A Vision for Machine Learning and Artificial Intelligence in Great Lakes Research and Management

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ABSTRACT

The Laurentian Great Lakes are a vital freshwater resource and a regionally significant natural system facing complex, persistent, and compounding challenges from climate change, nutrient loading, and invasive species. The increasing availability of observational data, coupled with advances in computational power and machine learning (ML) and artificial intelligence (AI) methods, presents an opportunity to address these challenges by improving data integration and enabling powerful data-driven models. This perspective article outlines a broad vision for applying AI in Great Lakes research and management. We review the current state of AI efforts across several key topic areas and propose a cross-disciplinary roadmap focused on advanced modeling, multi-modal data fusion, and operational forecasting. Realizing this vision will require sustained investment in open data infrastructure, shared computational resources, and inter-institutional collaboration. If successful, this roadmap will accelerate research progress, improve decision-support tools, and enhance the resilience and sustainability of the Great Lakes region's interconnected ecological and economic foundations.

SIGNIFICANCE STATEMENT

Machine learning (ML) and artificial intelligence (AI) present an opportunity for Great Lakes science and management. This article provides a brief overview of current AI applications and proposes a roadmap for the Great Lakes region. By outlining a path toward enhanced collaboration, open data sharing, and computational infrastructure, this vision seeks to accelerate research, improve forecasting capabilities, and ultimately enhance the effectiveness of Great Lakes management.

1. A Vision for AI-Driven Research and Management in the Great Lakes

a. The Great Lakes: Vital but Vulnerable

The Laurentian Great Lakes, a chain of five interconnected freshwater lakes, constitute a pillar of ecological, economic, and cultural significance for North America. As the world's largest group of freshwater lakes by surface area, they contain approximately 21% of the world's surface water (NOAA Office for Coastal Management 2025; Great Lakes Commission 2025). This immense resource provides drinking water for over 40 million people in the United States and Canada and underpins a regional economy with a gross domestic product of over $3.1 trillion, supporting key sectors such as manufacturing, commerce, and recreation (NOAA 2025). However, this multifaceted system is susceptible to pressure from environmental stressors, including regional climate change and biogeochemical perturbations such as nutrient loading. Understanding the complex interactions within the Great Lakes region is critical for effective forecasting and management.

b. Environmental Stressors and the Need for a New Approach

The Great Lakes region (GLR), which encompasses the Great Lakes, their drainage basin, and the St. Lawrence River, faces considerable challenges across multiple environmental dimensions. Lake surface heat waves and cold spells have increased in frequency and intensity in recent decades, displaying heightened variability on top of long-term warming trends (Abdelhady et al. 2025). Great Lakes water levels exhibit substantial fluctuations spanning hours to decades and longer, with both low and high extremes affecting infrastructure, navigation, and coastal communities (Gronewold and Rood 2019). Interannual variability in maximum annual ice cover has increased since the late 1990s, with a marked decline in accumulated freezing days and amplified interannual swings in ice extent, particularly after the winter of 1997-98 (Lin et al. 2022). Cyanobacterial blooms and hypoxic zones vary substantially year to year, driven by changes in discharge, nutrient loading, and meteorological conditions (Stumpf et al. 2012; Zhou et al. 2015), with impacts on drinking water quality, fisheries, and coastal communities.

For decades, a complex, binational array of research, nonprofit, management, and regulatory entities have been engaged in efforts to address these challenges. Considerable progress has been made in advancing understanding and forecasting capabilities for key environmental variables such as water levels (Fry et al. 2020), lake hydrodynamics (Wang et al. 2010; Bai et al. 2013), ice cover (Abdelhady and Troy 2025a), waves (Feng et al. 2020; Abdelhady and Troy 2025b), and ecosystem dynamics (Ozersky et al. 2021). However, these systems remain inherently difficult to predict; for example, water levels are affected by small residuals of several large freshwater fluxes, and many forecast inputs are only weakly constrained by sparse observations. Observing and monitoring networks have advanced, yet critical gaps in both spatial and temporal coverage persist, particularly during the winter months and in specific areas where in-situ data is sparse. Concurrently, substantial investment has been made in critical management areas, including the implementation of fisheries management plans (Tingley et al. 2019; Bunnell et al. 2023), tracking the spread of invasive species (Keretz et al. 2021), and evaluating strategies to reduce nutrient loading (Zhang et al. 2023a). These coupled and compounding challenges underscore the need to understand and manage the GLR as a highly connected system, where physical, biogeochemical, ecological, economic, regulatory, and other human dimensions are deeply intertwined.

c. The Case for Artificial Intelligence

Given the GLR's scale and complexity, current approaches to modeling and management are increasingly being pushed to their limits. Many existing tools rely on deterministic, process-based models that are constrained by computational cost, structural assumptions, and incomplete mechanistic understanding. Although process-based modeling remains a cornerstone of Great Lakes science and continues to provide indispensable insights into system dynamics, there are growing opportunities to augment these approaches with machine learning (ML) and artificial intelligence (AI), hereafter referred to collectively as AI for simplicity. AI tools are well-suited to extract patterns from high-volume, heterogeneous, multi-modal datasets; to learn flexible representations of systems where process knowledge is partial or uncertain; and to support tasks such as emulation, data fusion, and real-time forecasting that are difficult to achieve with traditional methods. Importantly, these methods are not a replacement for physical understanding, but a complement, enabling hybrid approaches that combine physical insight with data-driven flexibility. A focused, interdisciplinary effort to apply AI across the Great Lakes system offers the potential to advance forecasting, inform observing system design, and support adaptive, data-rich decision-making in a region characterized by complex dynamics.

d. The Great Lakes as a Digital Twin Test Bed

Beyond the benefits of AI for research and management, the nature of the GLR presents an opportunity to advance the field of environmental AI. The GLR can serve as a microcosm for developing data-driven predictive tools, particularly Digital Twins of natural systems (Blair 2021; Li et al. 2023; Hazeleger et al. 2024). Unlike the global ocean, which presents a modeling challenge of considerable scale, the Great Lakes constitute a closed and relatively manageable system. They are broad and diverse enough to encompass all the essential components of a coupled Earth system - cryosphere, land, water, biology, and atmosphere - all within a compact basin. This allows for the development and validation of AI approaches that integrate these diverse components. For example, while it is practically impossible to constrain large-scale evaporation estimates in the global ocean, the Great Lakes' size allows for more comprehensive direct measurements, providing data for validating AI-driven models of water and energy fluxes (Charusombat et al. 2018).

The distinct physical and ecological characteristics of each lake provide an ideal laboratory for testing transfer learning and generalizability (Willard et al. 2021; Chen and Xue 2025). For example, Lake Erie, with its high density of observational data, is a data-rich environment for training models. This raises the question: can a model trained on data-rich Lake Erie, which is relatively shallow and more influenced by a maritime climate, be adapted to predict conditions in data-sparse Lake Superior, which is deeper, colder, and more influenced by a continental climate (Kayastha et al. 2023; Wang et al. 2023; Xue et al. 2025)? Or is it arguably better to train the Great Lakes as a whole, integrated system (Sharma et al. 2018)? Furthermore, the binational nature of the Great Lakes requires collaboration across national boundaries and management entities (Krantzberg 2007; Johns 2022). This provides a unique challenge and opportunity to use AI to harmonize and integrate disparate datasets and management approaches, offering a test bed for addressing the global problem of transboundary data sharing and management (Jordan 2020). In this way, the Great Lakes offer a unique environment for pushing the boundaries of environmental AI, with the lessons learned potentially informing global efforts like the Digital Twin Ocean (European Commission: Directorate-General for Research and Innovation 2022).

e. Broader Alignment and Ethical Considerations for AI

As AI methods become increasingly integrated into environmental research and decision-support systems, it is important to evaluate their use not only in terms of performance, but also interpretability, stakeholder relevance, and resource use. In the GLR, with its diverse management needs, these methods offer potential capabilities for extracting insight, generating highly localized forecasts, and supporting adaptive planning. However, their integration raises important challenges around transparency and alignment with management practices. For AI methods to be meaningfully adopted by resource managers, policymakers, and relevant boundary organizations (Selzer et al. 2020), their structures and outputs must not only be accurate, but also understandable and trustworthy (McGovern et al. 2019, 2024). Interpretability, whether through post hoc explanation, hybrid physical-statistical modeling strategies, or inherently transparent architectures, is a prerequisite for institutional trust and long-term integration into operational and regulatory frameworks (Abdulameer et al. 2025). Cultivating a community of practice that prioritizes interpretability, transparency, and communication across disciplines will be central for making sure that AI methods support Great Lakes environmental governance rather than further complicate it.

At the same time, the computational demands of AI workflows raise important sustainability considerations. Training and deploying large-scale models can consume significant energy, while data center cooling systems often require substantial water withdrawals (Wu et al. 2022, 2024). While many AI applications in environmental science are relatively lightweight, the field must take seriously the need to align computational practices with climate and water stewardship goals.

In this paper, we present a vision for the development and deployment of AI in Great Lakes research and management. In Section 2, we briefly survey several key areas and use cases. In Section 3, we outline a broad pathway towards integrating AI into the GLR research and management landscape.

2. Applying AI to Great Lakes Challenges

Over the past several decades, researchers have made substantial progress in understanding the dynamics of the Great Lakes system, including land-lake-atmosphere interactions (Luo et al. 2012; Rowe et al. 2017; Xiao et al. 2018; Xue et al. 2017; Pringle et al. 2025). Many of these advances have been enabled by the development of increasingly well-resolved process-based models of the lakes, the surrounding landscape, and the overlying atmosphere (Xue et al. 2015; Xiao et al. 2018; Kayastha et al. 2023; Cannon et al. 2023, 2024), as well as by statistical regression models (Bai et al. 2012; Xiao et al. 2018). These tools have supported meaningful improvements in forecasting, long-term scenario planning, and adaptive management. However, they also exhibit well-documented limitations. For example, hydrodynamic models used to simulate stratification, energy exchange, contaminant transport, and evaporation often display persistent biases that are difficult to resolve; these limitations have implications for predicting lake levels, water quality, and ecological responses under changing climate conditions (Deacu et al. 2012; Fujisaki-Manome et al. 2020; Zhang et al. 2023b). Here we briefly explore the current state of Great Lakes modeling and forecasting, highlighting opportunities for AI integration.

a. Regional Weather Forecasting

Weather is a driver of many processes affecting the Great Lakes. Mid-latitude cyclones produce winds that drive lake currents and sediment transport, generate wave conditions that can lead to coastal erosion, and precipitation that can affect water levels (Schwab et al. 2006; Hanrahan et al. 2010; Fry et al. 2022). Extended cold periods can lead to ice buildup on the lakes, and conversely, anomalous winter warmth can open the lakes, creating conditions more favorable for wave activity. In the warm season, thunderstorms are a major producer of precipitation, potentially leading to substantial runoff with concomitant impact on the lakes. Likewise, these storms contribute to overlake precipitation and runoff into the lakes, which can affect water levels.

Sensitive dependence on initial conditions is a hallmark of many natural systems (Lorenz 1963). Consequently, estimating the full probability distribution is important for forecasting and assessing the likelihood of extreme events. With the advent of artificial intelligence-based weather prediction (AIWP) models (Pathak et al. 2022; Bi et al. 2022, 2023; Chen et al. 2023; Nguyen et al. 2023; Hatanpää et al. 2025), understanding how these models capture forecast uncertainty has become an important research topic. A recent study found that an AIWP model failed to reproduce much of the growth in inherent forecast uncertainty seen in physics-based models (Selz and Craig 2023). This insensitivity was most apparent when the analysis uncertainty was small. These findings suggest that, without physical constraints, AI models may struggle to estimate forecast uncertainty for systems where analysis error is low or improving, although hybrid or post-processing approaches may help mitigate this problem. Recent progress in diffusion-based ensemble weather prediction suggests that emerging methods may also address this limitation (Hatanpää et al. 2025).

b. Water Level and Hydrodynamic Forecasting for Coastal Resilience

Accurately predicting Great Lakes water levels is important for effective management, with implications spanning commercial shipping, recreational boating, municipal water supply, the resilience of coastal infrastructure to erosion, and the protection of communities from flooding (Neff and Nicholas 2005). The Great Lakes water balance is typically derived from a simple equation for net basin supply: overlake precipitation plus runoff minus evaporation (Quinn and Kelley 1983; Quinn 2009). Each of these components can be estimated using statistical, empirical, and physically based models, as well as through the interpolation of observations. For example, the Large Lakes Statistical Water Balance Model (L2SWBM) uses a Bayesian statistical framework that assimilates input datasets and infers feasible water balance component estimates (Gronewold et al. 2020; Do et al. 2020; O'Brien et al. 2024). AI offers new opportunities to improve and supplement these approaches (Chen and Xue 2025). For example, AI could be applied directly to estimate each component of the water balance (Girihagama et al. 2022; Wi et al. 2025).

Existing forecasting systems like the National Water Model (NWM) and NOAA's Great Lakes Coastal Forecasting System (GLCFS) represent a well-developed starting point for hydrological prediction in the Great Lakes (Johnson et al. 2023). The NWM, for example, combines process-based modeling with a wide range of data inputs to make streamflow and water level predictions. Likewise, the GLCFS provides real-time predictions of lake currents, ice, temperature, waves, and short-term water level fluctuations. However, due to its computational complexity, it does not simulate processes on coastal floodplains during flooding events. By integrating AI, we can potentially enhance the predictive accuracy and efficiency of these models. AI algorithms can optimize data assimilation, improve real-time anomaly detection, and capture complex interactions between hydrodynamic variables, potentially leading to more accurate forecasts and earlier warnings for extreme events like storm surges (Jeba and Chitra 2024).

Beyond just advancing predictive capabilities, AI also provides an opportunity to support decision making through automated multi-objective optimization of policies and operations. This is a critical opportunity, especially when learning from advancements made in water management and focusing on adaptive management in the Great Lakes (Abdel-Fattah and Krantzberg 2014; Stow et al. 2020). The most prominent example of this is the use of multi-objective optimization in the formulation of reservoir outflow release policies (Semmendinger and Steinschneider 2024). For instance, the regulation of Lake Ontario outflow aims to balance upstream and downstream impacts while optimizing performance across multiple objectives like ecosystem health (e.g. wetlands), navigation, hydropower production, and flood prevention. Automated multi-objective optimization approaches can help identify release policies that balance the tradeoffs between these objectives, and advanced techniques in AI and control theory (e.g. direct policy search, deep reinforcement learning) could further enhance these benefits.

c. Beaches and Water Quality

Great Lakes beaches are a vital part of the regional economy, but their extensive recreational use presents a significant public health challenge due to microbial contamination. Current management relies on slow, labor-intensive lab testing, creating a time lag that can expose swimmers to risks. While historical models, including multiple linear regression and mechanistic models, have been used, they have limitations in handling complex, nonlinear factors. AI is an emerging and powerful alternative that can potentially overcome these limitations, with successful applications already seen at both marine and freshwater beaches (Zhang et al. 2018; Bourel et al. 2021; Hasan et al. 2024). Beyond direct prediction, AI can also potentially improve existing mechanistic models and create hybrid frameworks. With over 1,400 beaches and a wealth of historical data in the Great Lakes region, there is considerable potential for AI to enhance beach management and provide more accurate and timely forecasts for public health and safety (Searcy and Boehm 2021, 2023).

Recent work has demonstrated the potential of AI to improve harmful algal bloom (HAB) forecasting in the Great Lakes. A key challenge is the development of models that can effectively incorporate long-term datasets from remote sensing and other sources (Caballero et al. 2025). When properly trained, AI models have been shown to capture the complex, non-linear dynamics associated with bloom development (Maguire et al. 2024; Caballero et al. 2025). These methods have also been used to identify phenological shifts in chlorophyll and microcystin concentrations, improving understanding of bloom onset, duration, and decline (Maguire et al. 2024). Ensemble-tree approaches, such as Bayesian additive regression trees, have proven effective for analyzing the influence of environmental drivers, including total phosphorus, on chlorophyll concentrations during both the growth and senescence phases of Lake Erie's summer blooms (Isabwe et al. 2025). Collectively, these studies suggest that AI can augment existing modeling and risk assessment frameworks, particularly by improving uncertainty quantification and probabilistic risk estimation (Caballero et al. 2025).

d. Sustainable Fisheries Management

The commercial, recreational, and tribal fisheries of the Great Lakes are collectively valued at more than $5 billion annually (Great Lakes Fishery Commission 2025). As in other freshwater and marine systems around the world, technological advancements are producing new types and larger volumes of data describing Great Lakes ecosystems that can be used in fisheries management. To process and make full use of these types of complex data, aquatic ecologists are increasingly turning to AI approaches (Rubbens et al. 2023). In aquatic ecology and fisheries science, AI applications can be broadly grouped into two categories: extracting meaningful ecological information from raw, complex observational data inputs, and improving ecological understanding of complex processes from processed data. Processing complex data inputs is a rapidly evolving area focused on the development of new tools for collecting management-relevant information. These tools include the analysis of video to monitor fisheries effort or catch/harvest (Hartill et al. 2020; Kaemingk et al. 2021; Khokher et al. 2022; Ovalle et al. 2022) to assess the abundance of both fish species of interest and their preferred habitats (DeCelles et al. 2017; Geisz et al. 2024). Researchers have also employed AI methods for interpreting acoustic (Mannocci et al. 2021; Precioso et al. 2022), telemetry (Klinard and Matley 2020), and genetic information (Whitaker et al. 2020) to understand fish population structure and movements and characterize fisheries impacts. Even when working with traditional fisheries data, such as catch statistics or biological information, disentangling the complex and often interacting environmental, ecological, and anthropogenic processes affecting fish populations can be challenging. For some tasks, such as species distribution modeling, AI approaches have been shown to have some advantages over other statistical approaches (Brodie et al. 2018). Thus, the relatively new but quickly expanding use of AI methods in aquatic ecology and fisheries science will provide future fisheries managers with both new sources/types of information and new descriptions of the processes regulating fish populations and the fisheries that target them (Rubbens et al. 2023).

e. Optimizing Observation Networks with Intelligent Data Pipelines

Observational coverage of the Great Lakes is currently highly uneven, ranging from extensively monitored Western Lake Erie to sparsely observed Lake Superior. AI offers a way to augment the observing systems and data pipelines that support Great Lakes research and management, moving beyond the prevailing "locations of opportunity" model. While community-driven and locally focused observing efforts have been important in the past and will remain so in the future, the search space for deploying new instruments is often too large to navigate without additional constraints. AI can help identify optimal locations for both static and mobile sensors (such as gliders and uncrewed systems), balancing scientific goals, physical constraints (including shipping lanes and environmentally sensitive areas), and user needs (Saad et al. 2020; Zhang et al. 2024). Recent advances in polar research and operations illustrate the feasibility of these approaches, even under harsh environmental conditions (Andersson et al. 2023; Smith et al. 2025). These approaches could also streamline data ingestion, quality control, and the creation of standardized metadata, which would reduce data latency and lessen the reliance on a single person to manage the entire system (Sreepathy et al. 2024). This efficiency could directly lead to improved nowcasting and forecasting from models that rely on these observations.

Beyond system optimization, AI has the potential to change how data is leveraged for decision-making and public engagement (Marmolejo-Ramos et al. 2022). AI could validate and make use of crowdsourced observations from the public, turning what is currently unusable information into a valuable data source for research and management (Huang et al. 2024). Furthermore, AI can take data from multiple sources and translate it into actionable information for various user groups, from resource managers to the public (Sun 2023). This is key to equitable service delivery to underrepresented populations, for example, by providing clear flood warnings for at-risk communities (Liu et al. 2025). Strategically monitoring how data is used can also help agencies to continually optimize their observing networks to best serve the needs of their users.

g. Challenges for Operationalization

One of the primary challenges in advancing AI for Great Lakes management is bridging critical gaps in data availability, stakeholder uptake, and operational readiness (Chu et al. 2011). On the data front, a major barrier is the labor-intensive process of manually analyzing remote sensing imagery to generate training datasets (Camps-Valls 2009). This slows the assessment of coastal impacts, such as changes to armored shorelines, and hampers the monitoring of sensitive ecosystems like wetlands. Addressing this gap will require automated methods for extracting observable indicators from imagery and other high-volume data streams (Ma et al. 2019; Abdelhady et al. 2022).

A second challenge involves building trust and adoption among stakeholders. Unlike traditional physics-based models, AI approaches are often viewed as "black boxes," making it difficult for users to understand how forecasts are produced. This underscores the need for transparency (McGovern et al. 2024), clear communication about model limitations and biases, and early engagement with users during tool development (Fleming et al. 2023).

Finally, operationalizing AI applications for routine use remains a significant hurdle. Doing so requires stable data pipelines, reproducible workflows, and the ability to run models efficiently and consistently; these conditions are required in order for AI tools support automated or semi-automated decision-making in time-sensitive management contexts (Ivanov 2022).

3. Building a Community of Practice for Great Lakes AI

The current norm of relying on individual researchers for new technology adoption is insufficient for the scale of the challenges facing the Great Lakes. Academic institutions and organizations with interests across Great Lakes research and management need to develop new mechanisms, or partner with those constructing such mechanisms, to help researchers to adopt new technologies (Liu and Jagadish 2024).

a. Fostering Collaborative AI-augmented Research and Management

Integrating AI into Great Lakes research and management requires bridging the gaps between domain expertise, technical skills, and the needs of decision makers. To make sure that these efforts are sustainable, the focus must shift from simply asking "can I model this?" to "what can I do with this capacity?" This approach promotes the use of AI for broader research applications, including hypothesis generation and testing (Sonnewald et al. 2021).

Establishing and maintaining a collaborative network is central to this effort. This community could be maintained as a distributed community of practice spanning the broader research and management sphere. Key partners, including the International Joint Commission (IJC) and NOAA's National Center for Artificial Intelligence (NCAI) and National Center for Environmental Information (NCEI) should be leveraged to contribute to and benefit from broader efforts such as those of the Integrated Ocean Observing System (IOOS). Sustained community-building activities, including workshops, conference sessions, and working groups, will help maintain momentum and foster collaboration across disciplines and institutions. The goal is to create a strong foundation for an interdisciplinary community focused on employing AI in Great Lakes research and management where it can add value, grounded in long-term relationship-building and shared purpose. Achieving this vision requires collaborative infrastructure that includes open-source tools, cloud-based data storage platforms, and effective data and software management. The foundation of this effort could be the creation of an accessible 'data lake' that contains analysis-ready data, reducing the burden on individual researchers and enabling easier collaboration across institutions (Giebler et al. 2019).

b. The Great Lakes Data Lake: A Vision for Integrated Data

A forward-looking vision for Great Lakes data management is the creation of a unified, binational "Great Lakes Data Lake" (GLDL). Building on successful real-time data aggregation efforts, such as those supported by the Great Lakes Observing System (GLOS), this platform would serve as a centralized hub for longer-term data relevant to research and management. By streamlining data access, the GLDL would support the integration of diverse datasets, including in situ observations, remote sensing products, and model outputs (Figure 1). The GLDL could also enable two-way communication with observational platforms and researchers, with up-to-date information helping to target new observing efforts. This integration would enable a more comprehensive, system-wide understanding of the Great Lakes, supporting both near-term decision-making and long-term strategic planning.

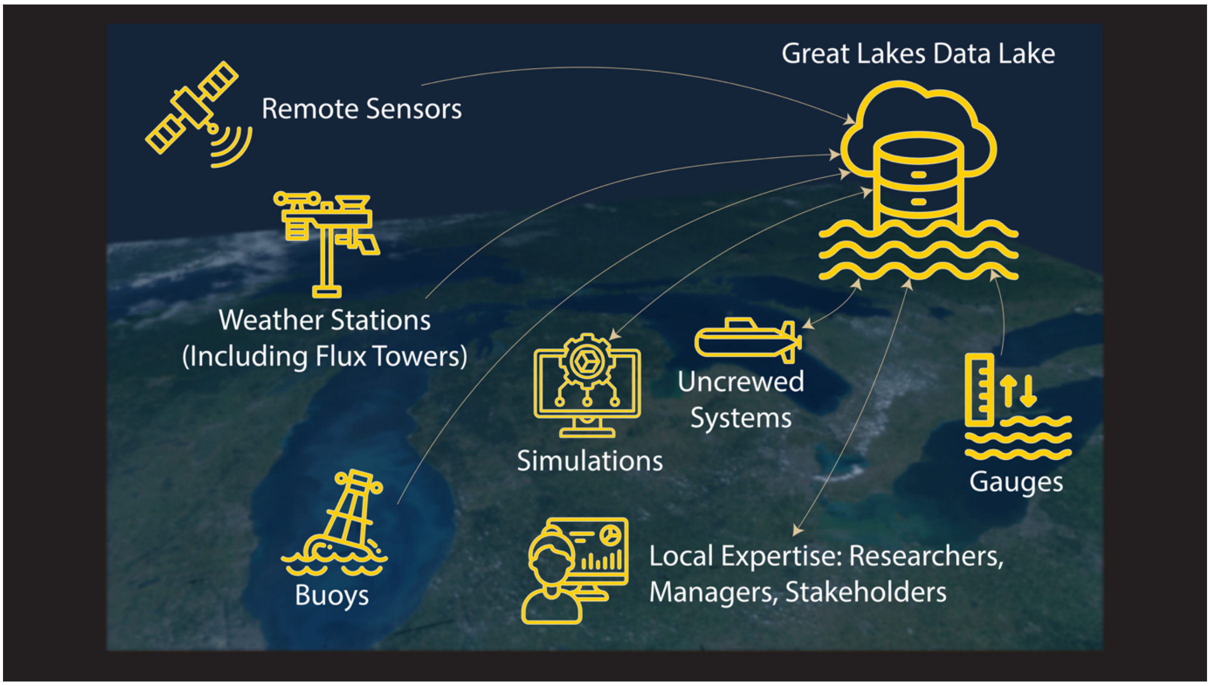

Figure 1. Schematic of the proposed Great Lakes Data Lake, where arrows indicate data flows.

The current Great Lakes data landscape is fragmented and "messy," and the community should prioritize making data FAIR (Findable, Accessible, Interoperable, Reusable) (Wilkinson et al. 2016). Tools like open cloud storage and repositories with DOI minting for datasets should be used to manage and share data effectively (Ramachandran et al. 2021). It's also critical to recognize that even freely available data can contain biases (e.g. hail data biased toward population centers) that can propagate into AI models (DeBrusk 2018). A centralized resource, modeled on the successes of the Pangeo community, could streamline data access and preprocessing, creating an analysis-ready data lake to support the entire community (Odaka et al. 2020).

To reinforce the rigor and credibility of AI applications, the Great Lakes community should also establish and adopt a set of best practices. This could include setting benchmarks and verification metrics for accuracy, uncertainty, feature importance, and generalizability. Explainable and interpretable models should be promoted alongside rigorous uncertainty quantification (McGovern et al. 2019). Community guidelines, like those provided by the Cooperative Institute for Research in the Atmosphere (CIRA) but tailored to the Great Lakes, should be developed to shore up consistency and quality (Ebert-Uphoff et al. 2021). Furthermore, the ethical implications of integrating general AI into environmental research and management must be addressed proactively.

c. Incorporating Domain Expertise

Physical constraints are usually not incorporated into the training process, and in some cases, applications are developed without full input from disciplinary experts. Employing physical constraints is one means of incorporating disciplinary expertise into these models. AI tools can be developed using physical laws to leverage data in data-sparse regions; such advanced data assimilation techniques have obvious potential. This also motivates collecting additional data, since training of AI tools fundamentally requires ample data. This data also assists in developing tools for smaller scales that affect decision-makers (e.g. AI weather models rely on 0.25-degree reanalyses, while thunderstorm scales are on the order of 10 km). Current technologies may also fail to capture extremes well, since such events are rare in the training data; albeit impressive case studies have been demonstrated by the newest AIWPs (Hatanpää et al. 2025). Moreover, extrapolation in the face of rapid climate change may lead to problems in using these tools to understand future risks. This may be mitigated to some extent using physics-based optimization, or AI/physics hybrid approaches. Given the early stage of this technology, the research today must focus on exploring what AI techniques can and cannot do in the context of Great Lakes problems and natural systems more broadly.

d. Outlook and Recommendations

1) SHORT-TERM (<5 YEARS) GOALS

The initial focus should be on leveraging current opportunities. This includes establishing and publishing benchmarks and contributing to community efforts like Pangeo (Odaka et al. 2020). Research and short-term prediction should be conducted on the data-rich areas such as water level, ice cover. Example Jupyter notebooks for the Great Lakes should be developed and shared, and community workshops and conference sessions should be held regularly to advance progress (EDS Book Community 2025). These efforts should align with, benefit from, and contribute to larger national and international programs for AI adoption (e.g. NOAA, NSF, DOE). Given the relatively small size of the community, it may be preferable to carve out "Great Lakes spaces" under existing or emerging frameworks, rather than trying to develop new infrastructure.

2) Medium-term (5-10 Years) Goals

In the medium term, the community should conduct retrospectives to assess progress and publish comprehensive reviews of successful AI use cases in the Great Lakes. For example, AI should be used to create a Great Lakes Earth system model to enhance the accurate seasonal to decadal predictability. Periodic meetings should be maintained to advance benchmarks and foster ongoing collaboration.

3) Long-term (>10 Years) Goals

The long-term vision is to create a sustainable and integrated research ecosystem. This involves fostering a workforce across institutions that operates from a shared foundation of tools and knowledge. AI should be integrated with traditional hypothesis-driven research to form a cohesive research model. Ultimately, the goal is the continuous and transparent integration of AI tools within operational and observational networks, creating a feedback loop between models and observations, powered by innovative research and AI technology, leading to a digital twin of the Great Lakes. We invite Great Lakes research and management groups to join these efforts and contribute to using AI to advance Great Lakes science and management through collaboration and community-building.

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