Representing Uncertainty: Does it Help People Make Better Decisions?

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If there is one thing that defines and limits our efforts to better understand extreme and rare events it is *uncertainty*. Uncertainty arises from both an imperfect understanding of the rare events and processes we wish to study (e.g., terrorism, natural hazards), and the imperfect, out-of-date, and incomplete data we must work with in order to try and understand these events and processes. No data are perfect. However, uncertainty is more than a technical "failing" of our data (e.g., measurement error); it arises, in part, because there are simply some things that are unknowable (Couclelis 2003) or, as Fischer (1999) articulates, may not be knowable with precision (i.e., inherent vagueness).[1] Nevertheless, outside of academic circles one rarely sees maps, GIS databases, or visualization systems that acknowledge these fundamental limitations. This omission is problematic because, as MacEachren (1992, p.10) notes:

> In the early stages of scientific analysis or policy formulation, providing a way for analysts to assess uncertainty in the data they are exploring is critical to the perspectives they form and the approaches they decide to pursue.

In the last 15 years, researchers in GIScience have made great advances in *defining*, *measuring*, *modeling*, and *visualizing* uncertainty and data quality (notably, Buttenfield, Clarke, Goodchild, MacEachren, Fischer, Beard, Ehlschlaeger, see references). Indeed, uncertainty has become a central issue in GIScience research with numerous conference sessions and journal articles devoted to the topic. Despite this sustained attention, a basic question that remains largely unanswered is whether displaying uncertainty helps users. In other words, ***does displaying uncertainty on maps fundamentally change the way people think and problem-solve and ultimately lead to better decisions***? In this paper I will (1) argue why we need answers to these questions, (2) briefly review and synthesize relevant research findings to date, (3) define what constitutes "better decisions," and (4) outline how we might proceed from here.

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[1] Plewe (2002) provides an excellent and comprehensive synthesis of the nature of uncertainty and how it has been conceptualized and handled within GIScience.

Current Research Questions

Given that there are three basic methods for incorporating uncertainty into maps—integrated symbols, split displays, and toggled displays (MacEachren et al. 1993)—which ones are most effective, under what circumstances, and why? What kinds of maps (e.g., isarithmic) work best with what kinds of methods of depicting uncertainty (e.g., focus)? How long does it take for users to begin incorporating map-based uncertainty information into the knowledge-construction process (i.e., into their map-reading schemata)? How does increasing the complexity of either the mapped data or uncertainty estimates of those data affect the map reader? Do different map-reading tasks (e.g., rate estimation versus pattern recognition) require different ways of representing uncertainty? Do novices and experts process uncertainty information differently? And perhaps most fundamentally, does incorporating uncertainty information act to *clarify the map*, as reported by Leitner and Buttenfield (2000) and Edwards and Nelson (2001), or *clutter the map*, as suggested by McGranaghan (1993)?

The Need for this Work

Goodchild, Chih-Chan, and Leung (1994) argue that information about the reliability of mapped data is critical for objective geographic analysis. Evans (1997) states "we have a responsibility to map-consumers to provide information about the reliability of mapped data and its representation, so that decisions based on maps are made with knowledge of the map's limitations." Although numerous methods for displaying uncertainty on maps have been developed (see MacEachren 1995), few have been formally tested with users. The need for this testing can be argued from both a theoretical and practical perspective. First, by better understanding how people cognitively work with uncertainty in the knowledge-construction and decision-making process, we can better direct our efforts to represent uncertainty whether on a map or in a database. Second, answers to these questions can help us to develop guidelines for "smart" GIS system defaults (Leitner and Buttenfield 2000).

Insights from Testing

Only a handful of formal studies have been done to determine (1) what impact (if any) the depiction of data certainty has on users or (2) how various methods compare to each other. **Schweizer and Goodchild (1992)** found that color lightness ("value") was not effective as a method for encoding data quality on bivariate choropleth maps that used saturation to encode the thematic data. The problem, they surmised, was that people do not see variations in lightness and saturation as independent, and simply conflated the two visual variables thinking, "darker equals more."

Evans (1997) compared four methods of depicting data quality on land-classification raster images: (1) static separate maps (one for the data, one for the metadata), (2) static integrated displays (using a bivariate color scheme), (3) animated non-controllable "flicker" maps, and (4) interactive toggle maps. Her results show that subjects both preferred and performed best with the static integrated display and the flicker map. Interestingly, no significant differences were found between experts and novices, nor between males and females, either in terms of accuracy, confidence, or user preference.

Leitner and Buttenfield (2000) tested saturation, texture, and value as means to encode certainty data by looking at timing, accuracy, and confidence within a spatial decision-support context. These authors found that "the addition of attribute certainty information significantly increases the number of correct responses for an easy siting decision, if either lighter value or finer texture is chosen to display more certain information" (p. 13). Like Schweizer and Goodchild (1992), these authors found saturation was not especially effective. They also found that for easy tasks, response times *decreased* with the inclusion of certainty information, but found no such difference in time for difficult tasks (either increase or decrease). This suggests that task type and task difficulty are important factors in determining the success of uncertainty information on maps.

Edwards and Nelson (2001) compared four methods for encoding reliability estimates in static graduated-circle maps. These authors found, to their surprise, that "focus" was a more effective method for depicting data certainty than "value" on their bivariate maps (n.b., their use of the word "focus" differs from MacEachren's). More generally, they found that integrated displays worked significantly better than separate displays in all cases, and by all indicators, and traditional verbal statements worked least well (subjects were both less accurate and less confident). These findings support the ideas of Muehrcke and Muehrcke (1992) and Fischer (1994) who argued that separate displays create more "work" for the reader, both perceptually (scanning) and cognitively (mentally overlaying text metadata and maps). When combined with Evans's (1997) results, there is growing evidence that integrated uncertainty symbolization (e.g., bivariate symbols) is superior to separate displays, at least in static maps.

Most recently, **Aerts et al. (2003)** examined how toggled and static depictions of uncertainty aided planners and decision-makers using a Web-based SDSS for urban growth. Their participants "acknowledged the usefulness of portraying uncertainty for decision-making purposes…and slightly favored the static comparison technique over toggling." This research is noteworthy because it wisely identified and tested actual end-users—in this case, urban planners—and, thus, supports the notion that our efforts to represent uncertainty on maps are both understood and valued by end-users (e.g., domain experts).

Discussion (where to go from here?)

Synthesizing the studies discussed above, improved performance is seen as making decisions with increased *confidence*, *speed*, or *accuracy/correctness.* Along with *user preference*, these performance criteria seem both logical and testable.

One general gap in this user-testing literature is a lack of longitudinal studies that seek to understand the "learning curve" associated with depicting uncertainty on maps. Knowing how users react in a test setting to maps they have likely not seen before ("cold" test subjects) makes it difficult to know how these maps could become integrated into their everyday intellectual activities. Another gap in the literature is the lack of efforts trying to uncover how depicting uncertainty on maps changes the way people think and problem-solve in a real-world context (e.g., federal agencies). Lastly, future research needs to more aggressively elucidate the difference between knowing that a test subject made the *correct choice* and knowing ***why*** *they made the correct choice* in a given situation. The latter is significantly more difficult to answer, but necessary if we wish to better understand how uncertainty interfaces with knowledge construction.

In contrast to the experiments outlined above, Agumya and Hunter (2002) provide an alternative perspective to understanding uncertainty in a GIS context, building on the idea of "fitness of use" (Frank 1998) and understanding the interplay of risks, costs, and benefits of using less-than-perfect data in the decision-making process (Covello 1987, Kaplan 1997): "(a) avoid the use of data that are not suitable for their intended purpose (that is, data whose consequences are unacceptable), (b) reduce any undesirable consequences to an acceptable level, and (c) devise ways of living with undesirable data when the adverse consequences caused by poor data do not alter our ultimate decision choice." By better drawing on the literature in relevant fields such as risk management and psychology, we may begin to more fully understand how depicting uncertainty on maps helps (or hinders) decision-makers. By doing this, the focus of our research shifts from the *outcomes* of the decision-making process to the *process itself* and how the depiction of uncertainty influences people's thinking. I believe this is a promising and important new direction for research in GIScience.

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