Evaluating implicit visualization of uncertainty for public policy decision support

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ABSTRACT: Decision makers increasingly rely on science to inform public policy decision-making. Although this 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 usable manner 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 believable representations does not provide a complete understanding of the potential consequences of decisions.

Developing uncertainty representations to reflect 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). Yet, visualizations often avoid the explicit inclusion of contextual information, such as explanations of risk and uncertainty. This research makes a 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 data. 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 presents 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 test. The paper reports on the results of the pilot study and how this method compares to methods for explicitly visualizing uncertainty.

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

1. Introduction

As an inherently geographic phenomenon, research on climate change exists throughout geography, with results and predictions commonly represented on maps and graphic displays. 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 projections and more realistic view to ease understanding (Abbasi 2005). Building believable visualizations, however, does not provide a means to understand the relationship between decisions, uncertainty and the decision outcomes.

Researchers acknowledge the importance of identifying and evaluating uncertainty in geographic analysis and outputs used for decision support. Decision makers also understand that uncertainty is an unavoidable component of policy decisions, especially when those decisions are informed by science. However, even though both researchers and decision makers understand the presence and importance of uncertainty, decision makers do not widely request visual methods for working with uncertainty in GIS, and uncertainty is often missing from geographic visualization. There is an apparent disjoint between uncertainty visualization research and its practical application (Goodchild 2006).

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, Clarke, and Keuper 2003; 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 2006; 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 posses differing experiences, expectations and goals.

The relevant form of uncertainty for a given decision problem is often determined by the user, context, and purpose of the data. This poses a significant challenge for visualization methods intended to facilitate informed decision making through the communication of uncertainty, as complex scientific representations may not support communication, since they are not easily understood. In these settings, the specific form of uncertainty might be less important than a general awareness of its presence. Moreover, many users consider *uncertainty visualization* either irrelevant or detrimental for successful data communication and insight generation (Cliburn et al. 2002; Slocum et al. 2003; Brugnach et al. 2007). In contrast, research suggests that decision makers now often view *uncertainty* itself as unavoidable, and potentially, as integral to 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 methods of working with uncertainty into methods for visual uncertainty communication. This requires moving from explicit and quantitative methods appropriate for science-based communication to more implicit visualizations that incorporate 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 shift from avoidance to acceptance, and even use, 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 makes a distinction between explicit and implicit uncertainty and visualizations. *Explicit uncertainty* is defined by the direct identification of gaps, errors, and unknowns displayed or represented through quantitative values (such as error bars) or qualitative estimations (certain versus uncertain). *Explicit visualization* refers to methods where uncertainty is extracted, modeled and quantified separately from the underlying information. In explicit representations, uncertainty is conceived as specific values, to evaluate as unique information, related to, but not the same as, the underlying data. *Implicit uncertainty*, by contrast, is linked to the decision making process, where uncertainty is an inherent characteristic of the data. Implicit uncertainty is more context dependent, where experience informs definition, interpretation and, potentially, representation. *Implicit visualization*, support exploration of the relationship between uncertainty and decisions, by integrating uncertainty and decision outcomes in the visualization. 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 representation supports adaptive decision making by allowing users to explore the relationship between decisions, outcomes, and uncertainty.

This research works to address the gap between uncertainty visualization research and practical application, presenting a method for implicitly visualizing uncertainty, specifically seeking to address the following:

- Do decisions made with implicit representations of uncertainty differ from those made with explicit representations of uncertainty?
- Do users perceive implicit representations as effective for supporting decision-making tasks?
- Are implicit representations seen as uncertain?

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

2. Visualizing Uncertainty

Researchers have sought the most appropriate and effective means of representing uncertainty to users, carrying out experiments comparing representational techniques. A common approach is to adapt Bertin's (1983) visual variables for visualizing uncertainty. Additional graphic variables, such as transparency, saturation and clarity have also been proposed (MacEachren 1992; Slocum et al. 2004) specifically for uncertainty visualization. Computer environments offer possibilities for uncertainty visualization, allowing users to manipulate the display of uncertainty by deciding how and when to display information (Fisher 1994; Ehlschlaeger, Shortridge, and Goodchild 1997; Cliburn et al. 2002; Aerts, Clarke, and Keuper 2003).

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. E*xtrinsic* 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 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).

The primary focus of most experiments has been on designing methods to communicate explicit values. MacEachren et al. (1998) developed and tested a pair of intrinsic methods for depicting "reliability" of data on choropleth maps. Newman and Lee (2004) evaluated both extrinsic and intrinsic techniques for the visualization of uncertainty in volumetric data. Leitner and Buttenfield (2000) focused on the alteration of the decision-making process by changing the representation, through systematically altering Bertin's visual variables.

Researchers have also 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.

3. Methods

At its most general, this study aims to identify whether implicit visualizations of uncertainty result in decisions that differ from those made with explicit visualizations of uncertainty. Additionally, this research explores whether implicit visualizations are seen as effective for decision-making, and if users interpret these representations as uncertain.

I conducted a human-subject test consisting of decision tasks related to water policy in a hypothetical western city. In the pilot 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 3.2) to avoid bias in selection of policy. Additionally, the order that participants saw the decision sets was randomized to avoid learning.

3.1 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) 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 3.2) 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 depicted 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.

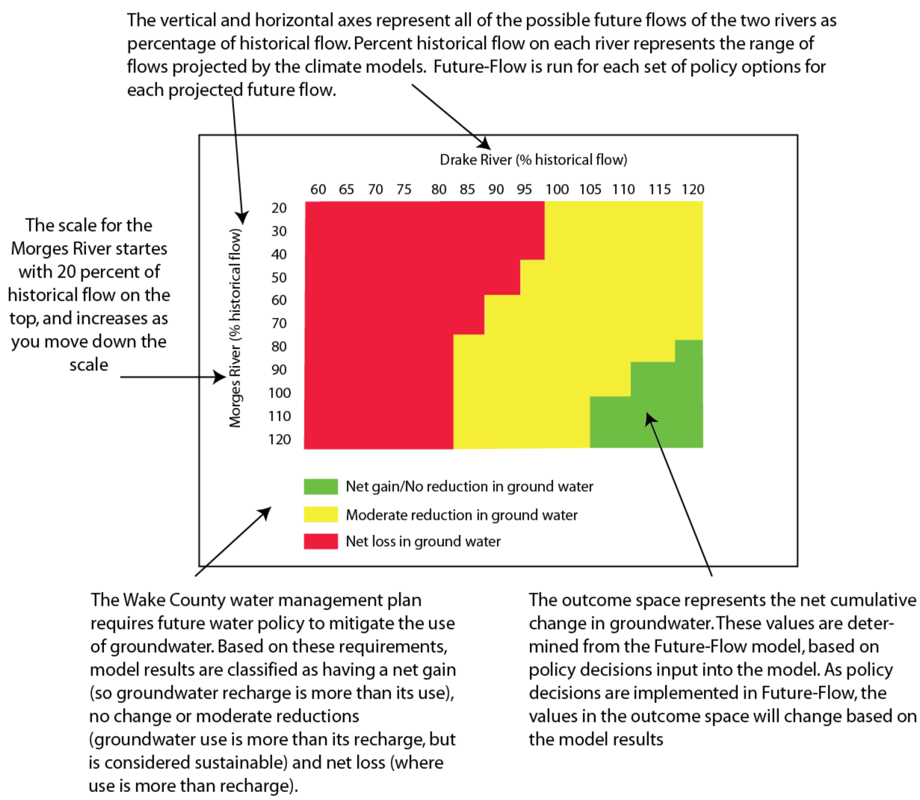
The policy choices did not change across the decision sets, but the order they were presented in varied. For example, in the implicit decision set the first policy shown was the No Change option, but for the no uncertainty decision set it was the growth plus education policy option.

3.2 Visualizations

3.2.1 Implicit Uncertainty Decision Set

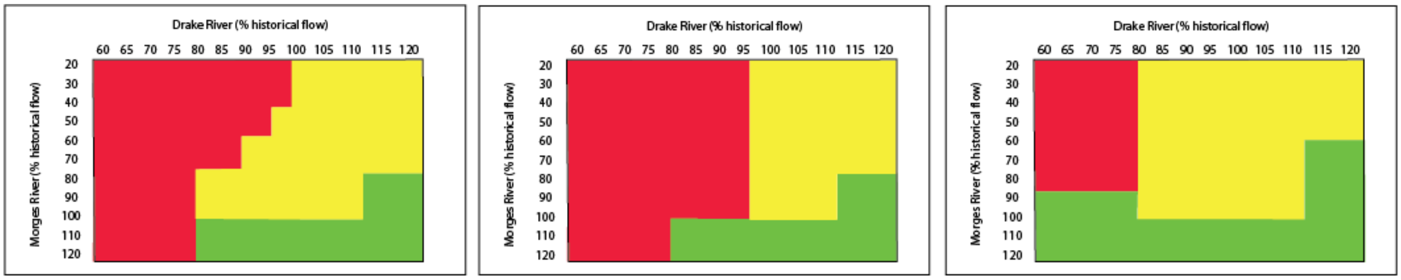
This research builds upon methods presented by Lempert, Popper, and Bankes (2003) for mapping Landscapes of Plausible Futures. The landscapes provide visualizations intended to aid in exploration of large, multidimensional data sets produced as output to robust decision making scenarios. In these landscapes, 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 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 this method is proposed as an implicit visualization of uncertainty. An example is shown in Figure 1. 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 in the water model, 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 ground water usage.

While this does not depict geographic space, it does reflect the spatial distribution of uncertainty across the possible futures of each river system. It allows decision makers to identify policies that result in the most robust strategies across the widest range of future possible climate conditions. Once these policies are selected, decision makers can further evaluated the geographic impact of the policy choices. The set of implicit policy maps from the pilot survey and their associated policy options are shown in Figure 2.



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.

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

Figure 2. Implicit uncertainty visualization decision set

3.2.2 Explicit Uncertainty Decision Set

This decision set depicted 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. 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. The visualizations for this decision set are shown in Figure 3.

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.

High Uncertainty | Modertate Uncertainty | Low Uncertainty

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

Figure 3. Explicit uncertainty visualization decision set

3.2.3 No Uncertainty Decision Set

The third decision set depicted 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.

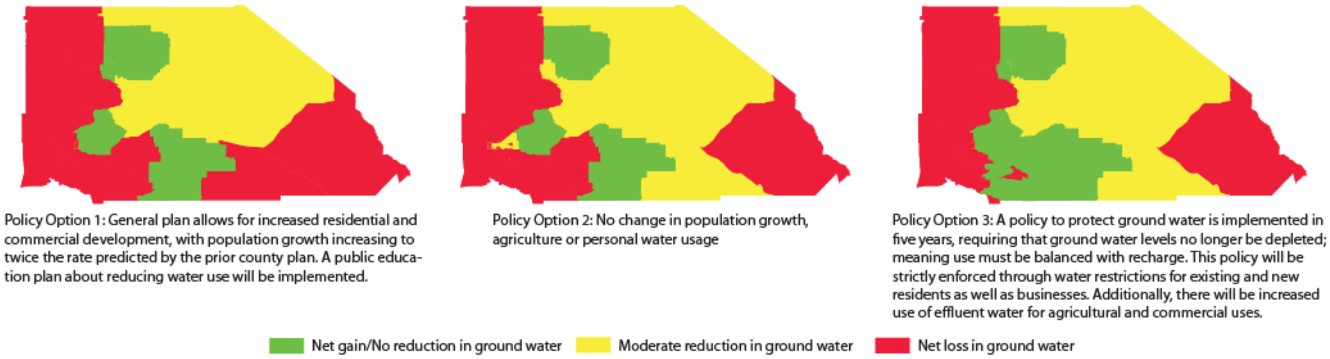


Figure 4. No uncertainty decision set

3.3 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 several questions:

- The visualizations of the model output for the range of future river flows (groundwater drawdown) is effective for evaluating the impact of policy decisions on groundwater
- The groundwater results in the visualization incorporates the uncertain impact of climate change on groundwater
- 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.

4. Results

This research focused on methods for representing uncertainty in GIS that incorporate decision frames of decision makers. An implicit method for visually representing uncertainty and outcomes as integrated information was evaluated through a case study of a hypothetical county facing the need to make policy decisions on growth and water use. In this work, water managers understanding of stationarity (their decision frame) was the basis for the implicit visualization. Uncertainty was operationalized as the unknown impact of climate change on the stationarity assumption, and in the implicit visualization, the outcome space was related to this uncertainty. A web based pilot study was conducted to evaluate whether implicit visualizations result in different decisions, are viewed as including uncertainty, and are effective for making decisions. Participants were drawn from GIScience faculty and researchers, GIS analysts working in decision support settings, planners and PhD candidates working with GIS. Forty surveys were collected in all, with ten partially completed surveys discarded.

4.1 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 rankings were first processed to allow easy comparison. The absolute value of the difference between the rankings for each region was calculated for each participant. A change in ranking from three to one would result in a score of two (three minus one), and a change from two to three would result in a score of one (three minus two). The minimum score between sets of rankings is zero, indicating no change, and the maximum is four indicating a complete reversal.

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% confidence interval around the mean difference for all participants: if the rankings from the decision sets were similar, this confidence interval should include zero. Each distribution was also evaluated to ensure it was close to normal prior to selection of a statistical test.

The difference between the rankings for the three decision sets was statistically significant for the comparisons identified at the beginning of this section. 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 1 presents the results of the t-test comparison for each of the ranking pairs.

Ranking Comparisons	Test Value = 0					
	t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit versus No Uncertainty	5.794	29	.000	1.733	1.12	2.35
Implicit versus Explicit	9.109	29	.000	2.267	1.76	2.78
Explicit versus No Uncertainty	4.267	29	.000	1.200	.62	1.78

Table 1. The results of the ranking comparison reflect statistically significant differences between the rankings for each decision set

This illustrates that the implicit uncertainty decision set resulted in rankings that differed significantly from rankings made with explicit or no uncertainty. This suggests that the visualization method influenced ranking choices and interpretation of decision problems.

4.2 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 2. 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, 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. Table 2 summarizes the results of the t-tests for the uncertainty responses for each decision set including the significance and confidence interval.

Uncertainty	Test Value = 0					
	T	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit	2.628	29	.014	.50000	.1108	.8892
No Uncertainty	-1.733	29	.094	-.36667	-.7995	.0662
Explicit	3.084	29	.004	.66667	.2245	1.1088

Table 2. The results of the uncertainty comparison indicate that both the implicit and explicit visualizations were seen as including uncertainty, while those without uncertainty were not

The tests show that for the implicit and explicit decision sets, users identified the outcomes as incorporating climate change uncertainty. This is indicated two ways in the analysis. First, 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. Additionally, the confidence interval for both includes only values greater than zero, which indicates a level of agreement, since positive values are associated with agreement in the coding.

For the no uncertainty decision set, the results fail to reject the null hypothesis with a significance greater than 0.05. Additionally, the confidence interval includes both negative values and zero, meaning that it is not possible to reject that users do not identify uncertainty in this set. 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.

4.3 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. 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.

Table 3 summarizes the results of the t-tests for the effectiveness responses for each decision set including the significance and confidence interval.

Effective	Test Value = 0					
	t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Implicit	6.289	29	.000	1.00000	.6748	1.3252
No Uncertainty	3.881	29	.001	.70000	.3311	1.0689
Explicit	4.173	29	.000	.76667	.3909	1.1424

Table 3. The results of the effectiveness comparison indicate that all three visualizations were seen as effective for evaluating the policy decisions

The tests show that for all three methods, users identified the outcomes as effective for evaluating the impact of policy changes on groundwater. . This is indicated two ways in the analysis. First, levels of significance for all three are less than 0.05. This allows rejection of the null hypothesis that the average response is zero, which would indicate that users were not sure whether they found the visualizations effective. Additionally, the confidence interval for all three 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 viable method for integrating uncertainty into visualization environments for decision support.

4.4 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.

The true/false responses were then compared with the ranking difference responses (Section 4.1) 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 there was 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 in responses. 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 know, 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.

Tables 4A-4C identify the results of the t-test for the use-based comparisons for each ranking comparison. 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 explicit versus no uncertainty ranking comparisons for individuals that responded that they used the visual information, which had a significance value of 0.104, which is larger than the alpha value 0.05.

Based on these results, there appears to be a discrepancy in how users responded to the question of whether they used the visualizations and their actions. When ranking differences were divided between those that indicated they did use the visual information and those that indicated they did not, the analysis showed that regardless of their response, the differences between rankings was statistically significant, a result that matched the overall analysis of the rankings (as discussed in Section 4.1). 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.

Implicit Uncertainty Use Response		Test Value = 0					
		t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
						Lower	Upper
False	Implicit vs. No Uncertainty Ranking Comparison	2.497	7	.041	1.750	.09	3.41
	Implicit vs. Explicit Ranking Comparison	5.612	7	.001	3.000	1.74	4.26
True	Implicit vs. No Uncertainty Ranking Comparison	5.231	21	.000	1.727	1.04	2.41
	Implicit vs. Explicit Ranking Comparison	7.599	21	.000	2.000	1.45	2.55

Table 4A. Implicit decision set use responses reflect a statistically significant difference in rankings for both the true and false groups. These results conflict with the expected distribution, since it would be assumed that participants who did not use the visualizations would not have had a change in rankings.

One possibility is that users were relying on heuristics to evaluate policy rankings for each decision set. When faced with uncertainty, individuals must evaluate both the likelihood and desirability of an outcome (Tversky and Fox 1995), often without a definitive knowledge of all the factors that may influence an outcome. Individuals learn to apply abstract mental rules (*heuristics)* that result in the most favorable outcomes, and reduce the complexity of assessing alternatives and outcomes. 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.

No Uncertainty Use Response		Test Value = 0					
		t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
						Lower	Upper
False	Implicit vs. No Uncertainty Ranking Comparison	3.873	15	.002	1.500	.67	2.33
	Explicit vs. No Uncertainty Ranking Comparison	4.341	15	.001	1.750	.89	2.61
True	Implicit vs. No Uncertainty Ranking Comparison	4.266	13	.001	2.000	.99	3.01
	Explicit vs. No Uncertainty Ranking Comparison	1.749	13	.104	.571	-.13	1.28

Table 4B. No uncertainty decision set shows similar responses to implicit, with the exception that the difference shown on the true comparison is not statistically significant.

Explicit Uncertainty Use Response		Test Value = 0					
		t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
						Lower	Upper
False	Explicit vs. No Uncertainty Ranking Comparison	4.382	6	.005	2.286	1.01	3.56
	Implicit vs. Explicit Ranking Comparison	4.500	6	.004	2.571	1.17	3.97
True	Explicit vs. No Uncertainty Ranking Comparison	2.865	22	.009	.870	.24	1.50
	Implicit vs. Explicit Ranking Comparison	7.800	22	.000	2.174	1.60	2.75

Table 4C. Explicit decision set use responses reflect a statistically significant difference in rankings for both the true and false groups. These results conflict with the expected distribution, since it would be assumed that participants who did not use the visualizations would not have had a change in rankings.

6. 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 a method for incorporating decision frames of stakeholders into uncertainty visualization. Doing this requires understanding what aspects of a problem are uncertain, that 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 pilot study, showing this integrated view (implicit) results in different decisions than explicitly representing uncertainty, while still be viewed as uncertain information. The results of this study will support further research into the effects of implicit uncertainty visualizations, as well as the development of additional implicit methods.

There are a number of factors about the administration of this survey could be modified if the survey were repeated. The repetitive nature of the survey made it take longer than anticipated to complete and resulted in 25 percent of the surveys being incomplete. 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, and then did not provide all of the requested demographics. For the remainder of the study, the important demographic information will be moved to the beginning of the survey to ensure it is completed.

Extensions of the study could include identifying whether decisions improve or more "correct" decisions are made with the inclusion of implicit uncertainty. Involving more decision makers and individuals that work with uncertainty would 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.

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