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Uncertainty-aware geospatial visual analytics

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Abstract:

Visual analytics (VA) is a paradigm for extracting novel insights through visual perception, cognition, and reasoning. It plays an important role in various applications, including medicine, digital humanities, urban planning, environmental sciences, etc. In the field of geography, visual analytics has already become a powerful tool for identifying the spatial patterns of geographic variables. Geospatial visual analytics (GeoVA) offers an intuitive insight into spatial phenomena, enabling people to understand the spatial processes deeply.

However, geospatial visual analytics can be misled without an awareness of uncertainty. On the one hand, the existence of uncertainty can result in a biased interpretation of geospatial data. For example, for each data point, the importance scores of its explanatory variables, including uncertainty values, can be calculated using explanation methods (e.g., BayesSHAP) (Slack et al., 2021). Figure 1a illustrates the data points with the variable contributing the most, which are represented by different colors. When the uncertainty is low, it is easy to distinguish which variable has a higher contribution. Nevertheless, in the case of high uncertainty, the overlapping uncertainty intervals in the explanation make it confusing which variable is more important. On the other hand, the uneven spatial distribution of uncertainty will also cause geographic bias in analyzing geospatial data. The uncertainty can vary spatially in different regions, leading to different interpretations for similar spatial patterns. As shown in Figure 1b, the data points are divided into four areas according to their uncertainty levels. In the regions with low uncertainty, the visualization reflects the actual situation about a model, so the viewer is able to make a correct reasoning. In contrast, in the regions with high uncertainty, the spatial patterns perceived visually are not reliable, and viewers will misjudge. The misinterpretation caused by spatially varying uncertainty is a so-called geographic bias problem. For this reason, no geospatial visual analytics can be effectively conducted without considering the uncertainty problem (Andrienko et al., 2010).

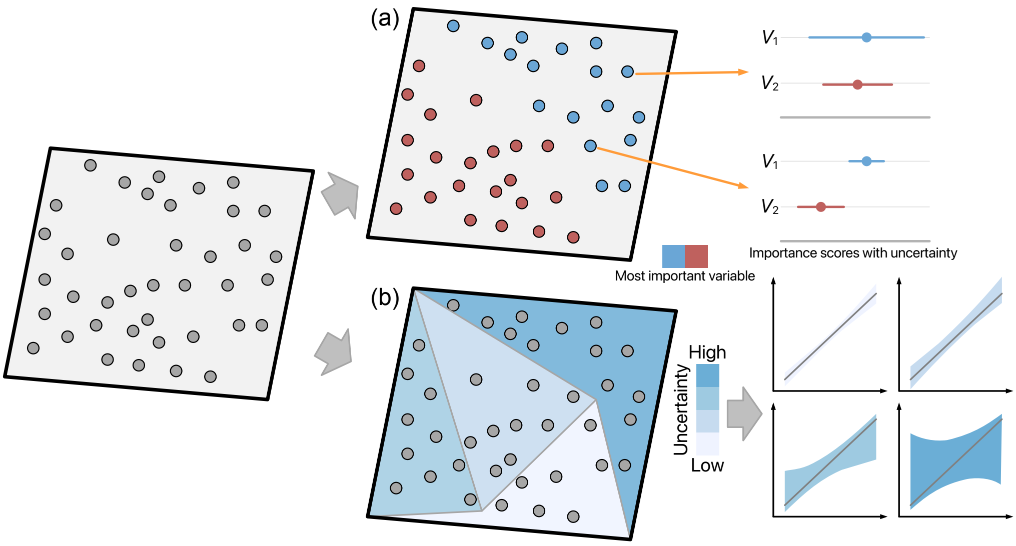

Figure 1. An illustration of how spatial uncertainty can be misled. (a) Uncertainty leads to wrong interpretation. (b) The uneven spatial distribution of uncertainty leads to geographic bias.

Despite the importance of uncertainty in visual analytics (Luo et al., 2024), a framework for uncertainty-aware geospatial visual analytics is lacking. Fortunately, many uncertainty quantification methods for geospatial contexts have emerged, such as GeoCP (Lou et al., 2024). In this work, we propose a novel visual analytics workflow (see Figure 2) that integrates

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quantification and visualization of geographic uncertainty with two goals. The first is to understand the hidden knowledge inside the uncertainty and study the geographic bias. The second is to improve trust and confidence in the process of interpretation and reasoning. Awareness of uncertainty enhances reasoning and allows viewers to explore interactively where and why there may be variability or errors, leading to in-depth understanding and insights, which in turn improve the selection of explanatory variables as well as the explainability of geospatial modeling. This work examines uncertainty-aware visual analytics using a case study of Seattle, in which the factors influencing the home sale price are analyzed. After adding coordinates as part of the input, we found that both the uncertainty and estimated house prices in rural regions dropped, indicating that the model may overestimate house prices too much. As a result, we should pay more attention to the modeling of urban-rural differences.

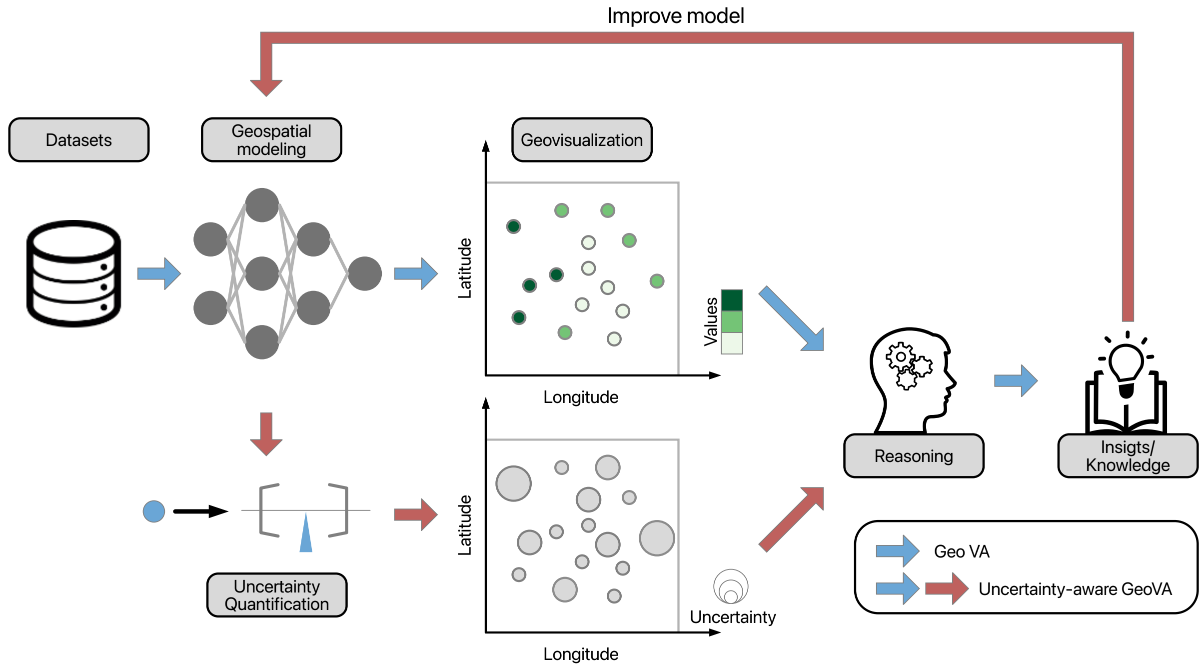

Figure 2. Workflow of uncertainty-aware geospatial visual analytics

References

Andrienko, G., Andrienko, N., Demsar, U., Dransch, D., Dykes, J., Fabrikant, S. I., Jern, M., Kraak, M.-J., Schumann, H. and Tominski, C., 2010. Space, time and visual analytics. *International journal of geographical information science* 24(10), pp. 1577–1600.

Lou, X., Luo, P. and Meng, L., 2024. Geoconformal prediction: a model-agnostic framework of measuring the uncertainty of spatial prediction. *arXiv preprint arXiv:2412.08661*.

Luo, P., Chen, C., Gao, S., Zhang, X., Majok Chol, D., Yang, Z. and Meng, L., 2024. Understanding of the predictability and uncertainty in population distributions empowered by visual analytics. *International Journal of Geographical Information Science* pp. 1–31.

Slack, D., Hilgard, A., Singh, S. and Lakkaraju, H., 2021. Reliable post hoc explanations: Modeling uncertainty in explainability. *Advances in neural information processing systems* 34, pp. 9391–9404.

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