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REVIEW

Intelligent Environmental Sensing Systems: Integrating IoT, Edge Computing, and Real-Time Analytics for Environmental Monitoring

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ABSTRACT

The intelligent environmental sensing systems are quickly transforming the sparse and retrospective monitoring to dense and decision-oriented environmental intelligence. This review brings together the manner in which integration of Internet of Things (IoT) sensing, edge computing, and real-time analytics facilitates timely detection, interpretation, and prediction of the environmental conditions across the applications, such as urban air quality, watershed and coastal surveillance, industrial safety, agriculture, and disaster response. We define end-to-end architectural patterns to organize devices, edge nodes, and cloud services to satisfy latency, reliability, bandwidth, and governance constraints with emphasis on event-time processing, adaptive offloading, and hierarchical aggregation. Then we look at sensing and infrastructure foundations, emphasizing the effects of sensor modality and power autonomy, connectivity, and the practices of calibration on the practicable analytics and eventual plausibility. It is on this basis that we examine real-time analytics pipelines and Artificial Intelligence (AI) techniques to preprocess, sensor combine, anomaly detect, and short-horizon forecast, with a focus on edge-deployable models, quantification of uncertainties, and query resistance to drift and domain shift. Lastly, we address the realities of deployment that condition operational success, such as lifecycle engineering, provenance-aware data management, security and privacy risks, ethical governance, and evaluation methodologies, which place end-to-end latency and field generalization as a priority. This review offers cohesion to algorithmic capabilities and systems engineering and governance to define an overall framework, show open areas of research directions, and provide practical recommendations

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on how to design trustworthy, scalable, and sustainable environmental monitoring systems.

Keywords: Internet of Things; Edge Computing; Real-Time Analytics; Sensor Fusion; Environmental Monitoring

1. Introduction

There is a subtle but radical transformation in environmental monitoring. Traditionally, state-of-the-art environmental monitoring has been limited to a few, high-fidelity, reference-grade air quality stations, hydrologic gauges, meteorological towers, and laboratory sampling campaigns, carefully crafted in the conquest of day-to-day delivery and long-term trends analysis [1]. Although these tools will always be necessary, they frequently have difficulties with the spatiotemporal variability of many contemporary environmental hazards, such as hyperlocal air quality around roads, fast-changing smoke plumes of wildfires, brief industrial discharges, temporary algal eruptions, flash floods, urban heat islands, and temporary noise or odor episodes. Meanwhile, the decision makers are getting more and more demanding of timely situational awareness as opposed to summaries in the rear-view mirror. The combination of this high level of variability and the requirement of real-time response is giving rise to the intelligent environmental sensing systems, that is, distributed networks, integrating Internet of Things (IoT) sensing, edge computing, and real-time analytics to convert raw environmental signals into actionable information [2,3].

Technical enablers of such a shift are in place, and their integration to ensure operational environmental monitoring is lopsided. Low-price sensors and embedded platforms have increased the range of possibilities not only in the density of deployment and geographical coverage but also in the ability to monitor environments at street level, building and industrial facilities, fields and watersheds, and transportation corridors. The innovations in wireless connections, like low-power wide-area network, up to the recent cellular and satellite backhaul, have limited the distance limitations on locating sensors in remote or infrastructure-deficient areas. Simultaneously, machine learning and streaming analytics have evolved out of research pipelines running offline to research toolchain pipelines that are capable of supporting continuous inference, anomaly detection, predictions, and automated alerts [4–6]. The lost component has always been the middle: how to compute, how to deal with the quality of data in the real world, and how to provide trustworthy decisions when the networks will not always be connected, and sensors are going to fail. This is increasingly being performed by edge computing, which is being deployed in gateways and local servers close to the data sources to support low-latency processing, reduce bandwidth needs, mitigate connectivity outages, and privacy-conscious analytics. Taken together, these advances provide a means of not only a more pervasive sense, but a more autonomous one and a more responsive one.

In spite of increasing deployment activity in smart cities, industrial monitoring, water resource management, agriculture, and disaster response, the same question persists in the minds of practitioners: What is the appropriate architectural division of labor between devices, edge nodes, and the cloud? What analytics functions run on-premise, and what needs to be agglomerated? What to do with getting low-cost sensors drifting, changing environmental conditions, and sparse ground truth? What do we assess in an end-to-end manner, which involves sensing, networking, computation, decision, and delivery, in a complete manner? And what are the ways of securing and governing systems that may be used in open locations, produce location-sensitive data, or elicit high-stakes interventions? The answer to these questions will need a synthesis that cuts across disciplines, sensor engineering, wireless networking, distributed systems, and applied machine learning, since the failures of any of these layers can compromise the value of operational. Many highly precise anomaly detectors fail to be helpful when telemetry is too late; many dense sensing systems are also counterproductive when models are not managed, or when edge intelligence fails to consider the uncertainty of models; whereas uncontrolled and untimely updating of models and conveying their uncertainty risks making edge intelligence unsafe [7,8].

In this review, we define intelligent environmental sensing systems as integrated sensing and computational frameworks that extend beyond conventional data acquisition by enabling adaptive operation, self-diagnosis, and context-aware decision-making in real time. Such systems dynamically adjust sensing strategies, detect and compensate for anomalies or sensor drift, and generate actionable insights through edge–cloud collaboration. This definition distinguishes intelligent systems from purely automated or AI-assisted monitoring approaches, emphasizing their capability for closed-loop, autonomous, and context-sensitive environmental management. This review is based on intelligent environmental sensing systems, which can be described as end-to-end pipelines, where (i) environmental data is collected by means of distributed IoT devices or hybrid sensing platforms (fixed and/or mobile), (ii) these data are processed and interpreted through edge and/or cloud computing, and (iii) timely outputs are provided, such as alerts, forecasts, maps and decision cues to facilitate the action of a human or automated agent[9–11]. This intelligence is not restricted entirely to deep learning. It involves any algorithmic aptitude that renders monitoring more versatile, educational, and dependable streaming analytics that employs event-time management; sensor exposure and spatiotemporal interpolation; drift identification and automatic quality management; anomaly identification relying on minimal false-alarm; and uncertainty conscious forecasting. Similarly, real-time is application dependent: it can take seconds to do safety-related industrial leak detection, minutes to provide flash flood early warning, and hours to make some decisions about water quality or smoke exposure. In doing so, edge computing is not considered a specific technology but as a strategy of architecture; to put a computation in sufficiently proximity to the sensing process as to satisfy latency, bandwidth, privacy, and resilience requirements.

To motivate why architectural and analytical choices vary across domains, **Table 1** summarizes representative application scenarios, decision objectives, and the dominant latency–coverage–constraint profiles encountered in practice.

Table 1. Representative application scenarios for intelligent environmental sensing and their typical targets, decision objectives, latency and coverage needs, dominant constraints, and common outputs.

Application Domain	Typical Targets	Decision Objective	Latency Need	Coverage Need	Dominant Constraints	Common Outputs
Urban air quality	$PM_{2.5}$/PM_{10}, NO_2, O_3, CO, VOC proxies + met	Hotspot detection, exposure mapping, advisories	Minutes	High spatial density	Sensor drift, siting bias, periodicity	Street-scale maps, exceedance alerts
Watershed/Coastal water	Turbidity, DO, pH, conductivity, chlorophyll proxies	Spill/Bloom detection, watershed management	Minutes–Hours	Sparse-to-moderate	Biofouling, remote power/Connectivity	Event alerts, risk indices, trend reports
Industrial emissions/Safety	Gas leaks, particulates, process indicators	Early warning, compliance, safety response	Seconds–Minutes	Site-specific	Security, false alarms, on-prem integration	Alarms, source localization hints
Agriculture/Soil health	Soil moisture/Salinity, microclimate	Irrigation optimization, stress detection	Minutes–Hours	Moderate	Energy autonomy, sensor heterogeneity	Prescriptions, anomaly flags
Disaster response	Smoke, heat, flood proxies, contamination	Rapid situational awareness, public warnings	Seconds–Minutes	Adaptive/Mixed	Infrastructure disruption	Alerts, nowcasts, uncertainty-aware guidance

One of the main reasons why edge-enabled environmental monitoring is necessary is that the amount of raw data and information that can be processed is usually mismatched[12]. Environmental signals tend to be noisy, redundant, and context dependent. Sampling at a higher frequency can be required to capture short events, but all the raw observations must be transmitted in real time, which can fatigue bandwidth budgets, raise power usage, and introduce latency due to network congestion or queues in cloud computing. Edge processing can provide data compression by utilizing urban knowledge and contextual understanding. Compression methods may be based on filtering and denoising signals, local extraction of features, local fusion of multiple nearby sensors, and transmission of only the salient summaries or the detected features. This is especially so when using battery-powered and solar-powered deployments whose energy usage is mostly done through radio transmission. Graceful degradation is also assisted by edge intelligence. In case of backhaul network failure, as happens in remote watersheds, mountainous wildfire areas, or post-disaster conditions, alerts can still be generated via local inference or refer to a store-and-forward mode until uplinks are re-established. In industrial applications and sensitive and private public implementations, edge processing can be used to further reduce the risk through curtailing the exposure of unprocessed, location-centric, or potentially identifying data.

Nevertheless, the trend in distributed intelligence presents new technical and governance issues. It is an area of environmental sensing that is subject to uncertainty and confounding. The sensor readings are affected by temperature, humidity, cross-sensitivities, biofouling, height of placement, airflow, and biomicro-environment. Inexpensive sensors may give useful relative information and improve coverage; nevertheless, the sensors need constant calibration and quality control to prevent false alarms. The machine learning models that are trained somewhere or at some time might not work somewhere else because of domain shift. There should be a trade-off between real-time anomaly detection and the operational costs of false alarms that can destroy trust and cause alarm fatigue. Another problem with edge deployments is lifecycle management: software stacks may be discontinued by heterogeneity across hardware platforms, compute resources need to be allocated over-the-air safely, and models need to be updated. Security is not a concept, and systems can be vulnerable to sensor spoofing attacks, data-to-data tampering, or poisoning attacks, which could deteriorate models or give spurious warnings. This means that such smart sensing should be combined with systems intelligence, which includes solid engineering policies towards reliability, provenance, security by design, and open governance [13,14].

The literature has, in turn, increased at a very fast pace, but is still in bits. The themes that sensor-related studies keep offering are mostly calibration, characterization of drift, and field validation, whereas systems and networking are more focused on the latency, throughput, and resource management aspects of the selection. Machine learning studies provide effective ways to detect and predict, but can be underspecified in operational requirements of intermittent connectivity, limited labels, or the fact of maintenance. What is required is the coherent viewpoint of considering the design decisions in the entire pipeline: the impact of sensing modality and location; the impact of networking limitations on sampling and reporting policies; the impact of edge-cloud segregation on model development and update frequency; and the evaluation metrics must be on the end-to-end performance as opposed to the accuracy of individual elements [3,15]. This is one of the syntheses that this review will seek to offer by grouping the field based on architectural patterns and practical requirements that are replicated across applications.

In particular, this article contributes to four aspects. First, it suggests an end-to-end reference system of smart environmental sensing machines and describes the functions of device, edge, and cloud layers, and defines typical forms of edge cloud collaboration (e.g., edge-first inference on cloud training, hierarchical aggregation, and event-driven reporting). Second, it integrates design with design sensing and infrastructure sensing and infrastructure design that includes sensor modalities, node and gateway design, power management, calibration strategies, and connectivity, all through the perspective of real-time operation and maintainability. Third, it questions real-time analytics and AI solutions and is specifically pertinent to environmental sensing, such as streaming data processing, sensor fusion, anomaly detection, spatiotemporal forecasting, on-device inference, Tiny Machine Learning (TinyML), federated and privacy-preserving learning, and uncertainty quantification and interpretability. Fourth, it describes deployment realities such as data governance, when relevant, data digital twins, reliability engineering, security and privacy, as well as ethical implications, including coverage bias, and environmental justice, and advises on the approach entailed by further evaluation that captures field presumably better behavior and reproducibility [3,16–18].

The rest of the paper will be structured in the following way. In Section 2, the end-to-end architecture of intelligent environmental sensing systems is given, and patterns are defined on the distribution of computation through the devices, edges, and through the cloud. Section 3 is the review of sensing modalities and infrastructure, such as the calibration and networking issues that are of relevance to real-time monitoring. Section 4 is devoted to real-time analytics and AI methodology with an accent on the notions of resilience, uncertainty, and edge-deployable learning strategies. Section 5 discusses deployment, governance, security, and evaluation, and is concerned with lifecycle management and operational measures. Lastly, a synthesis of the main lessons and an outlook of the future open research are presented in the last section (Section 6) of this article, which covers self-calibrating sensor fleets, multimodal fusion with satellite and mobile sensing, robust learning under domain shift and extreme events, and sustainable carbon-aware analytics.

Intelligent environmental sensing systems can transform this trend by providing a step change in the character of societies' monitoring and responding to environmental change: a shift in the sparse and retrospective measurement character to the dense, adaptive, and decision-making orientation of monitoring [19]. To make good that pledge, however, designs are needed, not only ingenious, but stable, safe, and responsible to the grim circumstances of the real world. The review is to be a guide to such design options, a roadmap to the new technical landscape, and an impulse to research that can get intelligent environmental monitoring on a large scale responsibly deployed.

2. End-to-End Architecture of Intelligent Environmental Sensing Systems

The intelligent environmental sensing systems can best be thought of as end-to-end pipelines wherein physical phenomena in the environment are converted into digital observations and subsequently into time-sensitive decisions [3,20]. Based on intelligent systems, systems such as sensing, computing, communicating, and analytics are explicitly co-designed to ensure that the logical features of device aspects, such as device latency, reliability, energy, and trustworthiness, respond to organizational demands. Unlike traditional monitoring, where such aspects are often not explicitly related to interpretation, sensing, and computing are horizontally connected, and communication and analytics are horizontally connected. Here, the architectural principles that are repeated on deployments are synthesized, and a reference view that aids in positioning the IoT devices, edge resources, and cloud services as complementary constituents of a single, flexible monitoring stack is proposed.

2.1. Reference Pipeline and Architectural Principles

One example of a typical reference pipeline is: Sensing and local signal conditioning are followed by data transport and intermediate processing, which then leads to analytics, visualization, and intervention. Although the actual implementation is different between the fields of air quality, water resources, industrial emissions, and disaster response, the architectural tensions are recurrent. Environmental signals are frequently noisy and highly context-dependent, triggering a motivation towards preprocessing and quality control of these signals at early stages. The bandwidth, cost, or intermittent connectivity of communication links often limits communication, which encourages selective transmission and event-driven reporting. A wide variety of applications demand time-sensitive results, and this drives the computation near the data sources to minimize end-to-end delay. Lastly, the environmental monitoring is commonly used over long periods under uncontrolled environments, which drives the architectures to be able to cope with sensor drift, changing environmental regimes, and evolving analysis requirements without relying on persistent human intervention [21].

The fundamental architectural tenet that ensues is that real-time is an end-to-end property and not a component property. High-speed anomaly detector fails to generate real-time monitoring in cases where sensor sampling is sparse, there is a high rate of packet loss, and/or cloud-side bottlenecks with a delay. On the other hand, large rate sampling and intense deployment will provide no actionable insight in the absence of calibration and uncertainty management. To this end, architectural design needs to discuss sensing, networking, edge computing, and cloud analytics as an integrated system where the performance of these systems needs to be measured in terms of common latency-accuracy-cost trade-offs [22].

2.2. Layered Architecture: Device, Edge, Cloud, and Application Planes

Several intelligent environmental sensing systems may be structured into a four-plane interacting layer architecture. The plane device is composed of sensors and embedded computing used to sample, perform some basic signal conditioning, and provide initial local storage [23,24]. Environmental examples of heterogeneous modalities on the device plane are electrochemical, optical, air sensors, turbidity and conductivity sensors in water, noise or machine monitoring acoustic and vibration sensors, cameras or multispectral imagers, and temperature, humidity, and radiation multiclimate packages. Devices frequently need to work under very tight power constraints and very poor environmental constraints, and this renders robustness and energy-conscious scheduling to be as crucial as crude sensing performance. In practice, the devices often have local checks of sanity, stamping, and limited buffering to deal with temporary disconnections.

Figure 1 provides a reference end-to-end architecture that clarifies the roles of the device, edge, cloud, and application planes and highlights where latency, governance, and feedback loops arise.

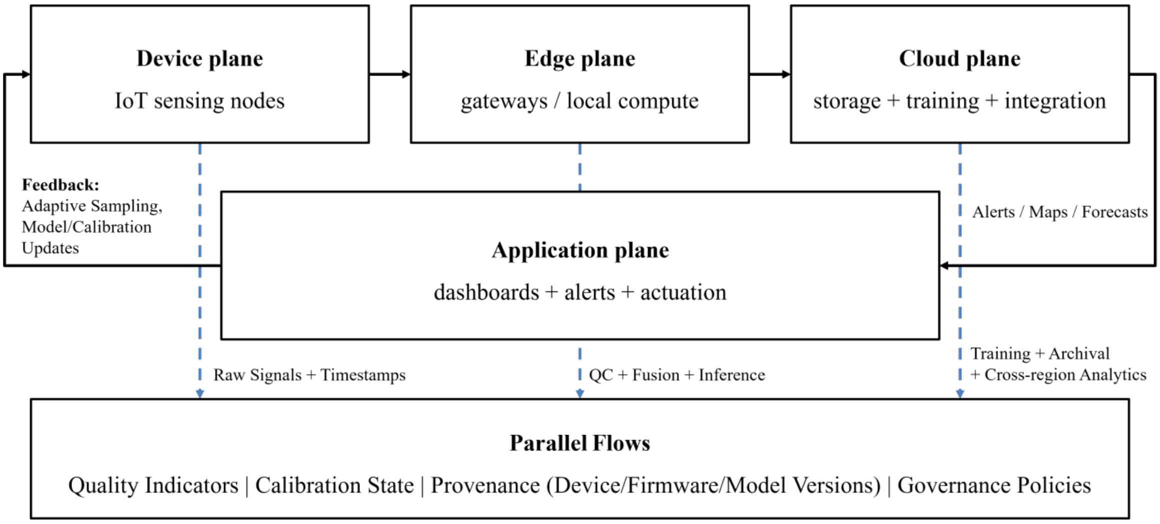

Figure 1. Reference end-to-end architecture for intelligent environmental sensing systems, showing the device, edge, cloud, and application planes, bidirectional feedback loops (adaptive sampling, calibration/model updates), and the parallel flow of measurements, quality indicators, and provenance metadata.

The edge plane is located close to the sensing assets and offers a level one scalable compute and coordination [9]. The physical locations of edge resources can include physically co-located gateway, roadside unit, base-station compute, on-premise industrial server, or small-form-factor edge clusters in municipal utility facilities. Operations that are generally the domain of the edge plane include aggregation of multi-sensor streams, low-latency inference, local fusion and interpolation, and compression/summarization of data before transmission, or security policies and data control are enforced at the interface between local networks and larger infrastructures. With device heterogeneity with cloud uniformity, the edge plane is also subject to mediation between protocols by protocol translation, protocol identity management, and protocol updates administered over-the-air. In the environmental deployments where there is intermittent backhaul, the edge plane is the continuity layer, which ensures continuity in the system during outages by providing store-and-forward behavior and local decision-making.

The cloud plane also offers elastic resources in long-term storage, fleetwide analytics, large-scale training of models, and cross-region data integration [9,25]. Cloud capabilities, especially the ability to provide historical context, e.g., trend analysis, seasonal baselining, and the ability to reprocess the data with better calibration or updated models, are of benefit to environmental monitoring. Other integrations with third-party data sources like meteorological reanalysis, land use and traffic proxies, satellite observations, and regulatory reporting systems have integrations at the cloud plane. Cloud platforms do not offer latency or reliance on connection, even though they allow centralized visibility and control. As a result, cloud functions are best combined with edge functions that pre-structure information, give priority to events, and ensure continuity.

The application plane is the plane containing interfaces and workflow within which monitoring outputs are used and responded to [2,3]. The application plane is, in certain instances, mostly human-facing, and it comprises dashboards, exposure maps, and alerting systems consumed by agencies, operators of facilities, or communities. When there are other cases, they involve machine-to-machine control loops, which in turn engage the ventilation response, modulate industrial processes, optimize irrigation, or emergency response. The application plane is a constraint on an upstream plane. An example is the alarm-fired workflows, which require interpretable alerts, stable false-alarm performance, and clear uncertainty communication, whereas planning-oriented workflows require calibrated system-aggregated indicators and reproducible reports.

The main feature of mature systems is the fact that these planes are not used as a one-way pipeline. They form feedback loops. Edge and cloud analytics make decisions that describe the adaptive sampling, inference on the placement of sensors, and refined calibration studies. Feedback on operators and the results of incidents is used to train the model and adjust the threshold. The policies of governance determine the data that is being stored, processed, and shared. Architecture is therefore more of a dynamic control process than a fixed data flow [3,26,27].

2.3. Edge–Cloud Collaboration Patterns

The intelligent environmental sensing is commonly characterized by edge-cloud collaboration, and several patterns seem to be recurrent in the literature and practice [28]. A typical trend is first edge inference that is based on cloud training and validation [29]. In such a design, the edge plane will execute lightweight models as event detection, initial classification, or short-horizon nowcasting and reserve more compute-intensive training cycles, global models, and periodic recalibration on the cloud plane. This trend is very much in line with conditions when quick local awareness is necessary, but world history enhances model development. It also helps in continuous improvement since, when the updated models are verified, they can be pushed to the edge nodes.

The second pattern is hierarchical aggregation, in which we have calculations at levels starting with devices, then progressing towards gateways, and then to regional nodes, and lastly, we get cloud services [9,30]. The different tiers do aggregation and quality control, respectively, that suit them. Sinus mode, signal conditioning, and outlier suppression are the concerns of device-level processing. Gateway processing level consolidates local sensors, implements a data schema, and produces concise summaries. The regional nodes can be across the neighborhoods or watersheds and enhance spatial modeling and coordinated response. The cloud has an inter-regional and intertemporal nature that will allow a wider situational awareness and policy-rich indicators. Hierarchical aggregation is a useful technique in large-scale monitoring programs where bandwidth and operational costs impose limitations on the transmission of raw data and where the local context should be maintained, and still learning should be possible over the fleet.

The third trend is event-based analytics, whereby continuous streams are tracked locally, but only salient events cause high-rate reporting or cloud bursting [31]. The environmental systems have a tendency to encounter the quiet majority problem: the majority of the observations can be taken as a baseline, and decision value is concentrated in a few episodes, including exceedances, spills, or a rapid change. Event-based designs rely on edge processing to identify candidate events and subsequently slow down sampling, send more information, or ask mobile assets to sensitize. The benefit of this pattern is to use fewer resources and increase responsiveness; however, there are design issues of missed detections, threshold tuning, and the requirement of strong baseline models in seasonal and diurnal variation.

Fourth is adaptive offloading; the tasks are relocated between edge and cloud based upon resource availability, network state, or urgency [32]. When the connectivity is stable, it is possible to send richer features or even raw segments to the cloud to create better cloud-side inference and archival. In the cases of outages or overload, the system might increase the use of edge inference and send only summaries, which are compressed, or batches delayed. The concept of adaptive offloading can be specifically applied to battery-powered deployments and remote locations where the energy and connectivity conditions can be extremely unpredictable. The architectural issue here is to formulate analytics in a way that avoids adverse effects on consistency, interpretability, and auditability of outputs when changing the contexts of execution.

Among these trends, one problem that keeps recurring is how model and data versioning are managed. The edge nodes can be operating on different versions of the model as they are being rolled out or because of intermittent opportunities to update. The streams of data can be indicative of calibration process variations or sensor replacement. Provenance should be a first-class architectural concern when it comes to environmental monitoring, where there is potential to contest decisions and where there may be regulatory consequences when reporting. Good edge cloud co-operation therefore needs to not only partition computation but also orchestrate software, models, calibration conditions, and metadata [10].

In order to compare these collaboration strategies, **Table 2** compares typical edge-cloud patterns in terms of task placement, conditions of best fit, and typical risks that may result in a lack of credibility in monitoring.

Table 2. Edge–cloud collaboration patterns in intelligent environmental sensing, summarizing typical edge vs. cloud responsibilities, application fit, and recurrent operational risks.

Pattern	Edge Responsibilities	Cloud Responsibilities	Best-Fit Situations	Key Risks/Failure Modes
Edge-first inference, cloud training	Real-time detection, local QC, feature extraction	Model training/Validation, global analytics, archival	Time-critical alerts; intermittent backhaul	Model/Version drift across sites; inconsistent provenance
Hierarchical aggregation	Local fusion and summarization; gateway buffering	Cross-region fusion; long-horizon forecasting	Large fleets; bandwidth-constrained networks	Over-smoothing can hide local failures/Events
Event-driven escalation	Baseline monitoring; trigger high-rate capture	Forensic analysis; event correlation across systems	"Quiet majority" streams with rare high-value events	Missed events if triggers fragile; threshold tuning
Adaptive offloading	Shift tasks based on energy/Connectivity	Elastic compute for heavy workloads	Remote/Energy-limited deployments	Output inconsistency when execution context changes
On-prem edge dominance	Low-latency inference; strict governance	Limited or periodic sync	Industrial or privacy-sensitive contexts	Reduced global learning; operational burden localizes

2.4. Data Semantics, Interoperability, and Time–Space Alignment

It is common to find that, in many cases, environmental sensing systems fail not due to poor-quality algorithms, but due to the impossibility of combining heterogeneous data reliably [7,33]. The semantic layer of an intelligent monitoring system is thus a uniform one that standardizes the meaning of measurements, the time stamping and geolocation of measurements, and the representation of uncertainty and calibration state. Environmental monitoring, in contrast to most other consumer IoT domains, requires high levels of comparability between time, devices, and locations. Measurements have to be associated with units, sampling period, sensor characteristics of response, and history of calibration. In the absence of these factors, downstream analytics leads to systematic bias in its amplification of inconsistency.

Time alignment is also important, particularly with real-time analytics. Numerous streaming applications, such as multi-sensor fusion, tracking plumes, and short-term forecasting, are prone to delay and clock drift. When data comes late or discontinuously as a result of buffering and patchy connectivity, event-time processing is required. Architectures in which timestamps are an orthogonal concept tend to produce fragile analytics, especially in distributed deployments that cut across a number of networks and administrative domains. Likewise, the spatial alignment demands attention to the representation of the sensor location, elevation, siting context, and mobility state. The effective measure of a sensor can vary with the wind or flow regimes or location relative to the sources of the emissions. Geospatial metadata, coordinate systems, and contextual descriptors, then, are of as much relevance to architecture as is the actual sensor value [34,35].

Another factor that interoperability establishes is the ability of the systems to scale and the ability of the systems to be integrated by multiple stakeholders [36]. The municipalities, utilities, industrial operators, researchers, and community groups are often involved in environmental monitoring. Exposing architectures with clearly defined interfaces, use of consistent data models, and integration with geospatial tools and time series databases make the integration of architecture cheap and allow cross-domain synthesis. Interoperability does not just stop at syntax but goes further to common definitions of the quality flags, the uncertainty assertions, and event types, without which meaningful fusion of heterogeneous streams is impossible.

2.5. Architectural Variants across Application Contexts

Even though the layered architecture has general applicability, the implementation varies based on the environmental situation and limitations in operations. In high-density city deployments of air quality, the systems can often use the large number of low-cost nodes with fewer reference-grade anchors [37]. Edge gateways can be installed either on the cabinets in the street, on the building, or in the cellular aggregation points. It is based on the architecture that focuses on spatial interpolation, hotspot detection, and exposure mapping, and edge processing is utilized to filter noise, anomaly detection, and bandwidth reduction.

Sensor networks used in watershed and coastal monitoring are often remote, power-limited, and sparse [38,39]. In this case, the architecture should be more resilient and store-and-forward in nature. The edge resources can be restricted to the rugged gateway, which undertakes the lightweight quality control and event detection to the cloud, which uses longer-term hydrological modeling, bloom risk prediction, and/or integration with the meteorological data. Event-driven escalation is appealing to communication limitations, where sampling and reporting should be increased in response to turbidity spikes, which signal erosion events or chemical proxies that signal contamination.

In industrial monitoring, the architecture can be installed inside controlled facilities and can make use of on-premise edge servers that are reliable, have power, and a local network/relay [40]. Edge inference is central in cases where the leak detection or process safety requirements are stringent in terms of latency. Security and governance are noteworthy as well, since data can be commercially sensitive, and adversarial tampering can lead to implications for safety. Intense identity management, partitioned networks, and regulated update systems are common in these systems, where cloud connectivity is selectively applied to fleet management and cross-site analytics.

Architectures in the context of disaster response, like in the case of wildfires, flooding, or chemical events, need to accommodate rapid deployment, mobility, and extreme infrastructure failures [41]. Opportunistic networks and mobile sensing platforms gain significance, and edge processing can be incorporated in vehicles or temporary field hubs. The architecture should have the ability to gracefully degrade, be partially covered, and give uncertain outputs to prevent misguided decisions with incomplete information.

In these variants, there is a general commonality that architectural success is given by the ability to match the location of the computation and the relocation of the data to the physiology of the problem and to the realities of operation. Phenomena in the environment change rapidly and have steep spatial gradients, yet the measurement of these phenomena is based on sensors whose response can drift, and the context of which can be unclear. Combining local intelligence, powerful semantics, and scalable cloud integration in architectures is more likely to deliver reliable value in comparison to those that perceive sensing as a mere data gathering activity [9,42].

The intelligent environmental sensing system architecture can best be characterized as an integrated co-optimization of the quality of sensing, communication, placement of computations, and reliability of analysis [43]. Devices give a proximity to the environment but can only work in severe circumstances. Edge resources can support low-latency and resilient intelligence, but have to deal with heterogeneity, energy constraints, and the complexity of the lifecycle. The cloud platforms offer size and history, but cannot replace the local reactiveness. The meaning of real-time and the degree of acceptable uncertainty is finally decided by the application layer. The end-to-end latency needs to be made explicit in the design of effective systems, as well as the integrity of data and models traveling through the pipeline. It is this architectural viewpoint that forms the basis of the following sections, where the sensing and infrastructure selections, real-time analytics, AI piping and deployment governance, and evaluation practices are explored in more depth.

3. Sensing, Networking, and Edge Infrastructure

Weaknesses: The intelligent environmental sensing systems are eventually limited by the physical and operational reality of the way measurements are obtained, transported, and processed in the field [21]. Though Section 2 outlined the end-to-end pipeline and edgecloud patterns of collaboration, the actual performance requires heavily the design of sensing nodes, communication substrate properties, and edge infrastructure capabilities that connect the heterogeneous devices into a coherent system. Environmental monitoring is not like much of the IoT world, where measurement errors are commonly dominated by context: the effect of temperature and humidity on gas sensors, the flow regime and biofouling of water probes, and the siting geometry of particulate measurements and the acoustic reflections of noise monitoring. Long deployment periods, periodic maintenance, and the requirement to work over seasonal cycles and extreme events are enhancement factors in these influences. It is thus a part that explores sensing modalities and platforms, node and gateway design, calibration and data quality at the source, networking and synchronization, and the edge computing stack as an integrated infrastructure issue, as opposed to a set of discrete components.

3.1. Environmental Sensing Modalities and Platform Choices

The space of measured variables is wide, and environmental monitoring applications provide different modes of error, dynamic response, and maintenance requirements. Gases that air quality sensors can be aimed at detecting include ozone, nitrogen dioxide, sulfur dioxide, carbon monoxide, and volatile organic compounds, as well as measures of particulate matter and meteorological covariates. Water conditions commonly encompass temperature, pH, turbidity, dissolved oxygen, conductivity, chlorophyll a or other optical substitutes, and, in certain contexts, measurements related to nutrients or contamination. Many of the applications of soil and agricultural sensing include the focus on moisture, salinity, and nutrient proxies, and microclimate that reflect on evapotranspiration and the stress of plants. Noise monitoring relies on calibrated microphones and signal processing authority to indicate metrics appropriate to the specifics of human sensory perception or standards, whereas that of radiation and industrial hazard monitoring can feature special detectors with uniquely challenging sampling and shielding requirements beyond what are suitable levels of common consumer-grade sensors [44,45].

In these fields, the choice of sensing modality cannot be made without the specific purpose of analysis [46]. Detecting the occurrence of events is often susceptible to high speeds of response and stable baselines, which is in contrast to laboratory-standard accuracy, as well as compliance and reporting, which need traceability to reference methods and sound calibration. The coverage and consistency of the forecasting and mapping tasks demand the use of the spatial coverage, which may prefer the use of the networks of moderately accurate sensors backed by solid fusion and calibration structures. The choice of the platform also demonstrates the logistics of deployment. Fixed installations are more stable in their siting and offer power opportunities; however, both can fail to detect localized gradients or moving sources. Mobile sensing, mounted on vehicles, drones, or wearable platforms, can bridge the gaps in space quickly and fix the spatial heterogeneity problem, yet with complex confounding due to observed variation mixing environmental change with mobility and changing exposure context. Hybrid systems are becoming popular, where fixed anchor points are used together with mobile surveys, whereby fixed sites are used to provide long-term baselines and mobile sites are used to provide targeted characterization.

Another factor is the relationship between environmental variables. Most of the sensors are cross-sensitive to confounders, which are also measurable. As an example, inexpensive gas sensors can need temperature and humidity correction, and optical particulate sensors can be vulnerable to hygroscopic proliferation because of humidity. Thus, systems with the right auxiliary sensors tend to be stronger than those that seek to individually measure a target pollutant. This can be followed by an architectural perspective where sensing nodes are viewed as multi-modal measurement systems that can be used to facilitate downstream inference, and not single sensor terminals [47].

3.2. Node and Gateway Design under Field Constraints

The environmental sensing nodes are generally created around a trade space between measurement fidelity, energy autonomy, ruggedness, and maintainability [48]. In most deployments, the resource that is most constrained is not raw compute capability but the capability to be able to run for several months unattended and have no changes in measurement behavior. Power system design is thus a key variable of sampling strategy and frequency of data reporting. The nodes that are battery-powered should be cautious in planning sensor warm-up, duty cycle radios, and peak loads of transmission. Solar-powered nodes have to contend with both variations in irradiance and seasonal variations, necessitating tight budgets in power (and storage) sizes. Enclosures in harsh environments need to support ingress protection with thermal control, and airflow needs to affect the validity of measurements, especially with air sensors, where confined stagnant sampling chambers can bias measurements.

Embedded computer options include low-power microcontrollers and single-board computers, and these options will impact how analytics will be located and the risk of operational failure [49]. Microcontroller-based nodes are better at deterministic timing and consuming less energy, with basic preprocessing, feature extraction, and event flagging, when combined with TinyML-class models. Single-board computers and platforms with greater capabilities enable more aggressive on-device analytics and more capable software stacks; however, they can have a greater risk of failure by virtue of storage wear, complex operating systems, and greater power consumption. The gateways used in most architectures have stabilizing effects in that they allow sensor nodes to have a smaller software footprint, yet still have local intelligence. A gateway may consolidate a group of nodes, protocol translation, security policies, and buffer data in times of network failures. It is also capable of sustaining local calibration logic and cross-sensor validation, which would be hard to achieve on highly resource-constrained devices.

Architectural requirements should be maintainability and lifecycle management, and not an afterthought [2]. Environmental nodes regularly need cleaning up, re-zeroing, refilling of reagents, or maintaining the optical path. A design that makes nodes hard to service, provides easy diagnostic telemetry, and has predictable failure behavior is lower cost of ownership and provides better data continuity. The facility to safely update via the air becomes imperative in long-term deployments, but there should be methods to maintain traceability of software and model versions. A sensing network with no confidence that the past readings are comparable to a particular firmware version, calibration state, and configuration parameter is going to have a hard time generating a defensible analysis.

3.3. Calibration, Drift, and Data Quality at the Source

The noise that characterizes environmental sensing is calibration, which is a problem due to the fact that not every target variable can be responded to in a straightforward and stationary manner by the sensors in the real world [50,51]. Even reference-grade instruments must be checked and maintained regularly, and even low-cost sensors may drift considerably over time, or due to contamination, environmental stress, or component variations. Smart sensing applications have the advantage of considering the calibration process as an ongoing process instead of a commissioning activity. This school of thought fits well with edge analytics and real-time analytics because drift may be identified and remedied in an incremental manner when the systems have constant bases, use reference anchors, and monitor contextual variables.

Calibration field techniques are either intense or sophisticated [52]. Co-location with reference stations is a gold standard of aligning low-cost sensors, although it can be operationally costly, and it might not resolve all the environmental regimes that it might encounter during deployment. Calibration site of rotation sensors may enhance consistency of the fleet, but comes with the logistical complexity and may create discontinuities in monitoring. In situ calibration methods seek to mitigate drift with ambient covariates, cross-sensor redundancy, or physics-based constraints. As a case, networks can take advantage of the spatial coherence of ambient concentrations, impose plausible limits on how fast changes can be, or can normalize measurements by meteorology to remove sensor artifacts due to environmental change. Edge computing is specifically helpful in this case since drift detection and quality control can be implemented closer to the data sources, which in turn will enable the system to mark the suspect measurements early enough, modify reporting behavior, and focus on maintenance even before the quality of data worsens significantly.

Figure 2 consolidates these practices into a lifecycle workflow that distinguishes automated and human-in-the-loop steps, making explicit how calibration state and model versions should be tracked for provenance.

Calibration is not the only problem of data quality. Often, environmental streams have missing values because of power loss or the sensor warming up [53]. They can be spiked due to electrical noise, condensation, or temporary interference. They could also contain valid extremes, like the fast rise of pollutants in the process of a fire or a drastic leap of conductivity in the process of a spill, which appear to be faults to unsophisticated filters. The strong quality control strategy should also be in a position to identify measurement artifacts and an important event, which is not a trivial inference problem. This drives an architecturally multi-stage pipeline of quality control where simple local detectors filter through high-level apparent faults and context-sensitive analytics of the periphery or cloud evaluate plausibility employing sensors on the surrounding, history, and environmental setting. The output is preferably not a binary good/bad indicator, but a structured quality signal with confidence scores, indicators of likely failure modes, and provenance of each decision to the rules or models that generated it.

Since sensing modality so heavily limits error modes and error mitigation opportunities, **Table 3** makes connections between common environmental sensor classes and common failure modes, as well as between practice, especially edge-enabled routines that minimize their effects in downstream inference.

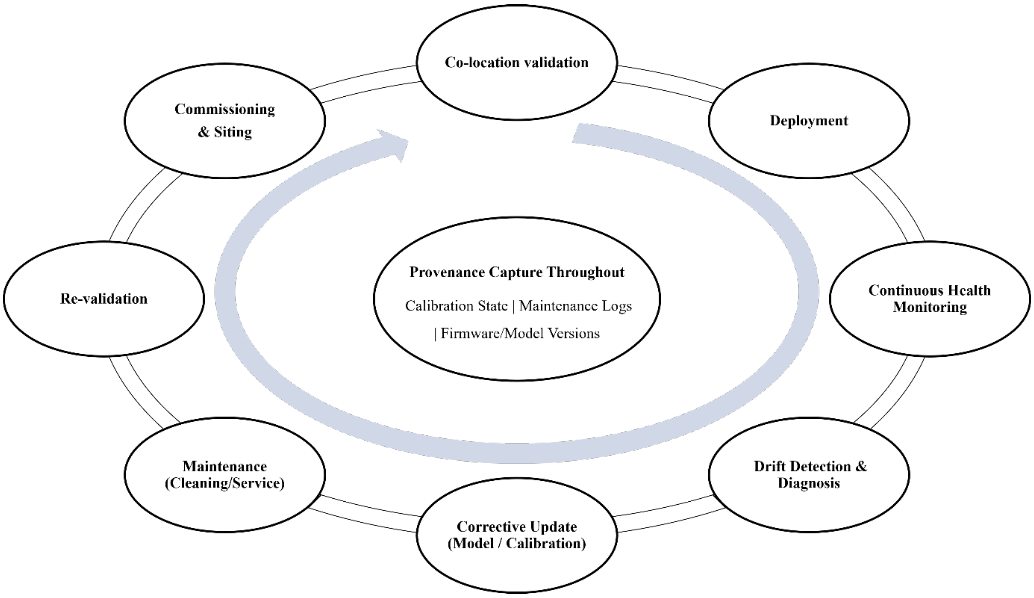

Figure 2. Calibration and drift management workflow across the sensing lifecycle, from commissioning and co-location validation to continuous health monitoring, drift detection, corrective updates, maintenance interventions, and re-validation, with provenance capture for calibration and model versions.

Table 3. Environmental sensing modalities and platforms, summarizing strengths, typical error/failure modes (e.g., drift, cross-sensitivity, fouling), and mitigation strategies including edge-enabled quality control and adaptive behaviors.

Modality/Sensor Type	Strengths	Typical Failure/Error Modes	Mitigation (System-Level)	Edge-Enabled Practices
Electrochemical gas	Low cost, deployable at scale	Cross-sensitivity; drift; humidity/temperature dependence	Co-location; covariate compensation; drift monitoring	On-edge baseline modeling; health scoring; adaptive recalibration triggers
Optical PM	High temporal resolution	Humidity effects; inlet contamination; calibration shifts	RH correction; periodic cleaning; reference anchors	Local denoising; event confirmation via nearby nodes
Water probes (DO/pH/cond./turb.)	Direct aquatic indicators	Biofouling; sensor aging; flow dependence	Anti-fouling measures; maintenance schedules; redundancy	Edge QC flags; anomaly corroboration; store-and-forward during outages
Acoustic/noise	Rich event signatures	Reflections; wind noise; calibration drift	Wind screens; calibration routines; site characterization	On-edge feature extraction; event classification; privacy-preserving summaries
Imaging/Multispectral	Spatial context and source cues	Lighting variability; occlusion; high bandwidth	Normalization; selective capture; compression	Edge pre-screening; upload-on-event; on-site redaction where needed

The representation of uncertainty is closely tied to calibration and quality control [54]. Environmental decisions often depend not only on point estimates but on whether an exceedance is sufficiently certain to justify action. Uncertainty can arise from sensor noise, calibration error, drift, spatial representativeness, and model approximation in fusion or forecasting. Systems that propagate uncertainty from the source, through edge summaries, into cloud analytics enable downstream components to make risk-aware decisions and reduce overconfident alerts. Practically, this requires consistent metadata that captures calibration age, last maintenance event, sensor health indicators, and the context under which correction models are valid.

3.4. Communication Substrates, Reliability, and Time Synchronization

A key factor in whether intelligent sensing can be operationally real-time or not is the layer of communication [55]. In many cases, environmental deployments are undertaken in areas with limited connectivity, like along a river, on mountainous terrain, on an industrial site with limited networks, or distributed farms. Connectivity options in such environments need to be compatible in terms of range, bandwidth, power usage, and cost. The low-power wide-area technologies are interesting in sparse data reporting and long battery life, and the cellular and high-throughput links may be useful in telemetry with more richness, firmware updates, and sampling rates. Remote monitoring can be supported by satellite connections, but could have latency and cost-related limitations that move more analytics to the edge.

Whenever networks are intermittently connected, reliability mechanisms are required [56]. Store-and-forward and buffering behavior allow the loss of data in the event of an outage but cause late arrivals and out-of-order streams, making real-time analytics more complex. To perform multi-sensor fusion and event reconstruction, there is frequently a need to reason in event time and not ingestion time, and this necessitates dealing with timestamps and clock discipline across nodes carefully. Time synchronization is not just a systems issue; thus, time synchronization is a precondition to a variety of environmental interpretations, such as plume tracking, source location, and the correlation between sensor observations and meteorological drivers. The architectures have to trade off the accuracy of the synchronization with the power and connection limits. In those cases where high precision is not available, the systems can use uncertainty-sensitive alignment explicitly representing the problem of timestamp error, which minimizes the chances of false causal interpretations due to misaligned data.

Communication is also engaged with energy consumption and local processing strategy [57]. Radio transmission has been found to dominate energy consumption in most low-power applications compared to sampling and computation. This drives architectures that minimize transmission volume by local summarization, adaptive sampling, and event-driven reporting. Non-coercive compression or under-reporting may, however, compromise the capability of detecting sensor failures, checking calibration, and running post hoc. One common design question is then how to apportion bandwidth between the data needed to make decisions and the data needed to diagnose the health of the system and the scientific interpretability of the system. Edge gateway may be used by keeping more detailed local logs and sending smaller segments of health information, and uploading selected raw segments when detected (with events) or in a maintenance window (with maintenance).

3.5. Edge Computing Stack and Operationalization

Edge infrastructure is the operational and computational substrate that renders the large sensor fleets manageable and provides low-latency intelligence [9,58]. The edge stack normally consists of data ingestion services, local storage to buffer data, a stream processing system, and run times to perform analytics models. The edge should also be capable of environmental sensing, managing, and authenticating devices, and providing secure update operations, since sensing nodes are often physically accessible and hence prone to being tampered with. The kind of edge hardware used determines the kind of analytics that can be executed, as well as reliability. Simple gateways can be powerful and energy efficient, more capable edge servers can use more capable models and multi-stream fusion, and more complexity and thermal and power.

End system software decisions have their own trade-offs. Containerization has the capability of making deployment simpler and allowing reproducible analytics across heterogeneous locations, although it can introduce overhead that is not appropriate when using small gateways. Lightweight ML runtimes are able to make use of on-edge inference, but need to be combined with streaming frameworks to support backpressure, late data, and fault recovery. Since the deployment of environmental monitoring is long-term, the edge stack must be accessible to teams of different expertise levels, which also increases the significance of observability: logging, metrics, health checks, and remote diagnostics. Unmonitored edge systems tend to remain silent, leaving data gaps or poor-quality data that is only found after a long period of time [59].

Infrastructure, in addition, is critical in cost management and sustainability. Edge processing will allow reducing the bandwidth requirements and will make decisions locally, which will reduce the cost of operation and enhance responsiveness, but it can also raise the energy consumption at the location. The best balance is contingent on the ability of the local computation to substitute the common transmissions, on the ability of the models to execute effectively on accelerators, and on access to renewable power to execute the deployment. Based on the energy state, the quality of connectivity, and the value of information that should be expected, these trade-offs are driving adaptive strategies that modify sampling and inference rates. The architecture is seen as positively impacting the environment through more explicit monitoring of energy budgets, and, where feasible, with the timing of operations that are compute-intensive, such as model updates, and times when ample amounts of power are available [60].

3.6. Integrated View: Infrastructure as the Determinant of Trustworthy Monitoring

The intelligent environmental monitoring sensing, networking, and edge infrastructure should be seen as one integrated system, which defines the viability and operational worthiness of downstream analytics [61]. The choice of sensors and platform influences data statistical characteristics and the nature of confounding to be handled in a model. The design of nodes and gateways determines the stability of measurements by seasonal cycles, and the fleet maintenance can be affordable. Calibration and quality control are the difference between insight and dense noise produced by dense sensing. The limits of communication define what can be conveyed and at what time, which defines the possibility of real-time detection and fusion. These components are connected via edge infrastructure to allow inference with low latency, outage tolerance, and steady control of device identity, software version, and metadata.

With infrastructure as a first-class concern, intelligent environmental sensing systems can escape a significant trap: analytics is the main source of intelligence, and the role of the field constraints and measurement integrity in defining the outcomes is underrated [62]. This foundation is then expanded in the following section, which discusses the most appropriate real-time analytics and AI techniques in combination with powerful sensing and edge infrastructure, and how such techniques can be reliable in the presence of drift, domain shift, and uncertainty common to environment monitoring.

4. Real-Time Analytics and AI for Environmental Intelligence

The interpretive fundamentals of intelligent environmental sensing systems are real-time analytics and AI [63]. They convert the diverse, noisy, and usually incomplete sensor feeds into predictions, maps, alarms, and estimates that are used to make time-constrained decisions. Real-time and real-time. In environmental monitoring, however, real-time hardly ever implies merely running something called a model in time. It involves consistent inference with delayed and lost data, non-stationary baselines due to weather and seasonal variations, sensor drift, and calibration variations, and the intense spatial heterogeneity that is the genesis of dense sensing to start with. The analytics layer should thus be formulated as an operational field that joins streaming calculation, statistical quality control, spatiotemporal logic, as well as uncertainty-conscious choice logic. This part will synthesize the real-time analytics pipeline that is widely implemented in practice and will assess the AI techniques that are most applicable to environmental intelligence, especially the edge-deployable designs and reliable results.

4.1. Streaming Analytics as an Operational Substrate

The data generated by environmental sensing networks are naturally represented as ones that vary over time, not as a static collection of data, and the behavior of all downstream analytics is affected by the choice of streaming substrate [64]. One of the key requirements is to identify the event and processing time. The observations may be received in a non-linear way when buffering telemetry devices, when buffering is delayed due to low-power links, or when buffering is reinstated after a disconnection. Even with purely arrival order analytics, fused estimates may suffer from a form of temporality, and alerts may be called too late or too early compared to the actual event in the environment. As a result, the mature systems embrace event-time processing, which relies on timestamps to coordinate data and explicitly deals with late arrivals. This is generally accompanied by windowing plans that specify the way statistics, features, or model inputs are calculated on a rolling basis. There is no arbitrary choice of window length. Short windows can capture sharp transients, but more noise is likely to be added, and false-alarm rates are likely to be higher. Long windows stabilize estimates, but the dynamics of onset that are important in emergency situations may be missed.

The streaming analytics should also be able to withstand backpressure and fluctuating data rates [65]. Bursts may also be triggered by environmental events, e.g., rapid transitions when the smoke intrudes or sudden increases in turbidity when a storm runs off. Meanwhile, some systems deliberately modify the sampling rates upon events. The analytics pipeline should be robust to these changes, which is the reason to design with graceful degradation by prioritizing critical computations, down-sampling less important streams, or resorting to approximate inferences when resources are limited. These issues become even more critical in edge deployments since they have limited compute and memory resources, and their throughput may be reduced due to power limitations.

In addition to throughput, streaming systems should not compromise interpretability and auditability [66]. The outcomes of environmental decisions are controversial, and the results of models can be used to conduct regulatory action or health guidance to the community. Real-time pipelines are consequently advantageous in generating not only outputs but also the contextual evidence of how the outputs were generated, such as the windows and other features that caused an alarm, the health of the sensor at the moment, and the uncertainty estimates on each inference. Architecturally, it means that streaming analytics is not just an implementation detail but the fundamental mechanism that allows for making sure that real-time intelligence can be traced throughout long-lived deployments. As previously summarized in **Figure 3**, operational real-time analytics often consists of a pipeline that consists of stages starting with event-time stream processing, preprocessing, context normalization, fusion, detection, forecasting, and uncertainty-aware decision outputs.

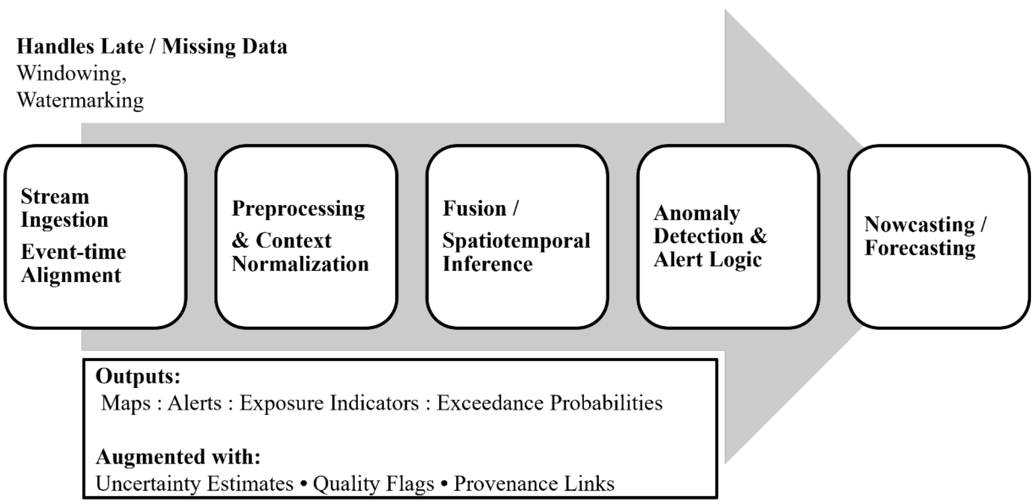

Figure 3. Real-time analytics pipeline for environmental streams, illustrating event-time processing (windowing and late data handling), preprocessing and context normalization, sensor fusion/spatiotemporal inference, anomaly detection and alert logic, and nowcasting/forecasting outputs augmented with uncertainty and quality flags.

4.2. Preprocessing, Feature Engineering, and Context Normalization

Environmental data are conditioned by confounding factors, which can overwhelm raw variability, especially with low-cost sensors [67,68]. Preprocessing is not merely denoising, then, as a kind of context normalization which may establish whether further AI activity is learning environmental structure or sensor artifact. The common preprocessing operations are outlier suppression, missing data, sensor response dynamics that are slow can be smoothed or deconvolved, and transformation to physically meaningful units. In real-time, preprocessing should be causal, i.e., it should not rely on future observations. This limitation may render certain offline methods inappropriate and incentivize filters that act progressively.

Even in deep-learning pipelines, feature engineering is still relevant since environmental models can gain from clear expression of meteorological situations, times cycles, and operational metadata [69]. An example is that the addition of temperature, humidity, wind speed, and direction or flow rate can be used to isolate true environmental variation and sensor cross-sensitivity. Likewise, a baseline can be stabilized by adding time-of-day and day-of-week in the urban environment, where the strong periodicity of traffic and activity can dominate the baselines. In the case of industrial systems, the operational state indicators might also be the key covariates that define the difference between process-driven emissions and ambient background. One of the most notable aspects is that the analytics pipeline must consider such contextual signals as first-class inputs, as very often it is hard to isolate the environmental phenomena and their drivers.

Normalization and baseline modeling are useful, especially in detecting events. A large number of environmental exceedances are characterized by local bases that vary between seasons, synoptic conditions, and long-term trends. An absolute value can consequently be poor in different regimes [70]. Adaptive reference behavior can be compared with baseline models, statistical or learned models, to determine anomalies. Real-time Baseline estimation needs to be resistant to contamination due to events, per se, and this is the motivation behind techniques that employ robust statistics, quantile-based baselines, or the explicit decomposition of background and event terms.

4.3. Sensor Fusion and Spatiotemporal Inference

The essence of modern environmental sensing is usually the ability to synthesize numerous inaccurate measurements into coherent spatiotemporal images [71,72]. Before sensor fusion takes place, it happens in several levels. Fusion at the local level can be used to make a combination of many modalities in a node to resolve cross-sensitivity and enhance stability. On the network level, fusion consolidates the observations on the surrounding nodes to minimize noise and enhance detection accuracy. By integrating ground sensors and external information at a regional level, e.g., meteorology, land use, traffic proxy, hydrodynamic model, or satellite retrievals, fusion produces both spatially complete and physically plausible maps and forecasts.

The geographical and time-based distribution of the sensors is a complex issue that makes it difficult to perform the process of inference spatially and at the same time over time [73]. The footprint of each measurement is affected by airflow, mixing, or flow pathways, and the representativeness of a sensor may vary with a change of conditions. As a result, interpolation techniques based on smooth spatial fields can inaccurately represent sharp gradients, point sources, or complicated terrain. In reality, the selection of a fusion technique can be seen as a compromise in operation. Kalman filtering, Gaussian processes, and kriging are classical methods of giving uncertainty estimates and can be computationally efficient when implemented correctly. Learned models, such as graph-based models and neural spatiotemporal structures, can learn the nonlinear relationships and incorporate contextual information; however, they must be carefully validated to prevent overfitting to specific locations or regimes.

One of the issues that keeps appearing is that fusion may mask local sensor failures on a network by averaging the results, which are realistic-looking but not correct. Strong fusion thus makes it necessary to explicitly integrate sensor health and quality flags into the inference [74]. In real-time operation, this may be as a weighting scheme, which down-weights sensors with drift or abnormal noise, or as a probabilistic model, which models sensor reliability as a latent state to be found. These kinds of designs connect fusion with quality control, once again driving the point that sound environmental intelligence comes about through pipelines that co-model environmental dynamics and integrity in measurements.

4.4. Event Detection, Anomaly Detection, and Alerting Logic

Numerous applications of intelligent monitoring with high impact are event-driven in nature [75]. The goal is to identify anomalies that would be of interest, including spikes of dangerous pollutants, industrial leakage, contamination incidents, algal spillage, or heat stress limits. In actual deployments, the greatest challenge is not the extreme signals detection but the meaningful events detection at an early stage, and the false alarms. False alarms have physical effects: they may initiate unneeded field response, destroy operator trust, and result in alarm fatigue, making it less responsive to genuine events. Simultaneously, false alarms may negate the whole essence of real-time surveillance. To encourage the alerting logic, the tension drives an integrated decision rule that is more than a model output but a combination of model scores, persistence criteria, spatial corroboration, and uncertainty thresholds.

The anomaly detection techniques range from rule-based thresholds and statistical change-point detection up to learned detectors [76]. The rule-based approaches are appealing to transparency and can be reasonable in well-characterized events, which, however, may not work in changing baselines. Statistical procedures that represent background variability can be better adapted, particularly those that are used when seasonality and meteorological covariates are included. Complex patterns can be learned by learned detectors, such as autoencoder-based reconstruction error, predictive models that signal when unexpected things are happening, or classification models trained on labeled events, but they are vulnerable to a relative lack of labels and domain shift. Ensuring environmental monitoring frequently does not come with large datasets of labeled incidents, and under these conditions, the unsupervised or loosely supervised methods are commonly used, though they have to be tuned and validated.

Multi-scale evidence is generally helpful in alerting logic. An isolated sensor spike can be a malfunction, but congruent changes on adjacent sensors, as per wind direction or wind paths, will be more likely to indicate an actual environmental event. Spatial validation, persistence requirements, and confidence scoring, which include a combination of several signals, are thus used in many systems. Used at the edge, this logic can cause adaptive behaviors, including adding the sampling frequency, asking mobile platforms to take more measurements, or adding detailed information to be uploaded to the cloud. Through these closed-loop interactions, it is possible to see how analytics may have a direct effect on sensing behavior, transforming the system into a more responsive and efficient system [21].

4.5. Nowcasting, Forecasting, and Predictive Environmental Intelligence

In addition to detection, intelligent systems have been working towards delivering predictive ability [3]. Nowcasting is concerned with refining the current state using raw sensor measurements in a way that is less accurate than achievable by conventional techniques and can be specific to the current condition or improve with delayed information. Forecasting further broadens this to near-future forecasts, which are useful in proactive activities that include the issuance of smoke exposure warnings, control of industrial process changes, predicting contamination propagation, or scheduling the field surveillance when situations are at risk.

Environmental setting Predictive modeling: It is difficult to predict the environment due to the interplay of both local sources and transport actions [77]. Most successful predictive systems tend to be a combination of models and data that are influenced by physics or domain knowledge. As an example, wind fields and atmospheric stability may be used to limit possible plume movement, and hydrological flow models may be used to limit contaminant transport. Even when generalization and avoidance of physically implausible predictions are desired in situations where full physics-based models are not possible at the necessary resolution, simplified constraints can be used to enhance generalization. Pure data-driven methods can discover correlations that allow predicting over short horizons using spatiotemporal models, but these have to be tested over seasons and extreme events in order to be found to be robust.

The need to measure uncertainty in a decision-relevant manner is also brought by operational forecasting [78]. To most of the stakeholders, knowing the specific predicted level is not as important as knowing the likelihood of exceeding a level in a given duration of time. Probabilistic forecasting is compatible with risk-based decision making and can be used as part of alerting systems, which can trade false alarms for missed events. Significantly, uncertainty can frequently be dominated by quantities not well modeled by model architecture, such as sensor drift, sparse coverage, and rapid regime change. The systems that clearly reflect such sources of uncertainty will be better placed to ensure trust even in an uncertain reality.

4.6. Edge AI, Resource Constraints, and Distributed Learning

The central element of the intelligent sensing vision is running analytics near the data source, but edge deployment puts constraints on model design that can redefine it [9]. Edge nodes can have few compute, memory, and energy resources, and can be forced to operate at a steady state with deterministic latency. These limitations encourage the lightweight models and effective inference plans. Quantization and pruning are model compression methods that can be used to decrease the cost of computation, but these techniques have to be applied with care to maintain calibration and robustness, especially when the model is applied to make threshold-based decisions. Simple models with powerful feature engineering may be preferred to complex models in a wide variety of environmental tasks with distribution shift and low label conditions, and are typically easier to interpret by operators.

The distributed learning strategies are appealing because data is not centralized due to bandwidth constraints, privacy issues, or governance restrictions [79]. Federated learning provides a way to learn common models in many sites without necessarily transferring raw data, but environmental data are unique due to big differences in local distributions in terms of geography, season, or sensor type. This non-uniformity may cause models that perform well on average but poorly in particular places. Construction of pragmatic federated deployments consequently frequently demands individualization tools, hierarchical training schemes, or domain adaptation techniques that maintain local faithfulness and enjoy the advantages of mutual learning. The other complication is that environmental monitoring is often based on site-specific calibration relationships. A structural configuration that does not place importance on these correlations can unintentionally confound sensor artifact with variation of the surroundings. Due to this fact, distributed learning is to be matched with the clear management of the calibration state and sensor metadata.

Practices of model update are more complicated in edge environments as well. The constant release of new models is capable of enhancing performance, but also leads to alerting behavior destabilization, complicated provenance, and inefficient comparison of measurements between time periods. Operational systems thus enjoy the advantage of rollouts in stages, shadowing of new models where they are run in parallel with no decisions regarding control, and explicit versioning, which associates each inference with the model and the configuration that was used. These are typical of mature software systems, but not yet commonly applied to environmental monitoring, where analytics pipelines are at times considered more of a research object than a part of operational infrastructure [80].

4.7. Trustworthy Analytics: Uncertainty, Explainability, and Robustness

Credibility is a pragmatic need in environmental surveillance since judgments have an impact on the safety of the people, their adherence to regulations, and resource allocation [81]. Credible analytics should start with meaningful uncertainty quantification for the end users. The scores of confidence should show not only model fit but also the quality of the data, sensor health, and representativeness. As an example, exceedance reported by a sensor that has just been calibrated should not be reported in the same way as exceedance that is supported by several healthy sensors. In the same way, forecasts are expected to show when conditions are not within the same regimes that occur during training, indicating high uncertainty.

Operationally, explainability is also important [82]. Environmental operators usually need to know the reason why an alert was raised, whether it indicates a feasible environmental process, and what evidence is in support of it. The contextual meaning of explainability has less to do with post hoc feature attribution and more to do with giving consistent accounts that are consistent with domain knowledge, e.g., the direction of the wind, how persistent it is, and how consistent it is across sensors. This can be assisted by edge systems that add diagnostic context on a small scale to alerts such as most recent trajectories, proximity sensor corroboration, and quality flags.

Resistance to drift and domain shift is possibly the challenge of environmental AI [83]. The models that are trained during one season can degrade during the next season, sensors become old, urban infrastructure evolves, and extreme events may lead to new conditions that are significantly beyond the historical experience. Strong analytics is then a mandate to continuously track model performance indicators, detect drift on input distributions and residuals, and retraining or recalibration triggers, which are controlled by explicit rules of operations. Catastrophic failure in the under shift can be minimized by hybrid designs that include physical constraints where feasible. However, at the end of the day, environmental intelligence cannot be trusted by a single algorithmic gimmick but by systems where uncertainty, provenance, and robustness are components of design.

The combination of real-time analytics and AI facilitates intelligent sensing of the environment by creating the means of interpretation, prediction, and action within a temporal framework. However, the unique systems requirements of environmental monitoring, nonstationary baselines, sensor drift, sparse ground truth, and high spatial heterogeneity imply that the outcome will rely on operationally founded pipelines, as opposed to isolated model action. Streaming substrates should be able to accommodate event time, late data, and bursts. Normalization of context should take place in preprocessing, but should not abort genuine extremes.

Fusion should be able to combine data quality and sensor reliability. Detection and alerting should have an equilibrium between early warning and the costs of a false alarm. Forecasting should be a quantification of the uncertainty in terms of a decision. Edge AI should take resource limits and lifecycle management into consideration. These needs drive the analytics stack to a harmonized field that connects the creation of the algorithm to the trustworthiness of the system. Section 5 extends this perspective and considers the deployment, administration, security, and assessment of such systems on real-world platforms where credibility is essential regarding operations, rather than analytical precision.

5. Deployment, Governance, and Evaluation in Real-World Systems

Throughout the shift between prototype sensing networks and reliable working systems, there is seldom a technical bottleneck that limits the transition [84]. Rather, it is influenced by the concomitant existences of deployment logistics, lifecycle maintenance, information governance, security and privacy imperative, and the difficulty of measuring performance in nonstationary environmental circumstances. The nature of environmental sensing is both temporal and locational: systems need to be seasonal and operational on the extremes, can withstand the severe conditions, and be decipherable and credible by a broad group of stakeholders. In contrast to most other IoT applications, where a service might be able to survive sporadic degradation, environmental monitoring may involve public health, regulatory, or even safety consequences that require a measure of responsibility. It is through this part that the practices and design factors that define the ability to maintain intelligent environmental sensing systems at scale are synthesized with a focus on reliability engineering, data management and semantics, security and ethics, and a set of evaluation methodologies suitable for real-time, edge case monitoring.

5.1. Reliability, Resilience, and Lifecycle Engineering

Continuity of credible operation is the most appropriate conception of environmental sensing, not just of device uptime [85]. A network may be technically online and generate biased or implausible measurements due to drift, change of siting, fouling, or degradation of the hardware by subtle mechanisms. On the other hand, a designed system can fail to connect temporarily without compromising the measurement integrity due to buffering, local validation, and strong recovery. This is the reason why reliability engineering cuts across several levels: sensor health, power and environmental robustness, communications continuity, edge software, and the operational processes that control maintenance and updates.

Field deployments often experience conditions that are uncommon in laboratory setups. Enclosures may become overheated or collect condensate, the inlets may be blocked up with insects and dust, and the water sensors may become biofouled or clogged with sediment. Such physical facts drive the motivation of designs that consider servicing as a normal lifecycle occurrence and not a failure. Sensor modality and environment should be informed of maintenance procedures and schedules, which are informed by telemetry predicting degradation. As an example, internal temperature, supply voltage, pump duty cycle, inlet pressure, optical signal strength, or baseline noise can be monitored to give early warning of an imminent failure. The practical usefulness of such telemetry is that it makes predictive maintenance possible, which limits the rate of corrupt data silently and eliminates long downtimes.

Resilience is directly related to the edge layer, as mentioned above. In most monitoring situations, the backhaul connectivity is not to be counted, particularly in cases of disaster when the environmental intelligence is most required. Resilient deployments thus embrace buffering and store-and-forward techniques that ensure continuity of data and the ability to make local decisions in the event of partitions. Graceful degradation is also a part of resilience in operational systems. Under conditions of resource limitations, prioritization of the system must be made on the most crucial functions, e.g., the maintenance of calibrated measurements and generation of conservative alerts, whereas the uploads or reprocessing that are not crucial can be postponed. The process of designing these degraded modes needs to be an explicit policy-making regarding what is considered essential in each application, and the policies in question must be disclosed to the stakeholders [86].

Software and model management are also a part of lifecycle engineering. The security vulnerabilities, as well as the calibration logic and better analytics models, tend to be patched through over-the-air updates. However, uncontrolled updates may compromise the comparability of time series and make alert auditing more difficult. Mature deployments hence enjoy versioned releases, rollouts in subsets of devices, and shadow operation where new analytics are run in parallel without making decisions that would be validated. These ensure that the threat of destabilising system behaviour is mitigated and traceability is maintained. In environmental monitoring, where historical data are often re-improved to understand trends, lifecycle engineering should require the same meticulousness in recording software, configuration, and model changes as sensor maintenance and calibration [87].

5.2. Data Management, Semantics, and Provenance for Environmental Streams

Intelligent environmental sensing is not merely about the storage of data [88]. It is concerned with the continuity of meaning across time and between heterogeneous devices to defend outputs. Environmental streams are contextual; a concentration value cannot be measured outside of its units, sampling mode, calibration condition, siting condition, and uncertainty. In the absence of these, subsequent reconciliation and prediction may generate fake news that seems reasonable, yet is not reliable. As a result of this, efficient systems will consider metadata, provenance, and quality signals as an equal data product that moves through the pipeline equally to measurements.

The time-series storage and geospatial indexing are usually operational deployments and support real-time dashboards, as well as retrospective analysis. The architectural issue is to handle multi-resolution data products. Real-time systems can generate minute-level summaries, event flags, and alert records to be consumed quickly, and also retain raw or high-frequency segments to be used in forensic analysis, recalibration, or model improvement. The conflict here is that storing all raw data may be costly, especially when dealing with large fleets and high-frequency modalities like acoustics or imagery, but excessive summarization may make subsequent validation impossible and compromise scientific use. One convenient solution is to store full-resolution data only at selected times, such as when an event has been detected, or at predetermined sentinel points, or in intervals of periodic diagnostics. This can be facilitated by edge storage, which can store raw data locally and only upload it when it is triggered by events or when it has connectivity and costs allow it to do so [89].

The capability of integrating data across agencies, projects, or geographic areas depends on semantics and interoperability [90]. Environmental programs can have a variety of stakeholders, with other instruments and data practices, and intelligent systems often have the goal of integrating IoT streams with external sources, including meteorology, satellite products, traffic proxies, and model outputs. Such integration can only be solid in the case that data models enforce similar naming, units, coordinate systems, time conventions, and quality flags. The presence of uncertainty and calibration lineage is equally important. In the case that the reading of a low-cost sensor has been adjusted using a site-specific model, the system is supposed to maintain the adjusted version, the training period, and the validity assumptions. Provenance allows users to understand the result correctly, and it can facilitate reproducibility when the analysis is revisited many months or years later.

When applied, the significance of semantic consistency is even more advanced by the use of digital twins and simulation-based components. A digital twin that satisfies sensor streams to determine the scenario depends on robust interfaces and definite uncertainty estimations. Practically, even partial digital-twin capability, i.e., simple use of simplified dispersion or transport models limited by sensor measurements, is useful because of smooth data standards and close coordination. The initial point is that environmental intelligence is not just calculated but rather preserved through the process of data governance, which maintains the interpretability over a period of time [63].

5.3. Security, Privacy, and Ethical Governance

In the deployment of IoT, security and privacy are considered as an addition, which is risky to the environmental sensing systems since they are vulnerable [91]. Most of the sensors are used in a public or semi-public environment, are physically available and networked, and can be shared or intermittently secured. The devices, gateways, and the analytics pipeline also form part of the attack surface. False alerts or concealment of actual events can be produced by sensor spoofing and tampering. Learned models may become corrupted by data poisoning, especially in systems that use continuous learning or systems that use weak supervision. Weakened update systems may host malicious firmware/model over a fleet. These are not just theoretical risks in the context of monitoring when the output is of economic and regulatory impact.

Security-by-design is usually initiated by identity and trust roots in devices, such as secure boot, signed firmware, and protected key storage, where practical [92]. Flexible communication systems minimize the threat of interception and manipulation, and update systems should also provide authenticity and integrity. However, environmental deployments should also take into account operational realities: field technicians might require useful provisioning workflows; connectivity can be too scarce to support heavyweight protocols; and devices can have limited compute. As such, security architectures need to be rigorous and deployable, and have a continuous check for anomalies in the behavior of devices, traffic patterns, and data signatures that could be indicative of compromise.

Even when the variables monitored are not necessarily personal, privacy will be an issue [93]. Environmental data of high resolution can allow determining the location, expose occupancy patterns, or disclose sensitive industrial processes. Mobile sensing platforms enhance this menace by gathering information across paths that can be associated with either individuals or personal amenities. Besides, in community monitoring, the exchange of data may have social and political consequences, including influencing property prices or building an understanding of a risky neighborhood. Ethical governance should thus have clear policies regarding the data granularity, retention, accessibility, and communication. It must be transparent: the stakeholders are supposed to know what is gathered, how it is handled, as well as what the uncertainties are. Equity matters are also at the center. The presence of monitoring networks may also unwillingly contribute to environmental injustice in that they can be deployed in a biased way, favoring better-resourced communities, and then under-observed vulnerable communities. Coverage, representation, and stakeholder participation. Governance frameworks that expressly consider and evaluate coverage, representation, and stakeholder participation are thus included in responsible system design.

As AI-based analytics inform an alert or intervention, ethics are further applied to explainability and accountability [63]. The systems ought to convey uncertainty and constraints openly, especially in extreme events where the models might be extrapolating untrained regimes. When deployed to a public-facing interface, any interface that puts forward numbers with no ambiguity may make people distrust it as soon as inconsistencies are found with reference tools or lived experience. A system that does not overconfidently assume and records its assumptions and has a feedback and correction mechanism is ethically robust.

5.4. Evaluation Methodologies and Benchmarking for Real-Time Systems

In environmental monitoring, evaluation is abnormally difficult since ground truth may be sparse, costly, and untrustworthy. The actual environmental state in most applications cannot be observed at the same resolution and scale as the sensing system is used. This renders inadequate the necessity to report just typical machine-learning measures or laboratory calibration outcomes. Real-time intelligent sensing systems need to be considered as integrated pipelines, in terms of metrics of sensing integrity, decision timeliness, and operational reliability in the field [94].

Table 4, to provide incentives for consistent reporting and to bring the experimental claims closer to the requirements of operations, defines the evaluation metrics in a layer-by-layer format that connects sensing integrity and timeliness to detection/forecasting performance, reliability, resource efficiency, and governance requirements.

Table 4. Evaluation metrics and reporting dimensions for intelligent environmental sensing systems, emphasizing end-to-end latency, detection timeliness, forecasting uncertainty, field generalization, resource efficiency, reliability, and provenance/security considerations.

Layer	Metric Category	Example Metrics	Why It Matters	Notes for Reporting
Sensing integrity	Accuracy and drift	RMSE/Bias vs. reference; drift rate; calibration age	Determines the credibility of analytics	Report regime (season/met), co-location design
Streaming timeliness	End-to-end latency	Sense-to-alert time; data freshness; late-arrival rate	Real-time is pipeline-wide	Include sampling interval, buffering, and network delays
Detection performance	Event quality	Precision/Recall; false-alarm rate; detection delay	Balances early warning and trust	Evaluate across baselines and extremes

Table 4. *Cont.*

Layer	Metric Category	Example Metrics	Why It Matters	Notes for Reporting
Forecasting quality	Predictive skill	MAE/RMSE; exceedance probability calibration; CRPS	Supports proactive action	Emphasize uncertainty and threshold exceedance
System reliability	Availability and resilience	Uptime, mean time between failure, recovery time	Sustained operation in the field	Distinguish "online" vs. "trustworthy" operation
Resource efficiency	Energy/Bandwidth/Cost	Energy per inference; bytes/Day; OPEX per site	Scalability and sustainability	Include power source assumptions and duty cycles
Governance/security	Integrity and traceability	Provenance completeness; update auditability; security incidents	Accountability in high-stakes contexts	Link outputs to model/config versions

Field validation by co-location and reference comparison is a foundational evaluation practice and cannot be done without co-location. The environmental conditions that are used during validation might be different from the conditions used during deployment, and performance could be affected by domain shift. As a result, evaluation is to be structured in such a manner that generalization is made between seasons, meteorological regimes, and extreme events. This may need time-split validation, as opposed to random splits, and location-holdout testing in which models are tested on sites they have not encountered during training. In the case of event detection, the test should be performed in terms of detection delay and false-alarm properties with realistic baselines. Detection delay is an important concern in most operational scenarios, since the goal is early warning, and classification accuracy does not matter [95]. There is an analogous measure of false alarms by frequency but by operational effect, e.g., whether they are clustered and hence the alarm fatigue.

Another important metric is end-to-end latency, and it must also be taken between physical sensing and the provided decision [11]. This encompasses sampling timings, sensor reaction dynamics, network delay, buffering conduct, edge processing time, cloud processing queues, and time taken to provide notifications or refresh dashboards. It is only important to measure the time of computational inference, which can be misleading when the main delays are elsewhere. Evaluation should also include energy and bandwidth costs when using the battery-powered application or remote deployments. Performance under limited connectivity, data transmitted per unit time, and energy per delivered inference are metrics that are more realistic to show the suitability of a system in a realistic picture than accuracy alone.

The problem of reproducibility and comparability is here to stay since environment deployments vary across the board. To enhance comparability, evaluation reports are to contain the comprehensive descriptions of the sensor type, the process of calibration, the deployment scenario, the schedule of maintenance, and the version of analytics models and preprocessing routines precisely. In case of systems that evolve with time, then the evaluation must record how and when models have changed and whether the performance metrics are a stable or a changing behavior of the model. Benchmarking may be supported when open datasets exist; however, the field must be aware that many datasets do not represent rare extremes as well as operational complexities (such as missing data and drift). A strict evaluation plan thus integrates guided benchmarking data with field testing indications, which are planned to undergo analysis under the circumstances in which they shall operate.

5.5. Operational Integration and Stakeholder-Centered Deployment

While intelligent environmental sensing systems increasingly rely on automated analytics and edge intelligence, human involvement remains essential for ensuring reliability, interpretability, and societal acceptance. Human-in-the-loop (HITL) design integrates domain experts, operators, and end-users into the sensing and decision-making workflow, enabling continuous system refinement and contextual validation [96]. In practice, human operators play a critical role in validating alerts and anomalies, particularly in high-stakes applications such as air quality warnings or disaster monitoring. Automated detections generated at the edge or cloud layers are often subject to expert review to reduce false positives and ensure appropriate responses. This interaction establishes a feedback loop in which human judgments inform model updates and system calibration.

System design is also informed by operational integration by determining alert thresholds, escalation logic, and expressing uncertainty [97]. One example is that a system that is required to issue an emergency response should have a tight false-alarm alerting threshold and be characterized by low false-alarm behavior, whereas a system that is only required to be used to gain situational awareness in an exploratory way can allow a higher number of false positives, provided that the system provides explanatory feedback. These choices must be clear-cut and reviewed at the system maturity. Feedback loops are necessary: incident reports, observations, and maintenance notes can serve as ground truth and be added to model refinement and calibration improvement by operators and communities. Structured feedback architectures that integrate it into analytics have a higher chance of getting better with time.

Beyond expert validation, feedback mechanisms from users and stakeholders contribute to system adaptability. For example, user-reported observations or corrections can be incorporated into model retraining pipelines, improving robustness to local conditions and previously unseen scenarios. Such mechanisms are particularly important in heterogeneous environments where purely data-driven models may struggle to generalize [98].

Furthermore, the integration of participatory monitoring and community science expands the scope of environmental sensing systems. Citizen-generated data, when properly validated and fused with sensor networks, can enhance spatial coverage and increase public engagement. Designing systems that support transparent data access, intuitive interfaces, and explainable outputs is therefore essential for fostering stakeholder trust. Finally, trust in intelligent sensing systems depends not only on technical performance but also on transparency, interpretability, and accountability. Providing clear explanations of model outputs, uncertainty estimates, and data provenance can help bridge the gap between automated analytics and human decision-making, ensuring that such systems are both effective and socially acceptable.

6. Conclusions

The smart environmental sensing systems are reshaping the scope of environmental monitoring of what can be delivered by providing dense, heterogeneous sensing with distributed computation and real-time analytics. The new paradigm does not consider monitoring a gradual process of pipeline of measurement to retroactive reporting, but as one of interpretation and the provision of decisions. In fields ranging from urban air quality to watershed protection, industrial safety, precision agriculture, and disaster response, the same fundamental lesson is applicable: environmental risk is usually local, dynamic, and episodic, and cannot be properly handled through the application of sparse measurements or delayed analysis. The combination of IoT sensing, edge computing, and streaming analytics provides a viable way to approach responsive, scalable, and more autonomous monitoring systems.

This review has contended that the attainment of the idea of environmental monitoring being intelligent is actually a problem of the end-to-end system. Distributed architectures, separating responsibilities both among devices and edge nodes, as well as among the cloud, can provide the ability to satisfy latency and resilience concerns and still enjoy the benefits of centralized training, long-term storage, and fleet-level governance. Nonetheless, these systems are limited to performance based on infrastructure realities, to the same extent as they are limited to algorithmic sophistication. The statistical characteristics of data and hence the bounds to the inferences that can be made are directly influenced by sensor modality, node design, power management, communications reliability, as well as calibration practices. Only the integrity of measurements and provenance of real-time analytics can be as credible, and strong pipelines must explicitly address the case of late data, missingness, nonstationary baselines, and domain shift.

The analytics layer has already grown mature, but environmental monitoring places some unique limitations, which deserve further investigation. Necessary tradeoffs between responsiveness and stability must be found in event detection, spatiotemporal fusion, and short-horizon forecasting to operational contexts with unavoidable costs associated with false alarms and undermined credibility. Edge AI provides the ability to make inferences with low latency and low bandwidth, which, however, come with the complexity of lifecycle inference in model deployment, versioning, and validation. The effective environmental intelligence has to rely on uncertainty-sensitive results, clear alert reasoning, and systems to identify and act on sensor and model drift. Practically, most effective methods would apply algorithmic innovations and strict operational discipline: progressive deployments, shadow testing, systematic quality control, and explicit provenance that identifies each output with calibration state and model version.

The governance and deployment eventually dictate the intelligent sensing systems to transcend pilots into a long-term effect. The engineers of reliability should consider maintenance, physical degradation, and the degraded-mode operation as the normal operating conditions. Data management has to be semantically and comparatively stable across time so that defensible analyses and integration across stakeholders and data sources can be done. It cannot be a peripheral aspect of security and privacy because field devices are exposed, and the data in high-resolution environments may be sensitive. To ensure that the outputs guide the audience narrative and resource distribution, ethics in governance (e.g., coverage bias) and environmental justice should be considered in the context of output monitoring. Evaluation practices should also change where the focus is on end-to-end latency, detection timeliness, false alarms, good behavior, seasonal and location robustness, together with resource efficiency, with realistic connectivity and power limits.

In the future, some directions seem to be particularly consequential. To begin with, self-calibrating and self-diagnosing sensor fleets, which include reference anchors, redundancy, and continuous quality modeling, may scale down operational burden, which is currently constraining. Second, multimodal fusion, which is a convergence of the ground IoT with satellite observations, mobile sensing, and physics-informed models, provides a path to fuller and more resilient situational awareness, especially during extreme events. Third, cross-site improvements could be promoted using distributed learning and privacy-preserving methods, such as federated and personalized modeling, which would not need to compromise local fidelity or governance limitations as long as non-IID environmental data and calibration heterogeneity are explicitly tackled. Fourth, quantification of uncertainty and interpretable, stakeholder-focused interfaces will also be essential in the establishment and maintenance of trust, particularly in situations where systems are applied to provide alerts to the public or regulatory bodies. Lastly, making sustainability a first-class objective: carbon- and energy-conscious sensing and analytics can bring the environmental monitoring infrastructure to the same level as other environmental objectives that it is destined to inform.

To recap it all, the combination of IoT, edge computing, and real-time analytics does not just modernize instrumentation but shifts the operational position of environmental monitoring from passive as a measuring tool to operational as a decision-making tool. To fulfill this promise on scale, co-designing is needed in sensing hardware, communications, distributed systems, analytics, and governance. Essential aspects are consistent, and when these components are combined, smart environmental sensing systems can give earlier warnings, more detailed insights, and fairer views of the environment and enable prompt actions to ensure health, ecosystem, and infrastructure remain safe in an increasingly unstable world.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Spiridonov, V., Ćurić, M., Novkovski, N., 2025. The New Era of Environmental Monitoring: Insights into Weather, Water, and Climate. In Atmospheric Perspectives. Springer Nature: Cham, Switzerland.

pp. 401–443. DOI: https://doi.org/10.1007/978-3-031-86757-6_14

[2] Fang, S., Xu, L.D., Zhu, Y., et al., 2014. An Integrated System for Regional Environmental Monitoring and Management Based on Internet of Things. IEEE Transactions on Industrial Informatics. 10(2), 1596–1605. DOI: https://doi.org/10.1109/TII.2014.2302638

[3] Ramani, D.R., Sujitha, B.B., Tangade, S., 2025. Smart Environmental Monitoring Systems: IoT and Sensor-Based Advancements. In: Suresh, A., Devi, T., Deepa, N., et al. (Eds.). Environmental Monitoring Using Artificial Intelligence. Wiley: London, UK. pp. 45–60. DOI: https://doi.org/10.1002/9781394270392.ch3

[4] Wilhelm, E., Siby, S., Zhou, Y., et al., 2016. Wearable Environmental Sensors and Infrastructure for Mobile Large-Scale Urban Deployment. IEEE Sensors Journal. 16(22), 8111–8123. DOI: https://doi.org/10.1109/JSEN.2016.2603158

[5] Bhuiyan, M., 2020. Solutions for Wireless Internet Connectivity in Remote and Rural Areas [Master's Thesis]. The University of Oulu: Oulu, Finland.

[6] Abbas, T., Eldred, A., 2025. AI-Powered Stream Processing: Bridging Real-Time Data Pipelines with Advanced Machine Learning Techniques. ResearchGate. DOI: https://doi.org/10.13140/RG.2.2.26674.52167

[7] Mahalle, P.N., Takale, D.G., Sakhare, S., et al., 2024. Machine Learning for Environmental Monitoring in Wireless Sensor Networks. IGI Global: New York, NY, USA.

[8] Belgacem, H., Chihi, I., 2025. Toward Reliable and Intelligent Sensor Systems: A Comprehensive Study of Fault Diagnosis and Mitigation. IEEE Sensors Reviews. 2, 511–536. DOI: https://doi.org/10.1109/SR.2025.3601092

[9] Ficili, I., Giacobbe, M., Tricomi, G., et al., 2025. From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI. Sensors. 25(6), 1763. DOI: https://doi.org/10.3390/s25061763

[10] Akanbi, A., Masinde, M., 2020. A Distributed Stream Processing Middleware Framework for Real-Time Analysis of Heterogeneous Data on Big Data Platform: Case of Environmental Monitoring. Sensors. 20(11), 3166. DOI: https://doi.org/10.3390/s20113166

[11] Fei, T., Mukhopadhyay, S.C., Da Costa, J.P.J., et al., 2024. Spatial Environment Perception and Sensing in Automated Systems: A Review. IEEE Sensors Journal. 24(14), 21813–21833. DOI: https://doi.org/10.1109/JSEN.2024.3379222

[12] Lee, C.-M., Hsieh, S.-H., 2026. Edge-enabled real-time framework for context-aware data acquisition and hazard alerting in smart construction sites. Automation in Construction. 181, 106642. DOI: https://doi.org/10.1016/j.autcon.2025.106642

[13] Channi, H.K., Sandhu, R., Singh, N., et al., 2025. Governance Frameworks for Smart Systems. In: Mahajan, S., Rocha, Á., Pandit, A.K., et al. (Eds.). Smart Systems: Engineering and Managing Information for Future Success, Information Systems Engineering and Management. Springer Nature: Cham, Switzerland. pp. 157–189. DOI: https://doi.org/10.1007/978-3-031-76152-2_11

[14] Nazeeya Anjum, N., Sumathi, S., Dheena Dhayalan, R., et al., 2025. Smart sensors for smart city environmental monitoring systems. In Digital Twin, Blockchain, and Sensor Networks in the Healthy and Mobile City. Elsevier: London, UK. pp. 17–33. DOI: https://doi.org/10.1016/B978-0-443-34174-8.00003-X

[15] Jing, L., Yao, D., Kun, Y., et al., 2026. Edge-cloud collaborative computing on distributed intelligence and model optimization: A survey. IEEE Communications Surveys & Tutorials. 28, 5049–5080.

[16] Plastiras, G., Terzi, M., Kyrkou, C., et al., 2018. Edge Intelligence: Challenges and Opportunities of Near-Sensor Machine Learning Applications. In Proceedings of the 2018 IEEE 29th International Conference on Application-Specific Systems, Architectures and Processors (ASAP), Milan, Italy, 10–12 July 2018; pp. 1–7. DOI: https://doi.org/10.1109/ASAP.2018.8445118

[17] Shrivastava, A., Husain, S.O., Madhavi, A., et al., 2025. ML-Powered Smart Sensor Networks for Sustainable Energy and Environmental Monitoring. In Proceedings of the 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG), Indore, India, 12 December 2025; pp. 1–6. DOI: https://doi.org/10.1109/ICTBIG68706.2025.11323831

[18] Wang, Y., Su, Z., Guo, S., et al., 2023. A Survey on Digital Twins: Architecture, Enabling Technologies, Security and Privacy, and Future Prospects. IEEE Internet of Things Journal. 10(17), 14965–14987. DOI: https://doi.org/10.1109/JIOT.2023.3263909

[19] Bhavani, K., Gajendra, N., 2024. Smart data-driven sensing. In Bio-Inspired Data-Driven Distributed Energy in Robotics and Enabling Technologies. CRC Press: New York, NY, USA. pp. 17–47. DOI: https://doi.org/10.1201/9781003530077-2

[20] Wani, A.K., Rahayu, F., Ben Amor, I., et al., 2024. Environmental resilience through artificial intelligence: Innovations in monitoring and management. Environmental Science and Pollution Research. 31(12), 18379–18395. DOI: https://doi.org/10.1007/s11356-024-32404-z

[21] Fascista, A., 2022. Toward Integrated Large-Scale Environmental Monitoring Using WSN/UAV/Crowdsensing: A Review of Applications, Signal Processing, and Future Perspectives. Sensors. 22(5), 1824. DOI: https://doi.org/10.3390/s22051824

[22] Mollah, M.H.-O.-R., Sultana, M.S., Kudapa, S.P., et al., 2023. Integration of IoT and Edge Computing for Low-Latency Data Analytics in Smart Cities and IoT Net-

works. Journal of Sustainable Development and Policy. 2(3), 01–33. DOI: https://doi.org/10.63125/004h7m29

[23] Vidakis, N., Lasithiotakis, M.A., Karapidakis, E., 2017. Environmental monitoring through embedded system and sensors. In Proceedings of the 2017 52nd International Universities Power Engineering Conference (UPEC), Heraklion, Greece, 28–31 August 2017; pp. 1–7. DOI: https://doi.org/10.1109/UPEC.2017.8231913

[24] Cao, X., Chen, J., Zhang, Y., et al., 2008. Development of an integrated wireless sensor network microenvironmental monitoring system. ISA Transactions. 47(3), 247–255. DOI: https://doi.org/10.1016/j.isatra.2008.02.001

[25] Mitton, N., Papavassiliou, S., Puliafito, A., et al., 2012. Combining Cloud and sensors in a smart city environment. EURASIP Journal on Wireless Communications and Networking. 2012(1), 247. DOI: https://doi.org/10.1186/1687-1499-2012-247

[26] Hino, M., Benami, E., Brooks, N., 2018. Machine learning for environmental monitoring. Nature Sustainability. 1(10), 583–588. DOI: https://doi.org/10.1038/s41893-018-0142-9

[27] Biber, E., 2013. The Challenge of Collecting and Using Environmental Monitoring Data. Ecology and Society. 18(4), art68. DOI: https://doi.org/10.5751/ES-06117-180468

[28] Manduva, V.C., 2020. AI-Powered Edge Computing for Environmental Monitoring: A Cloud-Integrated Approach. International Journal of Emerging Trends in Science and Technology. 1–21.

[29] Wang, Y., Yang, C., Lan, S., et al., 2024. End-Edge-Cloud Collaborative Computing for Deep Learning: A Comprehensive Survey. IEEE Communications Surveys & Tutorials. 26(4), 2647–2683. DOI: https://doi.org/10.1109/COMST.2024.3393230

[30] Tong, L., Li, Y., Gao, W., 2016. A hierarchical edge cloud architecture for mobile computing. In Proceedings of the 35th Annual IEEE International Conference on Computer Communications, San Francisco, CA, USA, 10–15 April 2015; pp. 1–9. DOI: https://doi.org/10.1109/INFOCOM.2016.7524340

[31] Ghosh, R., Simmhan, Y., 2018. Distributed Scheduling of Event Analytics across Edge and Cloud. ACM Transactions on Cyber-Physical Systems. 2(4), 1–28. DOI: https://doi.org/10.1145/3140256

[32] Liu, C.-F., Bennis, M., Debbah, M., et al., 2019. Dynamic Task Offloading and Resource Allocation for Ultra-Reliable Low-Latency Edge Computing. IEEE Transactions on Communications. 67(6), 4132–4150. DOI: https://doi.org/10.1109/TCOMM.2019.2898573

[33] Budi, S., 2018. Balancing Robustness and Redundancy in the Design of Environmental Sensor Networks [PhD Thesis]. University of Tasmania: Dynnyrne, Australia. DOI: https://doi.org/10.25959/100.00028539

[34] Folgado, D., Barandas, M., Matias, R., et al., 2018. Time Alignment Measurement for Time Series. Pattern Recognition. 81, 268–279. DOI: https://doi.org/10.1016/j.patcog.2018.04.003

[35] Nogueras-Iso, J., Zarazaga-Soria, F.J., Muro-Medrano, P.R., 2005. Geographic Information Metadata for Spatial Data Infrastructures: Resources, Interoperability and Information Retrieval. Springer: Singapore.

[36] Mshelia, Y., Zirra, A., Pantuvo, J.S., et al., 2024. Determinants of Interoperability in Intersectoral One-Health Surveillance: Challenges, Solutions, and Metrics. In: Darwish, D. (Ed.). Advances in Information Security, Privacy, and Ethics. IGI Global: London, UK. pp. 303–348. DOI: https://doi.org/10.4018/979-8-3693-6996-8.ch013

[37] Frederickson, L.B., Sidaraviciute, R., Schmidt, J.A., et al., 2022. Are dense networks of low-cost nodes really useful for monitoring air pollution? A case study in Staffordshire. Atmospheric Chemistry and Physics. 22(21), 13949–13965. DOI: https://doi.org/10.5194/acp-22-13949-2022

[38] Vitousek, S., Buscombe, D., Vos, K., et al., 2023. The future of coastal monitoring through satellite remote sensing. Cambridge Prisms: Coastal Futures. 1, e10. DOI: https://doi.org/10.1017/cft.2022.4

[39] Xu, G., Shen, W., Wang, X., 2014. Applications of Wireless Sensor Networks in Marine Environment Monitoring: A Survey. Sensors. 14(9), 16932–16954. DOI: https://doi.org/10.3390/s140916932

[40] Jamil, M.N., Schelén, O., Afif Monrat, A., et al., 2024. Enabling Industrial Internet of Things by Leveraging Distributed Edge-to-Cloud Computing: Challenges and Opportunities. IEEE Access. 12, 127294–127308. DOI: https://doi.org/10.1109/ACCESS.2024.3454812

[41] Khan, S.M., Shafi, I., Butt, W.H., et al., 2023. A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions. Land. 12(8), 1514. DOI: https://doi.org/10.3390/land12081514

[42] Alamri, A., Ansari, W.S., Hassan, M.M., et al., 2013. A Survey on Sensor-Cloud: Architecture, Applications, and Approaches. International Journal of Distributed Sensor Networks. 9(2), 917923. DOI: https://doi.org/10.1155/2013/917923

[43] Avlani, S., Seo, D.-H., Chatterjee, B., et al., 2022. EICO: Energy-Harvesting Long-Range Environmental Sensor Nodes with Energy-Information Dynamic Co-Optimization. IEEE Internet of Things Journal. 9(21), 20932–20944. DOI: https://doi.org/10.1109/JIOT.2022.3178422

[44] Casali, J.G., 2021. Sound and Noise: Measurement and Design Guidance. In: Salvendy, G., Karwowski, W. (Eds.). Handbook of Human Factors and Ergonomics. Wiley: London, UK. pp. 457–493. DOI: https://doi.org/10.1002/9781119636113.ch18

[45] Naik, R., Nagaswarupa, H.P., Darukesha, B.H.M., et al., 2024. Applications of Advanced Radiation Detection Systems. In Advances in Space Radiation Detection, SpringerBriefs in Molecular Science. Springer Nature: Cham, Switzerland. pp. 89–100. DOI: https://doi.org/10.1007/978-3-031-74551-5_7

[46] Paquette, L., Mott, B.W., Brawner, K., et al., 2016. Sensor-Free or Sensor-Full: A Comparison of Data Modalities in Multi-Channel Affect Detection. In Proceedings of the Educational Data Mining 2015, Madrid, Spain, 26–29 July 2015.

[47] Vikram, S., Collier-Oxandale, A., Ostertag, M.H., et al., 2019. Evaluating and improving the reliability of gas-phase sensor system calibrations across new locations for ambient measurements and personal exposure monitoring. Atmospheric Measurement Techniques. 12(8), 4211–4239. DOI: https://doi.org/10.5194/amt-12-4211-2019

[48] Yu, X., Ergun, K., Cherkasova, L., et al., 2020. Optimizing Sensor Deployment and Maintenance Costs for Large-Scale Environmental Monitoring. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems. 39(11), 3918–3930. DOI: https://doi.org/10.1109/TCAD.2020.3012232

[49] Álvarez, J.L., Mozo, J.D., Durán, E., 2021. Analysis of Single Board Architectures Integrating Sensors Technologies. Sensors. 21(18), 6303. DOI: https://doi.org/10.3390/s21186303

[50] Delaine, F., Lebental, B., Rivano, H., 2019. In Situ Calibration Algorithms for Environmental Sensor Networks: A Review. IEEE Sensors Journal. 19(15), 5968–5978. DOI: https://doi.org/10.1109/JSEN.2019.2910317

[51] Maijala, P., Shuyang, Z., Heittola, T., et al., 2018. Environmental noise monitoring using source classification in sensors. Applied Acoustics. 129, 258–267. DOI: https://doi.org/10.1016/j.apacoust.2017.08.006

[52] Bourgeois, W., Romain, A.-C., Nicolas, J., et al., 2003. The use of sensor arrays for environmental monitoring: Interests and limitations. Journal of Environmental Monitoring. 5(6), 852. DOI: https://doi.org/10.1039/b307905h

[53] Zhang, Y., Thorburn, P.J., 2022. Handling missing data in near real-time environmental monitoring: A system and a review of selected methods. Future Generation Computer Systems. 128, 63–72. DOI: https://doi.org/10.1016/j.future.2021.09.033

[54] Campbell, J.L., Rustad, L.E., Porter, J.H., et al., 2013. Quantity is Nothing without Quality: Automated QA/QC for Streaming Environmental Sensor Data. BioScience. 63(7), 574–585. DOI: https://doi.org/10.1525/bio.2013.63.7.10

[55] Stankovic, J.A., Abdelzaher, T.F., Lu, C., et al., 2003. Real-time communication and coordination in embedded sensor networks. Proceedings of the IEEE. 91(7), 1002–1022. DOI: https://doi.org/10.1109/JPROC.2003.814620

[56] Mahmood, M.A., Seah, W.K.G., Welch, I., 2015. Reliability in wireless sensor networks: A survey and challenges ahead. Computer Networks. 79, 166–187. DOI: https://doi.org/10.1016/j.comnet.2014.12.016

[57] Amutha, J., Sharma, S., Nagar, J., 2020. WSN Strategies Based on Sensors, Deployment, Sensing Models, Coverage and Energy Efficiency: Review, Approaches and Open Issues. Wireless Personal Communications. 111(2), 1089–1115. DOI: https://doi.org/10.1007/s11277-019-06903-z

[58] Özkan, C., Şahin, S., 2024. AI Applications in Real-Time Edge Processing: Leveraging Artificial Intelligence for Enhanced Efficiency, Low-Latency Decision Making, and Scalability in Distributed Systems. International Journal of Machine Intelligence for Smart Applications. 14(8).

[59] Abieba, O.A., Ubamadu, B.C., Hassan, Y.G., et al., 2025. Advanced Observability and Monitoring Practices for Enhancing Production Environment Reliability. World Scientific News. 204 (2025), 271–296.

[60] Melone, M., 2024. Eco-Efficient Cloud Manufacturing: A Paradigm for Energy Consumption Optimization [Masters' Thesis]. Politecnico di Torino: Turin, Italy.

[61] Ahmad, I., Zulfiqar, A., Shabbir, M., et al., 2025. Advanced sensors, monitoring, and control systems for environmental sustainability. In Smart Cities and Sustainable Manufacturing. Elsevier: London, UK. pp. 47–55. DOI: https://doi.org/10.1016/B978-0-443-26474-0.00007-5

[62] Yang, J., Zhang, C., Li, X., et al., 2010. Integration of wireless sensor networks in environmental monitoring cyber infrastructure. Wireless Networks. 16(4), 1091–1108. DOI: https://doi.org/10.1007/s11276-009-0190-1

[63] Alotaibi, E., Nassif, N., 2024. Artificial intelligence in environmental monitoring: In-depth analysis. Discover Artificial Intelligence. 4(1), 84. DOI: https://doi.org/10.1007/s44163-024-00198-1

[64] Hill, D.J., Minsker, B.S., 2010. Anomaly detection in streaming environmental sensor data: A data-driven modeling approach. Environmental Modelling & Software. 25(9), 1014–1022. DOI: https://doi.org/10.1016/j.envsoft.2009.08.010

[65] Chimariya, A., 2018. Streaming Data Analytics: Background, Technologies and Outlook [Master's Thesis]. University of Oulu: Oulu, Finland.

[66] Bate, A., 2023. Auditable Data Provenance in Streaming Data Processing [Master's Thesis]. University of Lisbon: Lisbon, Portugal.

[67] Chan, K., Schillereff, D.N., Baas, A.C., et al., 2021. Low-cost electronic sensors for environmental research: Pitfalls and opportunities. Progress in Physical Geography: Earth and Environment. 45(3), 305–338.

DOI: https://doi.org/10.1177/0309133320956567

[68] Nalakurthi, N.V.S.R., Abimbola, I., Ahmed, T., et al., 2024. Challenges and Opportunities in Calibrating Low-Cost Environmental Sensors. Sensors. 24(11), 3650. DOI: https://doi.org/10.3390/s24113650

[69] Zhong, S., Zhang, K., Bagheri, M., et al., 2021. Machine Learning: New Ideas and Tools in Environmental Science and Engineering. Environmental Science & Technology. 55(19), acs.est.1c01339. DOI: https://doi.org/10.1021/acs.est.1c01339

[70] Muller, R.A., 1977. A Synoptic Climatology for Environmental Baseline Analysis: New Orleans. Journal of Applied Meteorology. 16(1), 20–33. DOI: https://doi.org/10.1175/1520-0450(1977)016%253C0020:ASCFEB%253E2.0.CO;2

[71] Zhu, X., Cai, F., Tian, J., et al., 2018. Spatiotemporal Fusion of Multisource Remote Sensing Data: Literature Survey, Taxonomy, Principles, Applications, and Future Directions. Remote Sensing. 10(4), 527. DOI: https://doi.org/10.3390/rs10040527

[72] Yuanyuan, Z., Bin, Z., Cheng, S., et al., 2024. Review of the field environmental sensing methods based on multi-sensor information fusion technology. International Journal of Agricultural and Biological Engineering. 17(2), 1–13. DOI: https://doi.org/10.25165/j.ijabe.20241702.8596

[73] Tang, T., Zhang, J., 2018. Time-scale sensitive sensor applications in collecting and analyzing geographic event data. Annals of GIS. 24(4), 241–253. DOI: https://doi.org/10.1080/19475683.2018.1520299

[74] Lin, T., Ren, Z., Zhu, L., et al., 2025. A Systematic Review of Multisensor Information Fusion for Equipment Fault Diagnosis. IEEE Transactions on Instrumentation and Measurement. 74, 1–48. DOI: https://doi.org/10.1109/TIM.2025.3529577

[75] Sun, A.Y., Zhong, Z., Jeong, H., et al., 2019. Building complex event processing capability for intelligent environmental monitoring. Environmental Modelling & Software. 116, 1–6. DOI: https://doi.org/10.1016/j.envsoft.2019.02.015

[76] Tartakovsky, A.G., Polunchenko, A.S., Sokolov, G., 2013. Efficient Computer Network Anomaly Detection by Changepoint Detection Methods. IEEE Journal of Selected Topics in Signal Processing. 7(1), 4–11. DOI: https://doi.org/10.1109/JSTSP.2012.2233713

[77] Willard, J., Jia, X., Xu, S., et al., 2023. Integrating Scientific Knowledge with Machine Learning for Engineering and Environmental Systems. ACM Computing Surveys. 55(4), 1–37. DOI: https://doi.org/10.1145/3514228

[78] Kasprzyk, J.R., Nataraj, S., Reed, P.M., et al., 2013. Many objective robust decision making for complex environmental systems undergoing change. Environmental Modelling & Software. 42, 55–71. DOI: https://doi.org/10.1016/j.envsoft.2012.12.007

[79] Mustapää, T., Nikander, P., Hutzschenreuter, D., et al., 2020. Metrological Challenges in Collaborative Sensing: Applicability of Digital Calibration Certificates. Sensors. 20(17), 4730. DOI: https://doi.org/10.3390/s20174730

[80] Liao, Y., Mollineaux, M., Hsu, R., et al., 2014. SnowFort: An Open Source Wireless Sensor Network for Data Analytics in Infrastructure and Environmental Monitoring. IEEE Sensors Journal. 14(12), 4253–4263. DOI: https://doi.org/10.1109/JSEN.2014.2358253

[81] Baker, M., Schaltegger, S., 2015. Pragmatism and new directions in social and environmental accountability research. Accounting, Auditing & Accountability Journal. 28(2), 263–294. DOI: https://doi.org/10.1108/AAAJ-08-2012-01079

[82] Arashpour, M., 2023. AI explainability framework for environmental management research. Journal of Environmental Management. 342, 118149. DOI: https://doi.org/10.1016/j.jenvman.2023.118149

[83] Chauhan, B.V.S., Vedrtnam, A., Wyche, K.P., et al., 2025. Review on Artificial Intelligence in the Environmental Monitoring. In Prospects of Artificial Intelligence in the Environment. Springer Nature: Singapore. pp. 29–60. DOI: https://doi.org/10.1007/978-981-96-6863-2_2

[84] Trigka, M., Dritsas, E., 2025. Wireless Sensor Networks: From Fundamentals and Applications to Innovations and Future Trends. IEEE Access. 13, 96365–96399. DOI: https://doi.org/10.1109/ACCESS.2025.3572328

[85] Lazarescu, M.T., 2013. Design of a WSN Platform for Long-Term Environmental Monitoring for IoT Applications. IEEE Journal on Emerging and Selected Topics in Circuits and Systems. 3(1), 45–54. DOI: https://doi.org/10.1109/JETCAS.2013.2243032

[86] Digkoglou, P., Papathanasiou, J., 2025. Application of multiple criteria decision aiding in environmental policy-making processes. International Journal of Environmental Science and Technology. 22(8), 6967–6982. DOI: https://doi.org/10.1007/s13762-024-06101-w

[87] Da Costa, T.P., Da Costa, D.M.B., Murphy, F., 2024. A systematic review of real-time data monitoring and its potential application to support dynamic life cycle inventories. Environmental Impact Assessment Review. 105, 107416. DOI: https://doi.org/10.1016/j.eiar.2024.107416

[88] Leung, H., Chandra Mukhopadhyay, S. (Eds.), 2015. Intelligent Environmental Sensing, Smart Sensors, Measurement and Instrumentation. Springer International Publishing: Cham, Switzerland. DOI: https://doi.org/10.1007/978-3-319-12892-4

[89] El-Sayed, H., Sankar, S., Prasad, M., et al., 2018. Edge of Things: The Big Picture on the Integration of Edge, IoT and the Cloud in a Distributed Computing Environment. IEEE Access. 6, 1706–1717. DOI:

https://doi.org/10.1109/ACCESS.2017.2780087

[90] Miller, T., Durlik, I., Kostecka, E., et al., 2025. Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data. Electronics. 14(4), 696. DOI: https://doi.org/10.3390/electronics14040696

[91] Obaidat, M.A., Obeidat, S., Holst, J., et al., 2020. A Comprehensive and Systematic Survey on the Internet of Things: Security and Privacy Challenges, Security Frameworks, Enabling Technologies, Threats, Vulnerabilities and Countermeasures. Computers. 9(2), 44. DOI: https://doi.org/10.3390/computers9020044

[92] Cirne, A., Sousa, P.R., Resende, J.S., et al., 2024. Hardware Security for Internet of Things Identity Assurance. IEEE Communications Surveys & Tutorials. 26(2), 1041–1079. DOI: https://doi.org/10.1109/COMST.2024.3355168

[93] De Capitani Di Vimercati, S., Genovese, A., Livraga, G., et al., 2013. Privacy and Security in Environmental Monitoring Systems. In Computer and Information Security Handbook. Elsevier: London, UK, pp. 835–853. DOI: https://doi.org/10.1016/B978-0-12-394397-2.00047-7

[94] Coito, T., Firme, B., Martins, M.S.E., et al., 2021. Intelligent Sensors for Real-Time Decision-Making. Automation. 2(2), 62–82. DOI: https://doi.org/10.3390/automation2020004

[95] Suciu, G., Anwar, M., Ganaside, A., et al., 2017. IoT time critical applications for environmental early warning. In Proceedings of the 2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Târgoviște, Romania, 29 June–1 July 2017; pp. 1–4. DOI: https://doi.org/10.1109/ECAI.2017.8166451

[96] Ncube, M.M., Ngulube, P., 2024. Enhancing environmental decision-making: A systematic review of data analytics applications in monitoring and management. Discover Sustainability. 5(1), 290. DOI: https://doi.org/10.1007/s43621-024-00510-0

[97] Adepoju, A.H., Austin-Gabriel, B., Hamza, O., et al., 2022. Advancing monitoring and alert systems: A proactive approach to improving reliability in complex data ecosystems. Iconic Research and Engineering Journals. 5(11), 281–282.

[98] Bennett, N.J., Whitty, T.S., Finkbeiner, E., et al., 2018. Environmental Stewardship: A Conceptual Review and Analytical Framework. Environmental Management. 61(4), 597–614. DOI: https://doi.org/10.1007/s00267-017-0993-2