Communicating Uncertainty and Cataloging Bias in Spatial Data Science Education

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***Abstract*— Uncertainty is an unavoidable part of any spatial analysis, which makes quantifying and communicating uncertainty a requirement of any spatial data science study. However, current curricula leave students understanding the importance of uncertainty and concerned about potential bias, but without an actionable framework to improve their workflows or inferences. We propose a framework rooted in Bloom's Taxonomy for introducing these concepts to spatial data science students.**

Keywords—Uncertainty, Bias, Data Science, Education

I. INTRODUCTION

GIScientists and geographers recognize that understanding uncertainty, error, and bias is an essential part of spatial data science (SDS) education. Uncertainty is an unavoidable part of any spatial analysis, which makes quantifying and communicating uncertainty a requirement of any SDS study. SDS students are typically taught to quantify uncertainty using statistical techniques that measure variability in the results of a study, and are told to be on the lookout for systematic distortions that could bias their estimates and mislead their inferences. While conceptually sound, in practice this approach has several shortcomings. First, lessons about uncertainty, error, and bias raise awareness of these concepts, but often do not make a clear distinction between them, differentiate the different forms they can take, or explain how each concept relates to the others. Second, students are taught to measure uncertainty using statistical techniques that quantify the variability of study results, but which are not designed to measure uncertainties that arise during research design, data collection or processing. Third, compounding these issues, lessons often do not provide implementable frameworks for auditing SDS workflows that allow students to distinguish different forms of uncertainty and their consequences for inference. Ultimately, students are left understanding the importance of uncertainty and concerned about potential bias, but without an actionable framework to improve their workflows or inferences.

Addressing this situation should be a priority for educators because a limited understanding of uncertainty, error, and bias can impact decision making. Uncertainties capable of producing bias exist throughout the lifecycle of a SDS project [1], [2], [3]. When conceptualizing and designing studies, SDS students must translate domain-specific problem formulations into statistical and computational problems. How even the most basic elements of many domain-specific problems should be translated into SDS workflows is often unclear, which leaves a study design open to judgment calls that can result in bias. When gathering and preparing data for analysis, SDS students also often rely on 'found' data that are opportunistically collected using non-probability sampling schemes that are likely to introduce bias into analyses, and violate the assumptions needed to make statistical inferences [4], [5]. When implementing analyses, SDS students use abundant computational resources and flexible statistical frameworks that permit the testing of many alternative analytical specifications, which again creates the opportunity to select and report results in ways that can bias conclusions. SDS education must train students to recognize and assess uncertainties, errors, and biases arising from all of these stages in a SDS project lifecycle.

Geography provides a useful perspective on these issues because geographers have long recognized the unavoidable presence of uncertainty in their data and the accompanying potential for bias in their predictions and explanations. In the GIScience literature, uncertainty is broadly defined as the problems arising from imperfections in representing the real world in geographic information (GI) databases. However, this use of the term is not consistent across studies or clearly aligned with definitions used in other disciplines. The GIS&T Body of Knowledge has no less than eight entries on uncertainty located in four different knowledge areas, and the most encompassing of these entries point immediately to the additional terms, specialized forms, and alternative perspectives on the topic (see [6]).

Similarly, the concept of bias is frequently mentioned in literature, but with no consistently agreed-upon definition or overarching framework. Instead, geographers often present specific forms of bias relevant to the spatial process being studied. For example, Spatial bias, sometimes referred to as "geographical bias" or "cartographic confounding," is commonly discussed in volunteered geographic information [7], ecology [8], [9] and epidemiology [10] studies. Representative bias is discussed and evaluated in mobility studies [11] and accessibility indexes [12]. Links between

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uncertainty and bias are frequently presented in the context of the Modifiable Areal Unit Problem (MAUP), as attempts to quantify the bias introduced when selecting a spatial unit of analysis have been common for 40 years [13].

Uncertainty, error, and bias need to be moved to the forefront of the SDS curriculum. Neither the geographic nor the data science literature use consistent definitions of these terms, or describe in an accessible way how these fundamental concepts are related. This ambiguity can create confusion for students, impact decision making, and ultimately restrict who can participate in SDS. We address these issues in the remainder of this paper. We organize our work into three remaining sections. First, we introduce a framework for teaching uncertainty, error, and bias in SDS that emphasizes three core competencies - (A) understanding uncertainty, error, and bias, (B) identifying epistemic uncertainty and cataloging bias, and (C) quantifying epistemic uncertainty. Second, we turn our attention to implementation and discuss how our core competencies can be presented and assessed in the classroom. Finally, we conclude by re-emphasizing the benefits of quantitatively assessing and communicating uncertainty and briefly discuss how our approach can be used in a variety of SDS courses.

II. An Educational Framework for Uncertainty, Error, and Bias

To address current ambiguities in SDS education surrounding uncertainty, error, and bias, we propose a framework for introducing these concepts to SDS students. Rooted in Bloom's Taxonomy and the Convergence Curriculum for Geospatial Data Science, our approach emphasizes three central competencies - (A) understanding uncertainty, error, and bias, (B) identifying epistemic uncertainty and cataloging bias, and (C) quantifying epistemic uncertainty.

A. Understanding Uncertianty, Error, and Bias

Following the revised Bloom's Taxonomy, our framework first emphasizes the cognitive processes of remembering and understanding the factual and conceptual foundations of uncertainty, error, and bias. In addition to teaching students how to distinguish between uncertainty, bias, and error, we stress the importance of teaching the interrelationships that exist among these concepts. We advocate educators place particular emphasis on epistemic uncertainty because this form of uncertainty is directly related to bias, can be reduced by student actions, and, when addressed, can improve model development [14] and out-of-distribution prediction [15], [16]. Here we briefly outline essential definitions and relationships among these concepts drawing from statistical, data science, and geographic literatures.

We suggest that educators begin building student understanding of uncertainty, error, and bias by differentiating between aleatoric and epistemic uncertainty. Aleatoric or stochastic uncertainty is variability in the outcome of a study due to inherent randomness. Aleatoric uncertainty generally cannot be reduced by researcher actions and produces random errors that impact the precision of estimates, but leaves those estimates unbiased. In contrast, epistemic or systematic uncertainty stems from a lack of knowledge about the process being studied. Absent complete knowledge, data scientists must make design and analysis decisions which, when incorrect, can create systematic errors and lead to bias. In data science epistemic uncertainty is often further separated into model and estimation uncertainty.

Differentiating between aleatoric and epistemic uncertainty naturally sets up a discussion of error as the difference between the predicted value of a function and an unobserved true value. Our approach uses a statistical treatment to decompose error into bias and two forms of variance and link those elements to different forms of uncertainty. Following Hastie et al. [17], when the mean prediction of a model given data x is $\hat{y} = \int y\,\hat{p}_{Y|X}(y|x)dy$, the bias-variance decomposition of the squared prediction error is:

$$Var_{Y|X}(Y|x) + Var_D(\hat{y}|x) + E_D(\hat{y}|x) - E_{Y|X}(Y|x)$$

This treatment has several educational advantages. First, we can identify the portion of the expected prediction error caused by aleatoric uncertainty as $Var_{Y|X}(Y|x)$. It is also clear that this error cannot be reduced by researcher actions because modeling decisions captured in $\hat{y}$ are absent from this term. The term's dependence on x also makes clear how aleatoric uncertainty relates to the training data used to fit the model, and that the error attributable to aleatoric uncertainty will vary across samples. Second, students can also see that epistemic uncertainty is linked with the remaining estimator variance, $Var_D(\hat{y}|x)$, and bias, $E_D(\hat{y}|x) - E_{Y|X}(Y|x)$, both of which are determined in part the modeling decisions that structure $\hat{y}$. Pushed further, this decomposition can be used to link estimation uncertainty with the estimator variance and model uncertainty with bias and the well-known bias-variance tradeoff.

It is important to also point out the shortcomings of this treatment of uncertainty, error, and bias. Specifically, we believe it is essential that students understand the simplifying assumptions made when decomposing error and uncertainty and how those assumptions close off additional sources of uncertainty likely to be present in practical applications. For example, the statistical presentation above assumes the true probability model is present in the hypothesis space, that the data used in estimation are suitable for the purpose of the study, and that the data generating process is spatially and temporally stationary. In practice, none of the elements is usually known and in spatial analysis the last is commonly assumed to not be true. Discussing these issues highlights the wider set of uncertainties that can affect the variance and bias of estimates, and motivates a broader discussion of epistemic uncertainty, bias, and ways to account for each during the research design process.

B. Identifying Epistemic Uncertainty and Cataloging Bias

Once a foundational understanding of uncertainty, error, and bias has been established, we suggest expanding on the concept of bias and shifting to the development of analysis skills and procedural knowledge. Our objectives are twofold. First, we seek to reinforce that bias can emerge from systematic errors made when facing uncertainties at any stage of a data science project, not just those made in model estimation. Second, we seek to provide students with a list of errors and biases they can apply and expand upon when executing SDS projects. We favor an approach that synthesizes insights from three frameworks for uncertainty and bias tracing - geographic filters of uncertainty [3], total survey error [18], [19], and the catalog of bias [20].

We begin by providing a definition of bias linked to the many types of mistakes that can lead to distortions in results. Following the literature [21], we define bias as: *a systematic distortion, due to design problem, interfering factor, or judgment, that can affect the design or execution of a study and cause erroneous misestimation of the probable size of an effect or association.* This definition makes clear that mistakes made during data collection can produce an imbalanced representation of the target population. Data processing errors can remove locations or individuals from an otherwise representative sample. Model specification and data splitting decisions can shift estimates away from true values. Plotting and mapping decisions can spin results to support misleading conclusions.

With a definition in place, we suggest building a systematic understanding of potential sources of error and bias by first presenting Longley's filters of geographic uncertainty (FGU). Uncertainty in this framework is defined as the problems arising from imperfections in representing the real world in geographic information databases and is structured by four filters related to: the conception (U1), representation (U2), analysis (U3) and visualization (U4) of geographical phenomena.

U1 relates to the conception of place and attribute. Studying spatial relationships requires areal units with boundaries; however, defining geographic units of analysis is inherently subjective and faces many challenges. If the boundary of a spatial unit does not match the phenomena studied, errors such as scale problems and aggregation problems can be introduced (Openshaw, 1983). Similarly, the labels we assign to these units can be vague and ambiguous, failing to accurately reflect the phenomena. Uncertainty in measurement (U2) encompasses inaccuracies in both places (locations) and attributes. Vector models can introduce location errors through aggregation and coarse scaling, while field models often struggle with the issue of multiple classes within a single pixel. As for attributes, nominal labels are subject to misclassification, and continuous values can be inaccurate or imprecise. Still more bias can be introduced when addressing uncertainties during analysis (U3). For example, the inherent structure of spatial data requires specific specification of functional forms [22], and not accounting for this structure can inflate Type I error rates resulting in incorrect inferences. However, the authors also point out that analysis tools can assist measurement and communication of uncertainty and error. Similarly with visualization (U4), while uncertainty can be easily introduced by different interpretations of maps, we can also leverage it to provide feedback to tackle uncertainty at previous steps.

FGU naturally links with the Total Survey Error (TSE) framework, which emphasizes data as the structured product of research design decisions. Developed to identify systematic distortions introduced when designing and executing surveys, the TSE reinforces those epistemic uncertainties tied to conceptualization and measurement produce listable errors that can be scrutinized before and after data collection. Similarities can then be drawn to the FGU and traced back to the statistical definitions of bias and variance. Those comparisons should make clear that many sources of epistemic uncertainty identified in FGU and TSE are not directly represented by terms in the error decomposition, but can affect key terms, such as the dataset x within those equations.

Having reinforced the connection between uncertainty and error, we suggest further widening student understanding of bias by presenting the *Catalogue of Bias (COB)*. This growing collection, now encompassing 65 health study biases, is organized into four categories: conceptualization, selection, conduct, and reporting. Each entry defines a specific bias and explains its impact on the magnitude and direction of effects by providing an example. Some biases are cross-disciplinary and well-recognized in statistics and data science, such as collider bias, confounding bias, industry sponsorship bias, and data-dredging bias. Others are specific to the health field, such as informed presence bias and diagnostic suspicion bias. For general biases that affect all data science projects, this framework is helpful in explicitly outlining how uncertainty management in specific cases can impact outcomes in magnitude and direction. On the other hand, field-specific biases can inspire thoughts on how SDS might be subject to particular biases due to unique data collection methods (e.g., GPS, VGI, web scraping) and spatial analysis approaches. This framework aligns with FGU in showing how uncertainty can be introduced and propagated at every step of research and extends FGU by illustrating how different methods of handling uncertainty can lead to various systematic distortions (i.e., bias). Compared with TSE, it goes beyond the research itself and includes potential biases introduced by researcher belief, inequitable access of resources and other ethical concerns. Overall, the COB offers a finer resolution than FGU and a broader focus than TSE in discussing uncertainty and bias.

C. Quantifying Epistemic Uncertainty

In applied work, direct measurement and clear delineation of uncertainty, error and bias is difficult under the best of circumstances. As a result, our approach focuses on establishing a clear understanding of these issues and providing a flexible framework for parsing and scrutinizing potential sources of error and bias. Nonetheless, it is essential to quantify uncertainty and possible bias in SDS projects. We suggest educators introduce uncertainty quantification by teaching students to computationally test the predictability and stability of their results following the guidance of Yu and Kumbier [2],

[23]. This approach emphasizes the cognitive processes of creating and evaluating uncertainty measurements, and reinforces the need to evaluate decisions made at all stages of a SDS project.

Stability assessments stress-test the results of a SDS project to realistic changes in data processing, analysis, and reporting decisions made when facing uncertainty. SDS results are stable when they tend not to change under reasonable alternative workflows, and stable results garner greater trust. Concerns about stability are already well established in SDS and spatial analysis literature. Openshaw's exploration of the modifiable areal unit problem (MAUP) [13], [24], perhaps the most famous result in spatial analysis, is fundamentally a stability analysis that demonstrates the variability of statistical results when changes are made to the spatial support of data. The essential lesson of the MAUP can be expanded to all data processing and analysis decisions through stability assessment. Educators can follow Kedron et al. [25] suggestion to use specification curves to assess the stability of results, which visually and quantitatively demonstrates the [1], [26], [27] impacts of student decisions.

Following Yu and Kumbier, predictability assessments test whether results are generalizable to new, relevant situations. Predictability introduces the concept of external validity to the uncertainty, error, bias discussion. Predictability can be used to discuss how systematic errors and their resulting biases can imperil model generalizability and practical use. The best evidence for predictability comes from reliable re-use of a model with new data in new contexts. However, in many cases students will not have access to additional data that reflects new contexts or future scenarios. These issues are discussed in geographic literature on replicability. This reality creates an opportunity to introduce data splitting as a surrogate for external validation and the risk of bias from data leakage.

III. Pedagogical Implementation

The three central competencies of our approach to introducing uncertainty, error, and bias can be implemented in a variety of SDS courses using activities and assessments centered on the acquisition of critical skills (Table 1). Understanding uncertainty, error, and bias begins with prepared lectures that introduce the definitions of each concept and their interrelationships. Educators can use traditional quiz and exam formats to test definition recall, but we suggest the use of concept mapping to teach and assess conceptual relationships. As a form of active visual learning, concept mapping complements the statistical treatment of uncertainty, error, and bias for learners less familiar or comfortable with the statistical approach. Once definitions are established, educators can reinforce learning by asking students to classify different forms of uncertainty in a research case study and critique assignment.

Lectures can again be used to establish a conceptual understanding of the three uncertainty and bias frameworks. Here again we advocate for using an in-class concept mapping exercise to help students understand the shared foundations of the three frameworks, as well as their individual strengths and weaknesses. This exercise will give students a broader perspective on the types of error and biases potentially present in SDS projects. Next, focusing on the COB, we suggest asking students to identify and differentiate between biases in a set of applied SDS case studies and SDS datasets. Executing this task separately for completed studies and datasets will reinforce that different biases are rooted in different stages of a project lifecycle. An in-class discussion of these issues can facilitate further understanding by illustrating that in many instances bias identification is not simple. We expect students to identify different potential biases and hold different opinions about the magnitude of their impact. When conflicts occur, students can be asked to prepare written defenses of their positions or potentially debate their views in class.

Finally, we suggest lessons on epistemic uncertainty quantification use the Predictability, Computability, and Stability (PCS) framework to teach students to design and implement stability and predictability tests and make judgements about the reliability of results in light of their outcomes. In the classroom, educators can develop these skills

Table 1. Pedagogical Implementation of the Uncertainty and Bias Framework

	Bloom's Taxonomy		Implementation	
Skill	**Process**	**Knowledge**	**Activity**	**Assessment**
A. Understand Uncertainty				
Define uncertainty, error, and bias	Remember	Factual	Lecture	Exam
Explain interrelationships between uncertainty, error, and bias	Understand	Conceptual	Lecture	Concept Map
Classify uncertainty	Understand	Conceptual	Case Study	Critique
B. Catalog Uncertainty				
Integrate error and bias frameworks	Create	Conceptual	Lecture	Concept Map
Differentiate biases	Apply	Procedural	Discussion	Critique
Infer potential errors	Analyze	Procedural	Discussion	Debate
C. Quantify Uncertainty				
Design stability/predictability tests	Create	Procedural	Design Study	Problem Set
Implement stability/predictability test	Apply	Procedural	Comp Demo	Problem Set
Judge models and inferences	Evaluate	Conceptual	Discussion	Critique

by asking students to plan stability and predictability assessments for prepared research scenarios or their own project work. Assessment implementation and reporting can be taught using prepared computational demonstrations, and educators can share their code to facilitate student replication and elaboration in their own work. Yu provides a template that can be used to teach students how to document a PCS workflow as well as software packages in both Python and R [28], [29] that support simulations of reasonable alternative models. Kedron and Holler [30] provide a similar template for geographic workflows that emphasizes unique features of spatial analysis. Reproduction studies based on that template (see [31], [32]) can be used to support class discussions of uncertainty quantification, and as the basis of critique assignments where students are asked to judge inferences and conclusions after viewing reasonable perturbations of an analysis.

IV. Conclusions

To address current ambiguity surrounding concepts of uncertainty, error, and bias in SDS education, we present a framework for introducing these concepts to SDS students that is rooted in Bloom's Taxonomy and the Convergence Curriculum for Geospatial Data Science. We stress building an understanding of these concepts using clear definitions and a statistical framework. The bias-variance decomposition we use provides a helpful distinction between aleatoric and epistemic uncertainty, but does not cover the many sources of uncertainty outside of the modeling process that can also affect an SDS study. Consequently, our approach brings attention to additional sources of uncertainty by synthesizing insights from three frameworks that trace uncertainty, error, and bias across the entire lifecycle of a data science project. To bring these conceptual elements into practice, we advocate for the use of the PCS framework which trains students to measure the impacts of their decision making (stability) and the potential usefulness of their models in new contexts (predictability).

Because our educational approach provides a foundational understanding of uncertainty, error, and bias, it can be deployed in a variety of SDS courses. For example, our three-stage approach could be used as the first weeks of a methods course on uncertainty estimation. Subsequent weeks could derive error decompositions for different statistical models or branch into different quantification techniques. In contrast, a research design course could use our approach to prepare students to collaboratively design SDS projects with domain experts. Students could use the COB and TSE to structure discussions with collaborators seeking to prevent potential biases in their work, or use PCS documentation to plan stability and predictability analyses before data is collected and processed to prevent data leakage and bias. Finally, our approach could be inserted into the middle of a topic-focused course to help practice oriented students search for bias in past studies, or identify contextual factors that could contribute to uncertainty and error in their research domain.

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Credit Statement

Peter Kedron: Conceptualization, Writing - Original Draft, Writing - Reviewing and Editing.

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