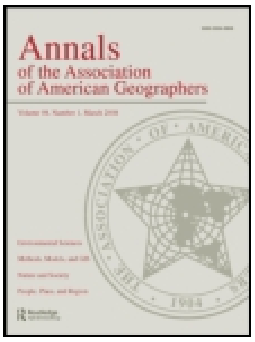

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Agreement between public policy decision makers and geographic information systems and visualization researchers about the importance of uncertainty in decision support sits in contrast to a disconnect in approaches to incorporating uncertainty into decision support tools. This disconnect does not arise from how these two groups define uncertainty but instead occurs because they approach uncertainty from different problem perspectives (Miller et al. 2008; Pohl 2011). Public policy decision makers regularly contend with uncertainty based on how proposed policies will affect the future, resulting in a solutions-oriented approach that relates uncertainty of future conditions to policy outcomes. For researchers, uncertainty more often reflects unknowns in data values or modeling processes, such as the difference between a measured or predicted value and the actual value, resulting in a knowledge-production approach that relates uncertainty to the validity and legitimacy of methods, models, and data to produce knowledge. The research presented here contends that this gap between research and practice (Brown and Vari 1992; von Winterfeldt 2013) stems from these differing perspectives. To bridge this gap, we examine decision science theories to explain decision makers' solutions-oriented approach to uncertainty. Decision science is concerned with understanding and improving how individuals or groups identify problems, make decisions, and learn from the outcomes. We then present a new methodology, implicit uncertainty visualization, that reflects how decision makers contend with uncertainty. Bridging this gap opens up opportunities to develop visualization methods and tools that help decision makers better deal with uncertainty in practice. *Key Words: decision making, decision support, uncertainty, visualization.*

公共政策制定者，与地理信息系统及可视化的研究者，一致同意决策支援中的不确定性的重要性，但此般意见一致，却与两者将不确定性整合进决策支援工具的方法的断裂形成对比。而此一断裂，并非源自于这两造群体定义不确定性的方式，而是由于他们以不同的问题视角处理不确定性而产生（Miller et al. 2008; Pohl 2011）。公共政策决策者，定期根据提议的政策如何影响未来，以对付不确定性，导致以解决问题为导向、将未来状态的不确定性连结至政策结果的取径。但对研究者而言，不确定性更经常反映数据值或模式化过程中的未知，例如评估或预测的值与实际值之间的差异，进而导致将不确定性连结至方法、模型与数据之于生产知识的有效性与合理性的知识生产取径。我们于此呈现的研究，主张此一研究与实践的断裂（Brown and Vari 1992; von Winterfeldt 2013），来自于上述差异化的视角。为了接合此一断裂，我们检视决策科学理论，以解释决策制定者以解决问题为导向来对付不确定性的取径。决策科学，关乎理解、促进个人或团体指认问题、进行决策，以及如何从结果中学习的方式。我们接着呈现一个新的方法论——内含不确定性的可视化，该方法反映决策制定者如何对付不确定性。接合此一断裂，将开启能够协助决策者在实践中更佳地处理不确定性的可视化方法及工具的发展契机。*关键词：决策制定，决策支援，不确定性，可视化。*

El acuerdo entre los encargados de tomar decisiones sobre políticas públicas y los investigadores de sistemas de información geográfica y visualización acerca de la importancia de la incertidumbre como apoyo a la decisión contrasta con una desconexión que tienen los enfoques para incorporar la incertidumbre como parte de las herramientas que pueden dar apoyo a la decisión. Esta desconexión no surge de la manera como estos dos grupos definen la incertidumbre, sino debido a que ellos la abocan desde diferentes perspectivas problémicas (Miller et al. 2008; Pohl 2011). Quienes toman las decisiones públicas corrientemente confrontan la incertidumbre pensando cómo afectarán las políticas propuestas el futuro, lo que resulta en un enfoque orientado a las soluciones, el cual relaciona la incertidumbre sobre las condiciones futuras con los resultados de las políticas. Para los investigadores, con mayor frecuencia la incertidumbre refleja lo que es desconocido en términos de valores de datos o en procesos de modelado, como la diferencia entre un valor medido o predicho y el valor real, lo cual resulta en un enfoque conocimiento-producción que relaciona la incertidumbre con la validez y legitimidad de los métodos, modelos y datos para producir conocimiento. La investigación que se presenta aquí sostiene que esta brecha entre investigación y práctica (Brown y Vari 1992; von Winterfeldt 2013) es causada por estas perspectivas diferentes. Para salvar la brecha, examinamos las teorías de la ciencia de la decisión con la intención de explicar el enfoque orientado a soluciones que siguen quienes toman decisiones sobre incertidumbre. A la

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ciencia de la decisión concierne entender y mejorar la manera como individuos o grupos identifican problemas, toman decisiones y aprenden de los resultados. Posteriormente presentamos una nueva metodología, la visualización de la incertidumbre implícita, que refleja la manera como los tomadores de decisiones lidian con la incertidumbre. Al vencer esta brecha se abren oportunidades para desarrollar métodos de visualización y herramientas que ayuden a los tomadores de decisiones a lidiar en la práctica con la incertidumbre. *Palabras clave: toma de decisiones, apoyo a las decisiones, incertidumbre, visualización.*

Public policy decision makers, defined here as individuals with useful decision-making knowledge or the ability to enact a policy, understand that uncertainty is an inescapable component of decision making (Schlossberg and Shuford 2005; Dong and Hayes 2012). Similarly, geographic information systems (GIS) and geovisualization researchers (referred to as researchers here) recognize the importance of identifying and evaluating uncertainty in analysis and outputs for decision support (MacEachren, Brewer, and Pickle 1998; Goodchild 2007; Moss 2007; Pebesma, de Jong, and Briggs 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 GIS uncertainty visualizations and tools as a constraint to making decisions, which might 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; MacEachren et al. 2005). Because there is agreement between decision makers and researchers that uncertainty is important, yet disagreement in how to incorporate it into decision support, we see this as a discrepancy between the way decision makers and researchers conceptualize uncertainty in decision problems.

Uncertainty is defined as the differences between reality and the knowledge, representation, or understanding of reality (Zhang and Goodchild 2002). Although there are many different definitions and forms of uncertainty, the discrepancy between the way decision makers and researchers conceptualize uncertainty does not arise from differences in their uncertainty definitions but, instead, emerges because they approach uncertainty from different problem perspectives (Miller et al. 2008; Pohl 2011). The goals, objectives, and experience of decision makers and researchers influence their problem perspective, which leads to different strategies for moving from an abstract understanding of uncertainty to an actionable representation of uncertainty.

From a policy perspective, decision makers regularly contend with uncertainty based on how current conditions or proposed policies will affect the future, resulting in a *solutions-oriented approach* that relates the uncertainty of future conditions to policy outcomes. Policymakers face the challenge of choosing from numerous, and often diverse, alternatives with far-reaching impacts. Uncertainty is inherent in these decisions, as it is difficult to project the impacts of policies when they depend on unknown future conditions (Comes, Hiete, and Schultmann 2013). The challenge increases with decisions under deep uncertainty, where the relationships between variables, the probability of future conditions, and the suitability of alternative outcomes are either unknown, unknowable, or are not agreed on among key constituents (Walker 2000; Lempert, Popper, and Bankes 2003). As a result of this solutions-oriented perspective, decision makers conceptualize uncertainty as the unknown influence of future conditions on decision outcomes.

From a research perspective, uncertainty more often reflects unknowns in data or modeling processes, such as the difference between a measured or predicted value and the actual or true value, resulting in a *knowledge-production approach* that relates uncertainty to the validity and legitimacy of methods, models, and data to produce knowledge. In GIS and visualization research, there is considerable literature that seeks to describe (Couclelis 2003; Worboys and Duckham 2004; Thomson et al. 2005), calculate and assess (Laskey, Wright, and da Costa 2010), and visualize uncertainty (Roth 2009; Sanyal et al. 2010). This broad literature has led to different uncertainty definitions, including terms such as error, validity, data quality, ambiguity, vagueness, and imprecision (Fisher 1999; Pang 2001). Even with the differing research goals and definitions of uncertainty, however, there is a shared perspective that seeks to quantify uncertainty. Quantification can be as complex as probabilistic estimates and as simplified as identification of values as certain or uncertain. The knowledge-production perspective results in a generalized view of uncertainty, which focuses on specific measures and representations of uncertainty for a wide range of data and model input, output, and propagation characteristics, including error, accuracy, reliability, precision, and quality (Edwards and Nelson 2001).

The ways in which policymakers and researchers approach uncertainty in decision problems exist almost as complements to one another. For policymakers tasked with evaluating decision outcomes for different policy alternatives, quantifying uncertainty is not beneficial, as decision makers conceptualize uncertainty as the unknown influence of future conditions on decision outcomes. Conversely, researchers conceptualize uncertainty as a characteristic that can be quantified, estimated, and to some extent agreed on by those involved in evaluation. To bridge these differences, we describe visualization methods based on theories from decision science. The field of decision science is centered on understanding and improving how individuals, groups, or organizations identify problems, make decisions about those problems, and learn from the outcomes (Kleindorfer and Kunreuther 1993). Through literature in both decision science and uncertainty visualization, the research presented here defines explicit and implicit uncertainty visualization (Deitrick 2013) as a way to connect researchers' and decision makers' understanding of uncertainty for use in GIS for decision support.

Literature Review

To motivate our approach to develop visualization 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 decision science literature. We then describe how this work is related to current uncertainty visualization approaches.

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). Ill-structured problems are broadly defined as situations where the elements of the decision problem, the existing or desired future state, and possibly even the definition of the problem are unclear and, therefore, methods to reach the desired outcome are not known (Malczewski 1999). 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 course of action is a merger among individual expectations, motives, beliefs, and desires. This affects 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, requiring 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 under uncertainty. Normative decision theories focus on how people should make decisions to facilitate better decisions through structured analysis. Conversely, descriptive decision theories focus on how people actually make decisions in practice. Prescriptive decision theories focus on what actual decision makers can and should do, incorporating both the specific context of the decision problem and decision-maker needs. In this way, prescriptive decision theories are based on both normative and descriptive theory. We describe these three theories in detail here.

Normative Decision Theories

Normative decision theories describe how decisions should be made. In normative theories, decisions are divided into four components: (1) alternatives, (2) possible future conditions, (3) probabilities of the future conditions, and (4) information about outcomes of the alternatives under differing future conditions (Jonassen 2012). Decision makers are assumed rational, capable of working through complicated decisions, and fully informed, and the uncertainties and probabilities for given alternatives are assumed to be agreed on, knowable, and known. The goal in normative approaches is not to explain or predict behavior but to facilitate better decisions through structured analysis of 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 representing probability and uncertainty (Manson, Ratick, and Solow 2002; Ascough et al. 2008). For example, UrbanSim, a widely known decision support tool, consists of nine individual models that integrate household location and mobility, economic location and mobility, employment location and mobility, land pricing, and transportation. Sevcikova, Raftery, and Waddell (2007) developed probability methods for assessing uncertainty in UrbanSim, finding that significant sources of uncertainty in the system must be identified to carry out a probabilistic assessment of uncertainty. This assumes that decision makers can rationally work through known and agreed on probabilities to reach a decision.

Although the normative approach might be beneficial for decisions where uncertainty can be identified and quantified through specific probability distributions, 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 on (Lempert, Popper, and Bankes 2003; Gober et al. 2010). Under conditions of deep uncertainty, the information needed to identify the optimal solution cannot be agreed on or often does not exist (Polasky et al. 2011). This leads to challenges in developing probability-based decision support tools for complex, deeply uncertain problems, such as climate change, economic futures, and transportation infrastructure planning.

Descriptive Decision Theories

Descriptive decision theories explore how people actually make decisions. In practice, decision makers rarely select alternatives based on purely rational choices the way normative theories suggest but instead base decisions on information about alternatives combined with affective feelings and emotions about those alternatives (Slovic et al. 2004, 2007). This is particularly true for decision makers with prior experience in the particular decision problem, as their beliefs, biases, and experiences with those problems result in decisions that are context and domain dependent (Rettinger and Hastie 2001; Jonassen 2012).

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). Framing refers to the different ways decision makers make sense of a problem, by selecting the relevant aspects, connecting those into a meaningful whole, and identifying the boundaries of the problem (Takemura 1994; Dewulf, Craps, and Dercon 2004). For example, when presented with a plan to open a previously closed preserve to recreational activities, developers, environmentalists, and policymakers might frame the plan differently. The developer sees a way to build amenities on the route to the area, the environmentalist sees a threat to the habitat, and policymakers see opportunities to increase tourism and tax revenue. It is the same plan but framed differently based on the desires, experiences, and biases of the individuals. The frame adopted by a decision maker is controlled both by the presentation of the problem (external framing) and the personal experiences, biases, and beliefs of the decision maker (internal framing). For example, whether a decision problem is framed positively or negatively influences the decision makers' approach to the problem (Tversky and Kahneman 1981).

Strategies to cope with uncertainty fall into three basic groups: reducing, acknowledging, and suppressing (Lipshitz and Strauss 1997). Reducing strategies include collecting, or waiting for, additional information before making a decision. The additional information does not necessarily need to be correct but needs to support the perception of consistency in what is known (Brashers 2001). Acknowledging strategies attempt to account for irreducible uncertainty when selecting a potential course of action and then identify ways to manage or avoid the potential impacts of the uncertainty (Chalkidou, Hoy, and Littlejohns 2007). Suppressing strategies include ignoring or altering the uncertain information (denial). Decision makers might suppress uncertainty with cursory attempts to reduce or acknowledge uncertainty (rationalization; Milkman 2012).

These strategies benefit problems where it is feasible to wait for and obtain additional information or where knowledge about uncertainty is sufficient to develop discrete courses of action. This assumes, however, that better knowledge will be achieved with more work, time, or effort allowing deep uncertainties to be converted to manageable statements of risk. The challenge is that more work and more information might not reduce uncertainty and could even expose previously unknown uncertainties. Moreover, some uncertainties might be irreducible, no matter the amount of additional information. Therefore, some decisions must proceed in the face of deep uncertainty. As a result, decision problems require methods for evaluating decisions in the face of these deep uncertainties.

Prescriptive Decision Theory

Prescriptive decision theory acknowledges that humans can be poor decision makers, integrating how decisions should be made with tools that facilitate better decision making. The development of prescriptive tools aims to fulfill two goals. Tools must be useful to decision makers, and decision makers must actually be able to use them. In effect, the goal is to prescribe how decision makers can approximate normative decision processes in practice. The result is a synthesis of normative and descriptive decision theories (Brown and Vari 1992).

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

Scenario planning offers a means to better handle evaluation of variable future conditions by exploring the long-term implications of decisions 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, Hines, and Collins 2007; Volkery and Ribeiro 2009). In public policy settings, scenarios allow decision makers to better understand how policies behave over a range of futures, as well as clarify their perceptions of the problem. This 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). Although the system was deemed easy to use, users would need to manually generate more and more scenarios to see the full range of impacts as the number of future states and policy alternatives increases.

Similarly, multicriteria decision making (MCDM) offers techniques to address uncertainty throughout the decision-making process (Malczewski 2006; Mosadeghi et al. 2013). These techniques involve defining objectives, selecting criteria to evaluate the objectives, applying mathematical methods to rank the alternatives, and finally choosing the best alternative. MCDM can be seen as a structured decision-making approach that implements scenarios in a way that accounts for decision-maker preferences for criteria and alternatives (decision-maker values), while providing algorithms to overcome uncertainty in the decision process. Within this framework, research concentrates on uncertainty in decision makers' preferences and knowledge as well as the uncertainty that arises from models (Malczewski 1999).

For both scenario analysis and MCDM, static policies that perform well in many or even most possible future conditions are unlikely (Walker, Rahman, and Cave 2001; Comes, Hiete, and Schultmann 2013). Rather, addressing deeply uncertain problems 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. The goal in robust decision making is to identify policies that perform well over a number of possible futures, so that policies are less sensitive to unknowns (deep uncertainties; Couclelis 2003). Decision makers can then evaluate each robust policy in detail.

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 statistical estimates or the written word (Tufte 1983; Hedges 1987).

Uncertainty Visualization in Cartography and GIS

The goal of this section is to describe different approaches for visualizing geographic uncertainty

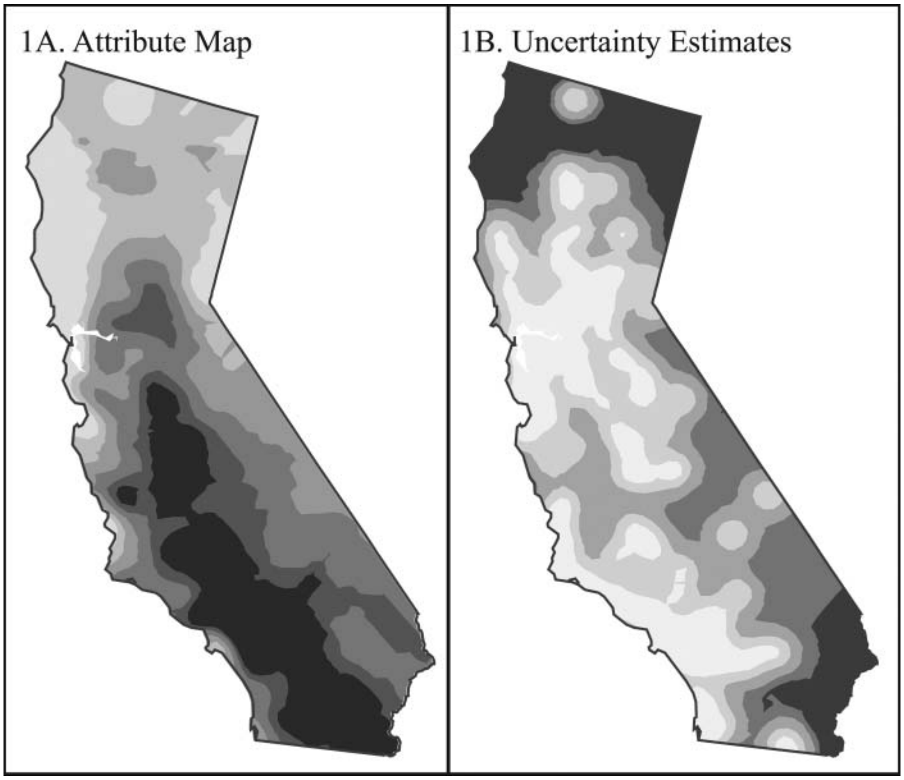


Figure 1. A map pair using value (light to dark) to depict (A) ozone levels and (B) related uncertainty estimates. In existing approaches, estimates can be qualitative (certain vs. uncertain) or quantitative (i.e., error estimates or probabilities), but an estimate must exist to create the uncertainty map.

including visual variables and cartographic representation and studies to evaluate their effectiveness for communicating uncertainty.

Visual Variables and Cartographic Representation

There are numerous methods for visualizing uncertainty when it is possible to provide quantitative estimates of uncertainty (Pham and Brown 2003; Li and Zhang 2006; Dong and Hayes 2012). Many methods begin with the adaptation of Bertin's (1983) visual variables, including size, shape, value, orientation, color, and texture, to represent both the attribute value and uncertainty. MacEachren (1992) described additional visual variables for representing uncertainty, such as transparency, saturation, and clarity. Several strategies exist for combining visual variables to incorporate uncertainty into the visualization of spatial data attributes. MacEachren (1992) proposed three approaches for this integration, specifically, map pairs, sequential representation, and maps combined (referred to here as bivariate approaches).

The first two approaches focus on univariate representations of data and uncertainty. Map pairs depict data (Figure 1A) and uncertainty (Figure 1B) on separate maps at the same time, often through side-by-side comparisons. Viard, Caumon, and Lévy (2011) used map pairs to depict geologic pressure and uncertainty to support the selection of a new oil or gas well site. Both the attribute and uncertainty were symbolized using similar multihued color schemes. Sequential methods integrate multiple univariate representations of data and uncertainty into a dynamic display that sequentially presents the data through methods such as toggling, flickering, or other animations. Fisher (1993) used animation to depict soil classification uncertainty using duration. The amount of time a grid cell was depicted as a specific soil class represented the chance of the cell actually being that class. Longer duration of a color implied lower uncertainty, so that these areas appeared to have more stable color.

Bivariate approaches depict data and uncertainty in a single visualization, falling into two general approaches: visually integral or visually separable. Visually integral approaches alter the data symbology so that both data and uncertainty are represented by a single visual

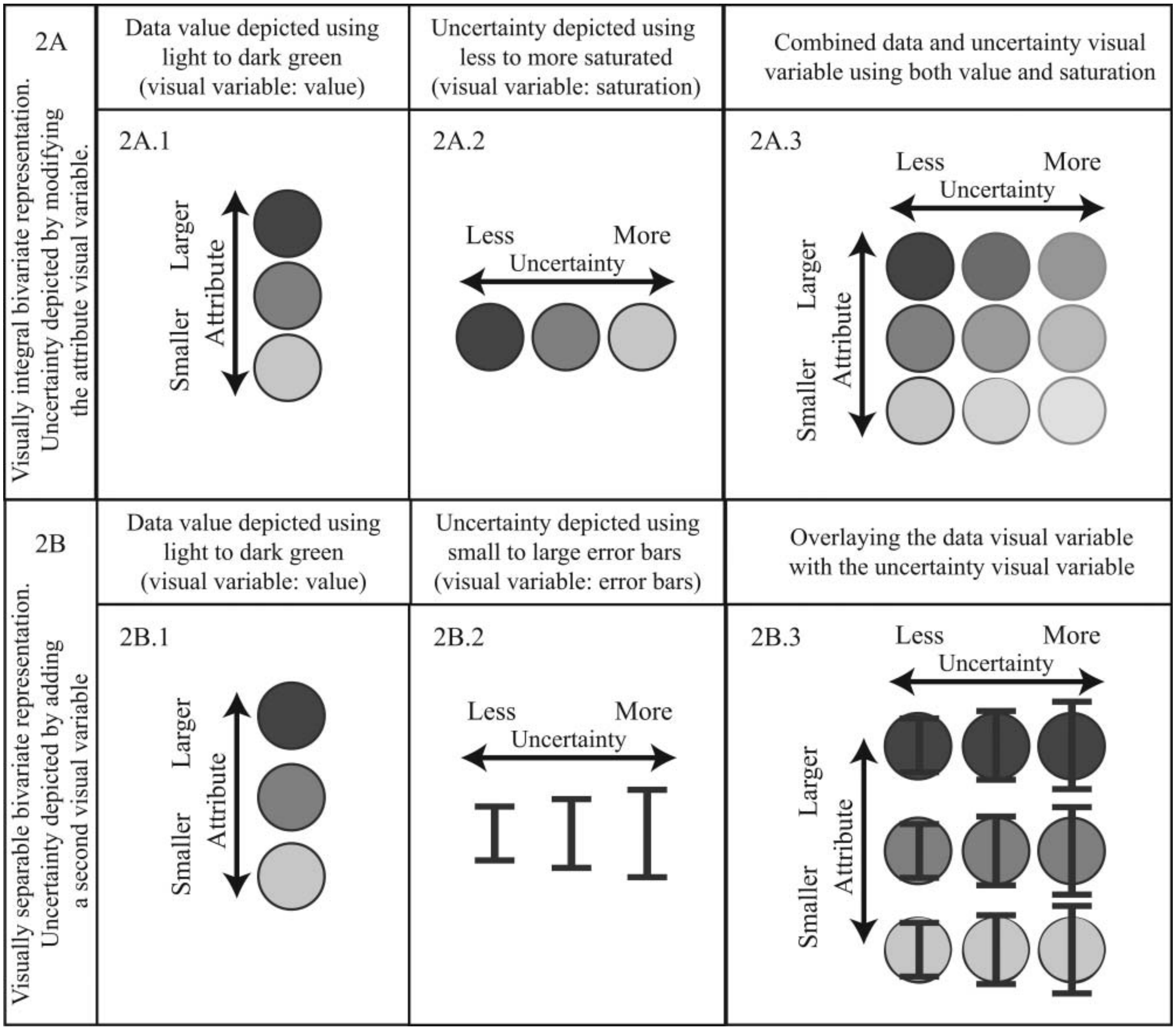


Figure 2. Bivariate approaches represent data and uncertainty in a single map by either (A) modifying the visual variable to represent both data and uncertainty or (B) adding a second visual variable to represent uncertainty.

variable. Figure 2A depicts a visually integral approach that merges value (2A.1) with saturation (2A.2). In the example, dark gray represents large attribute values (top row 2A.3). Using the combined value–saturation variable, areas of low uncertainty would be pure dark gray, whereas areas of high uncertainty would appear more washed out. The resulting visualization depicts data and uncertainty as a single attribute.

Visually separable approaches add a pattern, texture, or geometric object (e.g., glyphs or bars) to depict uncertainty. This combination of data and uncertainty is similar to overlay, where uncertainty is on top of the data. Figure 2B depicts a visually separable approach that overlays value (2B.1) with error bars (2B.2). In the example, areas with large attribute values would be dark gray, with low uncertainty areas including short error bars and high uncertainty areas including longer error bars. The resulting visualization depicts data and uncertainty as two separate attributes.

Although each of these approaches represents data and uncertainty differently, each presupposes that it is possible and desirable to quantify uncertainty in some way. This assumption underlies methods for visualizing data and uncertainty, as well as research seeking to evaluate those methods.

Evaluating Uncertainty Visualization

The primary focus of many uncertainty visualization studies is to develop generalizable methods that depict the form, source, amount, or presence of uncertainty in individual attributes or results. These studies typically focus on designing the visualization (Buttenfield 1993; Fauerbach et al. 1996; Sanyal et al. 2010), evaluating whether users were able to identify specific uncertainty values (Blenkinsop et al. 2000), and assessing the impact of uncertainty visualization on decision making (Hope and Hunter 2007; Riveiro et al. 2014). Results of specific techniques such as using glyphs (e.g., cylinders and cones) and transparency have shown that both visually separable and integral methods are useful for identifying uncertainty in mapped data (Newman and Lee 2004; Sanyal et al. 2010).

In the area of decision support, researchers have sought to identify the impact of uncertainty visualization on decision making through the inclusion of decision makers and differing decision tasks in their studies. Aerts, Clarke, and Keuper (2003) compared static representations with dynamic toggling and found that although planners and decision makers found the inclusion of uncertainty information as useful, they preferred the static representations to dynamic toggling between the maps. Deitrick and Edsall (2006) evaluated whether there were differences in decisions made using maps with and without uncertainty visualizations, finding that the impact of the uncertainty visualization was influenced by the decision task and framing of the decision problem. Cliburn et al. (2002) considered the experience of the user in evaluating the effectiveness of visually integral and visually separable uncertainty visualizations. Participants classified as decision makers found the less detailed integral visualizations effective for identifying areas of uncertainty but also indicated that they did not like seeing the uncertainty represented. The scientific experts were more readily able to use the more detailed and complex visually separable visualizations. Similarly, in a study examining how water managers use GIS to address uncertainty, Howard (2008) found that although decision makers indicated they used GIS to address uncertainty, they wanted to know how uncertainty impacts the outcomes of policy decisions.

It is important to note that several assumptions underlie the methods and studies discussed in this section, reflecting the way in which researchers conceptualize uncertainty. First, it is assumed that uncertainty, or at least uncertainty of interest, is both knowable and identifiable. Similarly, to be visualized, uncertainty must be quantifiable, such as through statistical estimates, quantitative ranges, or qualitative statements (e.g., less or more uncertain). Moreover, evaluations define effectiveness as an ability to identify specific uncertainty values, which assumes that identifying specific uncertainty values is useful to decision makers and that the values of interest can be quantified. Lastly, there is an assumption that the quantification of uncertainty is beneficial, applicable to the decision task, and usable by the decision maker, even if users do not currently work with uncertainty in that way. These assumptions pose a challenge for visualizing uncertainty to support decision making under deep uncertainty, where quantification of uncertainty is not possible or necessarily desirable. In this way, current approaches to uncertainty visualization are more normative in nature, reflecting what researchers think decision makers need to know about uncertainty.

Explicit and Implicit Uncertainty

The literature synthesized in this work presents two sides of uncertainty visualization for decision support. The decision science literature describes the various ways that decision makers incorporate uncertainty into their decision process. The uncertainty visualization literature, in contrast, reflects the ways that researchers incorporate uncertainty into their research process. Our goal here is to capture decision makers' solutions-oriented approach so that visualization tools can be built to address their important needs. Specifically, we introduce the concepts of explicit and implicit uncertainty as the foundation for developing prescriptive approaches to uncertainty visualization that are useful to, and usable by, decision makers (Kirchhoff, Lemos, and Dessai 2013).

Explicit uncertainty is linked to normative decision theories, reflecting what researchers think decision makers need to know about uncertainty. Implicit uncertainty is linked to both descriptive and prescriptive decision theories, integrating what decision makers actually do in practice with tools to support better decisions. Our objective is to use both explicit and implicit uncertainty as mechanisms to integrate what decision makers actually do in practice with tools to support better decisions. The following subsections define explicit and implicit uncertainty, provide examples to illustrate how visualization tools apply, and illustrate the interaction of implicit and explicit uncertainty in the decision process. We suggest methods for visualizing implicit uncertainty by adapting existing graphic methods to represent the outcomes for a water policy decision problem for a hypothetical city.

In the water policy decision scenario, water managers wish to evaluate the impact of water policy on future groundwater depletion using model projections based on future river flows. Water policy decisions traditionally rely on the assumption that it is possible to predict the future based on historical trends, which makes it possible to develop policy plans that (1) perform optimally for a single most likely future condition or (2) produce desirable outcomes over multiple plausible future conditions (Haasnoot et al. 2013). The impact of climate change undermines the assumption that historical trends will repeat into the future, introducing deep uncertainty into water policy decisions (Gober et al. 2010). In the scenario used here, the impact of climate change on river flows introduces deep uncertainty. The examples in the following subsections focus on depicting the impact of this deep uncertainty on groundwater usage (the policy outcomes). To provide continuity in the following discussions, examples in both the explicit and implicit subsections are based on this water policy scenario. A brief discussion of the uncertainty in the decision scenario, as it relates to explicit or implicit uncertainty visualization, is provided in the following subsections.

Explicit Uncertainty: Definition and Example

This section describes explicit uncertainty visualization methods. In contrast to the next section on implicit uncertainty, this section is deliberately brief. This is not to minimize its importance in our research but, rather, because explicit uncertainty methods and approaches are widely known—just not called such.

Explicit uncertainty is a data-centered approach, where uncertainty is conceptualized as gaps, errors, and unknowns displayed or represented through quantitative values (e.g., statistical estimates or error bars) or qualitative estimations (e.g., more or less uncertain; Deitrick 2013). Explicit uncertainty is linked to normative decision theories (Figure 3), reflecting what researchers think decision makers need to know about uncertainty in data and model outcomes to make more informed decisions. In GIS and visualization research, statistical estimates of uncertainty and its propagation inform the evaluation of data sources, models, parameters, and model and analysis outputs. Existing visualization methods, such as transparency or texture (MacEachren 1992) as shown in the prior section, focus on representing known or knowable uncertainties, assuming that better, and optimal, decisions result

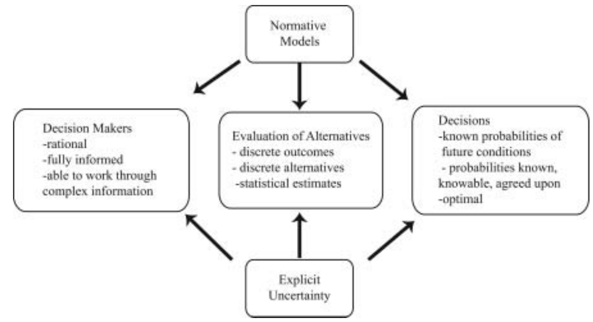


Figure 3. Explicit uncertainty as a normative model of decision making.

from the identification and evaluation of these values. As a result, current methods for visualizing uncertainty, as described in the prior section, are all explicit.

For the water policy decision problem, an explicit approach would provide decision makers with both the projected policy outcomes (based on the model results) and a quantitative or qualitative estimate of the related uncertainty. Outcomes (and uncertainty) would need to be determined for every policy alternative being considered. For the outcomes shown in Figure 4, the map on the left depicts the projected change in groundwater that would result from the proposed policy for a single assumed future condition. The map on the right depicts the uncertainty that corresponds to the model results. If additional policies, or additional future conditions, were considered, each would require a map pair. So, for example, if there were three policies being evaluated, with ten plausible future conditions, there would be thirty model result–uncertainty map pairs.

There are several assumptions underlying explicit uncertainty visualization that reflect normative decision theories. First, it is possible to quantify the probability of a single outcome, which requires some knowledge of the probability of the input parameters and their interaction. Second, the number of plausible futures will be limited enough to allow comparison of a small number of outcome and uncertainty map pairs. Finally, decision makers will be able to use the uncertainty estimates, and their comparison across multiple maps, to evaluate the outcomes of different decisions. Although explicit representations and statistical estimates of uncertainty might match researchers' knowledge-production approach to uncertainty, these do not necessarily reflect decision makers' solution-oriented approach for dealing with conditions of deep uncertainty in practice.

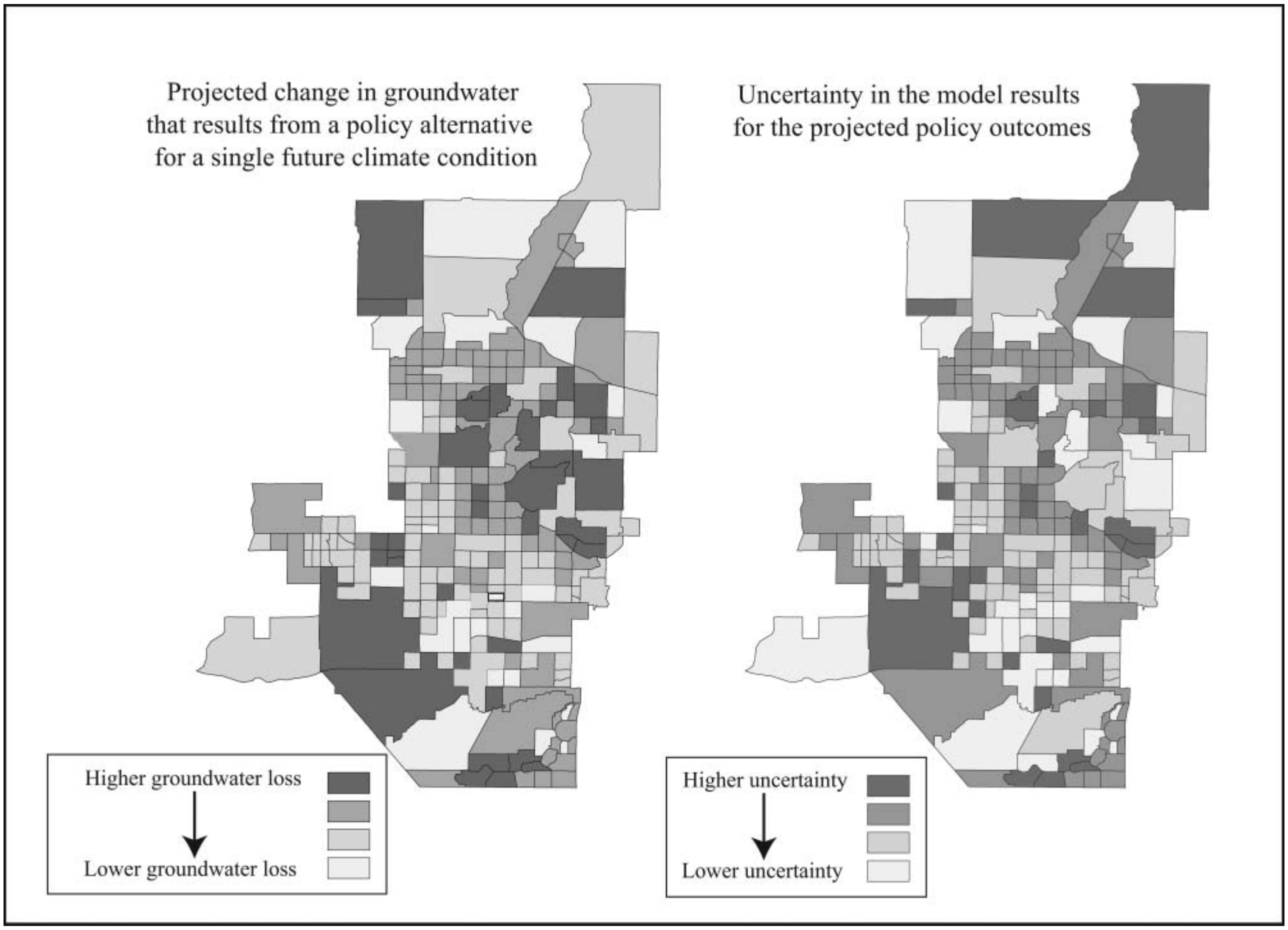


Figure 4. Map pairs depicting groundwater and uncertainty for a single future condition using light to dark symbology. The more future conditions considered, the more policy outcome maps or map pairs needed.

Implicit Uncertainty: Definitions and Examples

Implicit uncertainty is a user-centered approach to uncertainty. It builds on descriptive theories of decision making, acknowledging the impact of decision makers' experience, emotions, and knowledge on how they frame decision problems, without assuming that the probability of future conditions is known or knowable (Deitrick 2013). The relationship between descriptive decision theories and implicit uncertainty is illustrated in Figure 5. The goal of implicit approaches is to develop tools that are both useful to and usable by decision makers. Facilitating efforts to explore and understand the relationship between uncertainty and decision outcomes becomes key to identifying policies that are robust against uncertainty. This focus on providing visualization tools that increase decision makers' ability to understand the impact of uncertainty on decision outcomes is prescriptive in nature.

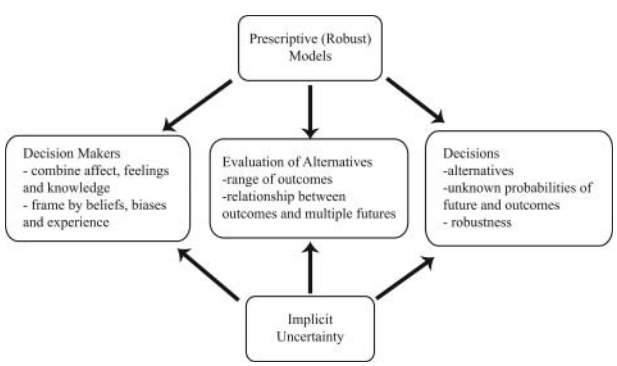


Figure 5. Implicit uncertainty as a descriptive model of decision making.

At the very least, decision makers are tasked with choosing between two alternatives. In these conditions, if a single future condition were considered, comparing projected outcomes would require only two sets of visualizations (outcomes and uncertainty for each alternative). As the number of policies being considered increases, the number of visualizations also increases. If there are multiple plausible future conditions, such as with climate change scenarios, the number of visualizations increases for each policy being considered. Evaluating multiple visualizations not only between policies but also between plausible future conditions poses a significant challenge for identifying decisions that are robust across a range of futures. As a means to address this challenge, implicit methods incorporate the full range of future condition assumptions for each policy alternative. The result is a continuous set of decision outcomes where uncertainty is integrated with the variable attribute, so that there is a single visualization for each policy being evaluated.

In the water policy example, the relationship between decision outcomes and uncertainty (impact of climate change) is depicted without the need for quantification. As with the explicit visualization example, the implicit examples depict projected changes in groundwater (decision outcome) that result from an increase in population (policy decision). With unknown impacts of climate change on future water supplies, it is not always reasonable to identify one or two plausible future conditions. For this scenario, there are two rivers that provide much of the water supply. The existing climate models project that in the future the rivers will produce approximately 20 to 120 percent of historical flows (climate uncertainty). Here deep uncertainty is operationalized as the range of projected impacts of climate change on future river flow.

The methods presented in the following subsections address the challenge of representing policy outcomes for all future climate conditions found in the water policy example. These examples represent several different approaches for visualizing relationships but share a similar solutions-oriented approach, relating uncertainty to its impact on decision outcomes. The matrix in Figure 6 organizes these implicit methods based on the following factors:

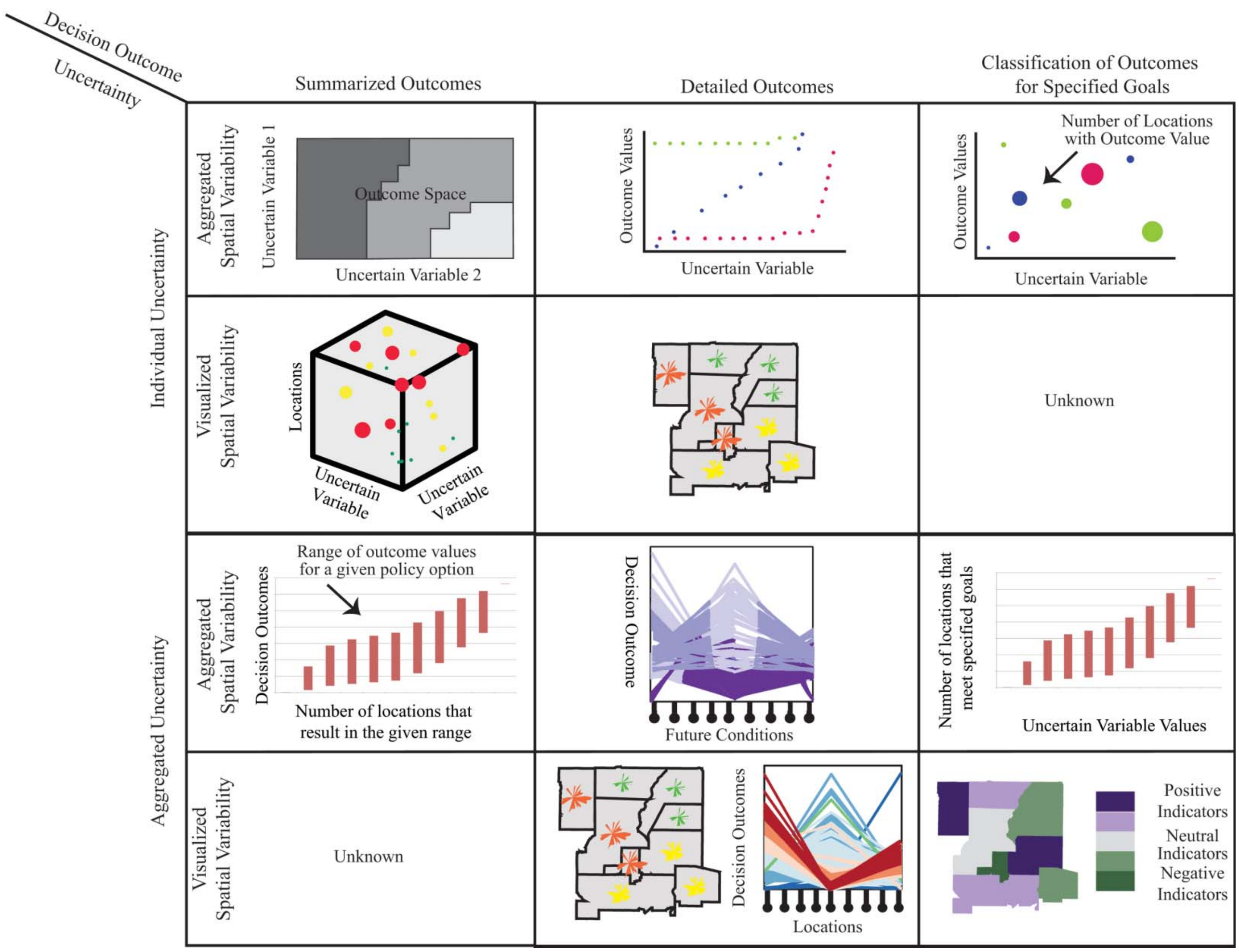


Figure 6. The matrix depicts the visualization solution space based on the way uncertainty and decision outcomes are conceptualized. (Color figure available online.)

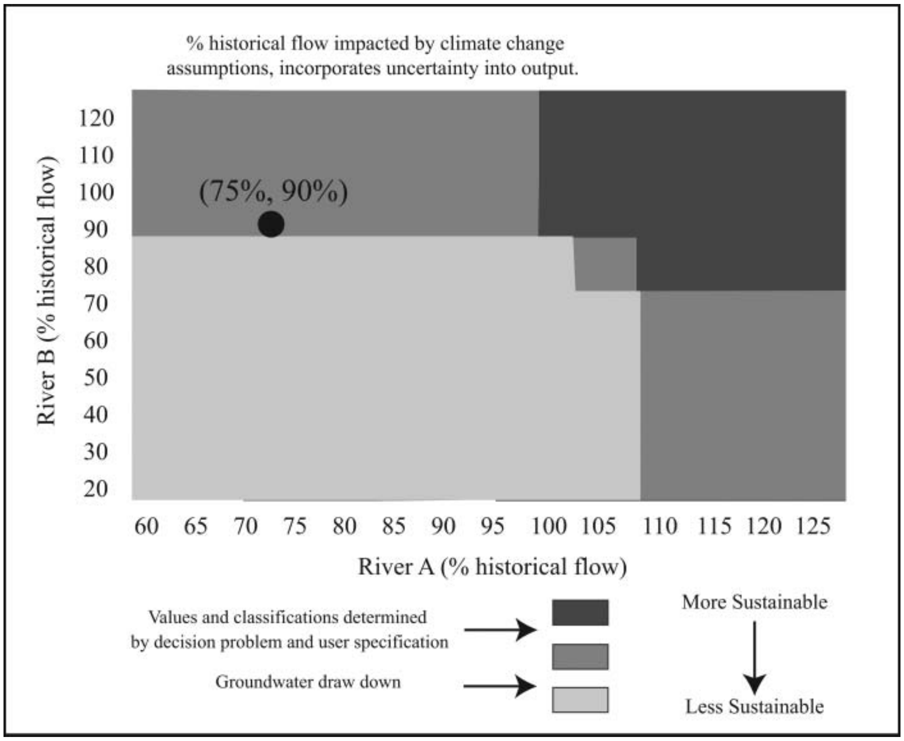


Figure 7. One outcome space map represents outcomes for a single policy for all possible future conditions. For the water example, the axes represent uncertainty as the range of future river flows.

- How is uncertainty defined and developed into an action plan? There are two classifications here. The first is that one or more individual uncertainties are visualized. These might not represent all uncertain inputs but represent the components considered most important or challenging. The second classification aggregates all uncertainty, so that no single uncertainty variable is considered separately. In the matrix, the first and second rows include individual uncertainty methods, whereas the third and fourth rows show aggregated uncertainty methods.
- How are decision outcomes presented? Outcomes can be summarized based on goals, locations, or uncertainty variables. Individual outcomes can also be represented for future conditions, uncertainty values, or locations. In the matrix, the first column includes summarized outcome methods, the second column represents detailed outcome methods, and the third column represents goal-based methods.
- How is spatial variability depicted? Visualizations either represent spatial variability directly or aggregate the variability into projected decision outcomes. In the matrix, the first and third rows show aggregate spatial variability approaches, and the second and fourth rows show approaches that directly represent spatial variability.

Outcome Space

Outcome spaces display the relationship between uncertain variables and policy outcomes in a two-dimensional space (Figure 7), where each axis represents one uncertain variable (Lempert, Popper, and Bankes 2003; Deitrick 2013). The two axes are selected based on the uncertainty important to the problem. Each coordinate pair represents one future condition in the outcome space. Policy outcomes are mapped to each future condition. Values are symbolized using actual outcome values or through classifications such as least-to-most robust or desirable. Resultantly, a single outcome space depicts outcomes for one policy over all plausible future conditions. Each additional policy requires one additional outcome space, so that the number of maps needed is the same as the number of policies being evaluated, regardless of assumptions about future conditions. This allows comparison of policies over a number of future conditions, where robust policies are identified by the outcome space with the largest area in the desirable range.

For the water policy example, the axes represent the percentage of historical flow for each river. The groundwater usage that results from the policy for each future condition is mapped to the corresponding coordinate. For example, if future conditions were assumed to be 75 percent (River A) and 90 percent (River B), then the projected decision outcome would be mapped to (75 percent, 90 percent; Figure 7). Groundwater usage is symbolized as most to least sustainable using a green, yellow, and red color scheme. This outcome space shows that sustainable outcomes (green areas) result from future conditions where moderate reductions in one river flow are counterbalanced by no reduction or moderate increases in the other river flow. Here, increases in flow on River A appear to offset decreases in River B, but the converse is not shown to be true.

Parallel Coordinate Plots

Parallel coordinate plots are line graphics that show the relationship between variables in multidimensional data sets (Edsall 2003). Parallel coordinate plots are basically representations of data tables. Attributes, represented by the columns in the table, are mapped onto the vertical axes. Observations (records), represented by rows in the table, are mapped along each of these vertical axes. Minimum values are mapped at the bottom of each axis and maximum values at the top. The points for a single record are connected with a line across the different axes. Patterns for the attributes are uncovered as the record lines converge or spread out across the axes. These are easily adaptable for implicit uncertainty.

As an implicit method (Figure 8), the columns (8.1) represent the geographic units being analyzed, such as parcels, census tracts, or counties. The records (8.2) represent the range of uncertainty scenarios or variables, such as multiple uncertain future conditions, uncertain variable values, or multiple assumptions about future conditions. The values being mapped (8.3) represent the policy outcomes for the uncertain condition for each geographic area. A line would connect the points for a single uncertain scenario (8.2)—for example, a single plausible future condition—across the different geographies. As the lines that represent each uncertain condition converge, it is possible to identify policies that result in desirable outcomes over multiple future conditions and across multiple geographies. Each parallel coordinate plot would represent the outcomes for a single policy.

For the water policy example, the vertical axes represent the water service areas impacted by the policy (8.1). The records are the futures that result from the range of projected future river flows (uncertainty of

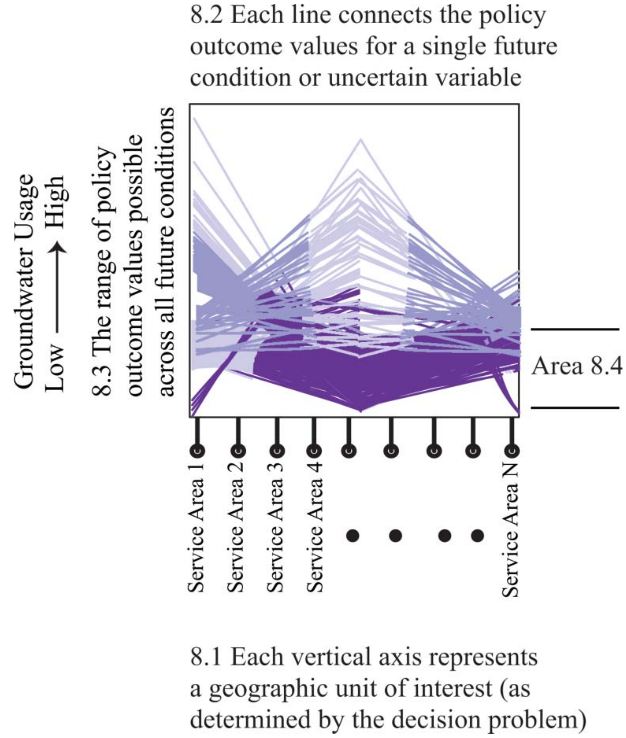


Figure 8. One parallel coordinate plot represents outcomes for one policy for all plausible future conditions, illustrating policy performance by geographic unit for multiple future conditions. (Color figure available online.)

climate change; 8.2). The values mapped onto each vertical axis represent the groundwater usage (policy outcome) that results for each future condition (8.3). Spatial variability might exist in the outcome values that are considered desirable. In the example, acceptable groundwater usage would be defined for each water service area. Policy outcomes for each future condition would be mapped as a single line, and values symbolized based on the groundwater usage goals for each service area. In area 8.4, for example, the outcome values are identified as acceptable for Service Areas 3-N (depicted as dark purple). Although Service Areas 1 and 2 have similar outcome values, they are depicted as light purple for not meeting the usage requirements for that area. The resulting variability in mapped values represents the relationship between uncertain future river flows and decision outcomes, as well as the spatial variability of the outcomes.

Goal Plots

Goal plots display the relationship between uncertain variable(s), policy goals, and geography in a two-dimensional graph (Figure 9). This approach is

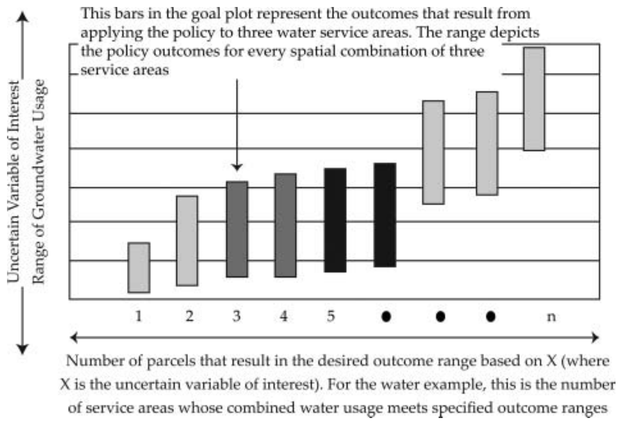


Figure 9. The *x*-axis of the goal plot represents the number of places where the policy is applied (X). The bar depicts the range (on the *y*-axis) of policy outcomes for every combination of X locations.

desirable when decision makers need to identify geographic areas or groups of areas (i.e., total acres, census tracts) that meet a certain goal (the policy outcomes fit a predefined criteria; Shimizu et al. forthcoming). Instead of depicting the full range of policy outcomes, goal plots illustrate the relationship between geographic area and policy outcomes (implicit uncertainty). In goal plots, the *x*-axis represents the number of locations where the policy would be implemented. The *y*-axis represents the range of policy outcomes (that result from uncertain future conditions). The bar represents the range of outcomes that result when the policy is applied to X locations over all plausible future conditions. The range reflects outcomes for all possible combinations of X locations. So, for example, in Figure 9, the second bar represents the range of outcome values that would result from implementing a policy in two locations. The bars are symbolized based on the groundwater usage and development goals of the decision problem.

For the water example, the desirable range of groundwater usage and minimum number of locations would be identified for the policy. Each value on the *x*-axis indicates the number of water service areas (X) where the policy is applied in the groundwater projection. The *y*-axis represents the amount of groundwater usage that results when the policy decision is applied to X water service areas. The bars in the graph depict the range of policy outcomes for all possible combinations of X water service areas. The bars are symbolized based on the groundwater usage and location goals. For example, a policy goal might be to minimize groundwater usage while also maximizing the number of locations where the policy is implemented. The goal plot would depict high groundwater usage and a large number of locations and low groundwater usage and a small number of locations as red (Figure 9).

Goal plots aid identification of policies that result in desirable outcomes for the largest number of locations (e.g., how many service areas could have the specified level of population growth while still meeting the groundwater use goal). The strength of goal plots is that they build on decision makers' solutions-oriented approach. With goal plots, implicit uncertainty can be operationalized in many ways, such as climate change impacts or the effects of alternate land use or development density.

Youden Plots

Youden plots are specialized scatterplots that display measurement uncertainty among different geographic locations (Wang et al. 2011). The plots can be adapted to represent implicit uncertainty with the uncertain variable on the *x*-axis and policy outcomes on the *y*-axis (Figure 10). Specific policy outcomes are mapped as the point that corresponds to the policy outcome value (*y*-axis) and the uncertain variable value (*x*-axis). Points can be symbolized for different policies (so multiple policies appear on the same plot; Figure 10A) and for geographic groupings (how many locations experience a given outcome; Figure 10B). With the addition of a *z*-axis, policy outcomes can be mapped to specific locations for all future conditions (Figure 10C). Symbol color can represent robustness of a given outcome or different policies.

For the water example, using the approaches shown in Figures 10A and 10B, the uncertainty of future water flows would be aggregated to the *x*-axis and groundwater usage would be depicted on the *y*-axis. If only a single policy were considered, the result would be a simple graph of outcomes and future water flow pairs. If additional policies were evaluated (e.g., imposing water regulations), outcomes for different policies could be visualized on the same graph using different colors to symbolize the different policies. Additionally, the number of locations that experience a given outcome can be visualized using symbol size (Figure 10B). For example, the Purple Policy is shown to result in high groundwater usage for all future conditions (Figure 10A). For the Orange Policy outcomes, Figure 10B (Point B1) shows that there is a range of low future river flows that result in a large number of locations with high groundwater usage. With the addition of the *z*-axis, groundwater usage can be mapped to

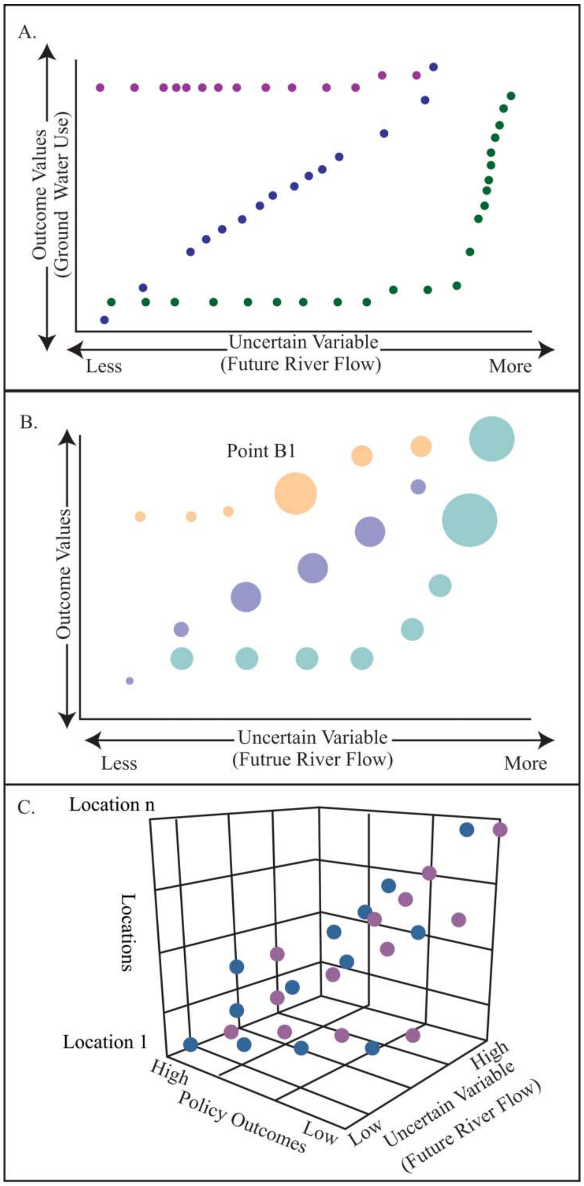


Figure 10. Visualizing outcomes from multiple policies, over all future conditions, makes it possible to identify policies that perform well over the largest range of futures or most locations using a single Youden plot visualization. (Color figure available online.)

specific water service areas for one or more policies (Figure 10C). Here, symbol color represents different policies, but color can also symbolize outcomes as less to more robust.

Star Plot Outcome Maps

When used as point symbols, star plots offer a cartographic representation of implicit uncertainty. Star plots (also called radar charts) represent multivariate data in a two-dimensional plot, where three or more variables are depicted on radii that start from the same origin (Klippel et al. 2009). If each future condition is viewed as a variable, then each radius in the plot represents the outcome for one future condition (Figure 11A). Each star plot represents outcomes for one policy over all future conditions for one geographic area. Maintaining the same minimum and maximum values for each plot offers a way to uncover outcome spatial variability. Maintaining the same radius location for each future condition makes it possible to identify outcome value trends across multiple policy alternatives or across geographies.

The general size and shape of each plot tells something about the policy outcomes. Plot size (relative to other plots) reflects the overall magnitude of policy outcomes for that geographic location (Figure 11B). For the water example, smaller plots reflect lower groundwater usage, whereas larger plots represent higher groundwater usage (Figure 11B). Plot shape reflects how susceptible a policy is to future condition assumptions. Plots with relatively uniform point lengths depict lower variability across future conditions, whereas less uniform point lengths suggest policies are more sensitive to future condition assumption.

Figure 11C depicts the projected groundwater depletion for the given policy for all future conditions for each water service area. The plots suggest lower outcomes for the northeast water service areas. Plots in this same area also show that future conditions represented in the upper left quadrant of the plots result in lower outcome values when compared to the rest of the future conditions.

Robustness Indicator Maps

Robust decisions result in outcomes that perform at a desirable level over a number of future conditions, with desirability measured according to criteria determined for the decision problem (e.g., maximum levels of groundwater use). Policy outcomes are classified and weighted using these criteria. The resulting robustness indicators are mapped for each area being evaluated. Robustness indicator maps present a summary of how well a policy's outcomes fit the decision criteria.

The inputs used to calculate the indicator for each geographic area are policy outcomes, robustness criteria, and weights. Outcomes for each future condition are determined for each area under evaluation. Robustness criteria identify outcome values that are considered desirable or undesirable for the decision problem (e.g., how much groundwater usage

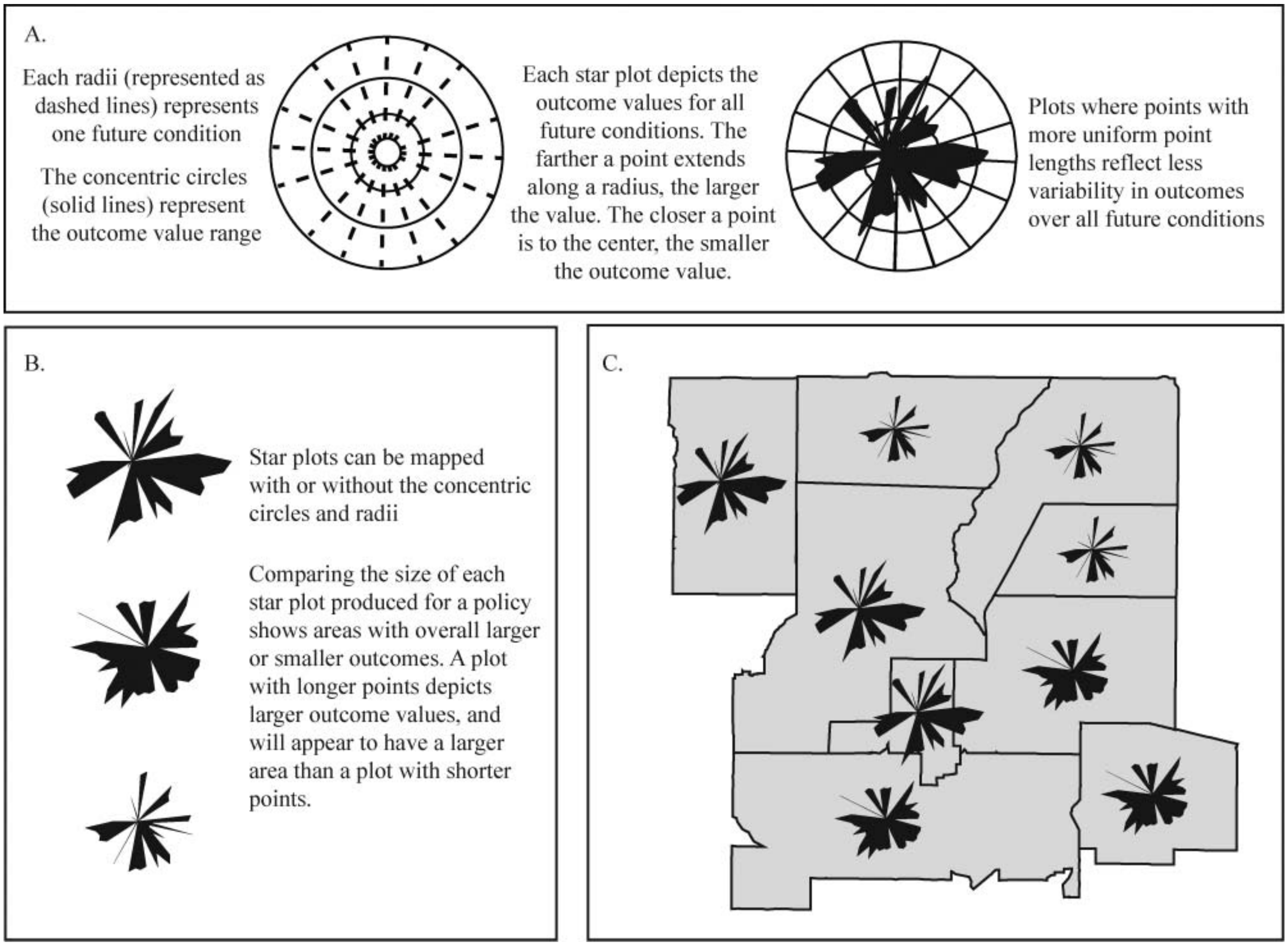


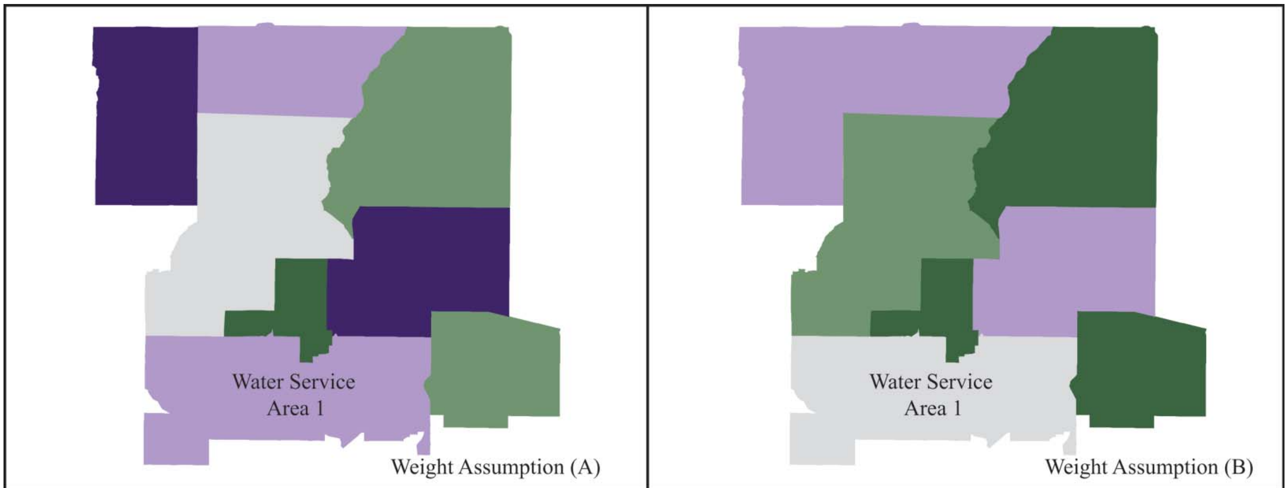
Figure 11. Each star plot represents all outcomes for a single policy. Because each star plot has the same scale and orientation, decision makers can compare outcomes across the region for a single policy and across maps for multiple policies.

is considered sustainable). Outcomes are classified using the robustness criteria, and the total number of outcomes included in each class is determined. These totals are then weighted using factors developed from decision maker values and goals. The weighted value sum is the indicator for that geographic area (Figure 12).

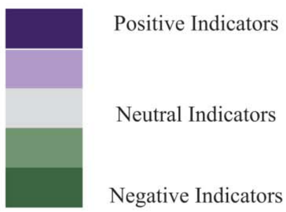
In the water policy examples, groundwater usage is split into three categories: sustainable, moderately sustainable, and unsustainable. For this example, two weighting scenarios are considered. In Weighting Assumption A, sustainable and unsustainable results are viewed as equally positive or negative, and moderately sustainable outcomes are viewed as somewhat positive. The resulting weights would be –1 for unsustainable, 0.5 for moderately sustainable, and +1 for sustainable. In Weighting Assumption B, sustainable and moderately sustainable outcomes are equally desirable, and unsustainable outcomes are unacceptable. The resulting weights could be –2 for unsustainable and +1 for moderately sustainable and sustainable. In both weighting cases, lower values would indicate less robust policies. In the resulting map example, the indicator for Water Service Area 1 is positive for Weighting Assumption A and neutral for Weighting Assumption B, reflecting the large increase in the unsustainable weighting factor. The resulting maps summarize the overall policy performance reflecting any spatial variability in policy outcomes.

Explicit and Implicit: The Uncertainty Continuum

Both explicit and implicit uncertainty can be beneficial throughout the decision-making process. The same information or outcomes could be represented either explicitly or implicitly, depending on where you



A sample indicator calculation is shown for each weight assumption based on decision problem with 100 future condition outcomes.



Weight Assumptions (A)	Number of Outcomes in Classification	Weight of Classification	Weighted Value	Indicator
Sustainable 1	50	1	50	30
Moderately Sustainable 0.5	20	0.5	10	
Unsustainable -1	30	-1	-30	

Weight Assumptions (B)	Number of Outcomes in Classification	Weight of Classification	Weighted Value	Indicator
Sustainable 1	50	1	50	10
Moderately Sustainable 1	20	1	20	
Unsustainable -2	30	-2	-60	

Figure 12. Robustness indicator values result from applying different weight factors to classified decision outcomes. Weights are selected based on policymakers' values. The results depict the spatial variability of these outcomes. (Color figure available online.)

are in the decision process. Figure 13 illustrates how uncertainty might change throughout the decision process.

The initial evaluation of a problem might include decision makers, domain experts, and GIS analysts. Interaction among these groups helps in problem conceptualization and definition, which in turn provides the constraints for developing a GIS model to evaluate potential policies. Here, analysts' and domain experts' considerations include identification of source uncertainty, as well as uncertainty introduced through the model or analysis. In this initial stage, domain experts and analysts might prefer or require explicit evaluations of uncertainty, including statistical estimates (Liu et al. 2008). 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 outputs, similar to error propagation.

Decision makers could be involved throughout the process as they work through identifying and operationalizing decisions for evaluation and assumptions about future conditions. As GIS analysts and decision makers move toward output evaluation, it might be necessary to return to prior steps in the process to reflect changes that come about due to differing decision alternatives or assumptions about future conditions. In these later stages, decision makers seeking to identify robust policies would benefit from implicit uncertainty. In the last stages, decision makers evaluate decision outcomes and related uncertainty. Here, the number of decision alternatives and future conditions, and the form of uncertainty, determines the total number of visualizations that would need to be evaluated. As seen in prior sections, for deeply uncertain problems it is not possible to use probability estimates to reduce future condition uncertainty, resulting in an unmanageable number of outcomes for visualization. Here, implicit uncertainty visualizations provide methods for visualizing the large number of outcomes and future conditions using significantly fewer visualizations. This approach provides a way for decision makers to eliminate policies that clearly do not meet outcome goals while identifying policies that warrant more detailed assessments and further consideration.

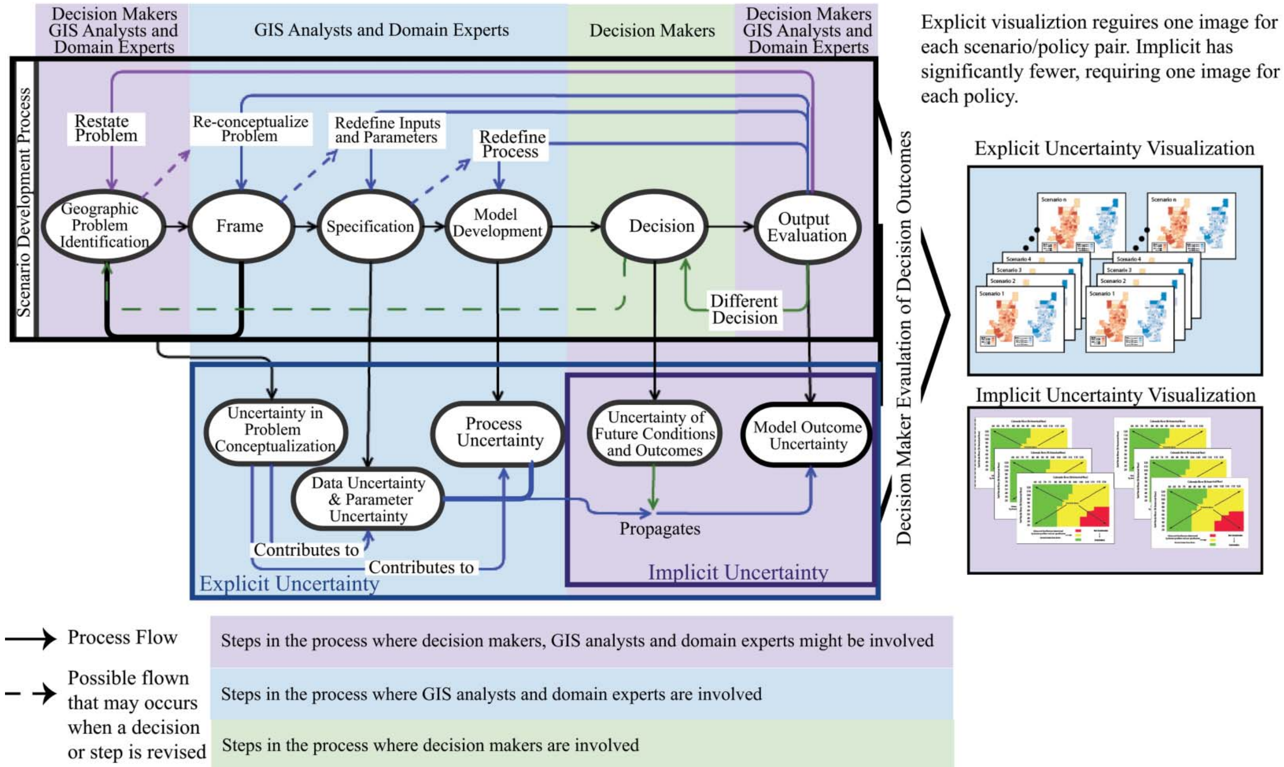


Figure 13. The decision process diagram depicts how explicit and implicit uncertainty exist throughout the decision process, impacted in part by the changing interactions between domain experts, GIS analysts, and decision makers. (Color figure available online.)

This continuum of uncertainty across the decision process reflects prescriptive decision theory, incorporating how different actors approach decision problems, while providing methods and tools that support more informed decisions.

Conclusions

Uncertainty is an inescapable component of decision making, with both policymakers and researchers acknowledging the importance of understanding the uncertainty involved in a decision. As policymakers are faced with more complex, deeply uncertain problems, there is an increased need for methods that communicate uncertainty in a meaningful and usable manner (Pielke, Sarewitz, and Dilling 2010; White et al. 2010). To increase the usefulness of uncertainty information, we presented several implicit uncertainty visualization methods as a means to support decision makers' understanding of deep uncertainty. These methods address the challenge of presenting, in a single visualization, the range of decision outcomes that result from uncertain inputs and variable future conditions.

The examples presented here represent a sampling of the implicit uncertainty visualization space. Additional methods, including those to further depict spatial variability, are needed. Achieving the goal of developing methods that are both useful to and usable by decision makers poses many challenges that could benefit from the integration of decision science theories with uncertainty visualization research. As researchers seek to develop uncertainty visualization methods that help decision makers cope with uncertainty, researchers need to acknowledge differences between the way researchers and decision makers conceptualize and work with uncertainty. This leads to several outstanding research challenges:

1. Understanding how different decision makers conceptualize uncertainty for specific domains.
2. Understanding when spatial variability is important to evaluation of the decision problem.
3. Developing typologies that relate domain-specific concepts of uncertainty to implicit visualization methods.
4. Developing methods that integrate decision makers and real problem settings into the

evaluation of the usability and usefulness of implicit visualization.

The research developed here suggests a framework for addressing these challenges through the identification of explicit and implicit uncertainty. Building on this research, these outstanding challenges are faced by both researchers and decision makers.

Researchers are challenged with identifying how decision makers interact with uncertainty and applying that knowledge to develop methods for decision support in that policy area. In decision science research, the focus has often been on understanding external decision frames. GIS researchers, though, need to uncover common internal frames and goals to develop usable support tools. 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. Efforts to evaluate several of these methods through human subjects testing are ongoing and will be reported in subsequent work.

Decision makers are similarly challenged to not only communicate what information they need to support decision making but also share with researchers information about how they operationalize uncertainty in decision making. Additionally, decision makers should be willing to work with new methods of decision support, including possibly combining new methods with existing approaches. Although this complicates the vision of developing standard uncertainty visualization tools for use in GIS, user-centered method development has the potential to connect researchers' knowledge-production and decision makers' solutions-oriented approaches to understanding uncertainty to support the use of uncertainty visualization for decision support.

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