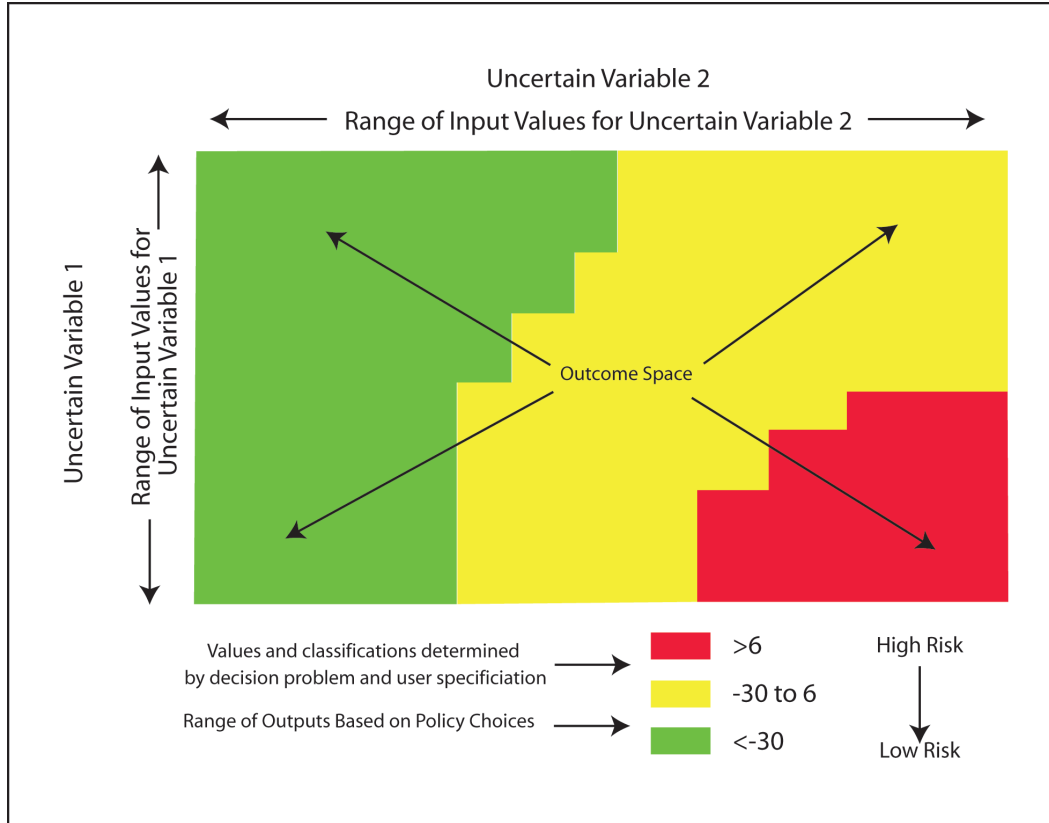


Figure 2.3. Implicit representation of uncertainty visualized as continuous values in an outcome space. Uncertain variables considered important to the decision problem are used as the axes. A model is run for the full range of uncertain values based on a set of policy decisions. The resulting outcomes for all model runs are shown as a continuous field in the outcome space.

Outcome spaces frame uncertainty in the context of a specific decision problem, similar to methods in robust decision-making. Individuals frame decisions based on their experiences, opinions and understanding of a problem. Accounting for these decision frames requires tailoring information to specific audiences, decisions, and mediums (Nisbet, 2009). Framing helps users relate core ideas to their own experiences, by placing uncertain information in context and making it relevant to the decision problem. Greater emphasis is placed on

some pieces over others to narrow down complex questions. Technical details vital to the understanding of science may not matter when deciding what should get done, who should do it, or why an issue even matters (Nisbet and Mooney, 2007). In water management, for example, the specific range of discharge values may not matter to decision makers, while the range of ground water draw down which results from these uncertain values might prove very important in making policy decisions on water rationing.

This chapter describes outcome spaces as a method for communicating uncertainty in climate change science to decision makers. As a context dependent approach, this chapter begins with a review of uncertainty in climate science and existing methods for communicating uncertainty.

2.3 Uncertainty in Climate Science Research

Climate models use quantitative methods to simulate the interactions of complex processes in the atmosphere, oceans, and land surfaces, projecting factors that would influence future conditions, such as population, land use, technology, and economic development. Simulations of future climate under climate change conditions contain a range of uncertainties in the spatial structure, scale, and timing of events and changes. These uncertainties result from numeric and structural differences between models, biases in datasets, and unknown processes in environmental and climate systems (Wu et al., 2005; Mearns, 2010). Assessing the suitability of a given model requires researchers to quantify several sources and forms of uncertainty within individual models as well as between models (Wu

et al., 2005;Mearns, 2010). Evaluation of these uncertainties presents the challenge of identifying specific probabilities for each model and input variable (Mearns, 2010).

Climate models provide discrete predictions about future climate conditions. While researchers strive to develop better models as well as quantifications of statistical uncertainty, identifying methods to weight these results based on the quality of the model and inputs are not widely used. The International Panel of Climate Change (IPCC) reports, for example, use multiple emission scenarios for future climate conditions, each with different assumptions (Ha-Duong et al., 2007;Schenk and Lensink, 2007). Models based on these assumptions are given equal weight, assumed to provide the same level of information about future climate conditions. Without guidance on how to interpret these multiple models, decision makers are left with multiple climate scenarios to consider, without any indication regarding the veracity of any one scenario (Ha-Duong et al., 2007;Schenk and Lensink, 2007). Future climate projections from each model developed using these emission scenarios, as well as how the differing assumptions of the scenarios affect outcomes of policy decisions in the model, are a form of implicitly defined uncertainty.

Research into the uncertainty of projections (outcomes) that results from comparing output from differing models exists, but efforts focus on manipulating the inputs to the models and quantitatively describing differences in the outputs as discrete uncertainty descriptions. For example, in an effort to explore the uncertainty of a hydrologic model of the River Thames, New et al. (2007) applied

probabilistic information while varying the parameters of the model. The researchers evaluated the difference in the predicted discharge as a means to show the uncertainty of the outputs. While the methods allowed researchers to identify both positive and negative changes in predicted flows, which differed from the single parameter runs of the model, these outputs exist as information separate from the underlying uncertainty. This explicit evaluation does not produce information about the relationship between the range of uncertainty and future river discharge projections. Providing this information offers a step towards integrating climate uncertainty into the process of decision-making.

2.4 Framing Uncertain Science for Decisions Under Uncertainty

Decision-making is the process that people go through to choose between alternatives or courses of action. Research in the psychology of decision-making focuses on the processes through which beliefs (knowledge, expectations) and desires (personal value, goals) merge and result in a decision (Hastie, 2001).

Decision problems are defined by the alternatives, consequences, and probabilities involved with a particular decision. Characteristics of the decision maker heavily influence individual decisions. Individuals frame decisions based on the concepts and values they associate with a particular course of action (Tversky and Kahneman, 1981). This reliance on context means people may frame a decision in many ways. Different decision frames arise due to many factors, such as individuals with multiple goals, or by a group of decision makers,

with each member having different experiences, expectations, and conceptual understanding of the problem.

Decision-making under uncertainty involves the evaluation of both the likelihood and desirability of an outcome (Tversky and Fox, 1995). However, this often proves challenging as decisions are generally made without a definitive knowledge of all the factors that may influence an outcome. When faced with decisions under uncertainty, individuals often revert to heuristics, or abstract mental rules to determine a course of action. Heuristics efficiently generate satisfactory outcomes in frequently encountered situations, as individuals learn to apply heuristics that result in the most favorable outcomes, reducing the complexity of assessing the alternatives and potential outcomes in these frequently met problems. Of course, there is no guarantee that, in any specific instance, heuristics are applicable for new situations or problems or will always generate the most favorable outcome (Patt and Zeckhauser, 2000). Because they are used and reused in different situations, incorrect heuristics can result in systematic errors and bias in decision-making (Tversky, 1974; Tversky and Kahneman, 1974).

This aptly describes decision problems that consider the impact of climate change, while illustrating the complexity of integrating climate into policy solutions. Decision-making requires evaluation of both the likelihood and desirability of an outcome. As mentioned previously, specific likelihood (probabilities) of climate models, conditions or relationships are often unknown. When expected or necessary information is missing, attempts to apply existing

heuristics using information contrary to your decision frame may fail or result in poor decision-making results.

Applying decision frames to science communication is working its way into applied research in decision-making under uncertainty. For example, in robust decision making, decision makers evaluate the outcomes of policy actions across a range of future possible conditions (uncertainties), building on decision makers experience managing highly uncertain situations while identifying and selecting strategies that perform well across the range of uncertainties. Groves and Lempert (2007) implemented robust decision-making in work with water managers in California to identify water policy options that were robust against the uncertainty of future climate change (Groves and Lempert, 2007;Groves et al., 2008). Researchers found that providing the water managers with climate change scenarios that represented a reasonable range of future conditions allowed managers to assess possible adaptation strategies. This model of decision support allows users to explore the relationship between a range of uncertain conditions and decision outcomes.

2.5 The Complexity of Uncertainty Communication

Visual displays mediate the assessment and dissemination of scientific knowledge (Cleveland, 1984a;Cleveland, 1984b;Arsenault et al., 2006). Visualization can convey complex and dense information, not easily communicated through the written word, and as such, has been the focus of much research in the visual communication of science (Tufte, 1983;Cleveland, 1984b;Hedges, 1987). There

are many reasons that visual displays are powerful means to support the dissemination and validation of scientific knowledge. First, they are absolute, transforming abstract ideas and ephemeral phenomenon into fixed, invariable patterns discernible by a wide range of individuals, scientists, and the public alike. Second, they quickly convey an overall impression of research, accessible without a great deal of effort by the user. Visual displays effectively use human capacity for pattern recognition to make complex, often dense information that might otherwise be difficult to communicate through words alone, more easily accessible. Third, they are scalable, allowing the visualization of phenomenon that might otherwise be unknowable due to their abstract, temporal, or physical scale. Finally, visualizations can be combined, allowing the identification of relationships and connections that might otherwise be undiscovered (Arsenault et al., 2006). These characteristics lend to the critical role of visualization in science communication—they are powerful because they are persuasive (Latour, 1990). Visual representation supports the task of supporting validity of an individual's scientific work. As such, visual inscriptions are central in science communication.

Uncertainty visualization research exists in diverse application areas (Hunter and Goodchild, 1995; Goodchild, 2000; Lucieer and Kraak, 2004; Heuvelink, 2005; Devillers and Jeansoulin, 2006b; Goovaerts, 2006) from error propagation to identifying uncertainty in climate science, yet approaches to representing uncertainty are often similar. Much of this research addresses uncertainty from a scientific standpoint, representing uncertainty in explicit and quantifiable ways, with the intention of developing widely applicable methods of

representation (Davis and Keller, 1997a;Cliburn et al., 2002;Zhang and Goodchild, 2002;Aerts et al., 2003a;Aerts et al., 2003b). In decision support, statistical and complex scientific representations may not be usable or beneficial for developing insights about the relationships between uncertainty, decisions, and outcomes. Moreover, while *uncertainty visualization* is considered either irrelevant or detrimental for successful data communication and insight generation (Cliburn et al., 2002;Slocum et al., 2003;Brugnach et al., 2007), decision makers often view *uncertainty* as potentially integral to the framing of a problem (Pahl-Wostl et al., 2007;Brugnach et al., 2008). This contradictory view of the uncertainty visualization as detrimental and uncertainty (not visually represented) as beneficial suggests that in decision support settings, a general awareness of the presence of uncertainty may be more important than knowing the specific form (or quantity) of uncertainty.

Several efforts in recent cartographic research have sought to bridge the gap between research and application as a means to facilitate the incorporation and use of visual uncertainty information (Cliburn et al., 2002;Aerts et al., 2003a;Bisantz et al., 2011;Verstegen et al., 2012). Researchers have sought the most appropriate and effective means of representing uncertainty to map readers, carrying out experiments comparing representational techniques (Blenkinsop et al., 2000;Slocum et al., 2003;Viard et al., 2011). A common approach is to begin with the adaptation of Bertin's (1983) visual variables, along with additional variables such as transparency, saturation, and clarity, for the representation of uncertainty (MacEachren, 1992;Slocum et al., 2004). Advances in computer

systems open new possibilities for uncertainty representation, including the interfaces that allow users to manipulate the display of uncertainty by deciding how and when to display uncertainty information (Fisher, 1994; Ehlschlaeger et al., 1997; Miller et al., 2003).

A majority of existing research focuses on explicit uncertainty visualization. For instance, Gershon (1998) proposed two general categories of representation strategy: intrinsic and extrinsic. Both categories rely on an explicit definition of uncertainty. Intrinsic techniques integrate uncertainty in the display by varying an existing object's appearance to show associated uncertainty. Although the uncertainty and "object" are depicted in a single representation, for example fuzzy lines to represent vague boundaries, uncertainty is still shown as separate from the underlying feature. Extrinsic techniques rely on the addition of geometric objects to highlight uncertain information, making the explicit nature of the visualization apparent through the use of separate objects to depict uncertainty. Explicit methods (including both intrinsic and extrinsic visualization) offer techniques for representing uncertainty of specific features or objects. Implicit visualization integrates the representation of uncertainty, data, and decision outcomes.

Often the individual decision frames of the user are not considered in current uncertainty visualization research. Moreover, when the importance of potential differences in users has been acknowledged, it is often included as an ancillary study, and not as the explicit and main focus of the study. The primary focus of most experiments has been on design of the representation and the ability of individuals to identify specific uncertainty values from those representations.

MacEachren et al. (1998) developed and tested a pair of intrinsic methods for depicting “reliability” of data on choropleth maps used in epidemiology. Newman and Lee (2004) evaluated both extrinsic and intrinsic techniques for the visualization of uncertainty in volumetric data comparing glyph-based techniques, such as cylinders and cones, with color-mapping and transparency adjustments. Leitner and Buttenfield (2000) focused on the alteration of the decision-making process by changing the representation, through systematically altering Bertin’s visual variables. In these cases, researchers made important gains in understanding the development of uncertainty visualization, but the usability of these visualizations by individuals trying to assess data for decision-making under uncertainty was never a particular focus.

Geographic uncertainty visualization research has also considered the influence of the user’s experience as an independent variable (Blenkinsop et al., 2000;Cliburn et al., 2002;Aerts et al., 2003a). In these studies, the focus has been on differences between novice and expert users, while factors such as comfort with uncertain information and their experience in making decisions are often downplayed. Blenkinsop et al. (2000) examined the performance of two user groups, one expert, and one novice, in determining classification uncertainty. While researchers discussed differences in users, results focused on the effectiveness of representation and not the manner in which different user experience influenced this effectiveness. Cliburn et al. (2002) focus on differences in decision makers in their development and testing of a visualization environment meant to allow decision makers to visualize the results of a water-

balance model. The study focused specifically on the effectiveness of intrinsic and extrinsic communication of explicit uncertain values in a decision support setting. Decision makers were overwhelmed by the complex extrinsic methods, while experts were able to access and use the detailed information more readily. For non-expert users, intrinsic methods that provide a more general representation of uncertainty were suggested as preferable to more complex and detailed forms of representation. Researchers proposed that to increase the usability of an environment, it is important to incorporate feedback from users, usability experts, and decision makers. Aerts et al. (2003a) also focused specifically on what uncertainty representations, toggling animation and a side-by-side static comparison, end users found most useful for specific tasks.

While there are a multitude of examples in existing literature of statistical and explicit representation of uncertainty, methods for linking uncertainty visualization and decision outcomes are lacking. In decision support settings, the goal is to support more informed judgments and evaluations by decision makers, and to provide insight into the effect of uncertainty on policy options. Existing methods do not offer means to evaluate or explore uncertainty in this manner. The disjoint between attitudes towards uncertainty and uncertainty visualization suggests that existing methods do not fit user decision frames. As previously discussed, decision frames encompass the perspectives used by decision makers to establish the boundaries and constraints of a decision problem and particular course of action (Tversky and Kahneman, 1981). In decision settings, focusing on the effect of uncertainties on policy outcomes offers a method to incorporate user

decision frames, allowing users to explore uncertainty and gain insight into the relationship between uncertainty and the (potential) consequences of their decisions. When reframing uncertainty in this way, the relationship between uncertainty visualization, outcomes, and decisions is emphasized over explicit representation frameworks that disassociate the method from the user.

2.6 Uncertainty Visualization as an Outcome Space

This research considers the application of outcome spaces as a method to visualize uncertainty in water planning due to climate change. A conceptual outcome space was developed for WaterSim, a simulation model of water supply and demand for the Phoenix Metropolitan area that integrates land use, climate change, water policy, and population growth. WaterSim allows users to adjust settings related to water supply, drought, population growth, agriculture, policy choices, and climate change to weigh the impacts of these choices on future water supply and sustainability (Gober et al., 2010).

Water systems are traditionally operated under the assumption of stationarity—the idea that natural systems fluctuate within an envelope of variability that does not change (Milly et al., 2008). Climate change challenges the stationarity assumption; as these changes alter the rate of river discharge, mean precipitation, and other aspects of the water cycle and water supply. Considering the implications of climate change on stationarity challenges the decision frames of water managers, often requiring them to evaluate multiple discrete scenarios based on varied climate change assumptions (Milly et al.,

2008; Craig, 2009). Uncertainty visualization offers an opportunity for decision makers to explore the relationship between climactic uncertainty (a challenge to the stationarity assumption) and the outcomes of policy decisions. This approach adapts the methods of robust decision-making by providing a visual method to evaluate the relationship between uncertainty and policy outcomes. The methods presented here conceptualize this relationship as a mapped space, where the impact of uncertain variables on decision outcomes can be explored.

Outcome spaces are adapted from visualization methods presented by Lempert, Popper, and Bankes (2003) for mapping Landscapes of Plausible Futures. The landscapes provide decision makers with interactive visualizations intended to aid in exploration of the output of robust decision-making scenarios. In these landscapes, the axes represent two uncertain variables important to the decision problem. Each intersection point between values on the axes represents the outcome of a given decision. The area within the landscape represents all possible outcomes (defined in this research as the outcome space) that can further be classified as regions of most/least robust outcomes.

For the purposes of this application, uncertainty is operationalized as the effect of climate change on the assumption of stationarity, in this case, changes to the historical flows in the Salt/Verde Rivers and the Colorado River. For WaterSim, the outcome space consists of the net cumulative change in groundwater (in thousand cubic meters) resulting from running a single set of policy choices in WaterSim. Instead of geographic coordinates, the uncertain variables represent the coordinates (on each axis), and the value in the outcome

space represents the attribute at that locations. This method of uncertainty visualization acts as an uncertainty map, representing all possible outcomes for a specific policy choice or decision based on two uncertainty variables. The conceptual model here incorporates two variables, but can be extended to multivariate representations.

With existing methods in WaterSim, users must select a single assumption for the future flow of the Salt/Verde River and Colorado River. These assumptions represent predicted percentages of historical flows on these rivers, such as 80% of historical flow, and account for the impact of climate change on flow. Once these assumptions are set, users use the model to select policy choices related to future population growth, agricultural land retirement, and residential housing density. The model is run for each set of policy choices using the assumed percentage of historical flows on the two river systems. If users want to see how changes in the assumptions about the rivers affect their policy decisions, they must rerun the model for each new assumption. This can result in thousands of possible outputs.

Outcome spaces eliminate the need to run the model for different assumptions about the flows on the rivers. Instead, policy decisions made by the user are run for all the possible combinations of future flows on the two rivers. These results are then output into a single outcome space for that policy run. A conceptual representation of an outcome space for WaterSim is shown in Figure 2.4. Actual outputs from WaterSim into a visualization environment are shown in Figure 2.5.

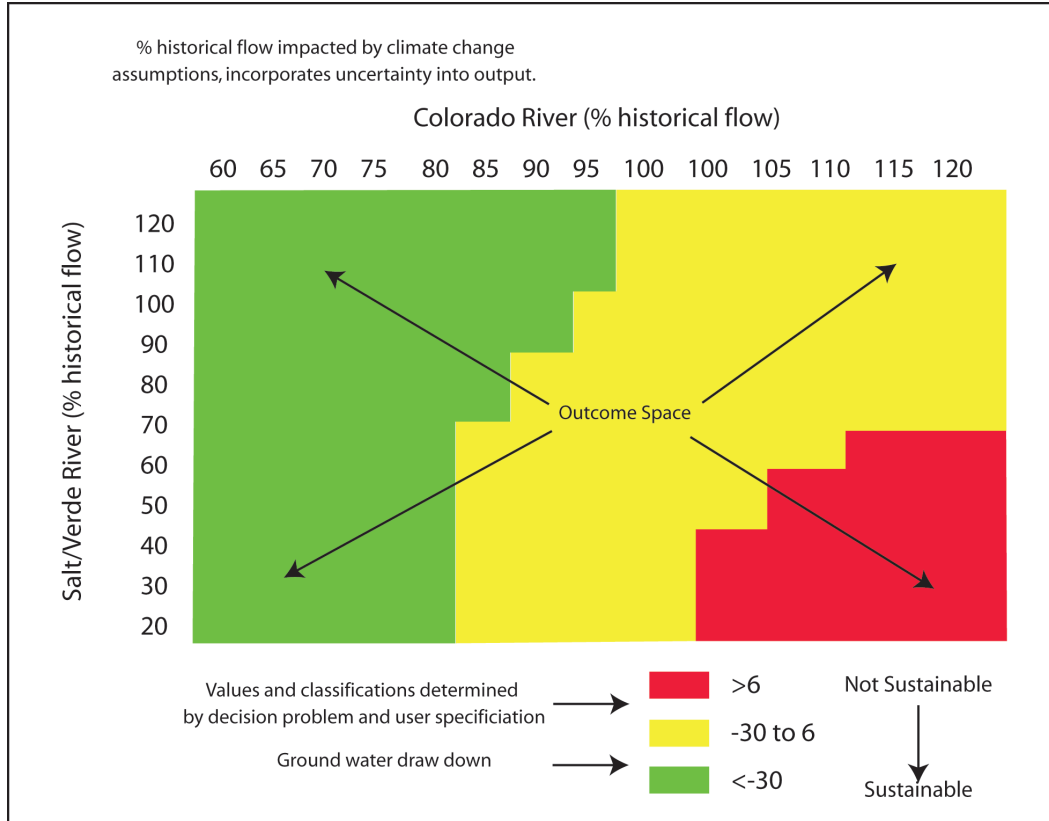


Figure 2.4. Conceptual outcome space showing change in ground water based on uncertain river flow

The vertical and horizontal axes of the landscape represent the future flows of the Salt/Verde Rive and the Colorado River as percentages of historical flows (Figure 2.5). This represents two of the significant uncertainty variables in the WaterSim model, incorporating the uncertain affect of climate change on river flow (one challenge to the stationarity assumption). The outcome space represents the net cumulative change in groundwater. The values mapped in the outcome space are output when the model is run after the selection of certain policy decisions, such as regulation of future population growth rates, retirement of agricultural land, and residential density. As the policy decisions are implemented

in WaterSim, the model runs for all possible river flows for the two rivers, resulting in thousands of outputs. These outputs are then mapped to the outcome space. This one space represents the full range of outputs for the specified policy choices. Additionally, areas within the outcome space are symbolized using a range of sustainable to not sustainable based on the amount of change in ground water usage.

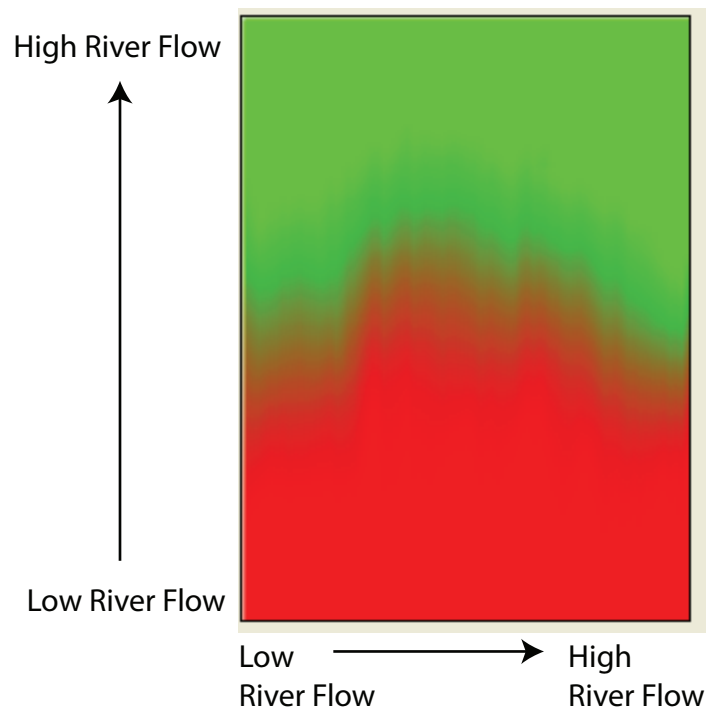


Figure 2.5. WaterSim outcome space (conceptual visualization environment). The values here represent a single policy decision implemented by the user run for all combinations of projected flows on the Salt/Verde River and Colorado River.

While the individual values mapped in the outcome space are discrete values from single runs of the model, when viewed as a continuous space, they present an overall view of the impact of both the policy choices and the climate uncertainty. As decision makers work through several possible policy alternatives, they can evaluate results for the entire range of possible output for those policy choices. This offers a chance to alleviate the concern that a policy choice that works well under one climate scenario (or one set of river flows) may not be the best choice under alternate conditions. Additionally, decision makers can compare the overall effect of differing policy decision, and question whether one policy poses more or less risk than another. For example, if one set of policy choices results in a majority of the outcome space showing as sustainable, that might pose less risk than policy choices that divide the outcome space evenly into sustainable/not sustainable. This removes the focus from climate uncertainty and places it on the actual policy choices and alternatives that make up the decision problem.

2.7 Conclusions

Scientists are challenged with the task of not only communicating uncertain science results to policymakers, but of providing information in a manner that overcomes the desire of decision makers to wait until more is known or the uncertainty is reduced (O'Neill, 2008). This research speaks to the challenge of overcoming this desire to wait to learn more, by evaluating methods to incorporate uncertainty that resemble decision-making processes and heuristics.

Outcome spaces support assessment of the relationships between uncertain variables and the results of policy decisions. Representing uncertainty implicitly as a physical space moves away from discrete results that imply a level of certainty to a continuous range of results that reflect the influence of uncertainty on policy outcomes. This allows decision makers to focus attention on the policy decisions and not on the technical aspects of what is unknown. Outcome spaces do not hide anything from decision makers, but instead provides a comprehensive representation in a context with which they are familiar, policy decision outcomes.

This research highlights the importance of considering the decision-making context of the user when evaluating and presenting uncertain information. Attempts to develop methods for representing uncertainty that span multiple forms and sources, varied domains, and all users do not address the decision frames of users or context of the decision problem. Outcome spaces address both the need to communicate uncertainty to users while also allowing them to work through ways to address uncertain conditions. If the goal is to support effective decision-making, and ultimately action towards mitigating and adapting to climate change, then the challenge of incorporating specific decision contexts into science communication is one with tangible benefits.

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Chapter 3

USING DECISION THEORY MODELS TO CONCEPTUALIZE AND DEVELOP UNCERTAINTY VISUALIZATION METHODS

This chapter will be submitted to the Annals of the Association of American Geographers in May 2012. This work was co-authored with Elizabeth A. Wentz. As first author, I was responsible for writing and formatting the manuscript for journal submission. I will respond to referee and editorial comments during the peer-review process.

3.1 Abstract

Public policy decision makers often contend with uncertain conditions and data. GIS and geovisualization researchers acknowledge the importance, and ubiquitous nature, of uncertainty in geographic data. Although there appears to be agreement between decision makers and researchers in the presence and importance of uncertainty in decision support, there appears to be a disjoint in approaches to incorporating uncertainty into decision models, and the resulting decision support tools.

Uncertainty for both decision makers and GIS researchers refers to incompleteness in knowledge in the past, present, or future. The distinction between decision makers and GIS researchers, however, does not arise from how they define uncertainty, but in how they conceptualize uncertainty.

Decision makers regularly contend with uncertainty in how current conditions or proposed policies will affect the future, resulting in a

generalized concept that relates uncertainty of future conditions to policy outcomes. For GIS and geovisualization researchers, uncertainty more often reflects what is not known about the relationship between a measured or predicted value and the actual or true value, resulting in a generalized concept of uncertainty that covers a wide range of data characteristics such as error, accuracy, and reliability. This work contends that the gap between research and practice (Brown and Vari, 1992) stems from this difference in conceptualization.

To bridge the gap between these conceptualizations of uncertainty, we examine in detail how decision makers conceptualize uncertainty and then identify visualization methods, referred to as implicit uncertainty visualization, that reflect this view of uncertainty. Approaching uncertainty visualization research through the lens of decision science creates a new approach to uncertainty, which can make sense to decision makers as well as GIS and geovisualization researchers. Bridging the gap in the conceptualization of uncertainty opens up opportunities for GIS and geovisualization researchers to develop uncertainty methods and tools that help decision makers better deal with uncertainty in practice.

Keywords: uncertainty visualization, decision-making models, decision support

3.2 Introduction

Public policy decision makers, defined here as individuals who have useful decision-making knowledge or the ability to enact a policy, understand that uncertainty is an inescapable component of decision-making (Lipshitz and Strauss, 1997; Maidment and Parzen, 1984; Schlossberg and Shuford, 2005; Dong and Hayes, 2012). Similarly, GIS and geovisualization researchers recognize the importance of identifying and evaluating uncertainty in analysis and outputs for decision support (MacEachren, 1992; MacEachren et al., 1998; Blenkinsop et al., 2000; Bastin et al., 2002; Bostrom et al., 2007; Goodchild, 2007; Moss, 2007; Pebesma et al., 2007). Nevertheless, specific visualization methods and tools for incorporating uncertainty into GIS are not widely used or requested by decision makers (Goodchild, 2006; Roth, 2009). Moreover, research indicates that decision makers often view these types of uncertainty representations as a constraint to making decisions, which may lead them to avoid solutions that employ uncertain information or to overly rely on the results of prior similar decision tasks (Cohen and Wallsten, 1992; Reece and Matthews, 1993). Because there is agreement between decision makers and GIS and geovisualization researchers that uncertainty is important, yet disagreement in how to incorporate it into decision models, we see this as a discrepancy between the way decision makers and GIS researchers conceptualize uncertainty.

Uncertainty for both decision makers and GIS researchers is defined as incompleteness in knowledge in the past, present, or future. The distinction between decision makers and GIS researchers, however, does not arise in the

definition of uncertainty, but rather in how it is conceptualized. This distinction emerges through specific experiences with uncertainty, resulting in differing generalized uncertainty concepts. Decision makers regularly contend with uncertainty in how current conditions or proposed policies will affect the future. The resulting generalized concept of uncertainty is that the outcomes of differing policies are impacted by future conditions. For GIS researchers uncertainty more often reflects what is not known about the relationship between a measured or predicted value and the actual or true value. The generalized view of uncertainty therefore covers a wide range of data and model output characteristics, including error, accuracy, reliability, precision, and quality (Edwards and Nelson, 2001).

To bridge the gap between these conceptualizations of uncertainty, we examine in detail how decision makers conceptualize uncertainty and then identify visualization methods that reflect this view of uncertainty. In particular, we examine decision making under conditions of deep uncertainty (Cox, 2012). Deep uncertainty refers to conditions where the relationships between variables, the probability of future conditions, and the suitability of alternative outcomes are either unknown or are not agreed upon among key constituents (Lempert et al., 2003). Through literature in both decision science and uncertainty visualization, this work presents implicit uncertainty visualization methods (Deitrick, 2012) as a way to connect researchers' and decision makers' understanding of uncertainty for use in GIS for decision support.

3.3 Literature Review

To motivate our approach to develop geovisualization methods that utilize theories in decision science, the literature presented here synthesizes prior work in two distinct areas. We begin with a detailed review of the decision science literature. We then describe how this work is related to current uncertainty visualization approaches.

3.3.1 Decision Making Under Uncertainty

Decisions, particularly those with associated uncertainty, represent often ill-structured problems in which the decision maker assesses two or more alternatives and then commits to one (Jonassen, 2012). For example, decisions of where to dispose of nuclear waste safely are ill structured in nature; there are conflicting data, participants often do not agree about appropriate assumptions, and there are often conflicting values. The process to evaluate alternatives and commit to a single choice as a course of action is a merger between individual expectations, motives, beliefs, and desires (Hastie, 2001). This impacts decision-making by influencing the way individuals evaluate the consequences of their choices (Hastie, 2001).

Most policy-based decision problems are complex and contain inherent uncertainty. These problems require iterative decision-making, where the selection of an alternative lays the foundation for evaluating the next decision. For example, a city's decision to restrict water usage would lead to additional decisions about how and when to implement restrictions.

There are three decision science theories that explain how and why people make decisions in conditions with uncertainty. Normative models focus on how people *should* make decisions in order to facilitate better decisions through structured analysis. Conversely, descriptive models focus on how people actually make decisions in practice. Prescriptive models focus on what actual decision makers can and should do, incorporating both the specific context of the decision problem and the needs of the decision maker. In this way, prescriptive models are based on both normative and descriptive theory. We describe these three models in detail here.

3.3.1.1 Normative Decision Making Models

Normative decision making models describe how decisions ought to be made. In normative models, decision are divided into four basic components: (1) alternatives, (2) possible future conditions of the world, (3) probabilities of the future conditions of the world, and (4) information about outcomes of the alternatives under differing future conditions (Jonassen, 2012). These models assume decision makers are rational, capable of working through complicated decisions, fully informed, and that the uncertainties and probabilities for given alternatives are agreed upon, knowable and known. The goal of normative theories of decision-making is not to explain or predict behavior, but to facilitate better decisions through structured analysis of decision alternatives and the probabilities associated with those alternatives (Schmoldt, 2001).

Computer-based decision support tools designed to support decision-making under uncertainty are often normative in nature, focusing on identifying, quantifying, and explicitly representing probability and uncertainty (Ascough II et al., 2008; Manson et al., 2002; Sevcikova et al., 2007). For example, a widely known decision support tool is UrbanSim, which consists of nine individual models that integrate household location and mobility, economic location and mobility, employment location and mobility, land pricing, real estate development, and transportation (accessibility). Sevcikova et al. (2007) developed probability methods for assessing uncertainty in UrbanSim in the land use and transportation policies. They found that significant sources of uncertainty in the system must be identified to carry out a probabilistic assessment of uncertainty. This approach assumes that the uncertainties are known, knowable, or agreed upon by those involved in the decision task, and that decision makers can rationally work through these probabilities to reach a decision. These assumptions are normative in nature.

While the normative approach is beneficial for decisions where uncertainty can be identified and quantified through specific probability distributions such as the UrbanSim example, this poses a significant disadvantage for decision-making under conditions of deep uncertainty. Deep uncertainty exists in decisions where there is disagreement on the state of future conditions and the probability distributions of alternatives and outcomes cannot be known or agreed upon (Gober et al., 2010; Lempert et al., 2003). Under conditions of deep uncertainty, the information needed to identify the optimal solution cannot be

agreed upon or often do not exist (Polasky et al., 2011). This leads to challenges in developing probability based decision support tools for complex, deeply uncertainty problems, such as climate change, economic futures, and transportation infrastructure planning.

3.3.1.2 Descriptive Decision Making Model

Descriptive models of decision-making, in contrast to normative models, explore how people actually make decisions. In practice, decision makers rarely select alternatives based on purely rational choices the way normative models suggest, but instead base decisions on information about the decision alternatives combined with affective feelings and emotions about those alternatives (Slovic et al., 2004; Slovic et al., 2007). This is particularly true for decision makers who have had prior experience in the particular decision-making situation. In domains where decision makers are knowledgeable about decision problems, they have beliefs, biases and experiences with those problems, resulting in decisions that are context and domain dependent (Cohen and Freeman, 1996; Rettinger and Hastie, 2001; Jonassen, 2012). Research into descriptive models of decision making describe the influence of framing and heuristics, which we explain here.

In descriptive models, decision problems are *framed* by the current conditions (context and domain), unconscious emotions, past experiences and expectations a decision maker associates with a particular course of action (Goffman, 1974; Tversky and Kahneman, 1981; Gamson et al., 1992; Bedford and Burgess, 2001). Framing refers to the different ways decision makers make sense

of a decision problem, by selecting the relevant aspects, connecting those into a meaningful whole, and identifying the boundaries of the problem (Takemura, 1994; Bedford and Burgess, 2001; Dewulf et al., 2004). The frame adopted by a decision maker is controlled both by the presentation of the problem (external) and the personal characteristics, experiences, biases and beliefs of the decision maker (internal) (Goffman, 1974; Tversky and Kahneman, 1981; Gamson et al., 1992; Takemura, 1994; Bedford and Burgess, 2001).

Different decision frames arise due to many factors, such as one person who has multiple or changing goals, or by many different decision makers, each having different perspectives, experiences, or conceptual understandings of the problem (Jonassen, 2012). For example, when presented with a plan to open a previously closed preserve to recreational activities, developers, environmentalists and policy makers might frame the plan in different ways. The developer may see the plan as a way to build amenities on the way to the area, the environmentalist might view the plan as a threat to the habitat, and the policy makers might see the plan as an opportunity to bring new visitors to the city and increase tax revenue. It is the same plan, but framed differently based on the desires, experiences and biases of the individuals.

There are mixed opinions about the effect of external framing on the ultimate decision made. Tversky and Kahneman (1981) show that the manner in which a decision problem is presented to decision makers, such as whether it is framed positively or negatively, can influence the way decision makers approach a problem, and ultimately their decision (referred to as the framing effect).

Takemura (1994), in contrast, suggests that the more a decision maker clarifies and works through the information involved in the decision problem, the less likely framing effects would occur. This is relevant for decision making under deep uncertainty where decision problems, data, and alternatives may be extensively reviewed and debated.

Descriptive models of decision making also refer to the use of *heuristics*, or abstract mental rules, to describe how decision makers determine a course of action. Individuals learn to apply heuristics that have in the past resulted in favorable outcomes. This approach reduces the complexity of assessing alternatives and potential outcomes in frequently met problems (Patt and Zeckhauser, 2000; Spiegelhalter et al., 2011). Heuristics can be evolutionary (partially hard wired), developed through individual learning, or selected and taught through social processes (Gigerenzer and Gaissmaier, 2011). For example, the heuristic of imitating the successful, speeds up learning about uncertain decision problems, and is useful in situations where decision makers have little knowledge (Hertwig and Herzog, 2009). Similarly, decision makers may develop internal narratives (stories) about the problem in an effort to minimize negative, or maximize positive, impacts on the outcomes of a decision (Jonassen, 2012). Heuristics are not good or bad, but their effectiveness depends on whether people select the proper heuristic for the decision problem. Since heuristics can be learned, this means that new heuristics (or approaches) to working through uncertain problems can be taught (Gigerenzer and Gaissmaier, 2011). Tools that

integrate these psychological components of decision making may better support how people actually work through uncertain decision problems.

The strategies used by decision makers to cope with uncertainty can be grouped into three basic strategies: reducing, acknowledging and suppressing (Lipshitz and Strauss, 1997). Strategies for reducing uncertainty include collecting additional information prior to making the decision or waiting for additional information before making a decision (Lipshitz and Strauss, 1997). The additional information does not necessarily need to be correct, but needs to support the perception of consistency in what is known (Brashers, 2001). When reducing uncertainty is not feasible or possible, decision makers employ methods to acknowledge uncertainty by accounting for that uncertainty when selecting a potential course of action and identifying ways to manage or avoid the potential impacts of the uncertainty (Lipshitz and Strauss, 1997;Chalkidou et al., 2007). Strategies for suppressing uncertainty include ignoring or altering the uncertain information (denial). Additionally, decision makers may suppress uncertainty with cursory attempts to reduce or acknowledge uncertainty (rationalization) (Lipshitz and Strauss, 1997;Milkman, 2012).

These strategies may be beneficial for problems where the possibility of obtaining additional information or waiting until additional information is available or is feasible, or when knowledge about uncertainty is sufficient to develop discrete courses of action to manage the risks. However, these strategies assume that better knowledge will be achieved with more work, research, time or effort allowing deep uncertainties to be converted to manageable statements of

risk. The challenge is that more work and more information may not reduce uncertainty, and conversely, may even expose previously unknown uncertainties. Moreover, some uncertainties may be irreducible, no matter the amount of additional information. Therefore, some decisions must proceed in the face of these deep uncertainties. As a result, deeply uncertain decision problems require methods for evaluating policies in the face of these deep uncertainties.

3.3.1.3 Prescriptive Decision Making Model

Prescriptive decision models acknowledge that humans can be poor decision makers. These models are concerned with the development of tools to support and enhance the decision-making process, focusing on the development of tools that fulfill two goals. Tools must be both useful to decision makers, and decision makers must actually be able to use them. In effect the goal of prescriptive models is to prescribe how decision makers can approximate normative decision processes in practice. The result is a synthesis of normative and descriptive models (Brown and Vari, 1992).

Prescriptive theories have resulted in varied approaches to bridge decision-making theory and practice. Some approaches focus on a structured sequence of activities. For example, decision trees offer a means to graphically depict available decision alternatives, the uncertainty and probabilities associated with those alternatives, and evaluations/measures of how well each alternative meets the objectives for the decision problem (Kingsford and Salzberg, 2008). This approach assumes discrete alternatives with known or knowable

probabilities. For decision making under deep uncertainty, these probabilities may not be known, and the identification of a discrete set of alternatives that perform well over variable future conditions may not be feasible.

Scenario planning offers a means to better handle evaluation of variable future conditions. Scenario planning was developed to explore the long-term implications of decision alternatives where specific probabilities for each alternative are not known. Scenarios identify plausible futures, describing possible ways the future can unfold, both positive and negative, through the use of narratives and "what if" scenario creation (Bishop et al., 2007; Volkery and Ribeiro, 2009). Scenarios allow decision makers to better understand how policies behave over a range of future conditions, as well as clarify their perceptions of the problem. This approach allows groups of decision makers with competing social or political interests to find common ground for decisions, a key element in policy making (Volkery and Ribeiro, 2009). For example, "What if?" is a scenario based policy-planning tool for projecting future land use demands and identifying locations suitable for those land uses (Klosterman, 1999). "What if?" allows users to manually create alternate scenarios and to visualize the impact of those choices on projected future land use, employment, and population trends. While the system was evaluated and deemed "easy to use" (Klosterman, 1999), users would need to manually generate more and more scenarios to see the full range of impacts as the number of future states, policy alternatives and input parameters increase.

With many plausible scenarios for future conditions, static policies that perform well in many or even most of these futures are unlikely (Lempert, 2002;Lempert et al., 2003;Walker et al., 2001). Rather, addressing problems with deep uncertainty requires policies that are robust across a range of plausible futures, instead of being optimized for a single best estimate of future conditions, resulting in a continuous range of outcomes. Rather than an optimal policy that performs the “best” for a given future condition, the goal in robust decision-making is to identify policies that perform well over a number of possible futures, so that policies that are less sensitive to unknowns (deep uncertainties) (Coullelis, 2003;Lempert et al., 2003). Decision makers can then evaluate each robust policy in detail (Lempert et al., 2003).

In robust decision-making, decision support tools that support the assessment of this range of outcomes over uncertain futures would be advantageous over those that provide discrete solutions and probability estimates of uncertainty. Visualization is well suited for communicating this level of continuous data, as visualization can convey complex and dense information in a single view, that otherwise would not be easily communicated through individual images or the written word (Tufte, 1983;Cleveland, 1984;Hedges, 1987).

3.3.2 Uncertainty Visualization in Cartography and GIS

Current uncertainty visualization methods incorporate quantitative and qualitative estimates of uncertainty into geographic visualizations (Aerts et al., 2003;Bostrom et al., 2007;Dong and Hayes, 2012;Li and Zhang, 2006;Pham and Brown,

2003;Viard et al., 2011). A common approach to representing uncertainty is the adaptation of Bertin's (1983) visual variables. These visual variables include size, shape, value, orientation, color, and texture. Along with these variables, graphic variables, such as transparency, saturation, and clarity have also been proposed to represent the varying degrees of uncertainty as information separate from the attribute (MacEachren, 1992;Slocum et al., 2004).

To further distinguish the types of uncertainty visualization methods, Gershon (1998) proposed two general visualization strategies: intrinsic and extrinsic. Intrinsic techniques integrate uncertainty in the display by varying an object's appearance to characterize the associated uncertainty (Figure 3.1). For example, fuzzy lines to represent vague or unknown boundaries are used in place of crisp lines for more known boundaries. The geographic object and the uncertainty are represented together as a single entity. Extrinsic techniques rely on the addition of geometric objects to highlight uncertain information. For example, a choropleth map may illustrate pollution levels in a watershed. The addition of hatch marks of varying density would depict the level of uncertainty in the pollution levels at a given location. The intrinsic and extrinsic categories of uncertainty representation both reflect GIS researchers' conceptualization of uncertainty that there is a qualitative or quantitative value associated with data and model results (Figure 3.1).

evaluating whether users were able to identify specific uncertainty values (Blenkinsop et al., 2000), and assessing the impact of uncertainty visualization data identification (Hope and Hunter, 2007; Xiao et al., 2007). Newman and Lee (2004) evaluated both extrinsic and intrinsic techniques for the visualization of uncertainty in volumetric data by comparing glyph-based techniques, such as cylinders and cones, with color-mapping and transparency adjustments. They found that while each method was useful for identifying uncertainty in the scenario test, the glyph techniques were most beneficial overall out of those presented in their work. Leitner and Battenfield (2000) focused on the how inclusion of uncertainty information impacts the decision-making process, by changing the representation, through systematically altering Bertin's visual variables, finding that inclusion of uncertainty clarified mapped information and reduced the time it took for people to make a selection.

Some researchers have also asked decision makers to evaluate the effectiveness of uncertainty visualization for specific uncertainty values for decision support (Leitner and Battenfield, 2000; Cliburn et al., 2002; Aerts et al., 2003; Slocum et al., 2003; Goovaerts, 2006). Findings suggest that uncertainty visualization methods are effective for communicating specific uncertainty values, but that (Aerts et al., 2003; Cliburn et al., 2002; Goovaerts, 2006; Slocum et al., 2003). Aerts et al. (2003) compared static representations with dynamic toggling to visualize uncertainty in a water balance model. They found that planners and decision makers found the inclusion of uncertainty information useful, preferring the static representations to toggling between the maps. Leitner

and Battenfield (2000) found that including certainty information in maps resulted in similar or faster decision times compared to a basic map with no certainty information presented. Because they used the term 'certainty' rather than 'uncertainty,' they essentially evaluated whether a positive framing effects would benefit the user. Although each of these studies shows uncertainty visualization to be effective for identification of specific uncertainty values, they do not evaluate whether the tools are usable for decision support settings.

Cliburn et al. (2002) evaluated the impact of experience on the effectiveness of uncertainty visualization in a water balance model. Here experience was operationalized as users being either decision makers or domain experts. That study found that complex uncertainty visualization methods overwhelmed the policy experts (decision makers), while scientific experts were able to use detailed and complex visualizations more readily in decision-making. The decision makers participating in the study indicated that they did not like to see the uncertainty. This is an interesting result, since even though the decision makers found the less detailed visualizations effective for identifying areas of uncertainty; they did not find the explicit identification of specific uncertainty values beneficial.

3.4 Explicit and Implicit Uncertainty

In this section we introduce the concept of explicit and implicit uncertainty as a way to approach uncertainty visualization that is prescriptive in nature, bringing tools to support evaluation of uncertainty in decisions in a manner useful and

usable by decision makers. Explicit uncertainty is linked more to normative models, theoretically defining what decision makers should know about data and model outcomes. Implicit uncertainty is linked to both descriptive and prescriptive models, integrating what decision makers actually do in practice into tools to support better decisions.

Explicit uncertainties are gaps, errors, and unknowns displayed or represented through quantitative values (e.g., error bars) or qualitative estimations (e.g., more or less uncertain) (Deitrick, 2012). In explicit visualization, uncertainty is conceived of as specific values or measures, related to, but not the same as, the underlying data. GIS researchers use explicit uncertainty to evaluate uncertainty in data sources, models parameters, and results. Most current methods for visualizing uncertainty, as described above, are explicit.

Explicit approaches to uncertainty visualization for decision support share traits with the normative models of decision-making (as shown in Figure 3.2). Like normative models that build on how decision makers should make decisions, visualization features such as transparency or texture (MacEachren, 1992), focus on representing known uncertainties, assuming that better decisions result from evaluation these values. There is an inherent assumption that decision makers can use statistical estimates to evaluate policy options. For many of these methods, the probabilities of future conditions must be known or knowable, and the goal of using these methods is to improve decisions by identifying optimal solutions. For decision support settings, specific statistical estimates of uncertainty for discrete

alternatives do not reflect how decision makers approach decision-making under uncertainty in practice.

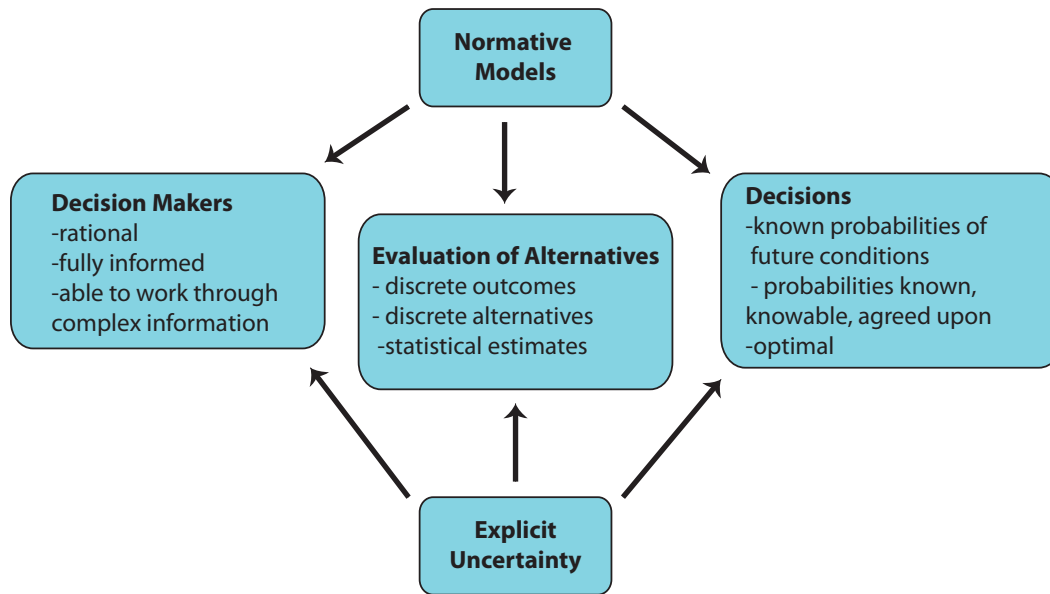


Figure 3.2 Explicit uncertainty as a normative model of decision-making

Implicit uncertainty represents how, in practice, decision makers consider a range of alternative decisions due to different data sources, model parameters, models, and policy choices (Deitrick, 2012). As such, the definition, interpretation and, potentially, representation of uncertainty is informed by the users and the domain. Implicit uncertainty is conceived of as being related to policy outcomes, so that the overall range of potential outcomes is as important as the geographic variability of the outcomes. Few geographic visualization methods represent implicit uncertainty.

Implicit visualization builds on descriptive decision approaches, acknowledging the impact of decision makers experience, emotions and knowledge on how they frame decision problems, without assuming that the probability of future conditions are known or knowable. The relationship between descriptive models and implicit uncertainty is illustrated in Figure 3.3. The goal of implicit visualizations is to develop tools that are both useful to, and usable by, decision makers in order to support more informed decisions through exploration of the relationship between uncertainty and decision outcome. The relationship between uncertainty and decision outcomes becomes key to identifying policies that are robust against uncertainty. This focus on providing tools that assist decision makers in integrating uncertainty visualization in decision-making is prescriptive in nature.

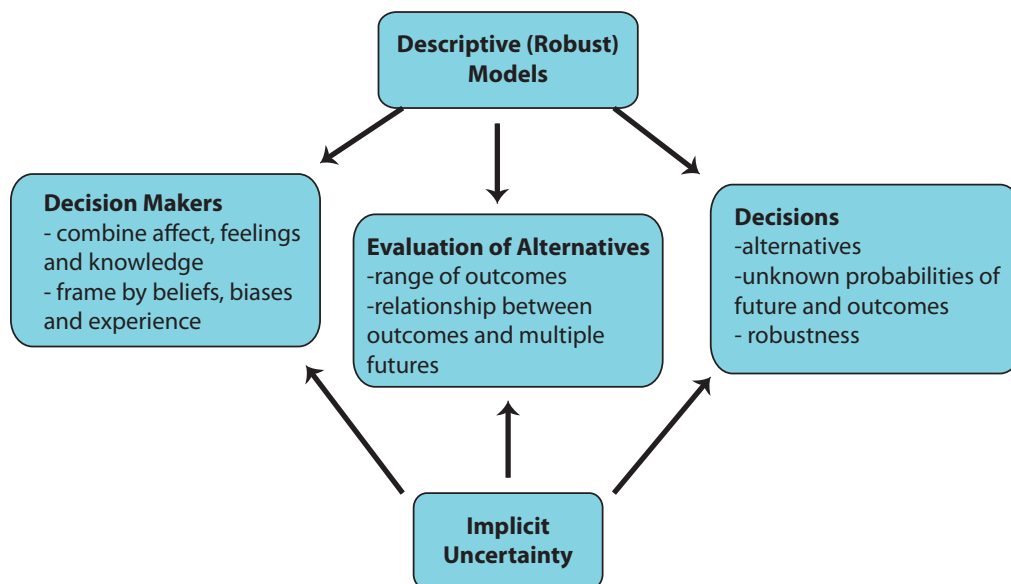
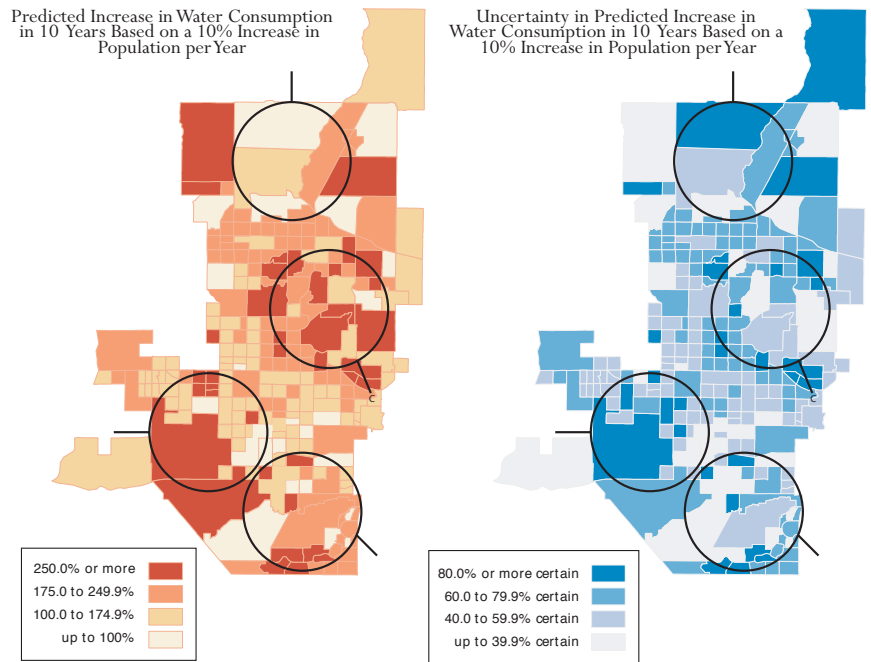


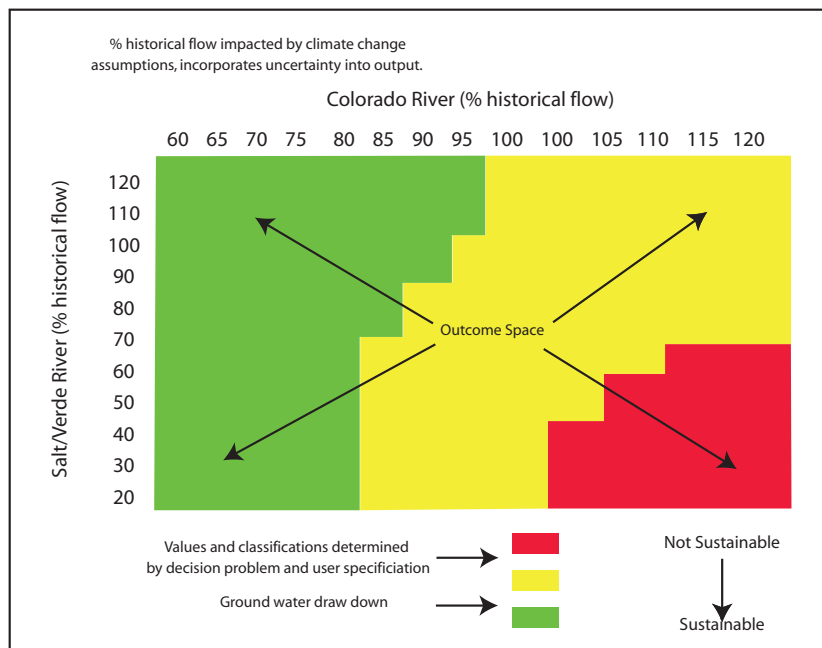
Figure 3.3 Implicit uncertainty as a descriptive model of decision-making

Examples of both explicit and implicit approaches are shown in Figure 3.4. In these examples, the impact of climate change on water sources in Arizona represents model uncertainty. In the explicit example, individuals using a model must select a single climate change scenario (for example, will there be 50 percent more water available or 50 percent less) for evaluating the impact of policy choices such as reducing population density. If they want to evaluate different climate change conditions, they run the model several times and examine the results independently. In the explicit example, model results are depicted for a single scenario with the uncertainty for that scenario depicted as a separate value, with emphasis placed on the geographic variability of the uncertainty. While this effectively depicts the data and model variability, it does not support decision maker evaluation of the impact of the uncertainty on policy outcomes.

If decision makers wanted to view the outcome of multiple policy choices, they would evaluate and compare just as many different scenario visualizations. In the implicit example, the visualization focuses on the relationship between the uncertain variables and the outcomes of policy choices. Here, users make a policy choice, and the resulting groundwater impact for the range of possible climate conditions available is visualized. In this case, the geographic variability of the uncertainty is propagated through the model results, with the overall impact of the different climate conditions shown in relation to the policy choices.



Explicit representation that emphasizes the uncertainty and predicted outcomes for one instance of the uncertain variables



Implicit representation that emphasizes the relationship between the uncertain variable(s) and the predicted policy outcomes

Figure 3.4 Explicit and implicit uncertainty

Both explicit (such as uncertainty in water flow predictions) and implicit uncertainty (the impact of the water flow uncertainty on policy decisions) are beneficial for decision support tools meant to aid in the identification of policies that support the long-term goals of decision makers. Uncertainty can be viewed as a continuum with explicit uncertainty at one end and implicit at the other. Similarly, decision-making can be seen as a process, starting with analysts and domain experts and eventually moving towards decision makers.

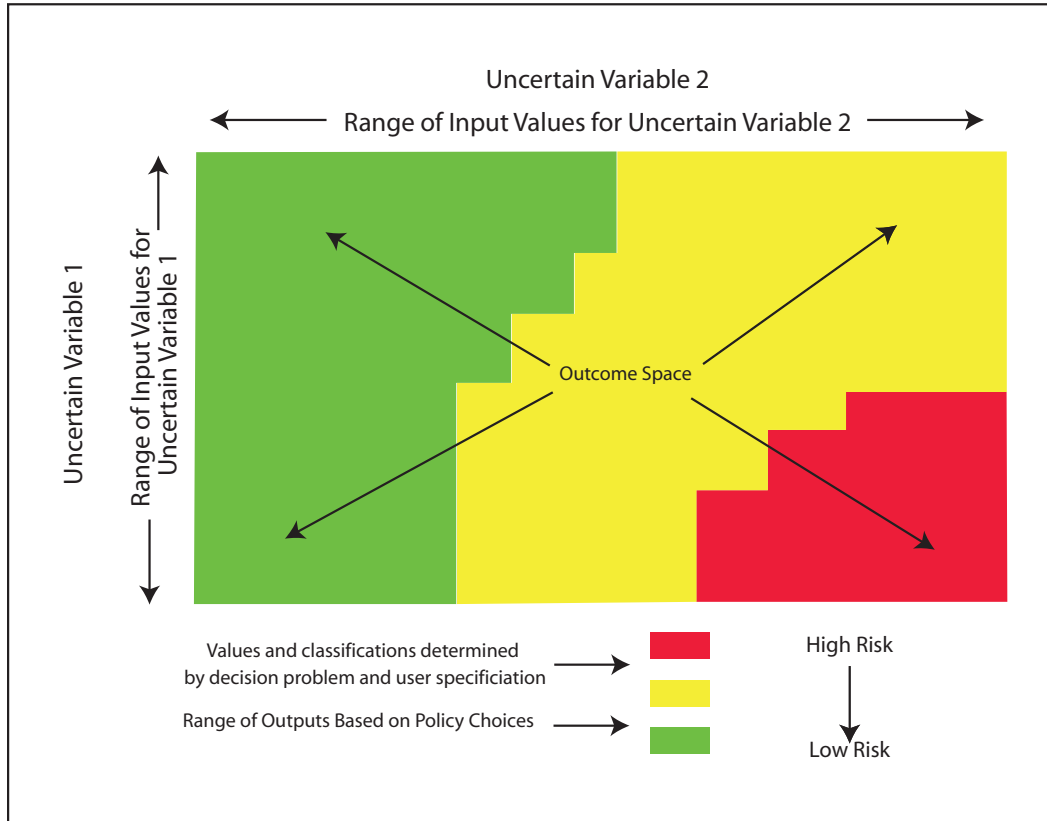
The form of uncertainty appropriate is determined by where you are in the process. During definition of the decision problem, identification of models and input data, individuals with domain or analysis expertise may prefer explicit uncertainty, where direct statistical evaluations are beneficial for their analysis. Initial evaluation of a problem often includes the identification of source uncertainty, as well as the form of uncertainty introduced through models, which often requires explicit evaluations of uncertainty, including statistical estimates (Liu et al., 2008). Identifying policies robust to specific sources of uncertainty would benefit from both explicit and implicit uncertainty representations. Interestingly attempts to identify and quantify the propagation of uncertainty in GIS outputs would be served by both explicit and implicit representations of uncertainty, as implicit representations serve as a summary of how uncertainty is expressed overall in model results, similar to error propagation.

3.5 Examples of Implicit Uncertainty Visualization

Methods for explicit representation of uncertainty currently exist, having been shown to be effective for identification of specific uncertainty values. The next step in uncertainty visualization for decision support is to adapt existing methods, or develop additional methods, to implicitly representation uncertainty. This section suggests ways to adapt existing methods for implicit uncertainty visualization.

3.5.1 Outcomes Spaces

Outcome spaces display the relationship between uncertainty variables and policy decision outcomes in a two dimensional graph (Figure 3.5). In an outcome space, each axis represents one uncertain variable, whose value varies over possible future conditions. The two axes are selected based on the uncertain variables important to the decision problem. The space is symbolized by organizing the range of outcomes into categories such as most to least robust or most to least desirable. Robustness or desirability is determined from user input or requirements of the decision problem (i.e. maximum levels of ground water use).



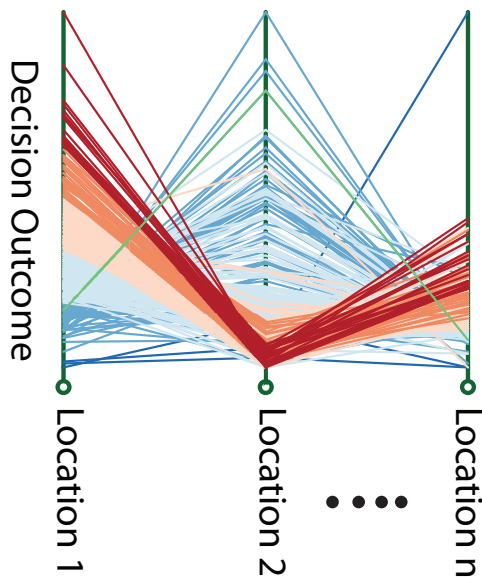
Source: Deitrick (2012)

Figure 3.5 Conceptual representation of an outcome space

The focus on decision outcomes aligns with policy makers need to evaluate policies over varying scenarios of future conditions, with uncertainty operationalized as the variability over future conditions. Unlike explicit methods in which the number of scenarios needs to be reduced to a small number, this type of visualization makes representing the range of future conditions possible. The uncertainty is represented implicitly through a range of possible outcomes in more than one variable. Implicit visualizations using outcome spaces allow evaluation of a policy decision over all possible futures in a single visualization space.

3.5.2 Parallel Coordinate Plots

Parallel coordinate plots are line graphics that show the relationship between variables in multidimensional datasets. Figure 3.6 illustrates a parallel coordinate plot for a single attribute over a region, showing the impact of uncertainty over geographic space. Each item on the x-axis represents a geographic “unit” that can be defined for the decision problem (e.g., a census tract, parcel of land, wet land area). The y-axis represents the range of uncertainty for an attribute, with smaller values being at the bottom and larger values being at the top. The outcomes for all possible future conditions can be symbolized based on the most/least robust/desirable based on the specifications of the decision makers or decision problem.



Results shown for each geographic area (defined based on the decision problem). The results can be symbolized (color) based on criteria identified by the decision makers (i.e. most to least robust or most to least desirable)

Figure 3.6 Parallel coordinate plot with specified geographies

As an implicit uncertainty visualization method, this offers a viable method for visualizing either multiple forms of uncertainty or geographic variability of uncertainty for a single attribute that varies over future conditions. Moreover, this approach offers a means to visually illustrate the spatial variability of error propagation in a model. For example, if evaluating the impact of zoning policies on trip generation for traffic, each position along the x-axis could represent a traffic analysis zone (TAZ). Uncertainty in the type of trips generated (vehicles, pedestrians, cycling, bus, etc.) could be represented based on different zoning policies. The outcomes of a policy would then be “mapped” onto the y-axis for each parcel, based on the amount of trips generated for a given trip generation assumption. That could be done for multiple policy conditions, and multiple combinations of land use, to identify the best option for the possible future conditions.

Parallel coordinate plots can also depict policy outcomes for multiple future conditions for each geographic unit under study. A benefit of this approach is that including the geography in an abstract way potentially removes the affective impact of seeing negative outcomes in the decision makers region. Here, multiple forms of uncertainty are reflected in the output, similar to uncertainty propagation in GIS analysis, while being integrated with the attribute information. This allows decision makers to focus on the outcomes of policies (however that is measured, for example, water usage) instead of requiring them to integrate outcomes and statistical estimates of uncertainty. The focus on outcomes also

supports a storytelling (Jonassen, 2012) approach to problem solving, as decision makers work through how their policies will impact the community.

Similar to the outcome space, this allows evaluation of which policy options result in desirable outcomes over the largest geography. With this method of spatial evaluation, where the spatial units are known, but not visualized on a geographic map, some of the affect that may occur when decision makers are aware of negative impacts on their “land” may be avoided.

3.5.3 Goal Plots

Similar to a bar chart, a goal plot is a visual method for identifying geographic areas that meet specific outcome goals of policy makers (Figure 3.7). The x-axis represents the range of policy choices and the y-axis represent the variability in geographic placement to meet that policy. In some decision support settings, policy makers may need to identify geographic areas (or groups of areas) that meet a certain goal (so the policy outcomes fit a predefined criteria).

For example, decision makers may want to know how many parcels could be developed and in what locations to minimize pollution load into a watershed. In these goal-oriented settings (Shimizu et al., in progress), the importance is on identifying the geographic areas (such as parcels of land for development) that meet the policy goals of the decision makers (pollution load). Goal plots offer a method for representing the uncertainty of future conditions, while allowing decision makers to identify the locations or combination of locations that meet their goals (Shimizu et al., in progress). The result is that goal plots build on

narratives and storytelling (what are the future conditions that decision makers see as desirable), while incorporating approaches that have worked in the past (goal oriented versus outcome oriented) as well as the goal oriented decision frame of the decision makers. Here uncertainty can be operationalized in many ways, including the impact of climate change, the differing types of land use being considered, and density of development.

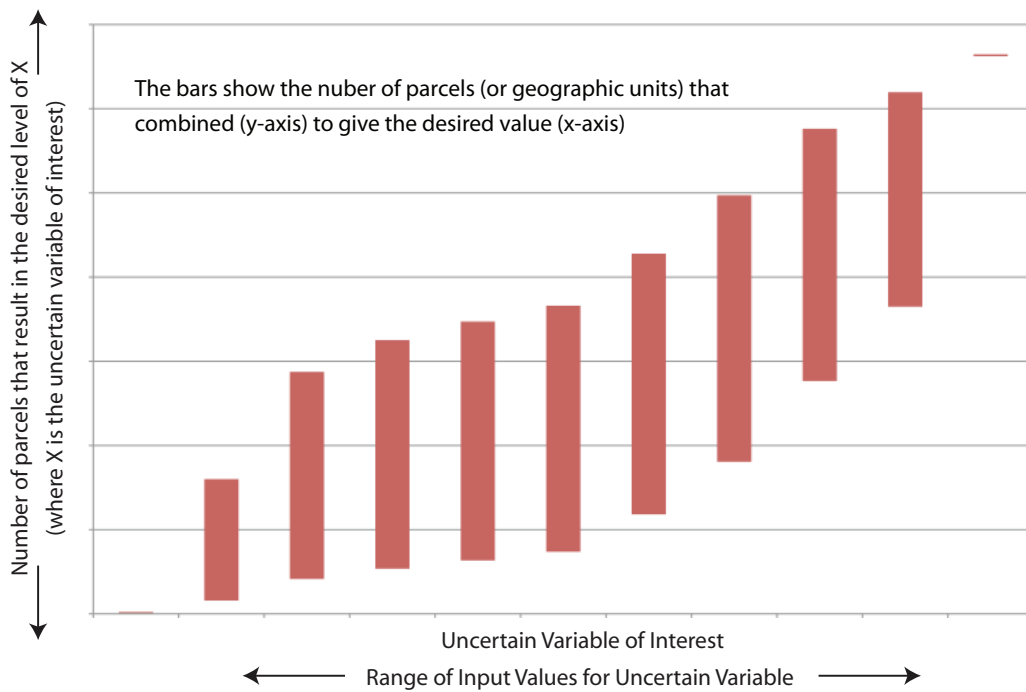


Figure 3.7 Conceptual goal plot relating number of parcels that meet a given criteria based on the uncertain variable of interest

3.5.4 Youden Plots

A Youden plot is a specialized scatterplot that displays measurement uncertainty among different geographic locations (Wang et al., 2011). In the classic Youden plot example, measurement from different laboratory results are reported. In this

example, both inter-laboratory (the same location does two runs of a test on the same sample) and between-laboratory (so two different labs do one run of a test on a sample) variability can be evaluated. Axes in the plot are drawn on the same scale, and a point in the plot corresponds to either the results of one laboratory for two different test runs or the results of two different labs for their test run. The resulting graphs represent the variability of results, and serve as a form of implicit visualization of uncertainty.

The Youden plots can be adapted to represent implicit visualization for decision support with uncertain variable shown on the x-axis and the model results for the policy option shown on the y-axis (Figure 3.8). The outcomes for a policy option for all of the uncertain values can be symbolized as points in the chart. These points can then be symbolized for different policies (so multiple policies on the same plot) or for geographic groupings (how many parcels receive the outcome value, similar to the goal plot). Using the Youden plot in this way, you can identify policies that work well over the largest range of possible futures and/or the most locations. Similar to the prior methods discussed, multiple policy outcomes can be visualized in a single graph, and uncertainty is operationalized as the variability of the selected attributes (on the axes) over future conditions.

An additional method for incorporating geography and implicit uncertainty would be to add a third dimension to the Youden Plot. In this form, locations could be shown on the x-axis, the y-axis is the uncertain variable and the z-axis is the model outcome. The symbols can be sized proportionally based on the number of future condition model runs that result in a given outcome. For

example, if a city was evaluating policies that would encourage reduction in water usage, they might identify a goal of at least a five percent reduction. If the uncertainty is operationalized as the percentage of people who decide to try to reduce their water usage, the model could be run for multiple scenarios for different percentages of public response. The results could be shown for each city, with the City on the x-axis, the amount of ground water on the y-axis and the percentage of the public participating in reductions on the z-axis. The symbols could be sized proportionally for the number of scenarios that result in a given reduction.

3.5.5 Linking and Brushing

Linking and brushing refers to the dynamic connection between two or more computer-based visualizations (such as a map, parallel coordinate plot or histogram). When an area in one of the visualizations is selected (via brushing) the same area is highlighted in the other visualization. For example, you select five square miles of census tracts in a map and the portion of the parallel coordinate plot that relates to those areas are highlighted. Linking and brushing offers a means to integrate implicit uncertainty methods, such as parallel coordinate plots, with a geographic map. The ability to connect multiple visualizations also supports robust approaches by allowing a synthesized view, and exploration, of both explicit and implicit uncertainty.

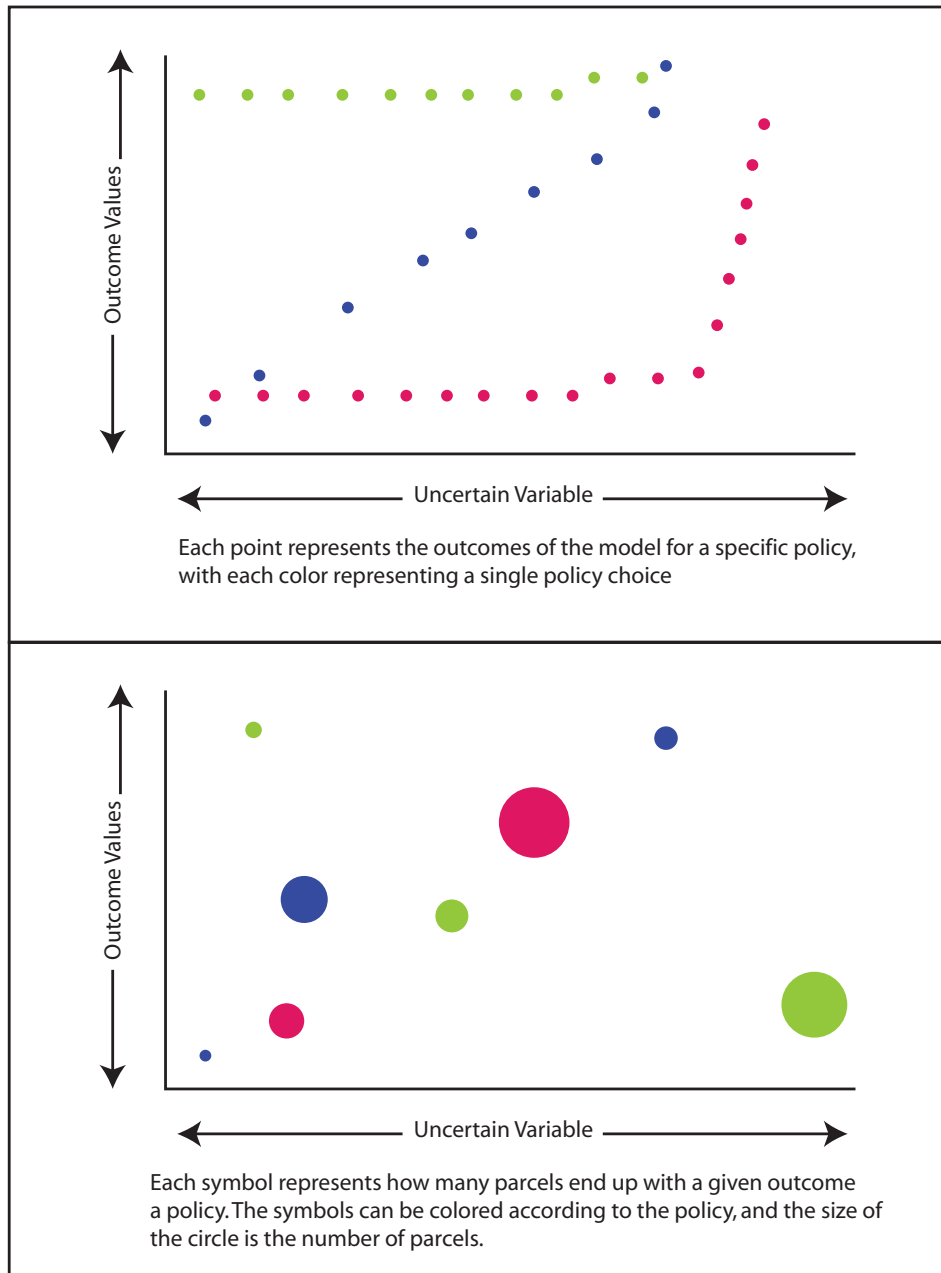


Figure 3.8 Adapted Youden plot relating uncertain variable of interest to outcome values by location

As described earlier, parallel coordinate plots can represent all parcels as axes in the plot. The scale for each axis would represent the policy outcome based on the uncertain variable. There would be multiple plots for each policy under evaluation. While geography is represented in the parallel coordinate plot, topological relationships are not visualized and individual plots have to be compared. Linking the parallel coordinate plot with a map allows additional visualization of uncertain outcomes. Here, if a given outcome range is considered desirable (such as specified range of reduction in water use) that area on one parallel coordinate plot can be selected for all of the areas under study. If the plots are linked, the same outcome range can be selected on the other parallel coordinate plots. Then the map serves as a means to summarize the number of policies that result in that desired outcome for each geographic unit (such as cities or census tracts). This identifies the variability of outcomes based on the uncertainty variable (range of outcomes per policy) and the geographic region (how many policies result in favorable outcomes for each geographic unit), allowing decision makers to evaluate which outcome is obtainable under the most future conditions or most policies.

3.6 Conclusions

Decision makers contend with uncertainty in their decisions, but instead of breaking uncertainty out as discrete, separate attribute information like GIS and geovisualization researchers might do, decision makers focus on how uncertainty impacts the outcomes of policy decisions for future conditions (Howard,

2008;Jonassen, 2012). Conceptualizing decision-making under uncertainty as a continuum offers a flexible interpretation of uncertainty, which evolves from explicit during initial analysis and discovery to implicit for evaluation and making the decision (Figure 3.9). For example, when analysts are evaluating input data uncertainty and model results, they may explicitly visualize or represent (statistically) input data uncertainty and then implicitly visualize the propagation of that uncertainty through the model using parallel coordinate plots. The continuum of explicit to implicit uncertainty is similar to normative, descriptive and prescriptive approaches to decision making.

For informed and effective decisions to be made, decision support and model results should depict uncertainty in a manner usable to decision makers so that the usefulness of the information increases (Liu et al., 2008). This builds on the concept of usable science where the objective is for researchers to relate the goals of their research to specific “on the ground” problems, strive to understand the needs of the policy decision makers, bring the needs of the user into the science process, and evaluate the results of research with the intended use (Pielke et al., 2010;White et al., 2010). Implicit uncertainty visualization is a step towards usable uncertainty visualization for decision support.

Methods that integrate uncertainty into the evaluation of policy decisions and their outcomes, builds on existing approaches to decision making under uncertainty (Brown and Vari, 1992;Volkery and Ribeiro, 2009). The challenge for researchers is the need to identify how decision makers interact with uncertainty, and apply that knowledge to develop methods for uncertainty

visualization for decision support in that policy area. In decision science research, the focus has often been on identifying decision frames outside of the individuals involved (so the external framing of a decision problem). However, to proceed to develop usable methods, GIS researchers need to uncover common internal frames and goals as well. Beyond understanding the decision domain, interacting with decision makers offers researchers a chance to clarify the manner in which uncertainty is conceptualized in the decision-making process.

Decision makers are similarly challenged, as they need to be willing to not only communicate what they need to support their decision making, but also share with GIS and geovisualization researchers information about how they operationalize decision-making. Additionally, decision makers must be willing to work with new methods of decision support, including possibly combining new methods with existing approaches. While this complicates the vision of developing standard uncertainty visualization tools for use in GIS, targeted development of techniques to support the use of uncertainty in policy decisions has the potential to bring uncertainty visualization from research into practice.

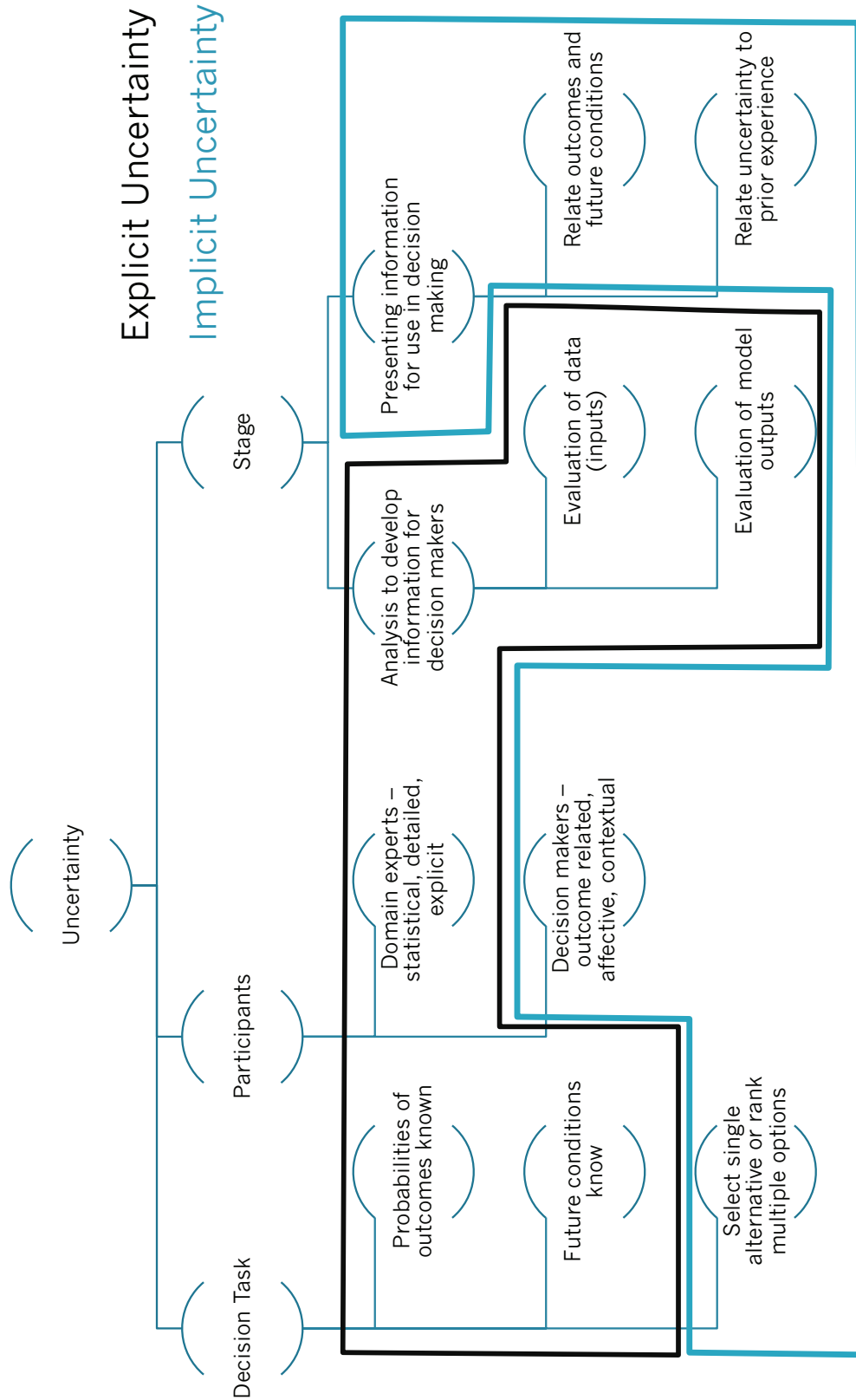


Figure 3.9 Uncertainty visualization and decision-making

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Chapter 4

EVALUATING IMPLICIT VISUALIZATION OF GEOGRAPHIC UNCERTAINTY FOR PUBLIC POLICY DECISION SUPPORT

This chapter was submitted to *Computers, Environment, and Urban Systems* in November 2012. This work was co-authored with Elizabeth A. Wentz. As first author, I was responsible for writing and formatting the manuscript for journal submission. I will respond to referee and editorial comments during the peer-review process. Changes made from the submitted work include minor editorial changes based on comments from the committee. This work is not substantially changed from the submission.

4.1 Abstract

Decision makers increasingly rely on science to inform public policy decision-making. Although the integration of science and policy offers the potential to support more informed decisions, scientific results are often not provided in a manner usable to decision makers. When faced with highly uncertain conditions, such as climate change, communicating science in a manner accessible to decision makers becomes even more important. In decision support settings, visualization of geographic information offers a powerful means to communicate uncertain science to decision makers. However, building convincing representations does not provide a complete understanding of the potential consequences of decisions.

Developing uncertainty representations that integrate the processes of decision-making under uncertainty offers a means to provide insight into the relationships between decisions, uncertainty, and outcomes (consequences of policy decisions). Nevertheless, visualizations often avoid the inclusion of explanations of risk and uncertainty. This research uses the distinction between explicit and implicit uncertainty for visualization in decision support. In explicit visualization, uncertainty is conceived of, and evaluated as, unique information, related to, but not the same as, the underlying data. Implicit visualizations embed uncertainty information into the representation, instead of expressing uncertainty as separate or additional information. When reframing uncertainty in this way, the relationship between uncertainty, outcomes, and decisions is emphasized over explicit representation frameworks that dissociate the method from the user.

This paper evaluates an implicit method for visualizing the impact of climate change uncertainty on policy outcomes in a water model for a hypothetical metropolitan area. The effectiveness of this method for visualizing the relationship between uncertainty and policy impacts was evaluated through a human subject study. The paper reports on the results of the study and how this method compares to methods for explicitly visualizing uncertainty.

Keywords: uncertainty visualization, outcome space, decision support, decision frames

4.2. Introduction

Mediated visual communication has played a central role in the climate change dialogue between science and policy—shaping perception and opinion, and as a result, influencing public policy (Corbett and Durfee, 2004;Smith, 2005;Boykoff and Boykoff, 2007). When used to support decision-making, these visualizations often do not include explicit explanations of risk and uncertainty (Carvalha and Burgess, 2005). Instead the focus is often on simple forecasts and visualizations that show discrete alternatives to ease understanding (Abbasi, 2005). Building convincing visualizations, however, does not provide a means to understand the relationship between decisions, uncertainty, and the decision outcomes.

Uncertainty broadly refers to what is not known about the relationship between a measured (or predicted) value and the actual value. Existing typologies of uncertainty include a wide range of data characteristics, such as quality, error, precision, completeness, and lineage. GIS uncertainty research often centers on these data characteristics, identifying, evaluating, or tracking spatial component of uncertainty in data. Research themes include visualizing the geographic distribution of uncertainty (Cliburn et al., 2002;Aerts et al., 2003a;Slocum et al., 2003), quantifying uncertainty and propagation (Goodchild, 1994;Heuvelink, 2005;Goovaerts, 2006) as well as applied research into geographic uncertainty in areas such as climate change, ecology, and planning (Devillers and Jeansoulin, 2006a;Isendahl et al., 2009;Gober et al., 2010). Although the topics and fields of application are diverse, the approach is often similar, focusing on presenting uncertainty in explicit and quantifiable ways, with the intention of developing

generalizable methods applicable to many different domains. This somewhat uniform approach to uncertainty visualization contrasts with the contextual nature of uncertainty in decision support settings, where diverse stakeholders often possess differing experiences, expectations and goals as they relate to their domain, but share common characteristics in addressing uncertainty in their decisions.

The relevant form of uncertainty for a given decision problem is often determined by the user, context, and purpose of the data. For example, science experts may prefer statistical estimations, while decision makers might prefer generalized information such as a scale of low to high uncertainty (Cliburn et al., 2002). This poses a significant challenge for uncertainty visualization methods intended to facilitate informed decision making, as decision makers may not easily understand or use complex scientific representations. In decision support settings, the specific form of uncertainty might be less important than a general awareness of its presence and its impact on decision outcomes.

Interestingly, a disjoint exists between decision makers' view of uncertainty and uncertainty visualization. Research suggests that many users consider *uncertainty visualization* either irrelevant or detrimental for successful communication and evaluation of alternatives (Cliburn et al., 2002; Slocum et al., 2003; Brugnach et al., 2007). In contrast, decision makers often view *uncertainty* itself as unavoidable, and potentially, as integral to their understanding a problem (Brugnach et al., 2008). This is a shift from the perception of uncertainty as something to eliminate or minimize in decisions to something that might help

guide choices. Visualization methods should build upon this attitudinal shift by incorporating existing ways of working with uncertainty in decision making with methods for visual uncertainty communication.

Developing uncertainty visualization methods useful to decision makers requires a shift from complex scientific visualizations to methods that consider the decision frame of the user. Decision frames encompass how individual experiences and beliefs establish the boundaries and constraints of a decision problem and course of action (Tversky and Kahneman, 1981). The perceptual change from avoidance to acceptance, and even use, of uncertainty by decision makers, changes decision makers' framing of a problem. Providing decision makers with methods that allow them to gain insight into the relationship between uncertainty and outcomes reframes uncertainty so that the relationship between the method and needs of the user are emphasized.

This research distinguishes between explicit and implicit uncertainty and visualizations as discussed in Chapter 3. *Explicit uncertainty* directly identifies gaps, errors, and unknowns, which are displayed or represented using quantitative estimates (such as error bars) or qualitative characterizations (certain versus uncertain). *Explicit visualization* refers to methods that extract, model and quantify uncertainty separately from the underlying attribute. In explicit methods, uncertainty is conceptualized as specific values, to evaluate as unique attributes, related to, but not the same as, the underlying data. *Implicit uncertainty*, by contrast, conceptualizes uncertainty as an inherent characteristic of the data. In decision support settings, implicit methods link uncertainty to decision outcomes.

Implicit uncertainty is more context dependent, where the decision problem informs definition, interpretation and, potentially, representation. *Implicit visualization* integrates uncertainty and decision outcomes into a single visualization, as one attribute. With these definitions, it is possible to explicitly define uncertainty (such as providing probability for a model projection), and then use implicit methods for visualizing that uncertainty (visualizing the range of probability values for several different models). Implicit uncertainty visualization supports decision making under uncertainty by allowing users to explore the relationship between decisions, outcomes, and uncertainty.

At its most general, this study aims to identify whether decision makers interpret implicit uncertainty visualization as representing uncertainty. Additionally, this study seeks to identify whether decisions made with implicit, explicit and no uncertainty differ. Lastly, this research explores whether implicit visualizations are seen as effective for decision-making, and if users interpret these representations as uncertain. Specifically this work seeks to address the following:

- Does implicit visualization of uncertainty result in policy decisions that differ from explicit/no uncertainty visualization?
- Are implicit representations of uncertainty perceived as effective for evaluating the robustness of a policy decision?
- Do users interpret implicit visualization as being uncertain?

The remainder of this paper begins with a brief review of relevant literature, and then presents the results of a human subject study where survey participants were asked to make policy decisions using both implicit and explicit uncertainty representations.

4.3. Visualizing Uncertainty

Researchers have sought the most appropriate and effective means of representing uncertainty to users, carrying out experiments comparing representational techniques. Many methods adapt Bertin's (1983) visual variables to visualize uncertainty, with researchers developing additional graphic variables specifically to visualize uncertainty, including saturation, crispness, clarity, resolution, and transparency (MacEachren, 1992; Slocum et al., 2004).

Explicit visualization strategies fall into two general categories: intrinsic and extrinsic (Gershon, 1998). Both rely on an explicit definition of uncertainty. *Intrinsic* techniques integrate uncertainty in the display by varying an existing object's appearance to show associated uncertainty. Although the uncertainty and "object" are represented in unified representation, such as using fuzzy lines to represent vague boundaries, uncertainty is still explicitly depicted as separate from the underlying data. *Extrinsic* techniques rely on the addition of geometric objects to highlight uncertain information. Here, the explicit nature of the uncertainty is more apparent, since the representation uses separate objects to depict uncertainty. These categories are suitable for both qualitative and quantitative descriptions of uncertainty. For example, model results might be

qualitatively identified as a range of certain to uncertain using hatch marks of varying density (extrinsic), while surface heights offer a method for representing error quantitatively (intrinsic).

Researchers have explored differences in interpretations and use between novice and expert users. Cliburn et al. (2002) developed an environment to allow decision makers to visualize the results of a water-balance model. The study found that the complexity and density of the representation methods seemed to overwhelm decision makers, while experts were able to use the detail more readily. They suggest that intrinsic methods provide a more general representation of uncertainty that non-expert users may prefer over more-detailed extrinsic representations.

4.4. Methods

I conducted a human-subject study consisting of decision tasks related to water policy in a hypothetical western city. In the study, participants were presented with a survey where they were part of a general council reviewing policy recommendations for reducing the impact of growth on groundwater. Participants were provided with maps showing predicted groundwater usage that would result from three sets of policies. They were asked to rank the policies from most to least robust, with the most robust choice being the policy that impacted groundwater the least over the widest range of future conditions. They did this for three *decision sets*. Each set had a different visualization strategy using either implicit uncertainty, no uncertainty or explicit uncertainty. Participants were also

asked to indicate whether they used the visualizations when making their rankings, whether they were effective for the task, and if they saw the information as including the uncertainty of climate change.

To test whether implicit visualizations resulted in rankings that differed from explicit or no uncertainty, all participants worked through the same three decision sets. There was no “correct” ranking, as the purpose of the ranking was to compare rankings and answers across the decision sets. With participants working through policy rankings using each of the visualization strategies, within participant responses could be compared for all answers. Other than the visualizations, efforts were made to keep the questions otherwise similar. The wording of questions for each decision set was kept the same, but the order that the policy options were presented was different for each decision set (see Section 4.4.2) to avoid bias in selection of policy. Additionally, the order that participants saw the decision sets was randomized to avoid learning.

This section describes the survey collection instrument as it was presented along with the analysis methods for the resulting collected data.

4.4.1 Scenario Overview

Water management systems are traditionally operated under the assumption of stationarity—the idea that natural systems fluctuate within an envelope of variability that does not change (Milly et al., 2008). Under the assumption of stationarity, water planners acknowledge the possibility of errors in estimation of

water inputs, but assume it is reducible through additional observations, improvements in data collections, or increased data.

Climate change, however, poses a challenge to the stationarity assumption; as changes to the Earth's climate are altering the rate of river discharge, mean precipitation, sea levels, and other aspects of the water cycle and water supply. Uncertainty visualization offers an opportunity for decision makers to perceive how climactic uncertainty (evidenced by changes to the stationarity assumption or changes to river flow) affects outcomes of policy decisions, through communication of the relationship between uncertainty and predicted policy outcomes.

For this study, uncertainty is expressed as the effect of climate change on the assumption of stationarity, in this case, changes to the historical flows of two hypothetical rivers. The implicit outcome space (Section 4.4.2) represents all potential outcomes for a given set of policy conditions for all future flows of the rivers. For this study, the outcome space consists of the net cumulative change in groundwater resulting from running a single set of policy choices for all predicted future river flows in the hypothetical model.

Study participants were presented with a scenario depicting current drought conditions in Wake County, a hypothetical city in the West. Survey participants were told that they were members of a water planning board tasked with evaluating three sets of policy options for managing future growth and water use. The goal of this planning board was to select the policy choice that provided the most robust options for future conditions. Participants ranked the following

policy choices for each decision set (corresponding to implicit, explicit and no uncertainty groups):

- No change in population growth, agriculture or personal water usage
- General plan allows for increased residential and commercial development, with population growth increasing to twice the rate predicted by the prior county plan. A public education plan about reducing water use will be implemented.
- A policy to protect ground water is implemented in five years, requiring that ground water levels no longer be depleted; meaning use must be balanced with recharge. This policy will be strictly enforced through water restrictions for existing and new residents as well as businesses. Additionally, there will be increased use of effluent water for agricultural and commercial uses.

The three policy choices did not change across the decision sets, but the order they were presented in varied. For example, in the implicit decision set the first policy shown was the No Change option, but for the no uncertainty decision set it was the growth plus education policy option.

4.4.2 Visualizations

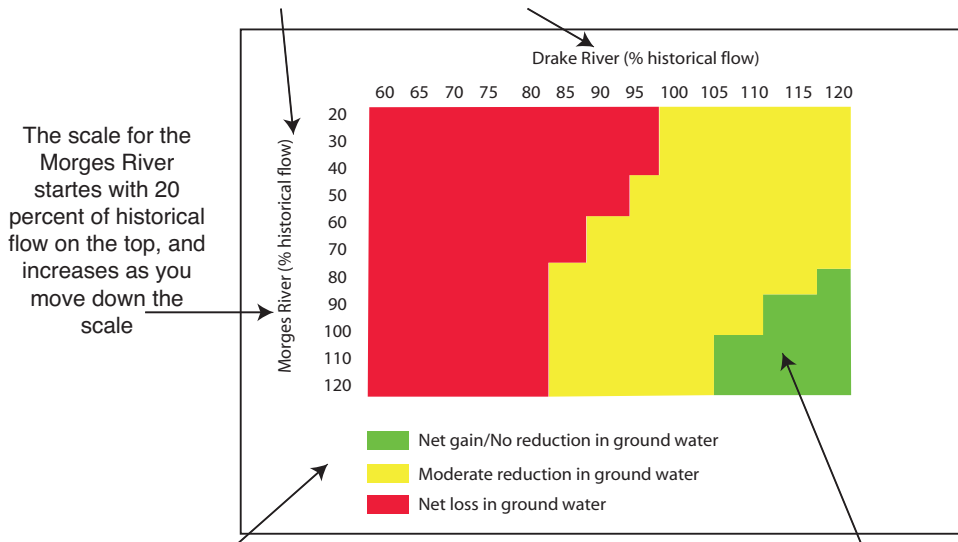
The survey included three decision sets that asked participants to rank policy choices. Each set included a different form of visualization for the results. In these visualizations, uncertainty is presented using two different spatial conceptualizations. Explicit uncertainty is shown on a geographic map, while

implicit uncertainty is shown using an outcome space (similar to a Cartesian coordinate graph). Both visualizations use similar colors and data representations (gain to loss in groundwater). The aim of this work is not to compare the actual symbology (the use of color) or the spatial representation (maps versus outcome spaces) to show one form of data, but to explore whether individuals understand that the visualizations are communicating uncertainty (spatial or otherwise). Moreover, this work seeks to evaluate whether implicit uncertainty is understood as uncertainty, as well as whether implicit visualizations communicate uncertainty in a manner usable for decision support. Since respondents are not evaluating the spatial variability of uncertainty, but seeking to identify policies that best meet the goals of the decision task, the conceptualization of space is not evaluated here. Each of the decision set visualizations are discussed in the following section.

4.4.2.1 Implicit Uncertainty Decision Set

This research builds upon the methods presented in Chapter 2 (Figure 4.1), which offer a means to represent the outcomes and associated uncertainty as a continuous space. In this representation, the vertical and horizontal axes represent two uncertainty variables identified as vital to the problem under consideration. Each point of intersection between values on the axes represents the outcome of a given scenario. The area represents all possible outcomes (defined as the outcome space) and can further be delineated into regions of no, mild, or overwhelming regret.

The vertical and horizontal axes represent all of the possible future flows of the two rivers as percentage of historical flow. Percent historical flow on each river represents the range of flows projected by the climate models. Future-Flow is run for each set of policy options for each projected future flow.



The Wake County water management plan requires future water policy to mitigate the use of groundwater. Based on these requirements, model results are classified as having a net gain (so groundwater recharge is more than its use), no change or moderate reductions (groundwater use is more than its recharge, but is considered sustainable) and net loss (where use is more than recharge).

The outcome space represents the net cumulative change in groundwater. These values are determined from the Future-Flow model, based on policy decisions input into the model. As policy decisions are implemented in Future-Flow, the values in the outcome space will change based on the model results

Figure 4.1 Elements of Outcome Space

For the implicit uncertainty decision set, the vertical and horizontal axes represent future flows of the hypothetical rivers as a percentage of historical flow. This represents two of the uncertain variables scenario, incorporating the uncertain impact of climate change on river flow (the challenge to the stationarity assumption). The outcome space represents the net cumulative change in groundwater. Additionally, areas within the outcome space are identified using a range of sustainable to not sustainable based on the amount of change in groundwater usage.

While this does not depict geographic space, it does reflect the continuous spatial distribution of uncertainty across the possible futures of each river system. It allows decision makers to identify strategies/policies that perform the “best” across the widest range of future possible climate conditions (most robust policy). Once these policies are selected, decision makers can further evaluate the geographic impact of the policy choices.

4.4.2.2 Explicit Uncertainty Decision Set

This decision set depicts model results for each policy choice assuming continued drought conditions for the next ten years along with the uncertainty of the model results. Here, uncertainty was explicitly represented using transparency, a visual variable shown effective for visualizing explicit uncertainty (MacEachren et al. 1998). This decision set used a geographic map as the base. While this differs from the implicit visualization, both depict an outcome space of model results with uncertainty. The visualizations for this decision set are shown in Figure 4.3.

4.4.2.3 No Uncertainty Decision Set

The third decision set depicts the geographic distribution of ground water drawdown assuming continued drought conditions for the next ten years. This was used as a control for comparison to both the implicit and explicit uncertainty visualizations. The no uncertainty decision set is shown in Figure 4.4.

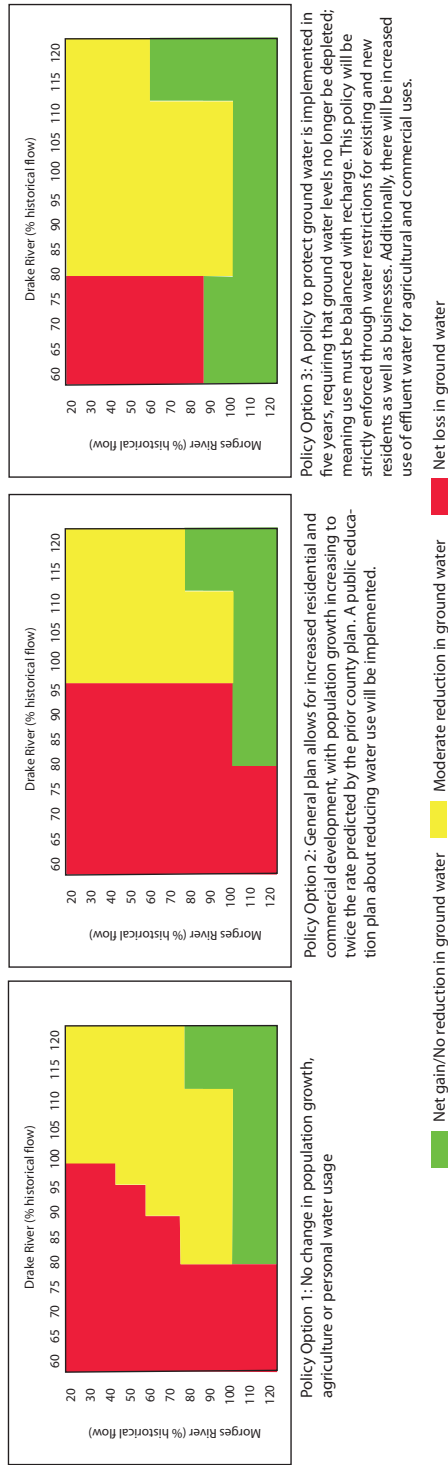


Figure 4.2 Implicit uncertainty visualization decision set

4.4.3 Decision Set Questions

For each decision set, participants were asked to use the visualizations to rank policy options from most to least robust. They were then asked to answer three questions:

- The representations incorporate the uncertain impact of climate change on future water supply.
- The representations are effective for evaluating the impact of policy decisions on ground water
- I used the represented outcomes to evaluate the impact of climate change on groundwater

These questions were used to evaluate whether participants were selecting the same policy option rankings across the decision sets, as well as to identify the manner in which they were using and interpreting the visualizations.

Additional demographic information was collected for identification that the sample was coming from a similar population. Questions included age and education, profession and research/work domain, as well as whether they agreed or disagreed with the following questions:

- Climate change is occurring (answered with a Likert Scale from 1 being strongly disagree to 5 being strongly agree)
- Computer models are effective tools for exploring the impact of climate change on water use and policy decisions.

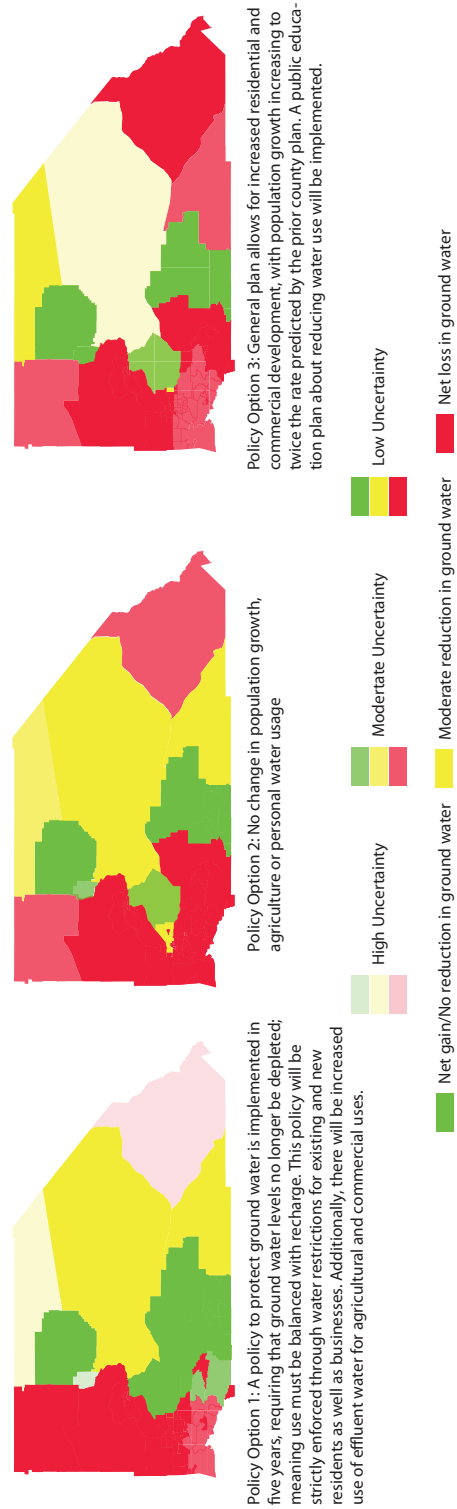


Figure 4.3 Explicit uncertainty visualization decision set

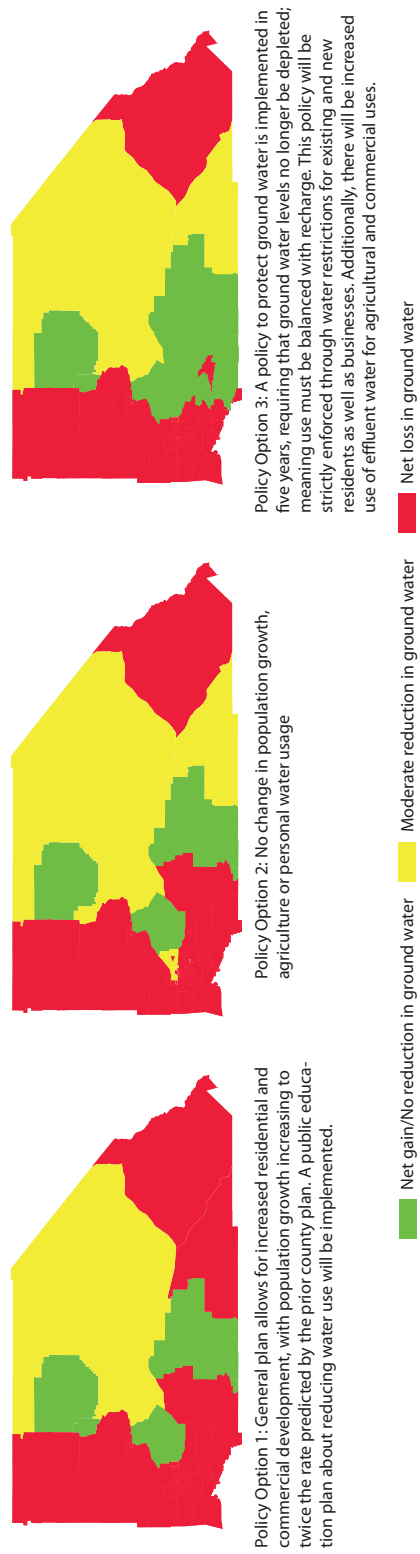


Figure 4.4 No uncertainty decision set

4.4.4 Survey Sample

Participants were drawn from GIScience faculty and researchers, GIS professionals working in decision support settings, employees working in the public sector with transportation, land use or water planning, project managers in private planning organizations, and PhD candidates working with GIS or decision support. Professionals in decision-making, public policy, research with public policy decision makers, or GIS professionals represent a challenging access group. Respondent driven sampling, offers a means to contact the population of study through other survey participants (Bernard 2012). For hard to sample populations, respondent driven sampling has been shown to produce samples that are more representative of the population under study than nonrandom samples (Hathaway et al., 2010). For the first round of distributions, individuals with experience in GIS and decision support or public planners were contacted and asked to participate. When they were finished, they were asked to provide a contact or suggestion for additional participants. After the initial two rounds, the requests continued, and the surveys were distributed. In the end, surveys were distributed to working groups in GIS and Decision Support as well as local public works agencies, planning companies and organizations researching robust decision-making and scenario planning. The survey was then distributed and shared through the individuals that received it from the initial email distribution. This offered a means to recruit participants with decision-making or GIS experience, both in professional and research settings. Demographic information about respondents is provided in Section 4.5.1.

4.4.5 Analysis

Responses for the three question types in each decision set were compared for each participant. The methods for evaluating the responses are discussed in the following sections.

4.4.5.1 Policy Ranking Comparison

For analysis of the policy ranking questions, a t-test was used to identify whether the responses between decision sets were significantly different. The rankings were first ordered so that all policy options were in the same order (so for example, the policy for no change was the first ranking listed for each decision set). Then the rankings were combined for each decision set into one number, so for example, an 321 would represent that the no change policy received a ranking of three. The difference between the rankings for each decision set was calculated for each participant. A difference of zero indicates that the participant chose the same policy ranking between decision sets, while a difference other than zero indicated a different in ranking. The null hypothesis for this test was that there would be no difference between the rankings for the decision sets, which would mean that participants were possibly choosing policy options based on personal preference and not the presented information. I evaluated this hypothesis by calculating a 95 percent confidence interval around the mean difference for all participants: if the rankings from the decision sets were similar, this confidence interval should include zero.

4.4.5.2 Do visualizations incorporate uncertain impacts of climate change?

For each decision set, participants were asked whether the visualizations included uncertainty about climate change. Participants responded using the scale strongly disagree, disagree, neither disagree nor agree, agree and strongly agree. These responses were then coded with strongly disagree as negative two, agree as negative one, neither agree nor disagree as zero, agree as one and strongly agree as two. This allowed evaluation of the average response for each decision set to identify whether responses were significantly different from zero (neutral) and whether they were positive (indicating agreement) or negative (indicating disagreement) using the reported confidence interval. For each decision set, a t-test was performed to identify whether the average response was greater than zero (indicating that the visualization included climate uncertainty). In this case the null hypothesis was that mean results were less than or equal to zero.

4.4.5.3 Is the visualization effective for evaluating the impact of policy changes on groundwater?

Participants were asked whether the visualizations were effective for evaluating the impact of policy decisions on ground water drawdown. Participants responded using the same disagree-agree scale used for the uncertainty question previously discussed in Section 4.4.5.2. These responses were then coded using the same negative to positive values as the uncertainty question. This allowed evaluation of the average response for each decision set using the t-test to identify whether responses were significantly different from zero (neutral) and whether they were

positive (indicating agreement) or negative (indicating disagreement) using the reported confidence interval. For each decision set t-test was performed to identify whether the average response was greater than zero (indicating that that it was effective). In this case the null hypothesis was that mean results were less than or equal to zero.

4.4.5.4 Comparison of change in rankings and indication of whether they used the visualization in decisions

Lastly, participants were asked whether they used the represented outcomes to evaluate the impact of climate change on groundwater. The purpose was to evaluate whether their answer to this question was reflected in the rankings, assuming that ranking would be different based on whether or not they indicated that they used the visual depiction in their policy decisions. Participants responded either true or false to this question.

True/false responses were then compared with ranking difference responses (Section 4.4.5.1) with the assumption being that if participants used the visualizations, then the ranking difference should be different from zero, and if they did not, then the ranking difference should equal zero. Each set of rankings was divided into two groups based on the true false responses. For each group a t-test was performed to identify whether the average response was greater than zero (indicating that a change in ranking between decision sets). In this case the null hypothesis was that mean results were equal to zero (indicating no change).

Decision sets were presented to participants in a random order to avoid bias and learning impacts. This means that it is not possible to know the order in which participants saw the decision sets. If the order of the decision sets was known, the change in ranking from one decision set to the next could be evaluated based on the responses to the use question for the second of the sets. For example, if a participant went through the implicit first, then explicit, their response to the use question for the explicit decision set should correspond to whether their answer changed from the implicit to the explicit rankings. Since the order is not known, the difference in rankings is evaluated for the use response for both of the decision sets in the ranking comparison. For example, for the ranking comparison between the implicit and explicit decision set, whether or not the ranking changed was compared to the use response for both the implicit decision set and the explicit decision set.

4.5. Results

The survey was conducted during summer and fall of 2012. The survey responses were analyzed for each of the four analysis types discussed in Section 4.4.5.

4.5.1 Demographics

One hundred and forty surveys were collected in all, with 54 partially completed surveys discarded, resulting in 86 completed surveys (n=86) and a rejection rate of 38 percent. Surveys were discarded if they did not provide responses for all decision sets or if they skipped the initial demographic questions.

Participant demographics illustrate similar age, education, and views on climate and modeling. The majority of respondents (92 percent) had a Bachelors degree or higher, with 65.1 percent having a Masters Degree or Doctorate. Approximately 76 percent of respondent were between the ages of 25 and 54, with approximately 52 percent between the ages of 35 and 54. Participant responses for age are shown in Table 4.1 and education is shown in Table 4.2.

Table 4.1. Survey participant age distribution

Age Groups	Frequency	Percent
18-24	7	8.14
25-34	21	24.4
35-54	45	52.35
55+	13	15.11
Total	86	100.0

Table 4.2. Survey participant education summary

Education Attained	Frequency	Percent
Associate degree	1	1.2
Bachelors Degree	24	27.9
Doctorate	18	20.9
Masters Degree	38	44.2
Professional degree	2	2.3
Some college, no degree	3	3.5
Total	86	100.0

When asked to indicate their level of agreement or disagreement about whether climate change was occurring, a majority of participants (91.8 percent) responded that they agree or strongly agree with the statement. Similarly, 86 percent of respondents indicated that they agreed or strongly agreed that computer models were effective tools for exploring the impact of climate change on water

use and policy decisions. Respondents indicated a range of professions including GIS Professional/Analyst, professor, project manager, water manager, decision maker, graduate student, government employee (transportation planning, water and tax), and researcher.

Based on the demographic responses and the targeted nature of the sample, survey participants were of similar ages and education (college degrees). Additionally, a majority shared common experience in GIS, decision support or project management or a combination of these experiences.

4.5.2 Policy Ranking Comparison

The rankings for each decision set were compared for each participant for the following pairs of decision sets: Implicit versus Explicit, Implicit versus No Uncertainty, and No Uncertainty versus Explicit. The purpose of this comparison was twofold. First, to identify whether participants were selecting the policy choices they favored personally, and second to evaluate whether the different visualizations resulted in differences in rankings for each decision set.

The difference between the rankings for the three decision sets was statistically significant for the comparisons identified at the beginning of this section. Table 4.3 presents the results of the t-test comparison for each of the ranking pairs. In this case, the actual rankings provided were not of interest, but only whether the rankings were different between the decision sets. This indicates that participants did not choose policy options based solely on their opinion of the

policy options listed, since the only element that changed for each decision set was the visualization.

Table 4.3. Paired differences results of the ranking comparison

Ranking Comparisons	T	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit versus No Uncertainty	-4.150	29	.000	-34.326	-50.770	-17.882
Implicit versus Explicit	13.196	29	.000	129.767	-113.125	-77.759
Explicit versus No Uncertainty	-10.731	29	.000	-95.442	110.216	149.319

4.5.3 Do visualizations incorporate uncertain impacts of climate change?

The responses to whether or not the visualizations incorporated the uncertainty impacts of climate change were evaluated for each decision set. The purpose of this evaluation was to identify whether participants understood that uncertainty was present in both the implicit and explicit visualization. The no uncertainty decision set served as a control, since it does not include uncertainty. Table 4.4 summarizes the results of the t-tests for the uncertainty responses for each decision set including the significance and confidence interval.

Table 4.4. Results of the uncertainty comparison indicate that both the implicit and explicit visualizations were seen as including uncertainty, while those without uncertainty were not

Uncertainty	Test Value = 0					
	T	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit	2.015	85	.047	.233	.003	.46
No Uncertainty	-4.442	85	.000	-.523	-.76	-.29
Explicit	6.406	85	.000	.651	.45	.85

The tests show that for the implicit and explicit decision sets, users identified the outcomes as incorporating climate change uncertainty. With significance values less than 0.05 we can reject the null hypothesis that the average response is zero, which would indicate that users were unsure of whether uncertainty was present. However, the p-value for the implicit uncertainty is 0.047, therefore this is not a strong rejection of the null hypothesis. Additionally, the confidence intervals include only values greater than zero, indicating a level of agreement, as positive values are associated with agreement in the coding. It is interesting to note that for the implicit uncertainty, the significance and confidence interval do not result in a strong rejection of the null hypothesis.

For the no uncertainty decision set, the results reject the null hypothesis with significance less than 0.05. Additionally, the confidence interval includes only negative values, which indicate disagreement. This evaluation serves as a control, as the no-uncertainty decision set does not represent uncertainty. The indication that implicit visualizations were interpreted as depicting uncertainty,

even though uncertainty was not expressly depicted, supports the hypothesis that it is possible to effectively communicate uncertainty without explicitly representing statistical uncertainty values.

4.5.4 Is the visualization effective for evaluating the impact of policy changes on groundwater?

Participant responses about the effectiveness of the methods for evaluating the policy options were evaluated for each decision set. The purpose of this evaluation was to evaluate whether there were differences in the perceived effectiveness of the methods. Table 4.5 summarizes the results of the t-tests for the effectiveness responses for each decision set including the significance and confidence interval.

Table 4.5. Results of the effectiveness comparison indicate that all three visualizations were seen as effective for evaluating the policy decisions

Effective	Test Value = 0					
	T	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit	5.410	85	.000	.570	.36	.78
No Uncertainty	5.410	85	.001	.570	.36	.78
Explicit	2.791	85	.006	.314	.09	.54

The tests show that for all three sets, users identified outcomes as effective for evaluating the impact of policy changes on groundwater. This is indicated two

ways in the analysis. First, levels of significance are less than 0.05. This allows rejection of the null hypothesis that the average response is zero, indicating that users were not sure whether they found the visualizations effective. Additionally, the confidence interval for each includes only values greater than zero, which indicates a level of agreement, since positive values are associated with agreement in the coding. Each method being rated as effective for supporting the decision task presented suggests that implicit visualizations of uncertainty offer a method that is comparable to explicit or no uncertainty for communicating decision outcomes. This is a surprising result, as prior research suggests that explicit uncertainty is not effective for evaluating decision outcomes.

4.5.5 Comparison of change in rankings and indication of whether they used the visualization in decisions

Tables 4.6A-4.6C present the results for the use-based comparisons. All of the results, with one exception, show a significant difference in rankings regardless of whether or not the participant indicated that they used the model results in their decisions. The one exception is the implicit versus no uncertainty ranking comparisons for individuals that responded that they used the visualizations, which had a significance value of 0.366 (based on the use question in the implicit decision set) and 0.149 (based on the use question in the no uncertainty decision set), which are larger than the alpha value 0.05. This is an interesting result, as it indicates that participants were either not aware that the visualizations were influencing them or there were other factors being used between the decision sets.

Based on these results, there appears to be a discrepancy between how users responded to the question of whether they used the visualizations and how they acted in selecting policy options. When ranking differences were divided between those that indicated they did and did not use the visual information, the analysis showed that regardless of their response, the differences between rankings was statistically significant, with the exception noted above, a result that matched the overall analysis of the rankings (as discussed in Section 4.5.2).

4.6. Discussion

In this paper I focused on evaluating the implicit visualization of uncertainty for decision support. The results suggest that implicit visualization offers a viable means for representing the relationship between uncertainty and decision outcomes.

An interesting result of this study was the discrepancy in participant responses to the policy ranking questions for each decision set and whether participants indicated that they used the visualizations to evaluate the policy outcomes. One possibility for this discrepancy is that users were relying on heuristics to evaluate policy rankings for each decision set. Individuals who indicated that they did not use the visualizations, but had different rankings, may have relied on prior experience or understanding to work through the decision. Future research could evaluate the impact of prior experience on the use of the visualizations by recording how the users interact with uncertainty visualizations.

Table 4.6A Implicit versus no uncertainty decision set use responses reflect a statistically significant difference in rankings for both the true group, but not the false groups

Implicit versus No Uncertainty Ranking Comparison and Use Response	Test Value = 0			
	t	Degrees of Freedom	Significance (2-tailed)	95% Confidence Interval of the Difference
			Lower	Upper
False	Implicit vs. No Uncertainty	22	.366	18.56
	Implicit Use Response			-48.30
True	Implicit vs. No Uncertainty	24	.149	9.44
	Uncertainty Use Response			-58.40
True	Implicit vs. No Uncertainty	62	.000	-22.33
	Implicit Use Response			-60.53
True	Implicit vs. No Uncertainty	60	.000	-19.24
	Uncertainty Use Response			-57.48

Table 4.6B. Implicit versus explicit decision set use responses reflect a statistically significant difference in rankings for both the true and false groups.

Implicit versus Explicit Ranking Comparison and Use Response		Test Value = 0				
		t	Degrees of Freedom	Significance (2-tailed)	95% Confidence Interval of the Difference	
				Lower	Upper	
False	Implicit vs. Explicit Implicit Use Response	2.393	22	.026	7.15	100.07
	Implicit vs. Explicit Explicit Use Response	3.165	27	.004	21.94	102.78
True	Implicit vs. Explicit Implicit Use Response	13.333	62	.000	94.37	128.45
	Implicit vs. Explicit Explicit Use Response	13.092	57	.000	-.13	1.28

Table 4.6C. Explicit versus No Uncertainty decision set use responses reflect a statistically significant difference in rankings for both the true and false groups

Explicit versus No Uncertainty Ranking Comparison and Use Response	Test Value = 0				
	t	Degrees of Freedom	Significance (2-tailed)	95% Confidence Interval of the Difference	
				Lower	Upper
False	3.911	27	.001	38.36	123.00
	4.145	24	.000	45.36	135.36
True	16.523	57	.000	134.87	172.06
	14.573	60	.000	125.89	165.95

The results of the effectiveness evaluation for explicit uncertainty appear to conflict with existing research that suggests explicit uncertainty visualization is not seen as beneficial by users. Future work should evaluate whether the supplementary information provided with the visualizations influences whether decision makers see explicit uncertainty visualization as useful. Inclusion of the scenario information creates a narrative to help decision makers understand the information in context. Narratives (or story telling) have been shown to be a strategy used for decision-making under uncertainty (Jonassen, 2012). The scenario included here may have assisted decision makers in integrating the visualizations into their framing of the problem.

There are a number of factors about the administration of this survey that could be modified if the survey were repeated. The repetitive nature of the survey made longer than anticipated to complete and resulted in a 38 percent rejection rate due to incomplete surveys. Streamlining the survey information and questions might increase the completion and response rates. This issue also impacted collection of demographic information for all participants, as once they finished the decision sets, they then did not provide all of the requested demographics.

Collecting information from a large sample of professionals and decision makers often proves challenging for random sampling procedures. Although respondent driven sampling methods offer a means to access these populations, the use of their results with parametric statistical tests are limited and must be done with caution. To overcome this challenge, future studies using respondent driven sampling might broaden the initial seed sample in order to gather more

responses, as well as analyze the social connections of the respondents. Focus groups and small group decision workshops could also provide valuable insight into the interpretation and use of these visualizations by decision-makers.

While this study sought to involve more decision makers and individuals that work with uncertainty to allow evaluation of how experience and domain knowledge (factors in how a problem is framed) influence whether implicit uncertainty informs decisions or is seen as uncertain, characteristics of this study group may have also impacted their ability or willingness to work through the visualizations in the policy decision process presented in this work. Decision makers, planners, and professionals experienced with uncertain decisions or complex data evaluation may be more inclined to work through the policy choices using the visualizations. Additional work to identify whether implicit uncertainty would be used or seen as effective by non-experts, and comparing these results to similar explicit visualizations, would provide insight into their potential use for communicating complex science to those without expertise in decision-making or science.

If future studies seek to directly compare the effectiveness of implicit and explicit uncertainty in order to identify which is more useful for decision support, comparable visualization would need to be tested. For example, either maps for both implicit and explicit or outcomes spaces for explicit and implicit. The aim of this work was to evaluate whether individuals interpreted the visualizations as including uncertainty information (spatial or otherwise), whether implicit uncertainty is understood as uncertainty, as well as whether implicit visualizations

communicate uncertainty in a usable manner. Since the visualization methods were not directly comparable, it is not possible to conclude from this work that one is more effective than the other.

Extensions of the study could include identifying whether decisions improve or more “correct” decisions are made with the inclusion of implicit uncertainty. Additional implicit visualization methods should also be evaluated such as the use of parallel coordinate plots, linking and brushing, or Youden Plots. Lastly, direct comparisons between explicit and implicit methods, as well as combined views, could aid in the development of an uncertainty visualization for decision support toolbox.

4.7. Conclusion

Incorporating uncertainty information into GIS data and output is a vital component for the effective use of spatial data to support decision making under uncertainty. This work focuses on evaluating a method for incorporating decision frames of stakeholders into uncertainty visualization. Doing this requires understanding what aspects of a problem are uncertain, the manner in which decision makers currently work through or interact with that uncertainty, and what information they need/desire when making decisions. As this case study demonstrates, implicitly representing uncertainty offers a means to integrate decision frames and uncertainty into a single visualization. The focus here shifts from the importance of individual uncertainty values to identifying the relationships and interactions between decisions, uncertainty, and outcomes. As

illustrated in this study, showing this integrated view (implicit) results in different decisions than explicitly representing uncertainty. Additionally, the implicit visualizations are still interpreted as including uncertainty. The results of this study will support future research into the effects of implicit uncertainty visualizations, as well as the development of additional implicit methods.

This material is based upon work supported by the National Science Foundation under grant no. BCS-1026865 Central Arizona-Phoenix Long-Term Ecological Research.

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Chapter 5

CONCLUSIONS AND FUTURE WORK

This final chapter summarizes the work presented in this dissertation and its relationship to existing work in uncertainty visualization. Additionally, it offers a discussion of future work that could follow from this dissertation. It will not be submitted for publication outside of this dissertation.

5.1 Conclusions

GIS researchers and policy decision makers acknowledge the importance of uncertainty in decision-making. Nevertheless, there is a lack of agreement on the usefulness of uncertainty visualization to support decision-making tasks.

Resultantly, even though decision makers must contend with uncertainty when working through complex decision problems, uncertainty visualization and tools for working with uncertainty in GIS are not widely used by decision makers in decision support applications. This dissertation suggests that this disjoint between research and application stems from differences in how researchers and decision makers conceptualize uncertainty.

Uncertainty for both decision makers and GIS researchers is defined as incompleteness in knowledge in the past, present, or future. The distinction between decision makers and GIS researchers, however, does not arise in the definition of uncertainty, but rather in how it is conceptualized. This distinction emerges through specific experiences with uncertainty, resulting in differing generalized uncertainty concepts. Decision makers regularly contend with

uncertainty in how current conditions or proposed policies will affect the future. The resulting generalized concept of uncertainty is that the outcomes of differing policies are impacted by future conditions. For GIS researchers, uncertainty more often reflects what is not known about the relationship between a measured or predicted value and the actual or true value. The generalized view of uncertainty therefore covers a wide range of data and model output characteristics, including error, accuracy, reliability, precision, and quality (Edwards and Nelson, 2001).

To bridge the gap between these conceptualizations of uncertainty, this dissertation examined in detail how decision makers conceptualize uncertainty, relating their conceptualization to existing uncertainty visualization methods. Through this synthesis, a new a new conceptualization of uncertainty was presented, termed explicit and implicit as a way to connect researchers' and decision makers' understanding of uncertainty for use in GIS for decision support. This dissertation explored uncertainty visualization as a means for reframing uncertainty in GIS for use in policy decision support through three connected topics.

The conceptualization of uncertainty visualization as an outcome space presented in Chapter 2 reframes uncertainty as the relationship between uncertainty and decision outcomes. The focus on decision outcomes aligns with policy maker needs to evaluate outcomes over varying plausible futures (their decision frames), offering advantages over visualizing specific uncertainty values for individual scenarios. This research speaks to the challenge of overcoming the desire of decision makers to wait to learn more when faced with uncertainty, by

evaluating methods to incorporate uncertainty that resemble decision-making processes and heuristics. Outcome spaces support assessment of the relationships between uncertain variables and the results of policy decisions. Representing uncertainty implicitly as a physical space moves away from discrete results that imply a level of certainty to a continuous range of results that reflect the influence of uncertainty on policy outcomes. This allows decision makers to focus attention on the policy decisions and not on the technical aspects of what is unknown. This approach aligns with descriptive and prescriptive models of decision-making, including robust decision-making, focusing on assessing alternatives over multiple plausible futures.

Building on the approach to integrating decision science theories into uncertainty visualization methods presented in Chapter 2, Chapter 3 developed a conceptualization of uncertainty, termed explicit and implicit, through a synthesis of existing decision science literature with uncertainty visualization methods. Through this synthesis explicit methods are linked to normative models of decision making that focus on how people should make decisions. Implicit uncertainty is linked to both descriptive (how people actually do make decisions) and prescriptive (developing decision support tools both support better decisions and are usable) integrating what decision makers actually do in practice with tools to support better decisions. The goal is to develop tools that are both useful to, and usable by, decision makers in order to support more informed decisions through exploration of the relationship between uncertainty and decision outcomes.

Building on descriptive decision making models, implicit uncertainty acknowledges the impact of decision makers experience, emotions and knowledge on how they frame decision problems, without assuming that the probability of future conditions are known or knowable. The relationship between uncertainty and decision outcomes becomes key to identifying policies that are robust against uncertainty. This focus on providing tools that assist decision makers in integrating uncertainty visualization in decision-making is prescriptive in nature.

Chapter 3 also adapts several existing visualization methods to illustrate implicitly uncertainty visualization. For example, outcome spaces display the relationship between uncertainty and policy outcomes in a two dimensional graph. The resulting visualization allows evaluation of the variability of uncertainty over the plausible future conditions. Parallel coordinate plots show the relationship between uncertain outcomes and geographic locations, with each axis representing a geographic unit (for example census tract, parcel, city). Goal plots offer a means to identify policies that meet predefined goals for different geographic areas. These methods provide a foundation for integrating decision science theories into uncertainty visualization tool development for decision support.

Chapter 4 evaluated the effectiveness of the implicit visualization concepts developed in Chapter 2 and Chapter 3. Results of a human subject study assessed the effectiveness of the implicit uncertainty visualization shown in Chapter 2 to support the identification of robust policy choices. The study suggests that implicit visualizations successfully communicated uncertainty about the scenarios

presented, and that participants appeared to use the information visualized to evaluate the policy choices. Additionally, participants indicated that the visualization methods were effective for assessing the policies presented. Interestingly, participants also indicated that the explicit visualizations of uncertainty were effective for supporting the policy task, a result which conflicts with prior visualization research results that show decision makers view uncertainty visualization as not meaningful or helpful to evaluating a problem.

The work in Chapter 4 also poses an evaluation of effectiveness that differs from prior studies, focusing on whether implicit representations produce different decisions from explicit methods, as well as whether users identify the representations as effective for evaluating the robustness of a policy choice for future conditions. This differs from much of the prior research that defines effectiveness as correct responses, time to respond, or the ability to discover specific values. This work also supports the proposal that visualizing the relationship between uncertainty and outcomes has the potential to communicate uncertainty to decision makers. This fills a gap in existing literature through a new evaluation of effectiveness for uncertainty visualization for decision support and a new direction for representing uncertainty as it relates to decision support tools.

These works are all connected through their integration of decision science and uncertainty visualization. Tools to communicate uncertain science in a manner usable to decision makers are vital as policy decision makers rely on scientific results to inform decisions under deep uncertainty. The level of detail and control in uncertainty visualization should vary based on whether the user is

the analyst, domain expert, or decision maker. As decision makers appear to accept the presence of uncertainty in the decision process, and indicate that their practices already incorporate “uncertainty visualization”, this work suggests that it is worth questioning why there is such apathy among users regarding demand for uncertainty visualization tools in GIS.

Conceptualizing decision-making under uncertainty as a process regards uncertainty as a continuum, evolving from explicit during initial analysis and discovery to implicit for evaluation and making the decision. If explicit visualizations are not beneficial for evaluating potential outcomes or presenting information to decision makers and the public, or if different decision tasks benefit from different forms of visualization, then apathy towards existing uncertainty visualization methods is reasonable since existing tools do not provide the necessary flexibility. This dissertation fills a void in uncertainty visualization research for methods that support communicating uncertain science in a manner usable to decision makers.

Existing uncertainty visualization research assumes that decision makers and GIS/visualization researchers have similar conceptualizations of uncertainty. Starting from decision science literature, this work suggests that there are decision makers and researchers conceptualization uncertainty differently. Developing methods that support evaluation of the relationship between uncertainty, decisions and outcomes builds on decision makers’ conceptualization of uncertainty offering an opportunity to bridge the gap between research and practical application.

5.2 Implications

Bringing uncertainty visualization from theory to practice has applications beyond water planning and climate change, as well as beyond the work presented here.

The use of geographic information and GIS in public policy decision support settings is vast, including transportation and land use planning, emergency management and hazards planning, and public health; implicit uncertainty visualization techniques can be developed and adapted to these different application areas. Existing techniques can be adapted to depict the complex relationships between uncertain data, policy choices, and outcomes of those choices. For example, parallel coordinate plots offer a viable means to evaluate multiple forms of uncertainty and the outcomes of policy decisions in single visualization. The outcomes of a given policy choice can be shown for all values of an uncertain (or multiple uncertain) variables, and then compared across decisions. Spiral graphs offer an additional option, showing the policy outcomes resulting from the “most certain” data values in the center, and the less certain results on the outside of the spiral.

The challenge for researchers is the need to identify how decision makers interact with uncertainty, and apply that knowledge to develop methods for decision support in that policy area. Beyond understanding the decision domain, interacting with decision makers offers researchers a chance to clarify the manner in which uncertainty is integrated into the decision-making process. Decision makers are similarly challenged, as they need to be willing to not only communicate what they need in decision support, but also share with researchers

information about the decision-making process so that researchers can identify the ways that decision makers work through uncertainty. While this complicates the vision of developing standard uncertainty visualization tools for use in GIS, targeted development of techniques to support the use of uncertainty in policy decisions has the potential to bring uncertainty visualization from research into practice.

5.3 Future Research and Challenges

New questions have been raised by this research. For example, the indication that both the explicit and implicit methods were seen as effective for evaluating the decision problem conflicts with prior research, and leads me to question further why uncertainty visualization tools are not common decision support tools.

Likewise, the discrepancy between users indication of whether or not they used the visualizations to make decisions, and differences in their responses, suggests that something other than the visualizations was influencing their decisions. This seems reasonable, as heuristics and prior knowledge influence decision-making.

Future research could examine the differences between individuals with experience in decision making with no domain experience and those with experience in GIS, the domain, and decision-making. I hypothesize that domain experience would influence the way that the visualizations were used, and whether or not decision makers were able to integrate the information into their decisions, even if it conflicted with their existing knowledge. This current research attempted to evaluate the experience of participants to ensure that they

had similar backgrounds and experience or exposure to decision-making or GIS, but this level of distinction in participants would require a more detailed survey of user backgrounds. Smaller surveys with face-to-face interviews and recruiting would offer a means to address this challenge of grouping users by experience and identify specifically how they were using the visualizations and prior experience to make the ranking choices.

Another question worthy of investigation is how users interact with the implicit visualizations in an interactive decision support setting, where they can select the policies and potentially the uncertain input variables to be shown on the axes. Interaction adds a new influence factor to the evaluation, which would have limited the ability of this current work to identify whether participants were responding to the visualization method itself or the interaction method. Additional studies to assess the effectiveness of these methods in an interactive decision support tool would offer insight into how they can be implemented in future tools.

Moreover, the impact of adding implicit visualizations to the decision process, where individuals narrow policy choices down using implicit methods, then evaluate the impact of each policy on specific regions, is an interesting next step in evaluation. This addition would explore the impact on decision processes instead of whether decision makers can use the information to assess policy options as done in this current work.

Lastly, future research could evaluate visualizations that account for multiple variables, or depict the propagation of uncertainty through a model. Parallel coordinate plots offer a means for both explicit representations of

outcomes as they relate to geographic space or temporal scales, as well as showing the relationships between uncertainty estimates and multiple scenarios. I think this is one of the most interesting future directions of this research, as providing a toolbox of implicit visualization methods would support a variety of decision frames and decision tasks.

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APPENDIX A

IRB APPROVAL AND SURVEY INSTRUMENT

To: Kelli Larson
Coor

From: Mark Roosa, Chair
Soc Beh IRB

Date: 06/04/2012

Committee Action: **Exemption Granted**

IRB Action Date: 06/04/2012

IRB Protocol #: 1205007828

Study Title: Visualizing uncertain science for decision support

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

Visualization for water planning decision support

Welcome and thank you for participating

My name is Stephanie Deitrick. I am a PhD student in the School of Geographical Sciences and Urban Planning at Arizona State University. I am currently recruiting people to answer questions on the influence of visual representation on decision-making. The survey will take 20-30 minutes to complete.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. The results of the research may be published, but your name will not be used. If you have any questions concerning the research study, please contact me at (602) 579-5001 or Stephanie.deitrick@asu.edu. Professor Wentz may also be contacted at wentz@asu.edu.

Participants in this survey will have the opportunity to be entered into a drawing for Amazon gift cards ranging from \$50-\$80 each.

If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Research Compliance Office, at (480) 965-6788.

Pre-Survey Questions

Please answer the following questions

1. Climate change is occurring

- 1- Strongly disagree
- 2 - Disagree
- 3 - Neither agree or disagree
- 4 - Agree
- 5 - Strongly agree

2. Computer models are effective tools for exploring the impact of climate change on water use and policy decisions

- 1- Strongly disagree
 - 2 - Disagree
 - 3 - Neither agree or disagree
 - 4 - Agree
 - 5 - Strongly agree
-

3. What is your age?

- under 18
 - 18-24
 - 25-34
 - 35-54
 - 55+
-

4. What is your highest level of education?

- Graduated high school or equivalent
 - Some college, no degree
 - Associate degree
 - Bachelor's degree
 - Masters Degree
 - Doctorate
 - Professional degree
-

5. What is your profession?

6. How long have you been in this profession?



Scenario Overview: Wake County

You are a member of the Wake County general council. Wake County is located in the Western United States. The main city is Wakeville with a population of approximately 600,000 people, approximately half of the county population. Over the past several decades, the County has seen population growth near or exceeding 30%.

Approximately 20% of Wakeville water is derived from groundwater and the aquifer is chronically over drafted. Recent droughts have exacerbated the situation, leading the County to impose water use restrictions that require extensive public outreach and upset residents. The County has convened the general council to review possible policy options and the potential impact on groundwater usage. Groundwater usage is being modeling using Future-Flow, which calculates aquifer levels based on water supply and demand using 20 climate change scenarios, land use, population, and water policy.

Selecting a given policy and climate scenario, Future-Flow displays alternate futures with predicted changes in groundwater supply. As a member of the council reviewing the County's water plan, you are presented with three alternate futures to assess the long-term impact of policy decisions on groundwater levels. Your goal is to identify which policy option results in the most robust outlook for groundwater usage over the possible future conditions for the entire County. Robust means that the policy choices balance use and demand over a wide range of possible future climate conditions.

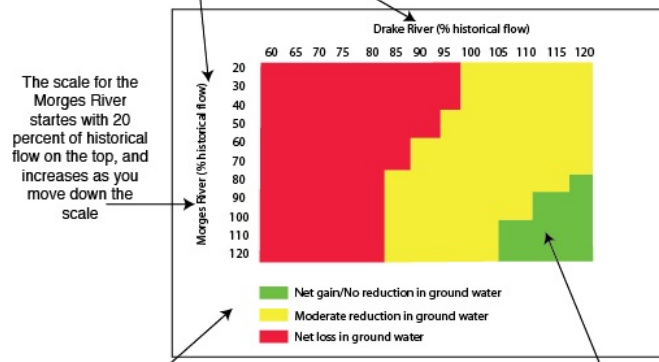
In the Decision Sets that follow, the three possible policy options for managing water use in Wake County are presented with a visualization of the projected ground water impact. Rank the policy options based on which you think is the most robust, providing the best balance of use and demand over a wide range of possible futures for long-range water usage for all of Wake County. After you make your selection, please answer the questions that follow.

Please note that the questions for each decision set are exactly the same. It is only the visualization methods that change.

Decision Set AC

The representations in this Decision Set show the resulting model results of groundwater use for **all possible future flows of the two rivers including increased drought and increased supply. This incorporates all possible future climate conditions of the twenty climate models in Future Flow.**An example output visualization from the Future-Flow model is shown below with explanation for each component.

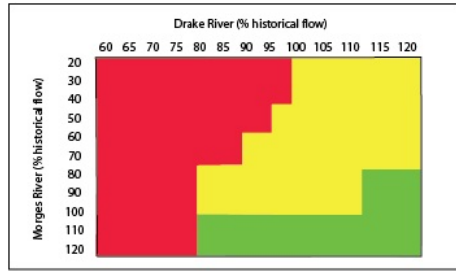
The vertical and horizontal axes represent all of the possible future flows of the two rivers as percentage of historical flow. Percent historical flow on each river represents the range of flows projected by the climate models. Future-Flow is run for each set of policy options for each projected future flow.



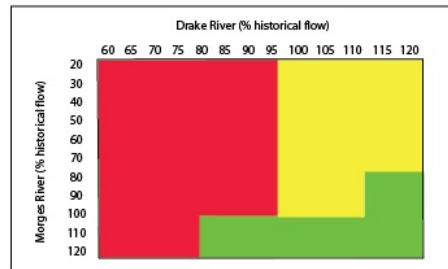
The Wake County water management plan requires future water policy to mitigate the use of groundwater. Based on these requirements, model results are classified as having a net gain (so groundwater recharge is more than its use), no change or moderate reductions (groundwater use is more than its recharge, but is considered sustainable) and net loss (where use is more than recharge).

The outcome space represents the net cumulative change in groundwater. These values are determined from the Future-Flow model, based on policy decisions input into the model. As policy decisions are implemented in Future-Flow, the values in the outcome space will change based on the model results

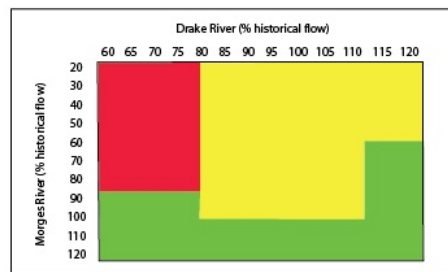
The representations in this Decision Set show the resulting model results of groundwater use for all possible future flows of the two rivers including increased drought and increased supply. **This incorporates all possible future climate conditions of the twenty climate models in Future Flow.** Please use the visualizations to rank the policy options from most to least robust based on which you think will provide the most robust outcomes for water in Wake County.



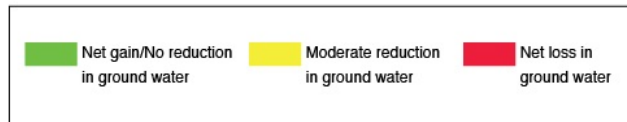
Policy Option 1: No change in population growth, agriculture or personal water usage



Policy Option 2: General plan allows for increased residential and commercial development, with population growth increasing to twice the rate predicted by the prior county plan. A public education plan about reducing water use will be implemented.



Policy Option 3: A policy to protect ground water is implemented in five years, requiring that ground water levels no longer be depleted; meaning use must be balanced with recharge. This policy will be strictly enforced through water restrictions for existing and new residents as well as businesses. Additionally, there will be increased use of effluent water for agricultural and commercial uses.



For this decision set, rank the policy options based on which provides the most robust outcomes for Wake County water. Use a scale of 1 to 3, with 1 being the most robust and 3 being the least robust.

	Most robust	Moderately robust	Least robust
Policy Option 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 3	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please answer the questions below based on the visualizations used in this section.

I used the represented outcomes to evaluate the impact of climate change on groundwater

- True
 - False
-

The representations are effective for evaluating the impact of policy decisions on ground water

- | | | | | |
|-----------------------|-----------------------|---------------------------|-----------------------|-----------------------|
| Strongly disagree | Disagree | Neither agree or disagree | Agree | Strongly agree |
| <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
-

The representations incorporate the uncertain impact of climate change on future water supply

- | | | | | |
|-----------------------|-----------------------|---------------------------|-----------------------|-----------------------|
| Strongly disagree | Disagree | Neither agree or disagree | Agree | Strongly agree |
| <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
-

Please provide any additional comments about your use of the visualizations for making your decisions.

Decision Set GN

The representations in this Decision Set only show the model results of groundwater **assuming continued drought conditions for the next ten years**. An example output visualization from the Future-Flow model is shown below with explanation for each component.

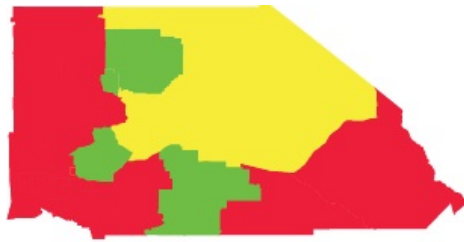
The geographic space represents the net cumulative change in groundwater. These values are determined from the Future-Flow model, based on policy decisions input into the model. As policy decisions are implemented in Future-Flow, the values in the county will change based on the model results. The results in this decision set reflect continued drought conditions for the next ten years



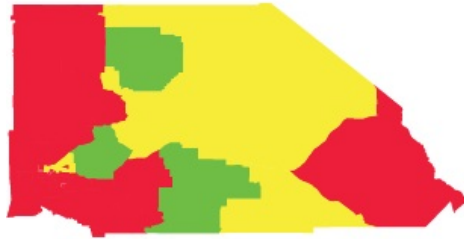
Net gain/No reduction in ground water Moderate reduction in ground water Net loss in ground water

The Wake County water management plan requires future water policy to mitigate the use of groundwater. Based on these requirements, model results are classified as having a net gain (so groundwater recharge is more than its use), no change or moderate reductions (groundwater use is more than its recharge, but is considered sustainable) and net loss (where use is more than recharge).

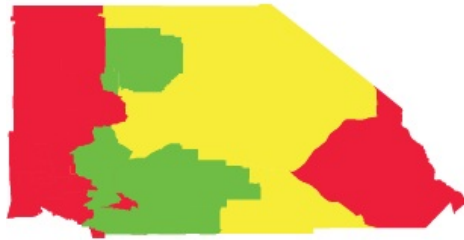
The representations in this Decision Set only show the model results of groundwater **assuming continued drought conditions for the next ten years**. Please use the visualizations to rank the policy options from most to least robust based on which you think will provide the most robust outcomes for water in Wake County.



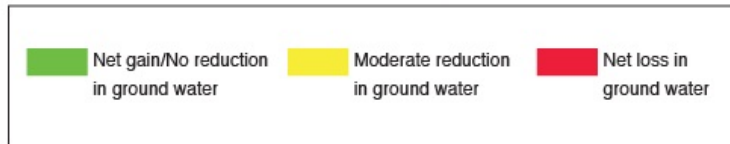
Policy Option 1 General plan allows for increased residential and commercial development, with population growth increasing to twice the rate predicted by the prior county plan. A public education plan about reducing water use will be implemented.



Policy Option 2: No change in population growth, agriculture or personal water usage



Policy Option 3: A policy to protect ground water is implemented in five years, requiring that ground water levels no longer be depleted; meaning use must be balanced with recharge. This policy will be strictly enforced through water restrictions for existing and new residents as well as businesses. Additionally, there will be increased use of effluent water for agricultural and commercial uses.



For this decision set, rank the policy options based on which provides the most robust outcomes for Wake County water. Use a scale of 1 to 3, with 1 being the most robust and 3 being the least robust.

	Most robust	Moderately robust	Least Robust
Policy Option 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 3	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please answer the questions below based on the visualizations used in this section.

I used the represented outcomes to evaluate the impact of climate change on groundwater

- True
 - False
-

The representations are effective for evaluating the impact of policy decisions on ground water

- | | | | | |
|-----------------------|-----------------------|---------------------------|-----------------------|-----------------------|
| Strongly disagree | Disagree | Neither agree or disagree | Agree | Strongly agree |
| <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
-

The representations incorporate the uncertain impact of climate change on future water supply

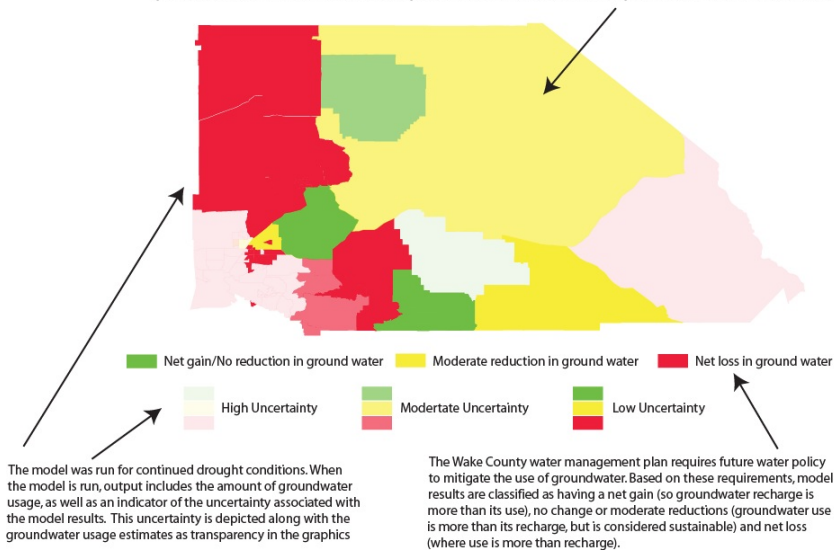
- | | | | | |
|-----------------------|-----------------------|---------------------------|-----------------------|-----------------------|
| Strongly disagree | Disagree | Neither agree or disagree | Agree | Strongly agree |
| <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
-

Please provide any additional comments about your use of the visualizations for making your decisions.

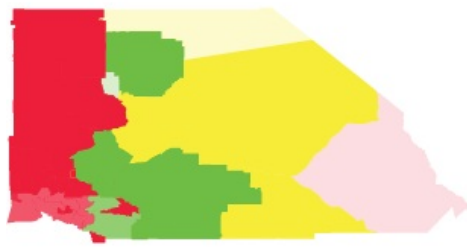
Decision Set GU

The representations in this Decision Set show the model results of groundwater **assuming continued drought conditions for the next ten years along with the uncertainty of the model results**. An example output visualization from the Future-Flow model is shown below with explanation for each component.

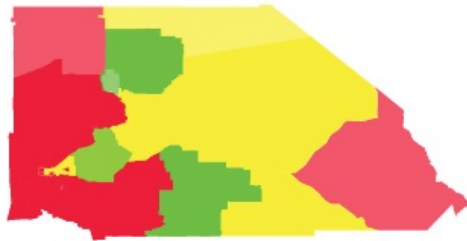
The geographic space represents the net cumulative change in groundwater. These values are determined from the Future-Flow model, based on policy decisions input into the model. As policy decisions are implemented in Future-Flow, the values in the county will change based on the model results. The results depicted using the choropleth map (using red, green and yellow) in this decision set reflects groundwater use with continued drought conditions for the next ten years.



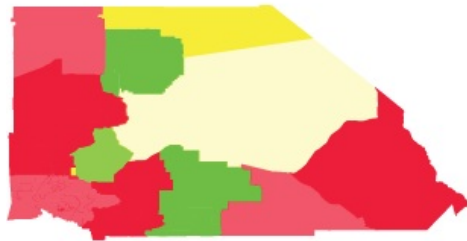
The representations in this Decision Set show the model results of groundwater **assuming continued drought conditions for the next ten years along with the uncertainty of the model results**. Please use the visualizations to rank the policy options from most to least robust based on which you think will provide the most robust outcomes for water in Wake County.



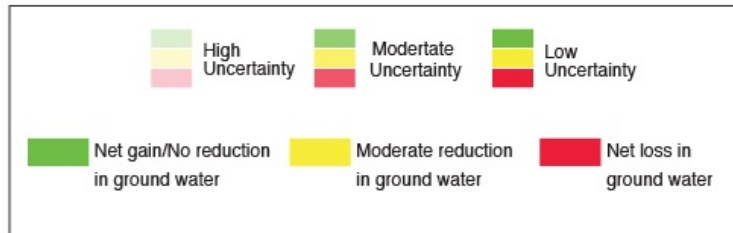
Policy Option 1: A policy to protect ground water is implemented in five years, requiring that ground water levels no longer be depleted; meaning use must be balanced with recharge. This policy will be strictly enforced through water restrictions for existing and new residents as well as businesses. Additionally, there will be increased use of effluent water for agricultural and commercial uses.



Policy Option 2: No change in population growth, agriculture or personal water usage



Policy Option 3 General plan allows for increased residential and commercial development, with population growth increasing to twice the rate predicted by the prior county plan. A public education plan about reducing water use will be implemented.



For this decision set, rank the policy options based on which provides the most robust outcomes for Wake County water. Use a scale of 1 to 3, with 1 being the most robust and 3 being the least robust.

	Most robust	Moderately robust	Least robust
Policy Option 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Policy Option 3	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please answer the questions below based on the visualizations used in this section.

I used the represented outcomes to evaluate the impact of climate change on groundwater

- True
- False

The representations are effective for evaluating the impact of policy decisions on ground water

- Strongly disagree Disagree Neither agree or disagree Agree Strongly agree

The representations incorporate the uncertain impact of climate change on future water supply

- Strongly disagree Disagree Neither agree or disagree Agree Strongly agree

Please provide any additional comments about your use of the visualizations for making your decisions.

Demographics

What is your experience with decision making in a professional setting?

Are you a

- Student
 - Faculty
 - Researcher
 - Other (please specify)
-

What is the geographic region of your primary work?

What is the major area of your work?

- Climate
 - Water
 - Decision Making
 - Uncertainty
 - Land Use/Land Cover
 - Other (please specify)
-

Where do you live?

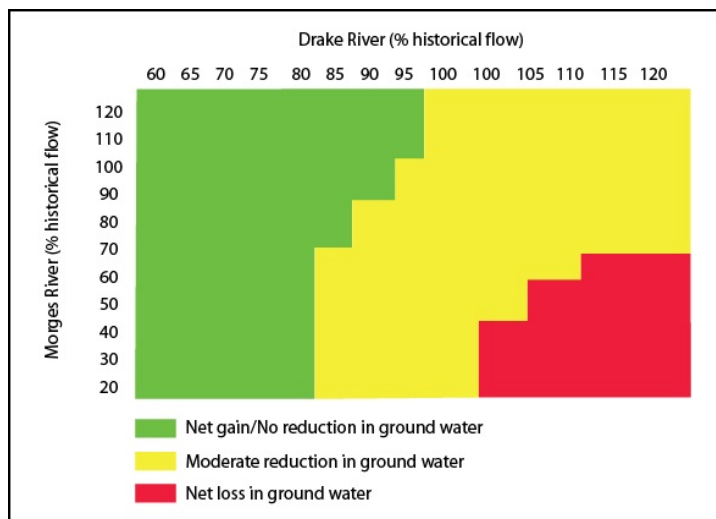
Exit Questions

Outcome maps that depict groundwater usage for all future river flows (example below) reflect the

uncertainty of climate change

- True
- False

If true, why? If false, why not?



Drawing entry

Thank you for taking the time to complete my survey. If you would like to be entered into the drawing for the gift cards, please provide the below requested information

Name

Email address

Thank You!

Thank you for taking our survey. Your response is very important to us.

APPENDIX B
STATEMENT OF PERMISSIONS

I declare that I have obtained explicit permission from my co-author, Elizabeth Wentz, for including two peer-reviewed scientific journal manuscripts as chapters in this dissertation.

Stephanie Deitrick