Journal of Environmental & Earth Sciences | Volume 08 | Issue 05 | May 2026

BILINGUAL PUBLISHING GROUP

Journal of Environmental & Earth Sciences

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REVIEW

Beyond Point Sampling: AI-Enabled Sensor Fusion and Holistic Frameworks for Aquatic System Intelligence

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ABSTRACT

The fast-changing environment is becoming a greater influence on aquatic systems, and the traditional approaches still look at conventional monitoring as point-based sampling, which under-samples the spatiotemporal variation and episodic dynamics. This review summarizes future trends toward ultraviolet sampling using Artificial Intelligence (AI)-enhanced sensor fusion and comprehensive conceptualizations of the intelligence of aquatic systems. We then explore how aquatic observation has evolved over the years by beginning with the limitations of fixed stations and grab sampling and moving on to multi-modal observations involving the incorporation of in-situ networks, remote sensing, and mobile autonomous systems. Subsequently, we are interested in AI methods that allow integration of heterogeneous streams of data with an accent on fusion architectures, representation learning, and hybrids that are based on data-driven inference and physics-based constraints. We elaborate on these developments with holistic models that combine sensor fusion with system-level modeling, such as digital aquatic twins, real-time assimilation, and adaptive spatiotemporal intelligence for detecting events and understanding processes. In a variety of uses, including water quality evaluation, ecosystem health surveillance, and hazards early warning, among others, we point out how the combination of AI and AI-sensing systems can be used to enhance state estimation, forecasting, and decision support in the face of uncertainty. Lastly, we discover unresolved issues, such as a lack of data, no stationarities in generalization, the limitations of computational and operational projects, and the need to have trustworthy, scalable aquatic intelligence, and outline future research opportunities. This review brings together sensing, AI, and systems thinking to create a roadmap on how to transform heterogeneous observations into

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ARTICLE INFO
Received: 8 February 2026 | Revised: 5 April 2026 | Accepted: 10 April 2026 | Published Online: 6 May 2026
DOI: https://doi.org/10.30564/jees.v8i5.13252

CITATION
Zhang, X., 2026. Beyond Point Sampling: AI-Enabled Sensor Fusion and Holistic Frameworks for Aquatic System Intelligence. Journal of Environmental & Earth Sciences. 8(5): 18–30. DOI: https://doi.org/10.30564/jees.v8i5.13252

actionable insights that result in resilient aquatic management.

Keywords: Aquatic System Intelligence; Sensor Fusion; Multi-Modal Sensing; Digital Twins; Physics-Informed Machine Learning

1. Introduction

One of the most complex and dynamic systems on the Earth is the aquatic systems: rivers, lakes, estuaries, coastal areas, as well as the open ocean. They are key in the biogeochemical cycling, climatic regulation, biodiversity maintenance, and human well-being [1,2]. Meanwhile, the systems are becoming more stressed due to climate change, land-use change, pollution, and more severe extreme events [3,4]. The need to understand, monitor, and manage aquatic systems, therefore, necessitates observational and analytical methods that have the capacity to measure multi-scale multi-process processes with adequate spatial and temporal faithfulness.

Historically, the use of point-based sampling of aquatic systems has been essential to aquatic system monitoring, including fixed monitoring stations, grab samples, and single-parameter sensors [5,6]. Although these techniques have been the basis of aquatic science for decades and can still produce quality, long-term records, they simply cannot capture the spatial heterogeneity or rapid temporal variability. The aquatic processes that characterize such processes as nutrient transportation, algae blooms, hypoxia, sediments, and dispersal of pollutants frequently have a strong gradient, nonlinear relationship, and episodic behavior, which cannot be sufficiently described using scattered point measurements. Consequently, the critical system states, as well as transitions, can be overlooked or incomprehensible.

To address these weaknesses, over the past few years, they have seen a rapid growth in aquatic sensing technologies. Developments in in-situ sensors, remote sensing, autonomous platforms, and Internet-of-Things (IoT) structures have facilitated the gathering of new amounts of data in physical, chemical, and biological scales. Satellite measurements can help in synoptic observation of surface properties on regional to global scales, unmanned aerial vehicles (UAVs) can provide flexible, high-resolution measurements of specific regions, autonomous underwater vehicles (AUVs) and gliders can provide persistence in sampling the subsurface, and smart sensor networks can provide near-real-time measurements with growing accuracy. Together, these advances have taken the study of water significantly past the boundaries of single-point sampling [7,8].

But the extension of the senses has also given rise to new problems. Aqueous data tend to be heterogeneous, varying in terms of spatial and temporal resolutions, uncertainty attributes, sampling rate, and measurement principles [9]. Assimilation of such a variety of data streams into a consistent interpretation of system behavior is a core source of bottleneck. Traditional data processing and modelling methods—which are, in most cases, optimized to handle well-structured data that is homogeneous—fail to fully take advantage of the wealth of contemporary aquatic data. The existence of such disparity between information and the information that can be used has become more evident as the sophistication of the monitoring systems increases [10].

It is against this background that artificial intelligence (AI) and machine learning have become potent instruments to extract patterns, relationships, and predictive insights from large, complex datasets. In water sciences, AI has already been effectively utilized in the prediction of water quality, mapping the habitat using images, detecting anomalies, and estimating parameters. Deep learning architectures, specifically, have shown good performance in general nonlinear, multidimensional, and multisource data. However, many of the current applications are single-task or single-stream oriented, and they tend to be black box predictors and are not part of a larger system with knowledge [11,12].

The idea of sensor fusion, which is facilitated by AI, is an important move in the right direction. Sensor fusion aims at synthesizing data provided by multiple sensors in order to create estimates that are more precise, stronger, and more informative than those recently created by using any single sensor. Combined with the latest AI methods, sensor fusion will resolve several critical problems in the field of aquatic monitoring, which are data sparsity, noise, and mismatch of scale. What is more important is that AI-enabled fusion allows shifting the descriptive data aggregation to the intelligent interpretation, where the observations are integrated, contextualized, and connected to processes dynamically[13].

In addition to technical fusion, an increasing appreciation is being made that aquatic systems must be treated as whole, interconnected systems, and not groups of independent variables[14]. Such a view coincides with the new paradigms of system intelligence, digital twins, and cyber-physical environment systems. Aquatic system intelligence in this context is the ability to sense system states using multiple modes, reason about observations using data-driven and physics-informed models, learn and evolve, and be able to make informed decisions about the uncertainty. To reach this level of intelligence, it is necessary to have not only sophisticated algorithms but also conceptual frameworks that bring sensing, modeling, and application together. **Figure 1** provides an overview of this evolution, illustrating the shift from point-based sampling to multi-modal sensing, AI-enabled fusion, and holistic aquatic system intelligence.

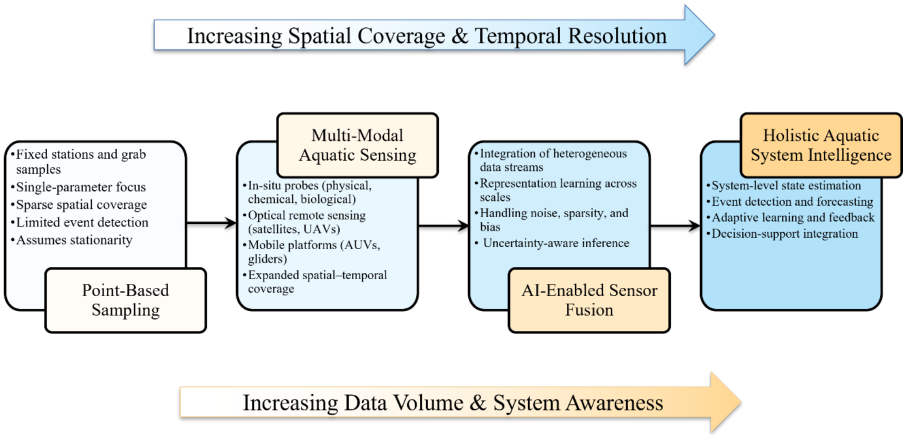

Figure 1. Conceptual evolution beyond point sampling, showing the progression from fixed and discrete measurements to multi-modal observation, AI-enabled sensor fusion, and holistic aquatic system intelligence.

The field is still disjointed despite its rapid advancement. In many cases, the reviews are dedicated to particular sensing technologies, a particular algorithm of AI, or a specific application. The syntheses of sensor fusion with AI techniques and holistic systems in aquatic systems are not extensively investigated. In addition, uncertainty quantification, interpretability, operational deployment, and governance are often considered secondary concerns, although they are very core concerns in real-world impact.

The present review concentrates on these shortcomings by discussing how the field of point sampling is changing into AI-based, connected solutions to the intelligence of aquatic systems[15]. Our vision is to offer an organized review of the potential of different sensing modalities to be integrated by complex fusion mechanisms, how AI could be able to improve system-level cognition, instead of single prediction, and how comprehensive models could be able to mediate between observation, modeling, and management. Instead of indexing algorithms on a case-by-case basis, this review focuses on the conceptual consistency, which points to shared values, repetitive issues, and new opportunities in fields and scales.

In particular, this paper (i) follows the history of transformation of traditional point-based monitoring to the multi-modal aquatic observation system; (ii) surveys state-of-the-art AI technologies in sensor fusion, i.e., data-driven and hybrid fusion; (iii) cross-cutting syntheses of emerging holistic frameworks of aquatic system intelligence, i.e., digital twins and adaptive learning systems; and (iv) critical challenges, ethical issues, and future research directions. It is through the combination of the views that are offered by the environmental sensing, artificial intelligence, and systems science that this review aims to convince the researchers and practitioners to move towards more intelligent, resilient, and sustainable aquatic monitoring and management methods[16–19].

Thus, we suggest that the future of the science of aquatics does not lie only in gathering additional information, but in creating smart structures that can be used to change heterogeneous observations into actionable information at the system level.

2. From Point Sampling to Multi-Modal Aquatic Observation

2.1. Conventional Point-Based Sensing in Aquatic Systems

During the majority of the previous century, the point-based paradigm of sensing prevailed in the observation of aquatic systems[20]. Empirical basis on hydrological, biogeochemical, as well as ecological processes in rivers, lakes, and coastal waters has been given by fixed monitoring stations, manual grab sampling, and single-parameter probes. These methods provide precise measurements and, in most instances, long and continuous time series, which are indispensable in trend analysis and regulation evaluation. Observations in the form of points have thus been dominant in setting the level of water quality, justification of numerical models, and environmental policy.

In spite of endowments, the fundamentals of point-based sensing methods inherently restrict the capacity of the methods to capture the spatial and temporal combinations of water systems. Discrete measurements are usually incapable of recording sharp slopes, localized effects, and transitory processes like the creation of algal patches, the resuspension of sediment, or the introduction of contaminants in sharp bursts. Spatial sparsity is further enhanced by the logistical and financial aspects of sparse sensor densities, particularly in big or distant aquatic locations. Due to this, system-scale inference directly on point measurements often involves very powerful assumptions about homogeneity and stationarity that might fail in apocalyptic changing environmental scenarios[21].

2.2. Expansion of Sensor Modalities and Observational Platforms

The last twenty years have seen technological advancements that have greatly increased the number of observational tools that can be used to monitor the aquatic environment. Long-term autonomous operation. Long-range in situ sensors have become capable of monitoring a broad diversity of physical, chemical, and biological variables at high temporal resolutions, and have greatly increased power efficiency and communications. Simultaneously, remote sensing technologies have become more fully developed and offer spatially continuous measurements of surface temperature, turbidity, chlorophyll a, and other optically active properties on regional to global scales[22–24]. **Table 1** provides a summary of representative sensor modalities, deployment platforms, and common observable variables to explain how contemporary observing aquatic spans affect supportively related domains and scale.

Table 1. Representative sensor modalities and observational platforms for aquatic systems, indicating typical variables and characteristic spatial–temporal scales.

Sensor Modality	Platform Type	Primary Variables	Spatial-Temporal Scale
In-situ probes	Fixed stations, buoys	Temperature, nutrients, and DO (Dissolved Oxygen)	Local, high-frequency
Optical remote sensing	Satellites, UAVs	Chlorophyll, turbidity	Regional global, episodic
Mobile in-situ sensing	AUVs, gliders	Profiles of physico-chemical variables	Local, regional, adaptive
IoT sensor networks	Distributed nodes	Multi-parameter	Local, regional, near real-time

Mobile and autonomous platforms have also further changed the way of aquatic observation. Unmanned aerial vehicles facilitate highly flexible, high-resolution mapping of the surface conditions and nearshore areas, whereas autonomous underwater vehicles, gliders, and drifters facilitate targeted and adaptive sampling of the water column. Such platforms have the ability to react to changing conditions, monitor dynamic aspects, and reach out to the environments that are either inaccessible or risky using conventional sampling. They are used together with fixed sensor networks and satellite observations in forming multi-layered observational systems that cut across a broad spectrum of spatial and temporal scales[25,26].

2.3. Characteristics and Challenges of Multi-Modal Aquatic Data

These changes to multi-modal observation have intensively augmented the amount, variety, and complexity of aquatic information[27]. Measurements vary not only in their resolution and coverage, but also in the uncertainty structure, sample frequency, and environmental sensitivity. Atmospheric effects and water constituents have an impact on optical remote sensing; in situ sensors can be subject to biofouling or calibration drift, and autonomous platforms usually have sporadic connectivity. These aspects bring about variations, which make it difficult to compare and integrate data sources directly.

Moreover, multi-modes are often not synchronous and spatially and temporally heterogeneous [28]. In the same way, high-frequency point measurements can be accompanied by few but spatially wide satellite overpasses, and mobile platforms create trajectories, as opposed to fixed time series. The conventional statistical and modeling methods are not usually well positioned to be able to reconcile the differences, hence, the underutilization of available information. The solutions to these issues would need techniques that can align, weight, and contextualize heterogeneous observations but retain the complementary strengths that they offer.

2.4. Toward Integrated Aquatic Observation Systems

With the realization of the shortcomings of single-sensing techniques, more recently, the focus has been on integrated observation systems, which are multi-sensor in nature, incorporating a variety of sensors and platforms. The objective of these systems is to exploit the spatial coverage of remote sensing, the temporal continuity of fixed stations, and the adaptive sampling of mobile systems in order to have a more comprehensive system awareness. Integration, as opposed to a technical exercise, is also an indication of a conceptual transformation whereby the aquatic observation is seen as a system-level, coordinated exercise [29].

This migration preconditions developed data integration and interpretation systems. Multi-modal observation not only offers the raw material for better understanding, but it is only through smart fusion and analysis that its full potential is likely to be achieved. The multifaceted nature of integrated datasets demonstrates the necessity of methods that go beyond data aggregation to inference, learning, and prediction. It is in this respect that artificial intelligence becomes a logical and even more inevitable part of the new generation of aquatic observation systems, which are the basis of sensor fusion approaches addressed in the next section [30,31]. An organized comparison between these two paradigms is presented in **Table 2**, showing that multi-modal observation enhances representativeness whilst posing new integration challenges.

Table 2. Comparison of point-based sampling and multi-modal aquatic observation paradigms in aquatic systems, summarizing differences in coverage, resolution, adaptability, and interpretability.

Aspect	Point-Based Sampling	Multi-Modal Aquatic Observation
Spatial coverage	Sparse, discrete locations	Continuous or semi-continuous, multi-scale
Temporal resolution	Periodic or fixed-interval	High-frequency to event-driven
Sensor diversity	Typically single-parameter	Physical, chemical, biological, optical
Adaptability	Static deployment	Mobile and adaptive platforms
Representation of heterogeneity	Limited	Enhanced through integration
Suitability for extreme events	Often inadequate	Improved detection and tracking

3. AI-Enabled Sensor Fusion for Aquatic Systems

3.1. Foundations of Artificial Intelligence in Aquatic Observation

The growing accessibility of big and diverse aquatic information has spurred the implementation of the field of artificial intelligence in aquatic science and engineering [13,32]. Regression-based models, tree ensembles, and kernel approaches were the first machine learning techniques to be introduced to learn empirical relations between the environmental variables and system responses. In more recent years, deep learning architectures have been popularized by their ability to discover hierarchical representations of high-dimensional data, e.g., images, time series, and spatiotemporal fields. These are well adapted to aquatic systems where nonlinear interactions and processes scale dependent are dominant.

Within the framework of the aquatic observation, AI models are becoming much more applicable as predictive models, but also feature extractors, pattern recognizers, and anomaly detectors [33]. Convolutional neural networks have made it possible to perform automated meaning derived from remote sensing images, recurrent and attention-based models have made it easier to describe temporal processes, and graphbased learning has helped to describe spatial relationships within river networks and coastal systems. These developments offer the methodological basis for the synthesis of information from varied modalities of sensing.

3.2. Sensor Fusion Architectures and Learning Strategies

The concept of sensor fusion in the aquatic systems can be loosely interpreted as the method of integrating multiple streams of data to come up with better and more dependable estimations of the system states[34]. There are differences in the way it is integrated within the learning pipeline that is created by an AI-enabled fusion architecture. Early fusion methods take as inputs the raw or low-level processed input of several sources and form a single representation, on which the models learn the cross-modal relations directly. Although this strategy might be as effective as needed, it may need to be normalized and aligned carefully, and may be vulnerable to missing data or noisy data.

Mediation fusion strategies aim at compromising flexibility and robustness by extracting modality-specific features and then combining them at latent levels. In this way, models are able to maintain sensor-specific properties and still learn shared representations that reflect system-level behavior. Late fusion instead takes predictions/outputs of materials at higher levels, a more general model tool, providing sensor failure resilience and modularity, although with possible reduced exploitation of deep cross-modal links. The fusion strategy selection is strongly associated with data availability, system goals, and operational limitations[35,36].

For eutrophication monitoring, where heterogeneous data (e.g., nutrient point samples, chlorophyll-a from remote sensing, and continuous DO sensors) must be integrated to capture slow-varying spatial gradients, intermediate fusion is preferred. It balances cross-modal feature learning with robustness to asynchronous sampling. For flood early warning, where rapid, event-driven decisions require resilience to sensor failure and missing data, late fusion is more suitable. Its modular design allows independent operation of rainfall, water level, and velocity sensors, with fusion occurring only at the decision level. Conversely, early fusion is rarely appropriate for operational aquatic systems due to high sensitivity to sensor noise and synchronization requirements, though it may be useful in controlled experimental settings.

3.3. Physics-Informed and Hybrid Fusion Approaches

Although data-driven AI models have shown excellent performance in most aquatic applications, they usually perform poorly in extrapolating, interpreting, and being physically consistent. In an attempt to overcome these drawbacks, physics-informed and hybrid methods have become a significant trend in AI-enabled sensor fusion. These techniques impose physical laws, process-based models, or domain constraints on the learning structures and consequently direct inference towards physically plausible solutions[36].

Hybrid fusion methods can be used in aquatic systems, where hydrodynamic or biogeochemical model outputs can be integrated with observational data from various sensors[37]. The AI models can be trained with the purpose of fixing the model biases, interpolating sparse observations, or performing real-time data assimilation. Using both mechanistic knowledge and information-guided flexibility, these methods can result in greater robustness and generalizability, especially when the conditions do not match past training data. It is this synergy that is necessary to capture the dynamics of complex systems, and at the same time have scientific credibility.

3.4. Uncertainty, Interpretability, and Robustness in Fusion Models

The sensor fusion in aquatic systems requires an effective approach to uncertainty that comes about due to measurement error, model assumptions, and variability of the environment. AI-powered fusion models are also adopting more probabilistic learning models, ensemble models and Bayesian models to measure the predictive uncertainty and to propagate sensor-level errors by the inference process. These are essential in making decisions that are risk-aware, particularly applications to forecast hazards and environmental management[38].

The interpretability and strength are also very significant issues. A black-box fusion model can be quite predictive but can provide less information about the major underlying process or sensor patterns. The recent developments in explainable AI, attention, and sensitivity analysis offer the means to explain the effects of various sources of data on the model outputs. Strong belt-and-whisker fusion is also developed to cope with missing data, sensor decay, and distributional changes, resulting in dependable performance in real-life scenarios. A combination of these concepts progresses the AI-powered sensor combination to previous stages of technical combination and moves aquatic intelligence to credible and applicable levels[39]. **Table 3** illustrates a general set of AI-enabling fusion strategies and trade-offs, which offers a realistic guide on the choice of architectures in the aquatic data-limited environment.

Table 3. AI-enabled sensor fusion strategies for aquatic systems, contrasting early, intermediate, late, and physics-informed fusion in terms of integration stage, advantages, and limitations.

Fusion Strategy	Integration Stage	Strengths	Limitations
Early fusion	Raw data level	Captures cross-modal interactions	Sensitive to noise and missing data
Intermediate fusion	Latent feature level	Balances flexibility and robustness	Increased model complexity
Late fusion	Output or decision level	Modular and fault-tolerant	Limited deep interaction
Physics-informed fusion	Model-constrained learning	Improved generalization and plausibility	Requires domain knowledge

4. Holistic Frameworks for Aquatic System Intelligence

4.1. Conceptualizing Aquatic System Intelligence

The overlap of sophisticated sensing technologies and AI-assisted data combinations has inspired the switch to separate analytical instruments into overall models of aquatic system intelligence. Here, intelligence can be defined as the capacity of an observational system that senses the environment using multi-modal sensing, interprets the sensations by combining data and models, and aids in adapting responses in an uncertain environment. The intelligent aquatic systems also focus on continuous learning, feedback, and reasoning at the system level in space and time, unlike the traditional monitoring systems, whose main focus is on observations[40].

This conceptualization is consistent with the overall advances in cyber-physical systems and Earth system science, whereby environmental processes are being modeled as more and more interconnected and dynamic networks. Aquatic system intelligence, therefore, does not just focus on sensor fusion but is also co-designed to include the sensing, modeling, and decision-support elements. These frameworks will be used to capture emergent behavior, to explain cross-scale effects, and to provide an opportunity to manage the aquatic environment proactively and not reactively[13].

4.2. System-Level Modeling and Digital Aquatic Twins

Another key aspect of holistic aquatic intelligence systems is the combination of AI with process-based models with system-level representations, sometimes known as digital aquatic twins. Digital twins are recreations of physical systems that constantly absorb observational information so that they learn to revise their status and enhance forecasting. These twins can be used in aquatic systems to combine hydrodynamic, biogeochemical, and ecological models with real-time sensor data to form a dynamic and changing representation of the system[41].

AI is a major contributor to the digitalization of aquatic twins in that it supports the assimilation of data, estimation of parameters, and correction of errors in the model. Surrogate modeling can be used to learn discrepancies between simulated and observed states, improve the representation on the subgrid scale, and decrease computational requirements in machine learning models. Being integrated into a digital twin system, AI-enriched models can offer a potent tool for scenario exploration, system response forecasting, and management intervention evaluation in a changing environment[42,43].

4.3. Spatiotemporal Intelligence and Process Understanding

Wholesome models of aquatic system intelligence are based on the interpretation of spatiotemporal patterns and not individual observations[38]. Aquatic processes tend to occur at many scales, with localized occurrences that affect downstream or system-wide behavior. Intelligent frameworks use AI to discover coherent structures, detect anomaly and characterize regime change that can be an indicator of a shift in system behavior.

The process-based understanding is facilitated in these frameworks by synthesizing sensor fusion outputs with system-level models. As an example, spatiotemporal learning methods may relate patterns on the surface to processes in the subsurface, or relate temporary disturbances to permanent ecosystem reactions. This integration not only allows for improved prediction but also improved interpretability because model outputs can be correlated with known physical, chemical, or biological processes[44].

4.4. Applications and Operational Integration

Full-body aquatic intelligence models are finding more and more applications in diverse fields of operation, such as water quality management, ecosystem health management, hazard early warning, and resource management. Intelligent systems are used in these applications to provide real-time situational awareness, adaptive sampling strategies, and uncertainty decision support systems. The skills of integrating streams of various data into coherent system states, especially in a complex and rapidly changing environment, are highly useful[45].

Another practical consideration brought by operational deployment is the aspect of scalability, reliability, and the involvement of stakeholders[46]. The holistic frameworks should be developed to operate within the context of real-life constraints, such as data unavailability, computational constraints, and varied user needs. In this regard, the issue of aquatic system intelligence development is an organizational and governance problem as much as it is a technical issue. These dimensions are critical to deal with to convert methodological advances into long-term environmental changes and precondition the discussion of issues and further directions in the next section. In an attempt to close the gap between conceptual design and operational realities, **Table 4** will summarize the main elements of holistic aquatic intelligence frameworks with their main capabilities and prevailing challenges.

Table 4. Holistic frameworks for aquatic system intelligence, linking core components (e.g., digital twins, adaptive learning, spatiotemporal intelligence, decision support) to capabilities, benefits, and deployment challenges.

Framework Component	Core Capability	Key Benefit	Major Challenge
Digital aquatic twins	Dynamic system representation	Scenario analysis and forecasting	Data and computational demands
Adaptive learning systems	Continuous model updating	Robustness to change	Stability and validation
Spatiotemporal intelligence	Event and regime detection	Early warning and insight	Interpretability
Decision-support integration	Actionable outputs	Policy and management relevance	Trust and governance

5. Challenges, Opportunities, and Future Directions

5.1. Data Limitations and Generalization Challenges

With the fast development of sensing technologies and AI methods, the intelligence of aquatic systems is still limited by basic data constraints. Even in many aquatic habitats, especially in developing or remote habitats, sparse or discontinuous observations persist. In data-rich environments, labeled data that can be used in supervised learning is usually scarce, expensive to acquire, or biased against particular conditions. These limitations prevent the creation of AI models that are reliable in generalization across systems, seasons, and disturbance regimes[45,47].

Generalization has been an issue of concern for AI-enabled holistic frameworks and sensor fusion[48]. Historically trained models are not likely to run well in new conditions caused by climate change, extreme conditions, or anthropogenic interventions. The solution to this problem is strategies of learning that are resistant to nonstationary, domain transferable, and time adaptable. Self-supervised learning, continual learning, and cross-system benchmarking are potentially promising directions that have not been sufficiently explored in aquatic applications.

5.2. Computational, Infrastructural, and Operational Constraints

The adoption of holistic aquatic intelligence systems can be associated with large computational and infrastructural requirements[49]. Resource-consuming High-resolution sensor fusion, real-time data assimilation, and AI-enhanced system modeling may be expensive, especially when used at large scales or at high frequencies. The challenge of how to balance the complexity of models and their operational feasibility is a continuing challenge, particularly for agencies and stakeholders with limited technical abilities.

It is further complicated by deployment constraints.

Failures in sensors and communication difficulties, and maintenance impose uncertainty and possible data gaps that need to be handled by intelligent systems. Strong system design, hence requires redundancy, fault tolerance, and adaptive workflows, which can fail gracefully instead of failing. These considerations serve as a reminder of the significance of co-designing AI models and observational systems in consideration of operational realities[50].

5.3. Interpretability, Trust, and Decision Support

With AI-driven structures shaping the managerial and policy decision-making process, the question of interpretability and trust becomes the dominant one. The stakeholders usually need a clear description of model outputs, especially when a trade-off between the ecological, economic, and social goals is demanded of them. Even accurate black-box predictions may not be adequate for developing confidence or justifying interventions.

An important opportunity is thus the development of interpretable and explainable AI approaches that can be applied to aquatic systems. Techniques that explain the relative importance of various sensors, variables, and processes can help to improve the level of understanding and create acceptance among the stakeholders. Also, decision-support tools should be designed to incorporate uncertainty quantification so that the risks and the levels of confidence can be considered by the users in a more explicit way to provide more informed and resilient management strategies[51,52].

5.4. Ethical, Governance, and Future Research Directions

The evolution toward intelligent aquatic systems raises broader ethical and governance considerations. **Figure 2** provides a synthesized roadmap of technical, operational, and governance challenges alongside corresponding research opportunities needed for scalable and trustworthy aquatic intelligence. The issue of data ownership, access, and privacy, especially cross-boundary or socially sensitive ones, should be considered to provide a fair and responsible use of new technologies. The systems of governance must also address the question of the interactions between automated or semi-automated systems of decision-making and human expertise and institutional processes[53].

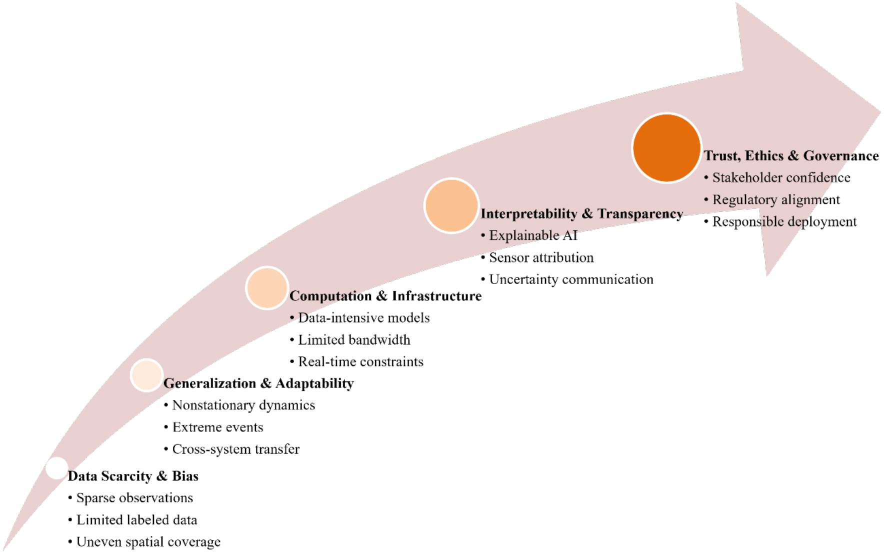

Figure 2. Challenges and future research roadmap for AI-enabled aquatic system intelligence, organizing barriers and opportunities across data, generalization, computation, interpretability, and governance.

In the future, it can be expected that future studies will focus on moving aquatic system intelligence toward an interdisciplinary approach. Some of the directions that are important are the creation of adaptive, self-learning systems that can change with changing environments; the integration of social and ecological aspects into system models; and the creation of open and standardized platforms for data sharing and model assessment. By overcoming such challenges and opportunities, the field can proceed to the realistically intelligent aquatic systems that can assist in the sustainable management of the era of environmental change in history [54,55].

6. Conclusion

The nature of change in aquatic systems is rapid and irreversible as a result of climate variability, increased human activities, and increased pressures on the available water resources. In this regard, the shortcomings of the classical point-based sampling have become more and more obvious, with the sparse and isolated observations having difficulty in taking into account the spatial heterogeneity, temporal dynamics, and nonlinear interactions that characterize aquatic systems. This review has also explored the new shift to AI-enabled sensor fusion and whole system approaches to aquatic system intelligence and how the developments in sensing, data fusion, and system modeling are transforming aquatic observation and knowledge.

We have followed the progression of the traditional methods of monitoring to the multi-modal observation systems that are based on in-situ sensors, remote sensing, and autonomous platforms on different scales. These technologies are said to offer unparalleled amounts of data, but their real potential is working together. Sensor fusion with AI has become a key enabler, providing solutions to address the issue of having disparate data streams, deriving consistent system states, and improving predictability. Notably, data fusion is not enough, but it is vital to incorporate physical knowledge, awareness of uncertainty, and interpretability into AI models to obtain robustness and scientific credibility.

Resting on these pillars, holistic approaches to aquatic system intelligence constitute a theoretical and functional transformation of the study and management of aquatic environments. These systems are also aligned with digital aquatic twins, adaptive learning, and system-level models by virtue of sensor fusion and system-level models, which are poised to cause these systems to become continuous perception, interpretation, and response. These methods not only enable better forecasting and detection of anomalies, but also promote a greater understanding of the process and make the decision-making process under uncertainty more informed. Their use in monitoring water quality, in the evaluation of ecosystems, and in predicting hazards highlights their general applicability and level of transformation.

Although these have been made, there are still considerable problems. The limitations of widespread use are still based on data scarcity, nonstationary generalization, and computational considerations, as well as the problem of trust and governance. Such challenges will only be dealt with through interdisciplinary cooperation, methodological exploration, and long-term investment in technical infrastructure and institutional capacity. It is also important to establish clear, ethical, and inclusive systems that will synchronize intelligent systems and society's demands and policy cycles.

Aquatic science, however, looking forward, aquatic science as a field should not just continue gathering information, but it must also grow intelligent systems that learn new things, are adaptable to new situations, and can be used to maintain a healthy and sustainable management of aquatic resources. By not just abandoning the point sampling model but adopting AI-powered holistic models, the aquatic research community is well-placed to develop a model that is more whole and actionable in understanding aquatic systems in a rapidly evolving world.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

No new data were created or generated in this study. As this is a review, it is based on data and information from previously published sources, which are cited in the reference list.

Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

The author declares that no artificial intelligence (AI) tools were used in the preparation of this manuscript.

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