Engineering xxx (xxxx) xxx

Contents lists available at ScienceDirect

Engineering

journal homepage: www.elsevier.com/locate/eng

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Environmental Monitoring as Intelligent Infrastructure: An Engineering Framework for Adaptive Environmental Management

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1. Introduction: Monitoring as environmental infrastructure

Environmental monitoring programs are the primary mechanism through which societies perceive environmental change in time to respond [1,2]. Long-term monitoring records change, characterizes extreme events, and provides the context necessary to interpret experimental results [3]. Monitoring is therefore both a scientific activity and a type of environmental infrastructure. It is the information base by which societies detect risk, evaluate policy, and assess whether interventions are effective.

Historically, long-term monitoring has enabled transformative discoveries. Continuous atmospheric measurements revealed a persistent increase in atmospheric carbon dioxide (CO_2), alerting society to the warming effects of fossil fuel use [4]. The monitoring of atmospheric chemistry led to the discovery of the Antarctic ozone hole, providing the first undeniable proof that human activity could damage planetary-scale systems; this resulted in the Montreal Protocol, the first universally ratified treaty in United Nations history [5]. Watershed-scale monitoring at the Hubbard Brook Experimental Forest produced one of the longest human records of precipitation and stream water chemistry, fundamentally shaping our understanding of ecosystem biogeochemistry, watershed function, and acid deposition [3,6–9]. These examples demonstrate that monitoring goes well beyond description; it is the skeleton upon which scientific discovery, environmental diagnosis, and policy development are built.

Yet most monitoring systems were developed for a slower and more predictable world. Contemporary ecosystems are increasingly shaped by rapid environmental change, nonlinear responses, and compounding stressors, including climate change, pollution, invasive species, altered hydrology, habitat transformation, and human development [10]. These pressures can generate thresholds, regime shifts, and cascading impacts that are difficult to detect using static indicators or periodic sampling. As a result, a fundamental mismatch has emerged between the dynamic pace of environmental change and the static, retrospective architecture of many monitoring programs.

This article argues that environmental monitoring must be redesigned as an intelligent engineering system, in which sensing, data integration, modeling, uncertainty quantification, and decision-making are coupled within a continuous feedback loop. Without this transformation, monitoring will remain reactive and increasingly inadequate for governing environmental systems under uncertainty. With it, monitoring can become adaptive environmental intelligence, capable of detecting change, reducing uncertainty, forecasting risk, and informing action at the speed required by contemporary environmental challenges. This conceptual transition is illustrated in Fig. 1.

2. The structural failure of conventional monitoring

For decades, environmental monitoring has been treated as a technical necessity: Collect data, assess status, and report trends [1,2]. This conventional monitoring paradigm is summarized in Fig. 1. The paradigm has produced valuable long-term datasets but has also created a false sense of adequacy. Many programs are designed to document conditions after the fact rather than detect emerging risks or guide timely action, resulting in monitoring programs that function less as early warning systems than as *post hoc* archives of environmental change [11].

The failure is not primarily a lack of data. Environmental monitoring systems have never been more technologically capable. Sensor networks, satellite platforms, autonomous systems, environmental DNA, and biological assessment tools now generate unprecedented volumes of information [12]. Operational monitoring already supports public health and environmental management in areas such as waterborne disease exposure, air quality, and pollutant surveillance [13]. However, the growth in data volume has not produced a proportional increase in decision-relevant insight. The central problem is architectural: data collection, storage, analysis, interpretation, and decision-making remain separated in space, time, and institutional responsibility (Fig. 1).

This fragmentation produces three major failures. First, monitoring systems suffer from a temporal lag (Fig. 1). Periodic field campaigns and delayed laboratory or statistical analysis limit the capacity to identify emerging risks; by the time many programs detect change, the system may have already shifted, sometimes irreversibly. Second, monitoring remains fragmented across

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https://doi.org/10.1016/j.eng.2026.09.007
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Please cite this article as: Y. Chen, S. Arsenault, K. Rokosz et al., Environmental Monitoring as Intelligent Infrastructure: An Engineering Framework for Adaptive Environmental Management, Engineering, https://doi.org/10.1016/j.eng.2026.09.007

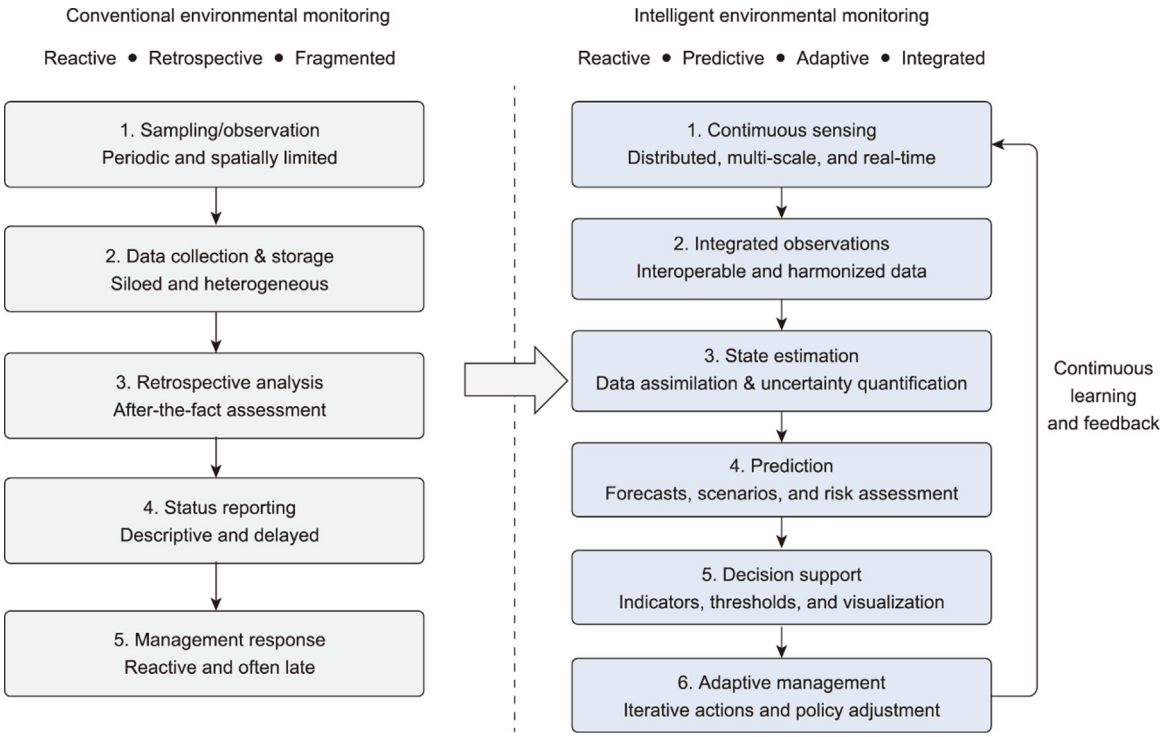


Fig. 1. The conceptual transition from conventional to intelligent environmental monitoring. Conventional monitoring relies on sequential observation and retrospective assessment, whereas intelligent monitoring integrates continuous sensing, state estimation, prediction, decision support, adaptive management, and continuous learning to enable environmental intelligence.

disciplines and institutions (Fig. 1). Biological, physical, chemical, and social data are often collected independently, stored in incompatible formats, and analyzed using different conceptual frameworks [14–16]. Third, monitoring outputs are weakly connected to action (Fig. 1). Many programs generate indicators of status or compliance without translating those indicators into operational decisions, risk forecasts, or adaptive management strategies [17].

In engineering terms, most monitoring systems are open-loop systems. They observe and report, but do not continuously update system understanding or adjust management actions at the pace of environmental change. Thus, monitoring systems are functioning as an archive instead of infrastructure for risk management. The central question is how to redesign monitoring so that sensing, analysis, prediction, and decision-making function as an integrated whole.

3. A reference architecture for intelligent environmental monitoring

Engineering disciplines routinely redesign systems when performance requirements change. Environmental monitoring should be no exception. The performance requirements for environmental monitoring have changed dramatically: Systems must now detect increasingly rapid shifts, integrate more diverse data streams, quantify uncertainty, provide early warning, and support prompt decision-making. These requirements cannot be met by linear monitoring workflows. They require a closed-loop architecture. Fig. 1 illustrates the conceptual shift from conventional monitoring toward closed-loop intelligent environmental monitoring.

We propose that next-generation environmental monitoring be designed as intelligent infrastructure organized according to the reference architecture shown in Fig. 2, with five tightly coupled components: ① *distributed sensing*, including field sensors, remote sensing, autonomous observatories, biological monitoring, and citizen or community observations; ② *interoperable data infrastructure*, in which heterogeneous data streams are standardized, quality-controlled, and made available for rapid analysis; ③ *data assimilation and uncertainty quantification*, through which observations are integrated with process or statistical models to continuously estimate system states; ④ *predictive modeling*, including digital twins that evolve alongside real environmental systems and simulate alternative futures; and ⑤ *adaptive decision support*, in which model outputs, uncertainty estimates, and risk indicators are directly linked to management action and evaluation. Together, these components form a continuous closed-loop engineering system linking sensing, prediction, decision-making, and adaptive learning (Fig. 2). Implementing these five components will improve temporal and spatial coverage, make data usable and trustworthy, establish confidence in system status, enable early warning and anticipatory management, and create closed-loop environmental governance (Fig. 2).

This architecture fundamentally changes the role of monitoring. Instead of a sequence of disconnected steps including sampling, storage, analysis, and reporting, monitoring becomes a continuous cycle: sense, integrate, estimate, predict, decide, and adapt. Information flows in several directions: from observations to models, from models to decisions, and from decisions back to monitoring design. This feedback loop is essential because environmental systems are dynamic and management actions themselves alter the systems being monitored.

Concepts such as digital twins are particularly important in this transition. A digital twin extends conventional modeling; it is a continuously updated representation of a real system that can assimilate observations, quantify uncertainty, and evaluate alternative scenarios. In environmental monitoring, digital twins could provide real-time situational awareness for watersheds, coastal zones, forests, lakes, fisheries, and urban systems. Their usefulness depends on the quality of the monitoring architecture that

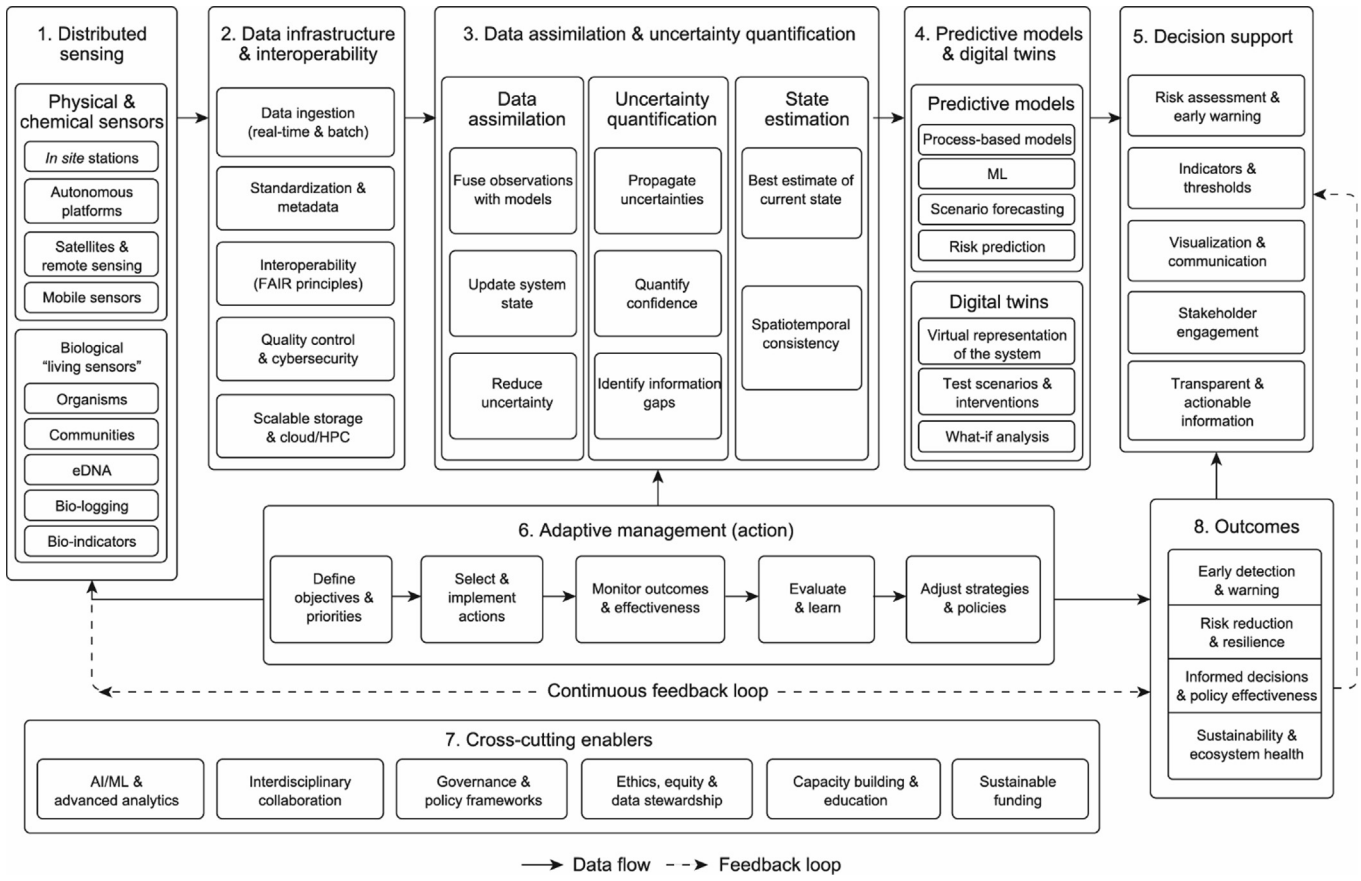


Fig. 2. A reference architecture for intelligent environmental monitoring. The proposed closed-loop engineering framework integrates distributed sensing, interoperable data infrastructure, data assimilation, predictive modeling, digital twins, decision support, adaptive management, and continuous feedback for evidence-based environmental management. FAIR: findable, accessible, interoperable, and reusable; eDNA: environmental DNA; HPC: high-performance computing; AI: artificial intelligence; ML: machine learning.

supports them. Without integrated observations and adaptive feedback, digital twins risk becoming static simulations rather than functional operational intelligence systems.

4. Biological systems as living sensors

Biological systems are central to this transformation and constitute one of the principal sensing components of the proposed monitoring architecture (Fig. 2). In environmental monitoring, biological observations are often viewed as complex, noisy, and difficult to rapidly interpret, which has limited their operational use. However, this complexity is also their greatest strength. Biological communities integrate environmental conditions over time and space, encoding cumulative impacts—such as hydrologic variability, temperature, water quality, habitat conditions, contaminant exposure, food-web structure, and acute or chronic disturbances—that no individual physical sensor can capture [16,18]. Biological signals are often delayed, nonlinear, and context-dependent, but they provide system-level information that is essential for understanding ecological risk. While a chemical sensor provides an isolated measurement of a pollutant at a specific time and place, biological communities reflect the ecological consequences of multiple interacting stressors across broad spatial and temporal scales. Biological monitoring should therefore be treated as an integral component of intelligent monitoring infrastructure.

In the past, biological complexity limited rapid interpretation and decision-making, but advances in machine learning (ML), ecological modeling, and data integration are easing this constraint. Modern computational methods can identify nonlinear patterns, extract signals from high-dimensional biological data, and link biological observations to environmental drivers [19,20]. While these tools do not eliminate uncertainty, they make it possible to use biological information more effectively and operationally.

In an engineered monitoring framework, biological systems can function as living sensors by providing quantitative constraints on system state, model performance, and risk detection. Changes in community composition, recruitment, phenology, physiological condition, or trophic structure may reveal cumulative stress before conventional indicators cross regulatory thresholds [21,22]. Integrating biological signals with physical and chemical data can improve early warning and reduce the risk of systemic blindness. Realizing this potential requires standardized biological observations, interoperable databases, analytical pipelines that quantify uncertainty, and model structures capable of assimilating biological signals. It also necessitates institutional willingness to move beyond compliance-focused indicators toward adaptive, intelligence-oriented monitoring.

5. From fragmented programs to intelligent monitoring systems

The transition from conventional to intelligent monitoring is as much architectural and institutional as it is technological. Adding new sensors to outdated systems will not resolve the underlying problem. Intelligent monitoring must be predictive, multi-scale,

autonomous where appropriate, and directly connected to decisions.

First, monitoring must become predictive. Environmental management increasingly depends on anticipating change rather than retrospective documentation. This requires tight coupling between observations and dynamic models so that system states can be continuously updated and early warning signals can be detected before critical transitions [11,23].

Second, it is essential that monitoring operates across scales. Local observations are essential, but environmental challenges such as climate change, biodiversity loss, altered hydrology, and pollution operate across regional and global extents. Monitoring systems must therefore link site-based measurements with remote sensing, regional models, and broader environmental datasets. Achieving this integration is also an engineering challenge, requiring advances in data architecture, interoperability, and computational design [24,25].

Third, monitoring must become more autonomous and resilient. Human-centered sampling is costly, slow, and spatially limited. Autonomous platforms, robotic systems, sensor networks, and automated observatories can expand spatial coverage and increase temporal resolution. However, these technologies introduce new engineering challenges: reliability, calibration drift, data validation, power supply, communications, cybersecurity, and failure detection. Intelligent monitoring infrastructure must be designed for robustness rather than just data acquisition.

Finally, monitoring must connect to society. Data collected and archived without translation into timely, actionable insight represents a failure of purpose. As illustrated in Fig. 2, prediction is embedded within a continuous feedback architecture connecting observations, models, management actions, and learning. An intelligent monitoring system must function as a platform for engagement, delivering decision-relevant information to policymakers, managers, communities, and the public.

6. Barriers and engineering priorities

Resistance to change remains a major barrier. Many environmental monitoring programs are constrained by legacy designs, rigid regulatory frameworks, and institutional inertia [26]. Standardized protocols are essential for continuity and comparability, but when treated as fixed endpoints rather than evolving components of system design, they discourage innovation. Funding structures often reward continuity over adaptation, reinforcing systems that are familiar but increasingly inadequate.

The integration of complex data streams is another hurdle. Intelligent monitoring requires the fusion of heterogeneous data streams with different spatial resolutions, temporal frequencies, uncertainty structures, and institutional ownerships. Engineering solutions are needed for metadata standards, data accessibility, quality assurance, uncertainty propagation, and computational scalability. Without these foundations, data abundance becomes data disorder.

A third obstacle is validation. Predictive and adaptive monitoring systems must be trusted. This requires transparent algorithms, rigorous uncertainty quantification, benchmark datasets, hindcasting, stress testing, and independent evaluation. ML can improve signal extraction and prediction, but it must be embedded within interpretable, validated, and decision-relevant workflows. Otherwise, there is a risk it will reproduce the central weakness of conventional monitoring: generating outputs that cannot be translated into management and policy decisions.

Governance is a fourth complication. Monitoring systems exist within institutions, legal frameworks, and political contexts. Transformation requires coordination across agencies, disciplines, and jurisdictions. It also requires open data principles, reproducible workflows, and mechanisms for public accountability. Monitoring is ultimately a social contract: Society invests in it and expects knowledge and accountability in return.

Engineering priorities should therefore address system-level integration rather than focusing on new instrumentation. Priority areas include interoperable monitoring platforms, data-assimilation methods for environmental systems, ecological digital twins, biological signal extraction, uncertainty-aware decision support, resilient autonomous sensing, cybersecurity for environmental infrastructure, and governance models that allow monitoring systems to evolve as risks change.

7. A call to action for engineers and policymakers

Incremental reform of monitoring systems is no longer sufficient. Continuing to fund monitoring systems that cannot keep pace with environmental change is not a neutral choice; it is a decision to remain partly blind to accelerating environmental risk. Policymakers should stop treating monitoring as a compliance requirement and begin demanding performance in the form of timeliness, predictive power, uncertainty transparency, and demonstrable impact on decisions. Standards that inhibit innovation should be revised, rather than protected.

Engineers play a central role in this transformation. Rather than solely a scientific endeavor, environmental monitoring is a problem of system design, integration, reliability, and performance. Engineers must move from building isolated instruments to developing fully integrated, decision-ready monitoring infrastructures. This requires crossing disciplinary boundaries, engaging directly with ecological complexity, and elevating biological monitoring from a secondary assessment tool to a core information layer in environmental intelligence systems.

The choice is stark. Monitoring can remain a fragmented archive of environmental change, or it can become intelligent infrastructure for adaptive management. In a rapidly changing world, only the second option is defensible.

8. Conclusions

Environmental monitoring stands at a crossroads. What is required is a fundamental shift in perspective: from monitoring as measurement to monitoring as intelligence, from fragmented programs to integrated systems, and from passive observation to adaptive management. Without this transformation, monitoring will become increasingly irrelevant to the decisions it is meant to inform. With it, monitoring can become one of the most powerful tools available for sustaining environmental systems under uncertainty. The engineering community should treat this transformation as a defining challenge. The task is to design monitoring systems that learn, predict, and support action, as opposed to just collecting more data. Environmental monitoring must become an intelligent infrastructure. The reference architecture presented in Fig. 2 provides one possible engineering blueprint for implementing intelligent environmental monitoring systems.

CRediT authorship contribution statement

Yong Chen: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Stephanie Arsenault:** Writing – review & editing, Validation. **Katrina Rokosz:** Writing – review & editing, Validation. **Abigail Costigan:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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