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WIP: Year Two Findings from a Water Science & Data Science CyberTraining Workshop

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Abstract
In this work-in-progress paper, we report findings from the second year of implementation of the WaterSoftHack data science workshop, a virtual, hackathon-centered NSF CyberTraining program situated in water science that culminates in a team-based hackathon. In this paper, cybertraining refers to training in cyberinfrastructure (CI), data science, machine learning (ML), and computational workflows for water science research rather than cybersecurity training. This work is part of an NSF CyberTraining project utilizing a design-based research approach to develop data science knowledge and skills in the water sciences. Building on formative findings from Year 1, the Year 2 iteration focused on refining the program structure while maintaining the core elements: intensive instruction, applied project work, and collaborative hackathon experience.

Participants were eighteen Fellows, including graduate students, postdoctoral researchers, and faculty members seeking professional development in data science. Fellows participated virtually, collaborating with teams on final hackathon projects. Data collection included pre- and post-workshop surveys and in-depth semi-structured interviews, with all five returning Fellows from Year 1 participating. Given the small matched cohort, we triangulated quantitative and qualitative analyses using Kirkpatrick's Four-Level Training Evaluation Model and the Context, Input, Process, Product (CIPP) framework to provide a comprehensive understanding of participant experiences. Because only four Fellows completed matched pre- and post-surveys, the quantitative findings are reported descriptively and directionally rather than inferentially.

Our analysis reveals several significant formative findings. First, the program successfully boosted participants' self-efficacy; they reported increased confidence and described acquiring advanced computational skills. Matched cohorts demonstrated directional gains in self-rated proficiency across core competencies, including CI prototyping, ML programming, and cloud computing. Participants credited hands-on practice and accessible instructional materials, such as Google Colab notebooks, for their progress. Fellows reported new familiarity with advanced models, including Transformers and Long Short-Term Memory (LSTM) networks, and increased confidence to apply these methods in their research.

Despite these successes, persistent challenges emerged that mirrored and intensified Year 1 patterns. The compressed three-week workshop timeline was consistently cited as creating an overwhelming pace and steep learning curve. Team dynamics challenges were more pronounced in Year 2, with uneven prior knowledge among team members contributing to interpersonal friction and perceived gaps in support during conflicts. Participants provided actionable recommendations for future iterations, including a Week Zero scaffolding period, earlier team formation, guided code walkthroughs, streamlined theory content, and clearer conflict-resolution protocols.

Keywords: *data science education; cyberinfrastructure; machine learning; hackathon; water science; mixed-methods evaluation; CIPP; Kirkpatrick*

Introduction and Problem Context

The increasing complexity of global water challenges, such as resource management, climate resilience, and sustainability, demands interdisciplinary approaches that integrate advanced computational methods with domain-specific expertise [1]. With its capacity to process, analyze, and model large datasets, data science has become a transformative tool in water science and hydrology. By leveraging computational tools such as ML, hydrological modeling, and geospatial analytics, researchers can address pressing questions in water resource management more efficiently and effectively. For this project, cybertraining does not primarily refer to cybersecurity literacy or training in confidentiality, integrity, and availability. Instead, it refers to cyberinfrastructure and computational-workflow capacity: using data pipelines, cloud or shared computing environments, ML models, and reproducible coding practices to support water science research.

The WaterSoftHack initiative, funded by the National Science Foundation CyberTraining program, is a multi-year effort to advance water science research through cybertraining and machine learning education. The project aims to democratize access to advanced CI tools and workflows within the water science community. Key objectives include fostering workforce competence in CI prototyping and workflow development, supporting innovation in sustainable water practices, and broadening the adoption of computational methods across the field. Accordingly, this study draws on training evaluation and program-improvement frameworks [2], [3], interdisciplinary earth and water science education [4], professional development research emphasizing active learning and relevance [5], AI and hackathon pedagogy [6], mixed-methods evaluation [7], and hackathon-based learning research [8], [9].

This WIP reports Year 2 formative findings and design implications. Two research questions guide the analysis: (RQ1) How does the WaterSoftHack program enhance data science competencies within water science contexts? (RQ2) What challenges and opportunities do participants encounter as they integrate data science into professional practices?

Year 2 included 18 Fellows, including graduate students, postdoctoral researchers, and faculty members seeking professional development in data science. Fellows participated virtually and collaborated in teams on final hackathon projects. The Year 2 workshop emphasized advanced ML approaches, including Transformers and LSTM networks, while retaining the core structure of intensive instruction, applied project work, and collaborative hackathon experience [8], [9].

Evaluation Framework and Methods

The workshop's development and evaluation followed a design-based research approach, emphasizing iterative refinement informed by participant feedback. This approach allowed the research team to connect Year 1 findings to Year 2 modifications and to use Year 2 evidence to inform Year 3 design choices (see Figure 1).

The evaluation used Kirkpatrick's Four-Level Training Evaluation Model [2] and the CIPP framework [3]. Kirkpatrick's model supported attention to participant reaction, learning, behavior, and results. The CIPP framework supported attention to context, inputs, process, and products. Together, these lenses provided a structure for interpreting both participant learning and the conditions that shaped their experiences [10].

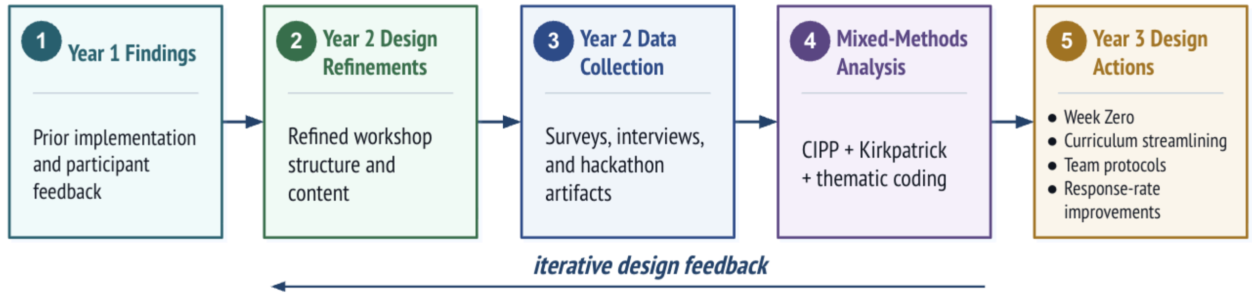

Figure 1. Design-Based Research and Evaluation Workflow

Data Analysis

As noted in the limitations, we were constrained by limited data availability (see Table 1). For qualitative analysis, we used a thematic codebook that integrated Year 1 codes with emergent Year 2 codes. The unit of analysis was either a single meaning unit from interviews or a complete open-ended survey response. Codes were organized around participant background and context; program experience and satisfaction; learning outcomes and self-efficacy; transfer/application/impact; challenges/barriers; and recommendations for program improvement. This approach is consistent with mixed-methods evaluation designs that integrate quantitative patterns with qualitative interpretation [7]. See Table 2 for code families and data sources.

Year 2 data source/participation pattern	Count
Fellows in the Year 2 cohort	18
Completed pre-survey	11
Completed post-survey	5
Completed both pre- and post-surveys	4
Completed interview	10
Completed both surveys and the interview	3
Returning Year 1 Fellows completing interview	5

Table 1. Year 2 data overview.

Quantitative Likert-scale items were analyzed descriptively and used as contextual evidence for qualitative themes rather than as the basis for inferential claims. Because only four Fellows completed matched pre- and post-surveys, we report directional descriptive changes rather than inferential tests. Statistical tests provide little evidentiary value with this sample size and imply precision not supported by the data.

Code family	Purpose	Primary data sources
BASE	Participant background, baseline skills, prior learning pathways, barriers, and goals	Pre-survey; interview Q1
REACT	Satisfaction, fit to goals, instructional quality, accessibility, and format	Post-survey quantitative/open-ended items; interviews

Code family	Purpose	Primary data sources
LEARN	Self-efficacy, preparation, foundational learning, and advanced technical challenges	Pre/post surveys; interviews
XFER	Application to research, networking, publication intent, and entrepreneurship/career transfer	Post-survey open-ended items, interviews and follow-up evidence
PROC	Implementation process, pacing, hackathon structure, team dynamics, support gaps	Post-survey open-ended items; interviews; hackathon observations/artifacts
INPUT	Recommendations for content, structure, duration, team formation, and materials	Post-survey improvement items; interviews
RESULT	Tangible outputs, including hackathon artifacts and publication momentum	Hackathon artifacts; interviews

Table 2. Narrative key for major code families.

Year 2 Findings

Finding 1: Self-Efficacy and Advanced Technical Skill Development

Participants reported improved proficiency ratings and increased confidence across targeted domains. Specific gains included familiarity with advanced models such as Transformers and LSTM networks. Matched pre/post data showed directional improvement across core competency areas, including CI prototyping, ML programming, and cloud computing. However, because the matched sample was small, these findings are presented as formative indicators rather than evidence of statistically significant change. Participants credited hands-on practice, accessible Google Colab notebooks, GitHub repositories, and applied examples as important supports for learning.

Finding 2: Applied Hackathon Work Supported Transfer and Research Momentum

The applied hackathon structure was described as more valuable than lectures alone [8], [9], as Fellows used workshop-based concepts to address water-science problems. Interviews documented direct application of workshop learning to dissertation projects, coursework, and home-institution research. Multiple teams described concrete plans to develop hackathon projects into formal academic products, such as conference papers or journal manuscripts.

Finding 3: Pacing and Cognitive Overload Remained Persistent Challenges

The compressed workshop structure was consistently cited as a challenge. Participants described the pace as overwhelming and noted that many concepts were introduced in a short period. These concerns mirrored Year 1 patterns but became more pronounced as Year 2 content included more advanced ML models. Participants recommended a Week Zero preparation period with curated readings, foundational refreshers, and model-specific primers, followed by the intensive instructional period.

Finding 4: Team Dynamics Required More Explicit Socio-Technical Support

Team dynamics challenges emerged due to uneven prior knowledge, role ambiguity, and differing expectations for contributions during the hackathon. Interview data documented at least one case of significant interpersonal conflict connected to mismatched skill sets and perceived gaps in support. Participants recommended clearer team roles, earlier team formation, team norms setting, and explicit conflict-resolution protocols.

Discussion: Implications for CyberTraining Design

These findings suggest that intensive, domain-anchored cybertraining can support near-term learning and transfer when Fellows work with authentic water-science problems and accessible computational tools [4]. At the same time, the Year 2 findings show that technical design and socio-technical design are inseparable. Advanced content requires scaffolding, and collaborative hackathon work requires intentional support for team formation, role negotiation, and conflict response [8], [9].

For future implementations, the evidence supports five design refinements: (1) a Week Zero scaffolding period; (2) streamlined Week 1 theory focused on models used in the hackathon; (3) more guided code walkthroughs explaining parameter and method choices; (4) earlier team formation and team-norm setting; and (5) clearer conflict-resolution protocols and follow-up structures to support publication momentum.

Limitations

Several limitations constrain interpretation. Year 2 included 18 Fellows, of whom 11 completed the pre-survey, 5 completed the post-survey, 4 completed both surveys, 10 completed interviews, and 3 completed both surveys and interviews. These response patterns create selection bias and limit the quantitative claims that can be made. We therefore use survey results as descriptive context and center qualitative themes as formative evidence for design improvement.

We cannot determine the causes of survey attrition from the available data. Plausible contributors include the workshop's intensive timeline, post-workshop workload, and the absence of stronger response incentives, but these remain hypotheses. The Year 3 evaluation should improve survey response rates by clarifying communication and offering modest incentives. One Fellow explicitly suggested incentivizing survey participation through a small gift-card lottery.

Finally, this WIP paper reports formative findings from a single implementation of one CyberTraining program. Findings should not be generalized to all water science training programs or all hackathon-based learning environments. Instead, the contribution is a transparent account of how mixed-methods evaluation can guide iterative design decisions in a domain-anchored computational workshop.

Conclusion

The Year 2 WaterSoftHack findings show that a virtual, hackathon-centered CyberTraining workshop can support reported self-efficacy, advanced technical exposure, applied research transfer, and publication momentum among Fellows in the water science community. They also show that success depends on more than technical content. Pacing, scaffolding, team dynamics, and conflict-response structures shape whether Fellows can convert intensive instruction into usable research practices. The Year 3 redesign will therefore emphasize Week Zero preparation, streamlined content, guided code walkthroughs, proactive team formation, clearer collaboration protocols, and improved evaluation response strategies.

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