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

Dani C. Jones[a], Jing Liu[b], Scott Steinschneider[c], Lauren M. Fry[d], Lacey Mason[d], Andrea Vander Woude[d], Jia Wang[d], William S. Currie[e], Silvia Newell[f], Nathan Fox[b], William J. Pringle[g], Mantha S. Phanikumar[h], Yi Hong[a], Anders Kiledal[i], Lindsay Fitzpatrick[a], Satbyeol Shin[e], Andrew Gronewold[e,i], Sage Osborne[j], David Wright[d], Dan Titze[d], Paul Roebber[k], Hazem U. Abdelhady[a,o], Alisa Young[d], Joeseph Smith[l], Shelby Brunner[l], Joseph A. Langan[d], Pengfei Xue[m,n]

[a] *Cooperative Institute for Great Lakes Research (CIGLR), University of Michigan, Ann Arbor, MI*
[b] *Michigan Institute for Data and AI in Society (MIDAS), University of Michigan, Ann Arbor, MI*
[c] *Department of Biological and Environmental Engineering, Cornell University, Ithaca, NY*
[d] *NOAA Great Lakes Environmental Research Laboratory (GLERL), Ann Arbor, MI*
[e] *School for Environment and Sustainability (SEAS), University of Michigan, Ann Arbor, MI*
[f] *Michigan Sea Grant, University of Michigan, Ann Arbor, MI*
[g] *Environmental Science Division, Argonne National Laboratory, Lemont, IL*
[h] *Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI*
[i] *Department of Earth and Environmental Sciences, University of Michigan, Ann Arbor, MI*
[j] *NOAA Pacific Marine Environmental Laboratory (PMEL), Seattle, WA*
[k] *University of Wisconsin–Milwaukee, Milwaukee, WI*
[l] *Great Lakes Observing System (GLOS), Ann Arbor, MI*
[m] *Michigan Technological University, Houghton, MI*
[n] *Argonne National Laboratory, Lemont, IL*
[o] *Texas A&M University, College Station, TX*

Corresponding author: Dani Jones, dannes@umich.edu

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 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 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 North American Great Lakes, a chain of five interconnected freshwater lakes, constitute a pillar of ecological, economic, and cultural significance. As the world's largest group of freshwater lakes by surface area, they contain approximately 21% of global surface freshwater (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 system is increasingly stressed by climate change and biogeochemical perturbations, including nutrient loading. Understanding these interactions is critical for forecasting environmental conditions and managing the region's natural and economic resources.

b. Environmental Stressors and the Need for a New Approach

The Great Lakes Region (GLR), which encompasses the lakes, their drainage basin, and the St. Lawrence River, faces challenges across multiple environmental dimensions. Lake surface heat waves and cold spells have increased in frequency and intensity in recent decades, with heightened variability superimposed on long-term warming trends (Abdelhady et al. 2025). Coastal water levels fluctuate across timescales from hours to decades, with both low and high extremes affecting infrastructure, navigation, and coastal communities (Gronewold and Rood 2019). Maximum annual ice cover has become more variable since the 1990s, alongside a decline in accumulated freezing days (Lin et al. 2022). Cyanobacterial blooms and hypoxic zones vary substantially year to year, driven by watershed runoff and river 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 binational network of research, management, and regulatory entities has worked to address these challenges. Progress has been made in understanding processes and forecasting key variables, including water levels (Fry et al. 2020), hydrodynamics (Wang et al. 2010; Bai et al. 2013), ice cover (Abdelhady and Troy 2025a; Memari et al. 2025), waves (Feng et al. 2020; Abdelhady and Troy 2025b), and ecosystem dynamics (Ozersky et al. 2021). However, these systems remain difficult to predict. For example, water levels depend on small residuals of large freshwater fluxes, and many forecast inputs are weakly constrained by limited observations. Monitoring networks have advanced, but critical gaps persist in spatial and temporal coverage, particularly in winter. Concurrently, substantial investment has been made in critical management areas, including fisheries plans (Tingley et al. 2019; Bunnell et al. 2023), invasive species tracking (Keretz et al. 2021), and nutrient reduction strategies (Zhang et al. 2023a). These coupled challenges highlight the need to treat the GLR as a connected system, where physical, ecological, and human dimensions are deeply intertwined.

c. The Case for Machine Learning and Artificial Intelligence

Given the GLR's scale and complexity, current approaches to modeling and management are increasingly strained. Many tools rely on deterministic, process-based models constrained by computational cost, structural assumptions, and incomplete mechanistic understanding. These models remain a cornerstone of Great Lakes science, but there are clear opportunities to augment them with machine learning (ML) and artificial intelligence (AI), hereafter referred to collectively as AI. AI methods are well-suited to extract patterns from high-volume, heterogeneous datasets, to learn flexible representations of systems where process knowledge is limited, and to support tasks such as emulation, data fusion, and real-time forecasting that are difficult with traditional methods. Rather than replacing physical understanding, these methods enable hybrid approaches that combine physical insight with data-driven flexibility. A focused, interdisciplinary effort to apply AI across the GLR could advance forecasting, inform observing system design, and support adaptive, data-informed decision-making.

d. The Great Lakes as an Environmental AI Test Bed

The GLR presents an opportunity to advance environmental AI, potentially serving as a microcosm for developing data-driven predictive tools, such as digital twins of natural systems (Blair 2021; Li et al. 2023; Hazeleger et al. 2024). Unlike the global ocean, which presents challenges of scale, the Great Lakes constitute a closed and relatively manageable system. They encompass key components of a coupled Earth system - cryosphere, land, water, biology, and atmosphere - within a compact basin, enabling the development and validation of integrated AI approaches. For example, while large-scale evaporation in the global ocean is difficult to constrain, the lakes allow for more comprehensive direct measurements, supporting validation of AI-driven models of water and energy fluxes (Charusombat et al. 2018).

The distinct physical and ecological characteristics of each lake provide a setting for testing transfer learning and generalizability (Willard et al. 2021; Chen and Xue 2025). Lake Erie, with its dense observational coverage, offers a data-rich training environment, raising the question of whether models trained there can be adapted to data-sparse systems such as Lake Superior, which differs in depth, temperature, and climate influences (Kayastha et al. 2023; Wang et al. 2023; Xue et al. 2025). Alternatively, models may be trained across an integrated GLR (Sharma et al. 2018). The binational nature of the lakes introduces challenges in harmonizing datasets and management approaches (Krantzberg 2007; Johns 2022), offering a test bed for addressing broader issues of transboundary data integration (Jordan 2020). In this way, the GLR provides a valuable environment for advancing environmental AI, with lessons applicable to 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, their use must be evaluated in terms of interpretability, stakeholder relevance, and resource demands. In the GLR, these methods offer potentialities for extracting insight, generating highly localized forecasts, and supporting adaptive planning, but their integration raises challenges around transparency and alignment with management practices. For AI methods to be meaningfully adopted by resource managers, policymakers, and boundary organizations (Selzer et al. 2020), their outputs must be demonstrably accurate within application-specific tolerances (McGovern et al. 2019, 2024). Enhancing model interpretability through post hoc explanation, hybrid physical-statistical approaches, and explainable AI (XAI) methods is a high priority for building institutional trust and long-term integration into operational and regulatory frameworks (Abdulameer et al. 2025). Implementing XAI for high-dimensional environmental data remains a challenging research frontier (Krell et al. 2023). Cultivating a community of practice that prioritizes interpretability, transparency, and cross-disciplinary communication will be central to positioning AI as an asset to Great Lakes governance.

Challenges related to data availability and usability also remain substantial. Observational datasets in the GLR are often sparse, heterogeneous, and collected at disparate spatial and temporal scales, particularly for in situ measurements. Preparing such data to be “AI-ready” requires significant effort in curation, standardization, and bias assessment, and remains a major bottleneck for robust data-driven modeling.

The computational demands of AI workflows further raise sustainability considerations. Training and deploying large-scale models can consume significant energy, while data center cooling systems require substantial water withdrawals (Wu et al. 2022, 2024). Even as many environmental AI applications remain relatively lightweight, aligning computational practices with climate and water stewardship goals will be critical.

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). These advances have been enabled by increasingly well-resolved process-based models of the lakes, surrounding landscape, and overlying atmosphere (Xue et al. 2015; Kayastha et al. 2023; Cannon et al. 2023, 2024), as well as statistical regression approaches (Bai et al. 2012; Xiao et al. 2018). However, these tools exhibit well-documented limitations. For example, hydrodynamic models used to simulate stratification, energy exchange, contaminant transport, and evaporation often show persistent biases that are difficult to resolve, with implications for predicting lake levels, water quality, and ecological responses (Deacu et al. 2012; Fujisaki-Manome et al. 2020; Zhang et al. 2023b). We briefly survey current modeling and forecasting approaches and highlight opportunities for AI integration.

a. Regional Weather Forecasting

Weather is primary driver of processes affecting the GLR. Mid-latitude cyclones generate winds that drive lake currents and sediment transport, produce waves that contribute to coastal erosion, and deliver precipitation affects water levels (Schwab et al. 2006; Hanrahan et al. 2010; Fry et al. 2022). Extended cold periods promote ice formation, while anomalous winter warmth increases open-water conditions and wave activity. In the warm season, thunderstorms produce much of the region's precipitation, driving runoff and influencing lake levels.

Sensitive dependence on initial conditions is a hallmark of many natural systems (Lorenz 1963), making probabilistic forecasting important for assessing extreme events. With the advent of AI-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 represent forecast uncertainty has become a key research question. One study found that an AIWP model failed to reproduce much of the growth in forecast uncertainty seen in physics-based models, particularly when analysis uncertainty was small (Selz and Craig 2023). This suggests that, without physical constraints, AI models may struggle to represent uncertainty in well-observed systems, although hybrid or post-processing approaches may mitigate this limitation. Recent advances in diffusion-based ensemble prediction (Hatanpää et al. 2025) and training approaches using Continuous Ranked Probability Score (CRPS) loss functions offer promising pathways toward reliable and computationally efficient probabilistic forecasts (Lang et al. 2026).

The GLR provides a useful setting for evaluating whether global AIWP and ensemble approaches can be downscaled to capture localized mesoscale phenomena, such as lake-effect precipitation and convective storms. The contrasting characteristics of the five lakes also support transfer learning experiments, testing how models trained in one region generalize to others.

b. Water Level and Hydrodynamic Forecasting for Coastal Resilience

Accurately predicting Great Lakes water levels is critical for management, with implications for shipping, recreation, water supply, coastal infrastructure, and flood risk (Neff and Nicholas 2005). Lake water balance is typically expressed as net basin supply: overlake precipitation plus runoff minus evaporation (Quinn and Kelley 1983; Quinn 2009). These components can be estimated using statistical, empirical, and physically based models, as well as observational interpolation. For example, the Large Lakes Statistical Water Balance Model (L2SWBM) applies a Bayesian framework to assimilate input datasets and infer feasible water balance components (Gronewold et al. 2020; Do et al. 2020; O'Brien et al. 2024). AI offers opportunities to complement these approaches (Chen and Xue 2025), including a direct estimation of water balance components (Girihagama et al. 2022; Wi et al. 2025).

Existing systems like the National Water Model (NWM), NOAA's Great Lakes Coastal Forecasting System (GLCFS), and NOAA's Great Lakes Operational Forecast System (GLOFS) provide a strong foundation for hydrological prediction (Johnson et al. 2023). These models integrate process-based approaches with diverse data inputs to produce real-time forecasts of currents, temperature, ice, waves, and water levels. However, they can be computationally expensive and often lack representation of floodplain processes during extreme events. AI-based surrogate models or emulators offer a potential pathway to improve both efficiency and predictive capability. Such approaches can enable higher spatial resolution, more frequent updates, and ensemble forecasting, supporting earlier and more reliable warnings of extreme events (Jeba and Chitra 2024).

Beyond prediction, AI also offers opportunities to support decision-making through automated multi-objective optimization of policies and operations. This is particularly relevant for adaptive management in the GLR (Abdel-Fattah and Krantzberg 2014; Stow et al. 2020).

For example, regulation of Lake Ontario outflow must balance upstream and downstream impacts across objectives such as ecosystem health, hydropower, and flood prevention. AI-based optimization methods, including direct policy search and deep reinforcement learning, could help identify policies that better balance these competing objectives (Semmendinger and Steinschneider 2024).

c. Beach Safety and Water Quality

Great Lakes beaches are a vital part of the regional economy, but their extensive recreational use presents a public health challenge due to microbial contamination (US Geological Survey 2013). Current management relies on labor-intensive lab testing, creating delays that can expose swimmers to risk. Existing approaches, including regression and mechanistic models, have limitations in capturing complex, nonlinear drivers. AI offers a promising alternative, with successful applications at both marine and freshwater beaches (Zhang et al. 2018; Bourel et al. 2021; Hasan et al. 2024). These methods can support direct prediction, improve existing models, and enable hybrid frameworks. With over 1,400 beaches and extensive historical data in the GLR, AI has the potential to enhance beach management and provide more timely public health forecasts (Searcy and Boehm 2021, 2023).

Recent work also demonstrates the potential of AI to improve harmful algal bloom (HAB) forecasting. A key challenge is integrating long-term datasets from remote sensing and other sources (Caballero et al. 2025). When properly trained, AI models can capture the nonlinear dynamics of bloom development and identity shifts in bloom timing, onset, duration, and decline (Maguire et al. 2024; Caballero et al. 2025). Ensemble approaches, such as Bayesian additive regression trees, have proven effective for assessing environmental drivers, including total phosphorus, in Lake Erie blooms (Isabwe et al. 2025). Collectively, these methods can augment existing modeling and risk assessment frameworks, particularly by improving probabilistic risk estimation (Caballero et al. 2025).

Rip currents pose a significant hazard to beachgoers, with 223 fatalities recorded from 2002 to 2020 (Liu and Wu 2022). These events have been the focus of recent AI-based monitoring efforts in coastal ocean settings (Dusek et al. 2019; de Silva et al. 2021; Khan et al. 2025). However, their prediction and monitoring remain relatively unexplored for Great Lakes beaches.

d. Sustainable Fisheries Management

The commercial, recreational, and tribal fisheries of the Great Lakes are valued at more than $5 billion annually (Great Lakes Fishery Commission 2025). As in other aquatic systems, technological advances are generating increasingly large and complex datasets that can inform fisheries management. To make use of these datasets, ecologists are increasingly turning to AI approaches (Rubbens et al. 2023). In fisheries science, AI applications broadly fall into two categories: extracting ecological information from complex observational data and improving understanding of ecological processes from derived datasets. Rapid progress is being made in tools for collecting management-relevant information, including video analysis to monitor fishing effort and catch (Hartill et al. 2020; Khokher et al. 2022; Ovalle et al. 2022) and assess species abundance and habitat use (DeCelles et al. 2017; Geisz et al. 2024). AI methods are also used to interpret acoustic (Mannocci et al. 2021; Precioso et al. 2022), telemetry (Klinard et al. 2021), and genetic data (Whitaker et al. 2020) to characterize fish population structure, movement, and fisheries impacts. Even with traditional fisheries data, such as stock assessments, catch statistics, or biological information, disentangling interacting environmental, ecological, and human influences remains challenging. For some tasks, such as species distribution modeling, AI approaches have demonstrated advantages over conventional statistical approaches (Brodie et al. 2020). As these methods continue to develop, they will provide fisheries managers with new sources of information and improved understanding of the processes regulating fish populations and fisheries (Rubbens et al. 2023).

e. Optimizing Observation Networks with Intelligent Data Pipelines

Observational coverage of the Great Lakes is highly uneven, ranging from extensively monitored Western Lake Erie to sparsely observed Lake Superior. AI may offer a way to augment observing systems and data pipelines, moving beyond the prevailing "locations of opportunity" model. While community-driven and locally focused observing efforts remain critically important, 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 (e.g. gliders), balancing scientific goals, physical constraints (e.g. shipping lanes, sensitive habitats), and user needs (Saad et al. 2020; Zhang et al. 2024). Recent advances in polar research and operations demonstrate the feasibility of these approaches, even in harsh conditions (Andersson et al. 2023; Smith et al. 2025).

These approaches could also streamline data ingestion, quality control, and metadata standardization, reducing and individual operators (Sreepathy et al. 2024). For a system like the Great Lakes with a sensitive dependence on initial conditions, rapid assimilation of quality-controlled observations with quantified uncertainties through stable data pipelines is critical for accurate nowcasting and forecasting.

Beyond system optimization, AI can potentially enhance how data is leveraged for decision-making and public engagement (Marmolejo-Ramos et al. 2022). For example, it could help validate and incorporate crowdsourced observations, transforming currently underutilized information into useful inputs for research and management (Huang et al. 2024). It can also integrate data from multiple sources and translate them into actionable information for various users, from resource managers to the public (Sun 2023). These capabilities are particularly important for equitable service delivery, such as providing clear flood warnings to at-risk communities (Liu et al. 2025). Monitoring how data is used can further inform adaptive improvements to observing network design.

g. Challenges for Operationalization

Advancing AI for Great Lakes management requires addressing gaps in data availability, stakeholder uptake, and operational readiness (Chu et al. 2011). On the data front, a major barrier is the labor-intensive analysis of remote sensing imagery to generate training datasets (Camps-Valls 2009). This slows the assessment of coastal impacts, such as changes to armored shorelines, and 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. If a manager is unable to discern the “why” behind a forecast, they cannot effectively account for the model’s potential biases or errors in high-stakes decision making. 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 for routine use remains a substantial hurdle. This requires stable data pipelines, reproducible workflows, and the ability to run models efficiently and consistently; these conditions are required for supporting 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 reliance on individual researchers for technology adoption is insufficient for the scale of the challenges facing the Great Lakes. Research institutions, operational forecasting centers, end-users must develop new mechanisms (or partner with existing ones) to support adoption across the research-to-operations pipeline (Liu and Jagadish 2024).

a. Fostering Collaborative AI-augmented Research and Management

Integrating AI into Great Lakes research and management requires bridging domain expertise, technical capacity, and the needs of decision makers. Achieving this will require a shift from asking "can I model this?" to "what can I do with this capacity?", enabling broader applications such as hypothesis generation and testing (Sonnewald et al. 2021).

Establishing collaborative network is central to this effort. A distributed community of practice could span research and management, connecting partners such as the International Joint Commission (IJC) and NOAA’s National Centers for Artificial Intelligence (NCAI) and Environmental Information (NCEI), and broader initiatives like 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 research and management where it can add value, grounded in long-term relationship-building and shared purpose. In practice, this effort is expected to build on existing institutional structures and partnerships with participation occurring through collaborative projects, workshops, and ongoing engagement with operational and stakeholder communities. To be impactful, this model can leverage the NOAA Service Delivery Framework, which emphasizes continuous user engagement and trusted relationships (NOAA Water Team 2020). Centering the research lifecycle on use-inspired product development and iterative feedback can help produce tools that are “useful, usable, and used” for regional decision support.

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 unified, binational "Great Lakes Data Lake" (GLDL) could serve as a centralized platform for data relevant to research and management. Building on existing real-time data aggregation efforts, such as those supported by the Great Lakes Observing System (GLOS), this vision emphasizes extending and interconnecting regional data systems rather than creating entirely new infrastructure. By streamlining access, the GLDL would support the integration of diverse datasets, including in situ observations, remote sensing products, and model outputs (Figure 1). It could also enable two-way communication with observational platforms and researchers, allowing updated information to guide new observing efforts. Together, these capabilities would support a more comprehensive, system-wide understanding of the GLR, informing both near-term decisions and long-term planning.

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

The current data landscape is fragmented; broader adoption of FAIR (Findable, Accessible, Interoperable, Reusable) data practices would help address this (Wilkinson et al. 2016). Open cloud storage and repositories with DOI minting can support effective data management and sharing (Ramachandran et al. 2021). However, even openly 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 efforts such as the Pangeo community, could streamline access and preprocessing by providing analysis-ready datasets for the broader community (Odaka et al. 2020). Progress will depend on both technical infrastructure and on community incentives for data sharing, including collaboration opportunities, alignment with operational needs, and recognition of data contributions.

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, could improve consistency and quality (Ebert-Uphoff et al. 2021). Ethical considerations surrounding the use of AI in environmental research and management must also be addressed proactively.

c. Incorporating Domain Expertise

Domain expertise can be incorporated into AI systems through multiple complementary approaches, including physical constraints, hybrid modeling frameworks, and expert-informed data and model design. 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. In addition to encoding physical constraints, domain expertise can also be incorporated through hybrid modeling approaches that combine process-based and data-driven components, as well as through expert-informed feature selection, training data curation, and evaluation strategies. This also motivates collecting additional data, since training of AI tools fundamentally requires a considerable amount of data, especially in the context of high-dimensional environmental systems. This data also assists in developing tools for smaller scales that affect decision-makers (e.g. most 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 promising case studies have been demonstrated by the newest AIWPs (Hatanpää et al. 2025). Given the early stage of this technology, the research today must focus on exploring what AI techniques can and cannot do. For example, two common “failure modes” for AI in environmental prediction are (1) data extremes, as AI methods can struggle with rare events that are underrepresented in the training data and (2) climate non-stationarity; models trained on historical data may be unreliable for long-term climate projections where future conditions deviate from those in the training dataset. Taken together, these considerations point towards a research framework in which AI models are developed in close collaboration with domain experts, with expertise informing model constraints, problem formulation, data selection, and interpretation of results.

d. Challenges in Integration Across Processes and Disciplines

While many current AI applications in the Great Lakes focus on individual processes or sub-systems, moving toward integrated, basin-level models introduces a different class of challenges. In addition to unifying datasets and making them generally accessible, integration requires coordination across disciplinary and institutional boundaries, where differences in data standards, modeling assumptions, and scientific priorities can limit interoperability. Even when these barriers are addressed, integrated AI models are inherently more complex than single-domain applications, as they must represent interactions across physical, biogeochemical, ecological, and human components of the system. This added complexity has implications for model design and interpretability. It also tends to increase data requirements substantially, as constraining multi-process models demands larger, more diverse, and better-aligned datasets. As a result, progress toward integrated AI will depend not only on improved data access, but also on advances in methods that can operate effectively under such constraints, including hybrid modeling, data assimilation, and transfer learning.

e. Outlook and Recommendations

The implementation of this roadmap is being catalyzed by the Great Lakes AI Lab, currently hosted by the Cooperative Institute for Great Lakes Research (CIGLR). In its current form, this effort is being advanced through summits (Jones et al. 2025), collaborative projects, and emerging partnerships with regional and national organizations.

1) SHORT-TERM (<5 YEARS) GOALS

Initial efforts are focused on leveraging existing opportunities. This includes establishing and publishing benchmarks such as (1) standardized, analysis-ready datasets curated by the community to allow “apples-to-apples” comparisons between different methods and (2) targeted evaluation tasks that represent the region’s characteristic stressors (e.g. lake surface heat waves, water level variability, interannual ice cover variability, harmful algal blooms). Research and short-term prediction could be conducted on the data-rich areas such as water level and ice cover. Example computational notebooks for community workshops and conference sessions (e.g. AGU, AMS, IAGLR) can help maintain knowledge transfer and a sustained effort (EDS Book Community 2025). These efforts may benefit from alignment with larger national and international programs for AI adoption (e.g. NOAA NCAI) and in so doing can provide benefits back to those larger programs. Given the relatively small size of the community, it may be preferable to carve out “Great Lakes spaces” under existing or emerging frameworks such as the Pangeo initiative (Odaka et al. 2020), rather than trying to develop new infrastructure.

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

Medium-term efforts will prioritize the active integration of Great Lakes AI progress with broader coastal-ocean AI advancements. By establishing cross-pollination with the wider coastal community, leveraging shared challenges such as rip current monitoring, storm surge prediction, and transboundary data management, we can ideally avoid isolated development silos. The community could also conduct retrospectives to assess progress and publish comprehensive reviews of successful AI use cases. For example, AI can support the development of integrated Great Lakes Earth system models 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 operate from a shared foundation of tools and knowledge. AI should be integrated with hypothesis-driven research to form a cohesive research model . Ultimately, the vision is to establish a sustainable and integrated research and management ecosystem supported by a skilled, interdisciplinary workforce in which AI tools are responsibly and transparently incorporated where appropriate within observational and operational systems. In this framework, digital twin capabilities serve as one of the technical foundations for creating a dynamic feedback loop between models and observations, providing the adaptive, data-rich decision support necessary to enhance the long-term resilience of the “vital but vulnerable” Great Lakes and the communities that depend on them.

Achieving this vision will require sustained coordination across research and management organizations. Key areas for engagement include developing and maintaining shared data infrastructure, advancing integrated modeling approaches across disciplines, and co-designing AI-enabled tools with observing system operators and decision-makers. These efforts provide multiple entry points for participation across institutions and sectors, and will be most effective when aligned with existing regional collaborations and operational needs.

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