Dimensions of Uncertainty: A Visual Classification of Geospatial Uncertainty Visualization Research

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Abstract. In recent years, geospatial uncertainty visualization techniques have taken a larger role in research as users increasingly utilize visualization due to its efficient mode of communication. With the many diverse approaches dealing with uncertainty visualization today, it is important to organize it in a meaningful way to help current researchers understand the field and identify areas to attend to. This paper visually classifies the current body of research on geospatial uncertainty visualization into different dimensions. A visual classification organizes and conceptualizes the entire research field in a new way and effectively and efficiently assists readers in quickly grasping the topics within a single geospatial uncertainty visualization research paper at a glance.

Keywords: uncertainty visualization; classification; dimensions; geospatial

1 Introduction

The inherent uncertainty of geospatial data [1] has engendered a critical research agenda addressing all facets of uncertainty including its identification, measurement, mitigation, and communication. Over the past few decades, a large portion of geospatial uncertainty research has focused on typologies and conceptual models [e.g., 1,2,3,4,5] as well as computation of uncertainty [e.g., 2,6,7,8] in order to organize, describe, and measure the numerous types of uncertainties (e.g. ambiguity, accuracy, completeness, consistency, currency, error, imperfection, interrelatedness, lineage, precision, subjectivity, vagueness). This foundational research serves as an important predecessor of newer research areas, one of which aims to communicate geospatial uncertainty through various visualization approaches. In recent years, these visualization techniques have taken a larger role in research as users have begun to adopt geospatial uncertainty visualization due to its efficient mode of communication. With the many new diverse approaches dealing with uncertainty visualization today, it is important to organize it in a meaningful way to help current researchers both understand the field and identify areas to attend to. This paper visually classifies the current body of research on geospatial uncertainty visualization.

2 Dimensions of Uncertainty Visualization Research

To organize the broad research topic of geospatial uncertainty visualization, we have reviewed the literature and systematically classified research in this subfield as comprising three main dimensions: visualization techniques and taxonomies, user effects, and stimulus effects. Additionally, several relevant sub-topics are included within each dimension. A graphic was subsequently designed (Figure 1) reflecting this classification in order to both organize and conceptualize the entire research field in a new way and to effectively and efficiently assist readers in quickly grasping the topics within a single uncertainty visualization research paper at a glance by only coloring subsections that are discussed in the paper.

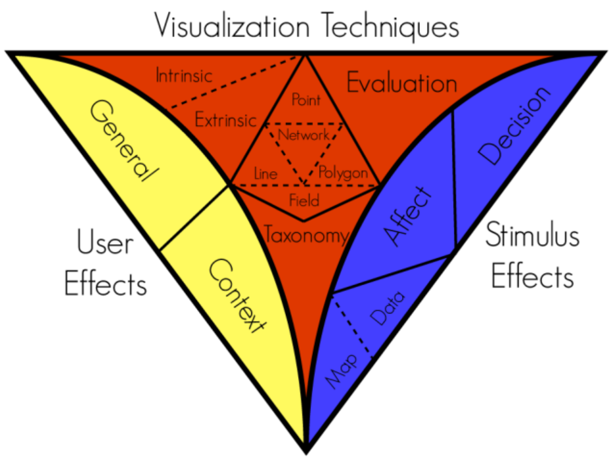

Fig. 1. Dimensions of uncertainty visualization research divided into three main categories (User Effects [yellow], Visualization Techniques [red], and Stimulus Effects [blue]).

These dimensions were borne through a systematic review of geospatial uncertainty visualization literature, identifying the main topics of each paper, and placing them into an unstructured list. Over time, topics were organized into similar categories, iterating the process and classification to find weak points and essential missing topics until none were found. This current version is the product of a thorough evaluation of the topics that we argue covers important points in geospatial uncertainty visualization research. We do not contend this is a completely exhaustive list, but rather an account of prominent and important concepts widely discussed in research.

Within the visualization techniques section, four sub-dimensions are identified: data type, taxonomy, technique, and evaluation. Five data types are further distinguished (i.e. point, line, polygon, field, and network), with each representing one type of data that a research article may utilize when representing uncertainty in a visualization. It is important to note that it is possible that multiple sub-dimensions may be used in a research paper (e.g. data types are not mutually exclusive in the visual classification as a researcher can employ multiple data types in either the same visualization, a comparison of visualizations, or a multi-stage research project). Thus, one may represent uncertainty of both a point and line object in the same research article and this visual classification will show both. Taxonomy refers to any article presenting some type of taxonomy of uncertainty visualization. When this is included in a research paper, all other sub-dimensions are ignored (i.e. not shaded/colored) in the visualization techniques dimension as it is expected that taxonomies will cover various visualization techniques and data types. The technique section specifies two ways to explicitly represent the data uncertainty as proposed by [9]: extrinsic or intrinsic. Extrinsic techniques incorporate new geometric objects to represent the uncertainty (e.g., adding arrows, bars, noise annotation lines) while intrinsic techniques incorporate the uncertainty within the existing object (e.g., altering brightness, color, blur, transparency) [10]. Finally, the evaluation sub-dimension indicates whether an article has evaluated a specific visualization approach.

The user effects dimension distinguishes two types of individual differences that a user may embody, ultimately affecting how they interact with a geospatial uncertainty visualization. General individual differences include any ability, heuristic, personality, etc. that is not directly related to the phenomena being mapped which may influence how a user interacts with the visualization. More specifically, these individual differences do not arise from exposure to or experience with the phenomena or visualization, but rather are relevant for how individuals will interact and behave in that experience. For example, general numeracy skills may allow an individual to better grasp probabilities, thus allowing them to better estimate the likelihood and risks of an approaching hurricane even if they don't have prior experience with a hurricane. On the other hand, contextually relevant individual differences (e.g. heuristics, prior experience) are those directly relevant to the phenomena being mapped. Thus, prior experience with a hurricane (an experience directly related to the situation visualized) may for example affect the way a user interacts with a map of hurricane storm surge flooding probabilities as well as the decisions he/she makes.

The final dimension describes effects the stimulus (i.e. the uncertainty visualization) has on the user, including user comprehension (of the map or data), affect or emotional response, and decision-making. We contend that many evaluation methods of geospatial uncertainty visualization only assess basic map-reading skills (comprehension of the map) with only a selective few evaluating if users truly understand the deeper uncertainties inherent in the data (actual comprehension of the data). [11] describe these differences as a surface or deeper comprehension of uncertainty attained by a map user. For example, in research by [12], they asked participants to identify areas of urban growth, where users only matched colors from the uncertainty map to the legend to find its associated uncertainty, only using basic map-reading skills rather than assessing a deeper comprehension. The second sub-dimension specifies research evaluating the affect of a visualization on a user including the elicitation of an emotional response (e.g. trust, confidence, worry, anxiety). The final section focuses on the impact an uncertainty visualization may have on decision-making.

For each research paper on uncertainty visualization, this typology can be used to visually represent which dimensions are discussed. Subsequently, the selected sub-dimensions will be colored in the visualization, one for each research article. This provides users with a quick overview, offering an efficient way to recognize the contents of an article quickly before reading in further detail. Additionally, the visual classification offers a new way to conceptually organize the field of geospatial uncertainty visualization research through a systematic organization of the literature. It is important to note however, that while some dimensions (e.g. intrinsic vs. extrinsic) may not be mutually exclusive within a research project (e.g. they may both be used in different stages of a larger research process, thus resulting in both sections highlighted for a single article), these divisions still afford a useful overview. For an example application of the concept, view the appendix

3 Outlook

While this classification may not be completely exhaustive, it reflects what topics we, as researchers in uncertainty visualization, view as prominent and important in the field. Currently, we are comparing our classification to other typologies in geospatial uncertainty visualization to identify if any topics have been overlooked. In future research, we plan to classify all of the geospatial uncertainty visualization research articles and assess any patterns including whether and how research has changed over the past several decades. Hopefully, this visual classification will serve to help researchers in geospatial uncertainty visualization and organize the field and articles in a useful way.

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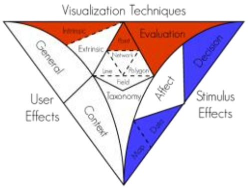
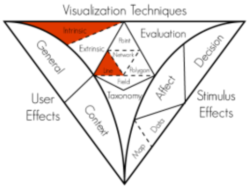
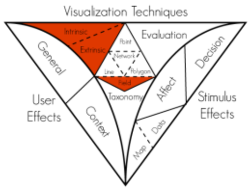
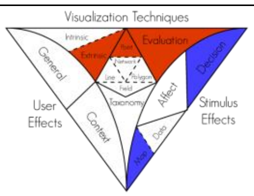
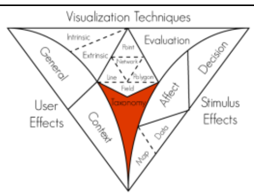
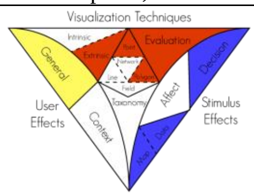
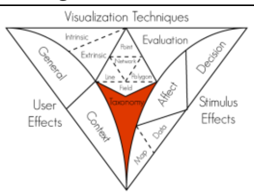
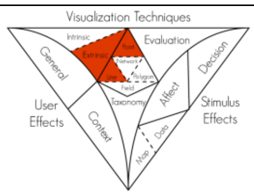
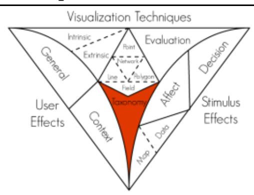
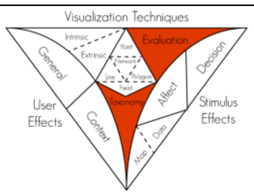
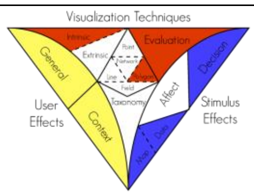
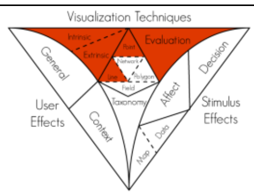
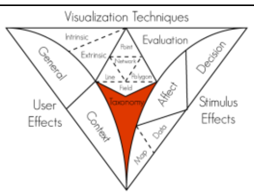
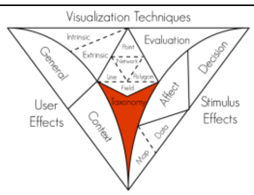
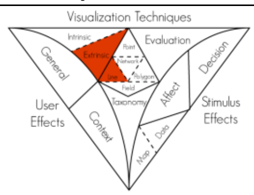
Appendix: Papers Classified With Uncertainty Dimensions Visualization

 Bisantz et al., 2011	 Boller et al., 2010	 Brus, Voženílek, & Popelka, 2013
 Finger & Bisantz, 2002	 Gershon, 1998	 Hope & Hunter, 2007
 Johnson & Sanderson, 2003	 Lodha et al., 2002	 Potter, Rosen, & Johnson, 2012
 Riviero, 2007	 Roth, 2009	 Sanyal et al., 2010
 Spiegelhalter et al., 2011	 Stephens, Edwards, & Dermeritt, 2012	 Stoll et al., 2013