Mapping Responsible Workflows for Geospatial Data Science: Developing the I-GUIDE Data Ethics Toolkit

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Abstract: AI workflows in geospatial data science offer significant societal benefits but raise ethical, transparency, and reproducibility challenges. Current ethical frameworks and tools are often hard to integrate into daily research practice. This paper introduces the I-GUIDE Data Ethics Toolkit (DET), a lightweight suite designed for users of the NSF-funded Institute for Geospatial Understanding through an Integrative Discovery Environment (I-GUIDE). Based on a longitudinal mixed-methods study—including surveys, interviews, and observations—we identified five design priorities: usability, anticipatory planning, distributed responsibility, comprehensive coverage, and policy compliance. We integrated existing AI and data research lifecycles into an eight-stage I-GUIDE Research Lifecycle, serving as the DET's foundation. The DET includes four tools: (1) Data Cards and (2) Model Cards to document provenance, bias, and usage constraints; (3) a Research Product Management Plan for project-level governance; and (4) MEG-AID, a checklist to manage and audit ethical and reproducibility tasks. Future work will embed DET into the I-GUIDE cyberinfrastructure, automating metadata extraction, bias diagnostics, and training modules to ensure responsible geospatial AI research practices.

I. Introduction

As scholarly researchers increasingly use AI, infrastructures like the NSF-funded Institute for Geospatial Understanding through an Integrative Discovery Environment (I-GUIDE) are emerging to support sustainability research. While promising significant benefits for decision- and policymaking, integrating AI into geospatial data science workflows raises critical ethical and reproducibility challenges [1], [2]. These challenges must be urgently addressed to prevent ethical harms, comply with legislation and policies, and maintain public trust in AI-supported research. Existing policy and practical solutions have seen limited adoption due to enforcement difficulties, inconsistent awareness, low incentives, and lack of specificity [3].

To tackle these issues, I-GUIDE has funded our work as its Data Ethics Team. Using insights from a longitudinal, mixed-methods case study, we developed the I-GUIDE Data Ethics Toolkit (DET)[1], a set of practical, interconnected, and lightweight tools tailored to support day-to-day research practices and project management [4]. This paper discusses the toolkit's development, conceptual foundations, and ongoing efforts to integrate it into the I-GUIDE platform.

II. Background

A. Challenges in Responsible AI Development and Deployment

The expanding use of AI in research and policymaking introduces significant ethical concerns, particularly when AI analyzes diverse datasets to inform decisions affecting communities and ecosystems [1].

Privacy and surveillance: Integrating datasets, such as satellite imagery with demographic information, poses risks to privacy by potentially exposing individual identities or locations, or endangering indigenous populations' resources or cultural artefacts [5]. Privacy governance approaches differ, with some emphasizing individual control over personal data while others assign responsibility to those collecting and using datasets [6].

Bias and discrimination: AI systems frequently reflect societal inequalities, leading to discriminatory outcomes based on race, gender, or other demographic factors [7]. Training datasets often reflect existing social inequalities. Group underrepresentation in these datasets can result in less accurate outcomes for, or exclusion of, that group, while overrepresentation can result in unfair targeting of group members [8]. Geospatial datasets are often richer and more accurate for urban than for rural areas, thereby reinforcing preferential treatment in resource allocation, infrastructure planning, or environmental protection [9].

Communicating uncertainty: Effective use of AI system outputs relies on decision-makers understanding limitations of datasets and models, although these limitations are often not communicated effectively. Outputs of geospatial models can be affected considerably by many factors, including spatial and temporal scales employed [10], while spatial heterogeneity can also adversely impact the performance of models developed for one location when they are used in other locations [11].

Accountability: Transparency, explainability, and interpretability: At the core of these challenges is accountability, or whether those impacted by AI-driven decision-making can challenge the basis of decisions. Accountability in AI relies on transparency (openness about a model's workings), explainability (ability to justify model outcomes), and interpretability (clarity of explanations for affected non-experts) [12].

Reproducibility and reuse: Computational reproducibility, the ability of others to rerun a study's data, code, and models, and obtain the same results, is crucial for research integrity [13]. It requires that a study's digital products be findable, accessible, and well-described. Additionally, given the expense of generating datasets and models, governments and funding agencies promote reuse of existing datasets and models for new research [14].

[1] I-GUIDE Data Ethics Toolkit available at: https://github.com/ptdarch/I-GUIDE-DET

B. Compliance Requirements: Policy and Legislation for Reproducible and Responsible AI

The global legislative landscape for AI is evolving, with the European Union (EU) enacting the General Data Protection Regulation (GDPR), which gives EU citizens rights over their personal data, and the Artificial Intelligence Act (AI Act), which regulates AI use according to its risk of harm [15]. Both GDPR and the AI Act have some exemptions for researchers, allowing data to be used for research under certain conditions, and exempting AI systems used exclusively for research from oversight. However, researchers who aim to influence decision- and policymaking beyond academia must comply with these laws. These laws can also apply to researchers outside the EU their AI systems use data about EU citizens or are used in ways that affect EU citizens, or if their models are subsequently used (e.g., for reuse or reproducibility purposes) within the EU. In the US, the White House's Office of Management and Budget released policies for AI acquisition and use by federal agencies in April 2025 [16]. These policies impose multiple requirements on AI systems considered high risk. Researchers who aspire to integrate their models or research outputs into federal government operations or decision-making should take these policies into account.

Oversight of scholarly research is undertaken by bodies including an institution's Institutional Review Board (IRB) and funding agencies. An IRB focuses primarily on maximizing the benefits and minimizing the harms of a project involving people, ensuring that benefits and risks of harm are distributed fairly, and promoting respect for impacted groups [17]. Meanwhile, major funding agencies such as NSF and the EU's Horizon Europe mandate data management plans to promote data and model reuse [18].

C. Approaches to Promoting Research Reproducibility and Responsible AI Practices

The impacts of AI systems result from complex interactions between multiple actors and systems [19]. Development of responsible and reproducible AI is a "problem of many hands", where responsibility for addressing issues is distributed across these elements, challenging traditional accountability structures [20]. This challenge is significant in geospatial data science, where datasets and models involve multiple stages of processing, often have chains of provenance involving people outside of the research team, and outputs are fed into policy or planning processes [1]. To promote reproducible and responsible AI and research practices, stakeholders have devised organizational policies, infrastructure, and practical tools. However, uptake of these remains patchy, emphasizing the need for a more integrated approach.

1) Promoting responsible AI practices

Organizations are increasingly publishing statements of principles and policies for responsible AI development and use [21]. For instance, Google's AI Principles articulate ideals of fairness, transparency, and accountability. These statements have been critiqued as overly broad, difficult to translate into practice [3]. In response, some standards organizations have released AI development lifecycle models and frameworks to address ethical harms. For instance, the US National Institute of Standards and Technology (NIST) produced its Artificial Intelligence Risk Management Framework (AI RMF) [22], which focuses on how to mitigate ethical risks at different model development stages and the International Standards Organization (ISO) and the International Electrotechnical Commission (IES) released a joint standard describing the AI development lifecycle (Fig. 1) [23].

There has been a proliferation of technical and non-technical tools that aim to integrate responsible AI practices into workflows [24]. For instance, the Open Data Institute's (ODI) Data Ethics Canvas aims to foster understanding of a system's impact and harms [25], while Google's Data Cards Playbook seek to enhance transparency by providing structured templates for recording key features of datasets [26]. However, these tools face challenges to their uptake due to increased workload, and a lack of assignation of responsibility and enforcement within a project [27]. These frameworks, standards, and tools may be particularly difficult to apply in geospatial scientific research, where datasets are diverse and contextual nuances are paramount.

2) Promoting reproducible and reusable research outputs

In the wake of funding agency requirements, stakeholders have developed principles, infrastructures, and tools and methods to support researcher compliance [28]. However, provision and uptake of these supporting measures remains patchy [13].

The FAIR (Findable, Accessible, Interoperable, and Reusable) Principles are a widely referenced framework, setting out criteria to ensure that datasets are reusable [29]. Achieving FAIRness requires planning from the earliest stages of a research project, and production of thorough metadata and provenance records. In practice, these requirements are hard meet due to factors such as limited training and provision of necessary resources for researchers, deadline pressures, and bureaucratic burdens [30].

To support researchers in planning data and model curation, data management organizations have released data lifecycle models that delineate stages at which various curation actions are taken. An influential model is the Digital Curation Centre's (DCC) Curation Lifecycle Model (Fig. 2) [31]. Other infrastructural support for researchers includes consulting services and training provided by research libraries [32], and technical infrastructure such as form of data and code repositories [33]. However, these infrastructures often struggle to secure sufficient resources to check and augment metadata and other provenance information [34], instead on the efforts of the data and model producers to create necessary documentation.

Achieving reproducibility, reuse of data and models, and responsibility in geospatial data science and AI is critical to mitigate harms, ensure policy compliance, and gain and sustain trust of policymakers, and affected communities. Principles and policies alone can be too abstract, while the mere existence of tools does not guarantee uptake in the absence of policy enforcement and incentives. Existing approaches for responsible AI are insufficiently tailored to research, and geospatial data science in particular.

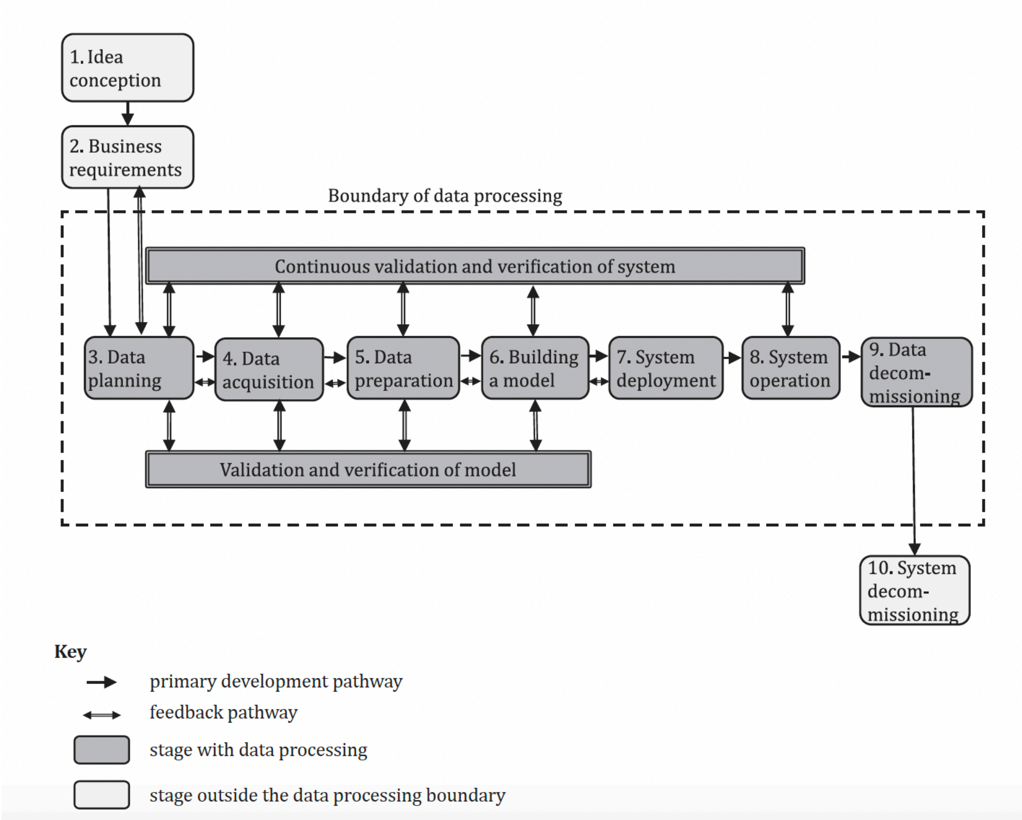

Fig 1. The ISO/IEC AI System Life Cycle [23]

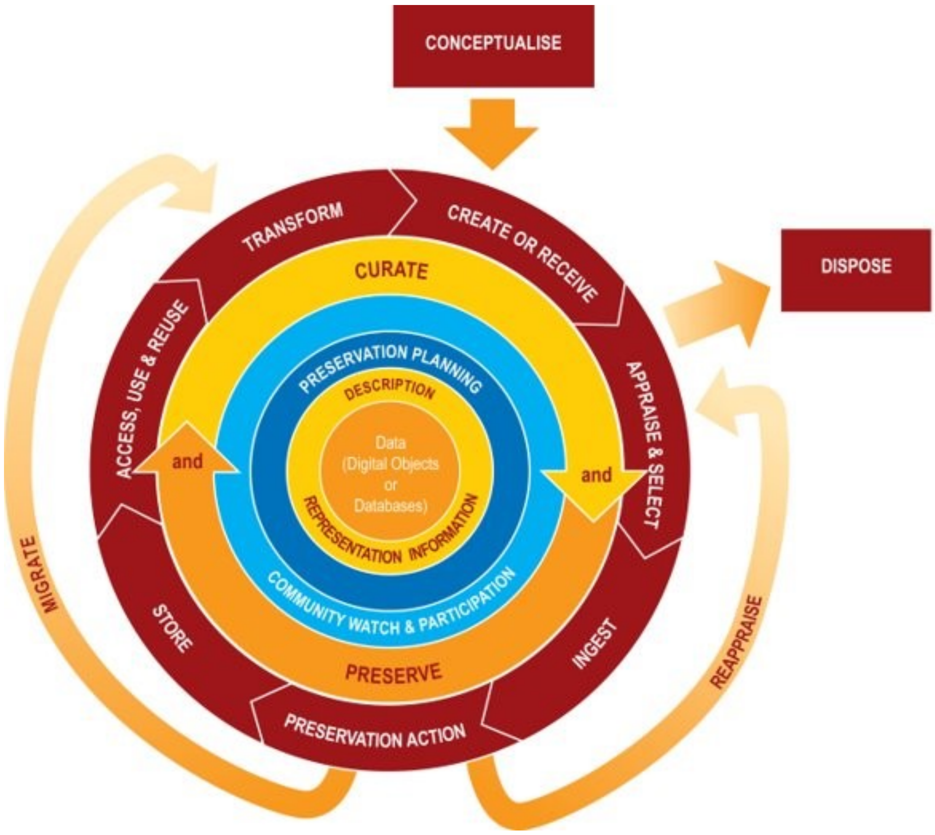

Fig 2. The Digital Curation Centre Curation Lifecycle Model [31]

III. Methods

The development of the I-GUIDE Data Ethics Toolkit (DET) drew on an ongoing, longitudinal, mixed-methods case study of I-GUIDE platform users. This study has allowed us to characterize platform users' workflows, including identifying when they make decisions and take actions that have ethical significance, understanding their work contexts and barriers to adoption of tools, what training and experience they have in responsible and reproducible research practices, and what form of support they desire. We employed three methods: surveys, interviews, and observation [35]. Using a range of methods enabled triangulation, allowing us to cross-check findings across multiple sources of data. The survey also enabled us to generalize our findings.

We distributed a survey to researchers drawn from the I-GUIDE user community, recruited at the project's spring 2023 All Hands' Meeting, with 20 responses. The survey was designed to capture quantitative data regarding ethical and reproducibility issues researchers faced in their work, and the challenges they encountered in addressing these issues. The survey utilized Likert-scale and multiple-choice questions that enabled quantitative analysis, and open-ended responses that provided contextual richness.

Our interviews and observation have focused on a group of researchers who are using the I-GUIDE platform as it is being built. This team is modelling the risks of failure, and the resulting societal risks, of aging dams across the United States. They integrate diverse data sources, often using models that are composites of multiple other models, with the aim of informing policy- and decision-making about where to target interventions to mitigate the risks of dam failure. The second and third authors conducted 20 semi-structured interviews with aging dams researchers, including researchers who produced the underlying models that are used by the aging dams team. Each interview lasted approximately 45 to 60 minutes, was carried out via video conferencing, and recorded and transcribed with the consent of the interviewee. Questions focused on topics their workflows, the ethical and reproducibility dilemmas and challenges they face, prior training or support they have received, and desired features that could be incorporated into a data ethics toolkit. We analyzed the interviews using a grounded theory approach, allowing themes to emerge from interviewees' answers [36]. Interviews provided complex levels of qualitative depth and detail that could not be gained from survey results, complementing the contextual richness the survey data provided.

Over a period of three years being embedded within I-GUIDE, our team has conducted participant observation by attending a variety of key activities within the I-GUIDE research community, including project meetings, team meetings, cross-team collaboration meetings, technical workshops and training sessions hosted by the project, and domain conferences attended by I-GUIDE project members and platform users. This observation allowed us to observe firsthand how decisions regarding data collection, model training, and ethics and reproducibility considerations were made. Participant observation presented profound detail surrounding cultural and social context and its influence on the I-GUIDE researchers' decision making. Data from participant observation complemented the survey and interview data by allowing us to better understand the processes observed through participant observation and the relationship between researchers' individualized approaches and research team solutions.

IV. Developing the I-GUIDE Data Ethics Toolkit (I-GUIDE DET)

We developed a strategy for embedding responsible, reproducible, and FAIR practices in the workflows of I-GUIDE platform users. Once we overcame scoping challenges, we prioritized building the I-GUIDE Data Ethics Toolkit (I-GUIDE DET), for which we established design priorities, constructed an I-GUIDE Research Lifecycle model, and developed a suite of four tools.

A. Scoping Our Work

A comprehensive strategy would involve: tools, policies to incentivize or enforce tool use, and statements of principles. However, this approach would require considerable resources and disruption to I-GUIDE platform users' workflows. While I-GUIDE provided us with an opportunity, rare among NSF cyberinfrastructure projects, of funding work on AI ethics, our limited resources meant we had to ask whether we should focus on establishing principles and policies to promote top-down change, or on taking a bottom-up approach by developing tools for integration into workflows? We chose the latter. One reason was to meet expectations of I-GUIDE leaders and the NSF for concrete deliverables. Moreover, researchers in our study expressed a preference for practical and lightweight tools, due to pressures like publication expectations. We met researchers where they are, designing tools for tangible, incremental, and persistent improvement. We also realized that focusing on tools does not mean sidelining principles or policies. Instead, embedding the toolkit directly into platform workflows can make toolkit use a requirement for platform users, fostering a culture of accountability without separate policies.

B. Design Priorities for the Toolkit

Underpinning toolkit development were five priorities, drawn from case study insights and extant literature and policies:

1. **Usability:** Interviewees consistently expressed a preference for tools that would fit into their established workflows. Interviewees also requested each tool should be accompanied by clear instructions, leaving minimal ambiguity;
2. **Support for advance planning:** Tasks of creating adequate documentation, curating models and datasets, and mitigating ethical harms become progressively more difficult the later they are undertaken in a project's lifecycle. The toolkit should encourage embedding of responsible and reproducible AI practices from the earliest stages of a project;
3. **Distribution of responsibility:** The toolkit should address the problem of many hands by clearly delineating tasks, assigning responsibilities for completing these tasks, and monitoring progress;

4. **Comprehensive coverage of ethical issues and requirements for FAIRness and reproducibility**;
5. **Compliance with policies and legislation:** Use of the toolki should enable compliance with the policies and legislation to which I-GUIDE platform users are subjected, providing a significant incentive for toolkit uptake.

C. The I-GUIDE Lifecycle Model

We integrated existing research data and AI lifecycle models to develop the I-GUIDE Lifecycle Model (Fig. 3). Our lifecycle model was tailored to I-GUIDE workflows iteratively, drawing on our case study to identify actions that geospatial data science researchers take, mapping these actions to stages of the lifecycle model. The Lifecycle model comprises eight stages:

1. **Defining the research problem:** articulating research objectives, defining the project's scope, planning project workflows and schedules, and identifying key audiences for research outputs;
2. **Acquiring and creating datasets:** this stage breaks down into substages, each with distinct tasks. Ethical and reproducibility-related issues can manifest very differently across substages:
   2a. *Acquiring secondary datasets:* finding, accessing, and evaluating datasets produced by others; identifying and complying with terms of use;
   2b. *Collecting primary non-human subjects' datasets;*
   2c. *Collecting primary human-subjects' datasets:* including gaining IRB approval, selecting and recruiting participants, and undertaking informed consent processes;
   2d. *Collecting primary datasets from web scraping or other digital activities:* including determining whether IRB approval is required, and complying with platforms' terms of use;
3. **Processing and cleaning datasets:** organizing, cleaning, anonymizing, and annotating datasets; producing metadata;
4. **Storing datasets:** selecting and using storage systems, setting access controls, ensuring backups;
5. **Acquiring and creating models:** this stage breaks down into substages, each with distinct tasks:
   5a. Acquiring existing model: testing and adapting models produced by others; complying with terms of use;
   5b. Building and training a custom model;
6. **Integrating multiple models into a single model:** including training and testing the resulting model;

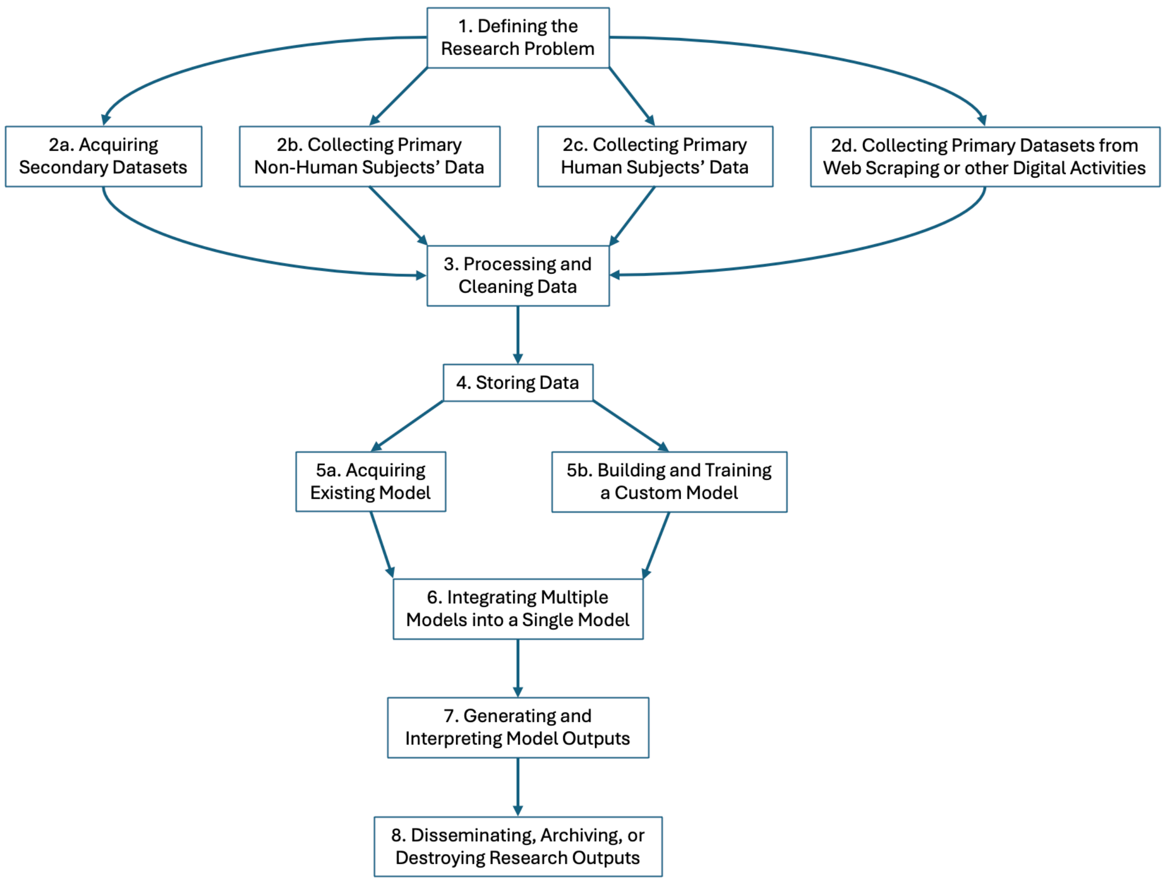

Fig 3. The I-GUIDE Lifecycle Model

7. **Generating and interpreting model outputs:** including outputs that aid explainability and interpretability;
8. **Disseminating, archiving, or destroying research outputs:** including publishing findings and communicating model and data limitations, archiving and making accessible datasets and models, and securely destroying sensitive datasets.

D. Developing the I-GUIDE Data Ethics Toolkit (I-GUIDE DET)

The I-GUIDE toolkit comprises four interconnected tools. Each tool is a template to be completed by I-GUIDE platform users. Two (**I-GUIDE Data Cards** and **I-GUIDE Model Cards**) are documentation templates, while two (**I-GUIDE Research Product Management Plan and I-GUIDE Management of Ethical Geospatial Artificial Intelligence and Data Science (MEG-AID)**) are project management and planning tools.

We focused on tools for documentation, given its central role in reproducibility, FAIRness, and accountability. We also chose to develop management tools to support planning, and to allow assignment of responsibility. To promote usability, we maximized the amount of multiple-choice and tick-box options, short answer fields with specific instructions, and integration across tools.

1) Documentation tools: I-GUIDE Data and Model Cards

Researchers consistently reported that traditional documentation tools were overly burdensome and did not fully address ethical issues. We began developing improved documentation tools by reviewing 21 existing AI governance tools, and tools to support FAIR and reproducible practices. Evaluation criteria were derived from the case study: specificity, adaptability, lightweight design, domain relevance, and support for AI ethics and/or reproducibility. We selected the open-source Google Data Cards Playbook to underpin our documentation tools. We adapted and streamlined the Playbook, reducing its complexity to make it lightweight, and adding instructions, tick-box fields, and default options. We added fields relating to datasets' spatial coverage and coordinate systems. We shared interim versions of the Data Card with researchers for feedback. The resulting I-GUIDE Data Card supports documentation of dataset overview, characteristics, provenance, sensitivity, transformations, applications, benchmarks, and ethical concerns. It also includes fields that prompt reflection on appropriate and inappropriate uses of the dataset.

We then adapted the Data Card into a separate tool: the I-GUIDE Model Card, tailored to models. The Model Card includes sections on model overview, provenance, adaptation/customization, performance and evaluation, transparency, interpretability, and ethical risks, training data, inputs and outputs, integration with other models, explainability limitations, and model fairness. These cards provide structured documentation that extends beyond conventional metadata. Their use can fulfil mandates for data and model management, and legislative requirements. They enable transparency and accountability by exposing critical information about a dataset. They also ensure sufficient documentation to promote FAIRness and reproducibility.

2) Project management and planning tools

The I-GUIDE Research Project Management Plan (RPMP) was developed to assist planning, coordinating, and tracking key aspects of data and model stewardship throughout a project. The RPMP prompts researchers at the start of a project to define their research aims and expected audiences, thereby ensuring that approaches to explainability and interpretability are appropriate to these audiences. It also helps facilitate reproducibility and model and data reuse by asking researchers to specify in advance their data and model needs, and ensure consistent standards throughout their project about file formats and naming conventions, metadata schema, storage and access practices, and more. By encouraging researchers to think early on about their dissemination plans and the long-term fate of their data and models, whether they will be shared, embargoed, archived, or destroyed, the RPMP enables them to plan accordingly. The RPMP also requests that researchers specify relevant legal and policy compliance obligations to ensure their work practices meet these standards throughout the project. Finally, the RPMP also allows tracking of a project's research objects, and linking models and datasets to their respective Model and Data Cards and to the publications they support, further promoting reproducibility. Completing the RPMP will satisfy the data management plan requirements of major funding agencies, such as NSF, NIH, and EU Horizon. Finally, by incorporating structured multiple-choice fields and guided short responses, the RPMP minimizes the bureaucratic burden while ensuring critical strategic elements are not overlooked.

The final tool, the I-GUIDE Management of Ethical Geospatial AI & Data Science (MEG-AID) was developed to support teams in planning and tracking ethical, reproducibility, and FAIR-related actions across the I-GUIDE lifecycle. MEG-AID is structured around the I-GUIDE Project Lifecycle and is formatted as a detailed checklist or matrix. It provides a task list for each lifecycle stage. To reduce bureaucratic burden, it only specifies tasks to be taken at each stage that have significance in addressing issues relating to ethical, reproducibility, and/or FAIRness. For each task, the tool provides a concrete tip for completing the task, allows project managers to specific the team member(s) responsible for completing the task, and tracks task completion status. It also describes which issues are addressed by the task, providing a rationale to reassure researchers that each task has a purpose.

By using MEG-AID at the outset of a project, researchers can ensure they address issues at the relevant stage of a project, and ensure necessary compliance with policies, and legislation. Many of the tasks specified by MEG-AID involve adding information to fields in the Data and Model Cards, and the RPMP. Full adherence to MEG-AID will result in completion of these other tools. For instance, MEG-AID helps ensure that during data collection, teams assess privacy risks, obtain informed consent, and review licensing terms. Later in the lifecycle, it prompts researchers to complete or revise sections of the Data or Model Cards, validate model outputs, and evaluate dissemination plans for clarity. The burden of MEG-AID is minimal because completing the fields of the tool simply requires a name and task status be provided for each task. MEG-AID draw from the insight that ethical, reproducible, and FAIR research is everyone's responsibility, and that it involves action at every stage of a project.

V. DISCUSSION AND CONCLUSIONS

The I-GUIDE Data Ethics Toolkit (DET) provides a concrete, actionable means to embed responsible, reproducible, and FAIR AI practices into the daily work of geospatial data science researchers. Our work exemplifies a pragmatic approach in which ethical challenges are not treated as abstract ideals but are transformed into practices that can be planned, assigned, documented, and completed. The toolkit assists with compliance with funding agency requirements and regulatory frameworks, with addressing societal concerns, and with fostering and sustaining public trust in AI-supported research.

The work of pursuing responsible, reproducible, and FAIR research is neither a one-time event, nor something that can be resolved solely through technical fixes, nor something that is the responsibility of one person within a project. Instead, it must be conceived as an iterative, collective process that requires reflection and adaptation throughout. This perspective is particularly embodied in MEG-AID, which enables teams to anticipate ethical issues, assign responsibilities, and track progress at every stage of the project. Similarly, the Data and Model Cards are not just repositories of technical metadata; they are documents that record elements critical to achieving transparent, accountable, reproducible and FAIR research practices.

Next steps will prioritize integrating the DET into the I-GUIDE cyberinfrastructure so that the tools will function inside the platform rather being separate paperwork, for example by automating extraction of metadata, thereby completing some fields of Model and Data Cards, and testing fairness. Embedding these steps in the workflow minimises administrative effort, while facilitating policy enforcement-by-design as the workflow may not advance until required tasks are completed.

As challenges evolve, the principles and structures embedded in the I-GUIDE DET offer a framework that can adapt to future needs. By empowering researchers to make responsible choices visible and traceable, the I-GUIDE Data Ethics Toolkit lays a robust foundation for more responsible, reproducible, FAIR, and ultimately more effective geospatial research.

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REFERENCES

[1] T. A. Nelson, M. F. Goodchild, and D. J. Wright, "Accelerating ethics, empathy, and equity in geographic information science," *Proc. Natl. Acad. Sci.*, vol. 119, no. 19, p. e2119967119, May 2022, doi: 10.1073/pnas.2119967119.

[2] P. Kedron, W. Li, S. Fotheringham, and M. Goodchild, "Reproducibility and replicability: opportunities and challenges for geospatial research," *Int. J. Geogr. Inf. Sci.*, vol. 35, no. 3, pp. 427–445, Mar. 2021, doi: 10.1080/13658816.2020.1802032.

[3] D. Schiff, B. Rakova, A. Ayesh, A. Fanti, and M. Lennon, "Explaining the Principles to Practices Gap in AI," *IEEE Technol. Soc. Mag.*, vol. 40, no. 2, pp. 81–94, Jun. 2021, doi: 10.1109/MTS.2021.3056286.

[4] P. T. Darck, K. M. Abrams, and I. Kong, *I-GUIDE Data Ethics Toolkit (I-GUIDE DET), v1.0*. (Apr. 20, 2025). Zenodo. doi: 10.5281/ZENODO.15252431.

[5] R. Tsosie, "Tribal data governance and informational privacy: Constructing indigenous data sovereignty," *Mont Rev*, vol. 80, p. 229, 2019.

[6] H. Nissenbaum, *Privacy in Context: Technology, Policy, and the Integrity of Social Life*. Stanford, CA: Stanford Law Books, 2009.

[7] B. Heinrichs, "Discrimination in the age of artificial intelligence," *AI Soc.*, vol. 37, no. 1, pp. 143–154, Mar. 2022, doi: 10.1007/s00146-021-01192-2.

[8] WangAngelina, KapoorSayash, BarocasSolon, and NarayananArvind, "Against Predictive Optimization: On the Legitimacy of Decision-making Algorithms That Optimize Predictive Accuracy," *ACM J. Responsible Comput.*, Mar. 2024, doi: 10.1145/3636509.

[9] J. Láng-Ritter, M. Keskinen, and H. Tenkanen, "Global gridded population datasets systematically underrepresent rural population," *Nat. Commun.*, vol. 16, no. 1, p. 2170, Mar. 2025, doi: 10.1038/s41467-025-56906-7.

[10] E. Shook and S. Wang, "Investigating the Influence of Spatial and Temporal Granularities on Agent-Based Modeling: Investigating the Influence of STGs on ABMs," *Geogr. Anal.*, vol. 47, no. 4, pp. 321–348, Oct. 2015, doi: 10.1111/gean.12080.

[11] J. Mökander and R. Schroeder, "AI and social theory," *AI Soc.*, vol. 37, no. 4, pp. 1337–1351, Dec. 2022, doi: 10.1007/s00146-021-01222-z.

[12] D. Kaur, S. Uslu, K. J. Rittichier, and A. Durresi, "Trustworthy Artificial Intelligence: A Review," *ACM Comput. Surv.*, vol. 55, no. 2, pp. 1–38, Feb. 2023, doi: 10.1145/3491209.

[13] C. Willis and V. Stodden, "Trust but verify: How to leverage policies, workflows, and infrastructure to ensure computational reproducibility in publication," *Harv. Data Sci. Rev.*, vol. 2, no. 4, 2021, Accessed: Apr. 20, 2025. [Online]. Available: https://par.nsf.gov/biblio/10312030

[14] I. V. Pasquetto, C. L. Borgman, and M. F. Wofford, “Uses and Reuses of Scientific Data: The Data Creators’ Advantage,” *Harv. Data Sci. Rev.*, vol. 1, no. 2, 2019, doi: 10.1162/99608f92.fc14bf2d.
[15] M. Nisevic, A. Cuypers, and J. De Bruyne, “Explainable AI: Can the AI Act and the GDPR go out for a date?,” in *2024 International Joint Conference on Neural Networks (IJCNN)*, IEEE, 2024, pp. 1–8. Accessed: Apr. 21, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10649994/?casa_token=xkeO8qLhrzgAAAAA:79wmka4uhmL39mqWdVC06D7n3nNBKMSkXPGad7GhTTbgmwgcWaAooVWifLJJfwH46Flgp5CzmoS5
[16] “White House Releases New Policies on Federal Agency AI Use and Procurement,” The White House. Accessed: Apr. 21, 2025. [Online]. Available: https://www.whitehouse.gov/articles/2025/04/white-house-releases-new-policies-on-federal-agency-ai-use-and-procurement/
[17] J. Metcalf, “Big data analytics and revision of the common rule.,” *Commun ACM*, vol. 59, no. 7, pp. 31–33, 2016.
[18] M. Williams, J. Bagwell, and M. N. Zozus, “Data management plans, the missing perspective,” *J. Biomed. Inform.*, vol. 71, pp. 130–142, Jul. 2017, doi: 10.1016/j.jbi.2017.05.004.
[19] O. Kudina and I. Van De Poel, “A sociotechnical system perspective on AI,” *Minds Mach.*, vol. 34, no. 3, pp. 21, s11023-024-09680–2, Jun. 2024, doi: 10.1007/s11023-024-09680-2.
[20] N. Helberger, J. Pierson, and T. Poell, “Governing online platforms: From contested to cooperative responsibility,” *Inf. Soc.*, vol. 34, no. 1, pp. 1–14, Jan. 2018, doi: 10.1080/01972243.2017.1391913.
[21] T. Hagendorff, “The Ethics of AI Ethics: An Evaluation of Guidelines,” *Minds Mach.*, vol. 30, no. 1, pp. 99–120, Mar. 2020, doi: 10.1007/s11023-020-09517-8.
[22] E. Tabassi, “Artificial Intelligence Risk Management Framework (AI RMF 1.0),” National Institute of Standards and Technology (U.S.), Gaithersburg, MD, NIST AI 100-1, Jan. 2023. doi: 10.6028/NIST.AI.100-1.
[23] International Organization for Standardization and International Electrotechnical Commission, *ISO/IEC 5338:2023 Information Technology - Artificial Intelligence - AI System Life Cycle Processes:2023*, 2023. Accessed: Apr. 20, 2025. [Online]. Available: https://www.iso.org/standard/81118.html
[24] S. Schmager and S. Sousa, “A Toolkit to Enable the Design of Trustworthy AI,” in *HCI International 2021 - Late Breaking Papers: Multimodality, eXtended Reality, and Artificial Intelligence*, vol. 13095, C. Stephanidis, M. Kurosu, J. Y. C. Chen, G. Fragomeni, N. Streitz, S. Konomi, H. Degen, and S. Ntoa, Eds., in Lecture Notes in Computer Science, vol. 13095. , Cham: Springer International Publishing, 2021, pp. 536–555. doi: 10.1007/978-3-030-90963-5_41.
[25] Open Data Institute, *Data Ethics Canvas*. (2021). Open Data Institute. [Online]. Available: https://theodi.org/insights/tools/the-data-ethics-canvas-2021/
[26] M. Pushkarna, A. Zaldivar, and O. Kjartansson, “Data Cards: Purposeful and Transparent Dataset Documentation for Responsible AI,” in *2022 ACM Conference on Fairness, Accountability, and Transparency*, Seoul Republic of Korea: ACM, Jun. 2022, pp. 1776–1826. doi: 10.1145/3531146.3533231.
[27] E. Ruttkamp-Bloem, “The Quest for Actionable AI Ethics,” in *Artificial Intelligence Research*, vol. 1342, A. Gerber, Ed., in Communications in Computer and Information Science, vol. 1342. , Cham: Springer International Publishing, 2020, pp. 34–50. doi: 10.1007/978-3-030-66151-9_3.
[28] C. L. Borgman, P. T. Darch, I. V. Pasquetto, and M. F. Wofford, “Our knowledge of knowledge infrastructures: Lessons learned and future directions,” Jun. 2020, Accessed: Apr. 20, 2025. [Online]. Available: https://escholarship.org/uc/item/9rm6b7d4
[29] M. D. Wilkinson *et al.*, “The FAIR Guiding Principles for scientific data management and stewardship,” *Sci. Data*, vol. 3, p. 160018, Mar. 2016.
[30] B. W. Bishop, C. Hank, J. Webster, and R. Howard, “Scientists’ data discovery and reuse behavior: (Meta)data fitness for use and the FAIR data principles,” *Proc. Assoc. Inf. Sci. Technol.*, vol. 56, no. 1, pp. 21–31, 2019, doi: 10.1002/pra2.4.
[31] S. Higgins, “The DCC curation lifecycle model,” *Int. J. Digit. Curation*, vol. 3, no. 1, pp. 134–140, 2008.
[32] C. Tenopir *et al.*, “Academic Librarians and Research Data Services: Attitudes and Practices,” *IT Lib Inf. Technol. Libr. J.*, no. 1, pp. 24–37, 2019.
[33] P. T. Darch, A. E. Sands, C. L. Borgman, and M. S. Golshan, “Library cultures of data curation: Adventures in astronomy,” *J. Assoc. Inf. Sci. Technol.*, vol. 71, no. 12, pp. 1470–1483, Dec. 2020, doi: 10.1002/asi.24345.
[34] K. R. Eschenfelder, K. Shankar, and G. Downey, “The financial maintenance of social science data archives: Four case studies of long-term infrastructure work,” *J. Assoc. Inf. Sci. Technol.*, vol. 73, no. 12, pp. 1723–1740, Dec. 2022, doi: 10.1002/asi.24691.
[35] S. N. Hesse-Biber, D. Rodriguez, and N. A. Frost, “A Qualitatively Driven Approach to Multimethod and Mixed Methods Research,” in *The Oxford Handbook of Multimethod and Mixed Methods Research Inquiry*, S. N. Hesse-Biber and R. B. Johnson, Eds., Oxford University Press, 2015, p. 0. doi: 10.1093/oxfordhb/9780199933624.013.3.
[36] A. Strauss and J. M. Corbin, *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. SAGE Publications, 1998.