Trends and Technologies in Environmental Monitoring: A Review of Sensors, Communication, and AI-Enabled Systems

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***Abstract*—Wireless Sensor Networks (WSNs) are foundational for addressing modern environmental monitoring challenges driven by climate change. This review provides an integrated analysis of the trends and challenges, examining sensing technologies for water, soil, and air, alongside communication protocols and best practices. We consolidate advances across sensors, networking, and system-level challenges, including energy efficiency, security, and the integration of the Artificial Intelligence of Things (AIoT). By bridging these multidisciplinary domains, this work serves as a foundational guide for future research and the development of next-generation monitoring systems.**

***Index Terms*—Environmental monitoring, Wireless Sensor Networks, Internet of Things (IoT), LoRaWAN, Artificial Intelligence of Things (AIoT).**

I. Introduction

The increasing urbanization and climate change have diverse impacts on different layers of society, threatening individuals in vulnerable situations during disasters such as floods, or affecting agricultural production due to climatic variations [1]. These phenomena highlight the need for monitoring systems that can provide more data on environmental conditions and help us monitor, analyze, and predict such events [2].

When we talk about environmental monitoring, we refer to a wide range of applications and devices. Particularly in remote and hard-to-reach areas, this represents a significant technical challenge. The vastness of these territories, combined with adverse environmental conditions and the growing demand for real-time data, requires technological solutions that are robust, cost-effective, and scalable [3], [4].

While many reviews focus on specific aspects such as soil sensors or water level measurement, few provide an integrated perspective combining sensing technologies, communication infrastructures, energy efficiency, artificial intelligence, and security. This review addresses that gap by consolidating advances across soil, water, and air monitoring domains to highlight overlooked technologies and guide future research toward scalable, intelligent, and resilient environmental monitoring solutions.

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II. Water Level Sensors

A. Hydrostatic Pressure Sensors

Traditional water level monitoring methods, like staff gauges and limnigraphs, remain common in natural environments. Limnigraph sensors operate on hydrostatic pressure principles, where pressure transducers measure the water column height using the relationship $P = \rho g h$, where ρ is water density, g is gravitational acceleration, and h is height. Their reliability drops in flood conditions due to damage or obstruction risks [5].

B. Ultrasonic Level Sensors

Ultrasonic sensors estimate distance via acoustic time-of-flight: a short burst (typically 4–10 cycles at 20–200 kHz) is emitted and the echo delay t is converted to distance using $d = \frac{vt}{2}$.

Recent work focused on open-channel flood monitoring demonstrates that low-cost modules can achieve sub-3% mean error after targeted compensation. MasoudiMoghaddam *et al.*. [6] validated a GY-Us42-based design in laboratory and turbulent field conditions (including foamy, aerated surfaces) using: temperature-based sound speed correction, filtering of spurious multipath or splash-induced echoes (median/Hampel), and mechanical alignment to minimize sidewall reflections. Pereira *et al.* [7] identified the HC-SR04 as a technically and economically viable option for short spans (< 5 m) when mounting geometry and obstruction shielding are controlled. Bresnahan *et al.*. At [8], the authors emphasized accessibility of the technology, highlighting adoption in education, citizen science, and early-stage research due to low unit cost (US$5–15) and simple interfacing.

C. LiDAR-Based Level Measurement

LiDAR (Light Detection and Ranging) systems for hydrometric applications derive distance by measuring the propagation characteristics of emitted laser radiation and its backscattered return from a target surface. Two dominant time-of-flight (TOF) architectures are employed in modern (often solid-state) implementations: (i) pulsed TOF and (ii) amplitude modulated continuous wave (AMCW) TOF [9]. In pulsed TOF systems, short optical pulses (typically nanosecond to sub-nanosecond width at 905 nm or 1550 nm) are emitted and the round-trip delay Δt is measured with high-resolution time-to-digital converters (TDCs). The distance is obtained by

$$d = \frac{c\,\Delta t}{2} \tag{1}$$

where c is the speed of light. AMCW TOF LiDAR instead launches a continuously emitted, amplitude-modulated optical carrier; distance is inferred from the measured phase shift $\Delta\phi$ between transmitted and received envelopes:

$$d = \frac{c\,\Delta\phi}{4\pi f} \tag{2}$$

where f is the modulation frequency. Pulsed TOF excels at long range and strong ambient light resilience, while AMCW can achieve fine precision at shorter to medium distances with simpler per-pixel electronics [9]. Advances in solid-state beam steering (MEMS mirrors, optical phased arrays, rotating polygon replacements) reduce mechanical complexity, enabling compact low-power modules suitable for distributed river monitoring nodes. Key error sources for water level applications include surface specularity (leading to low diffuse return), beam incidence angle, internal temperature drift of laser driver and detector gain, and atmospheric scattering under fog or heavy rain.

Field-oriented studies highlight the performance of low-cost near-infrared LiDAR for hydrometry. An inclined-beam configuration demonstrated by Tamari and Guerrero-Meza leverages suspended sediment and turbidity to enhance backscattered signal strength; higher particle concentrations improved range stability, enabling accurate flash-flood stage retrieval with ±0.08 m error while keeping sensor hardware safely on the river bank [10]. Paul *et al.* provided a technical evaluation showing that despite the intrinsically low reflectivity of calm water, a commercial low-cost unit attained relative errors of 0.1% over 30–35 m ranges, outperforming typical ultrasonic sensors in maximum span; however, pronounced sensitivity to internal temperature underscored the necessity of thermal compensation (e.g., on-board thermistors with calibration lookup tables or real-time drift modeling) [11]. Complementing these, Santana *et al.* compared a low-cost LiDAR directly against a conventional limnigraph (hydrostatic pressure) installation, reporting equivalence within ±0.05 m to a physical metric scale and negligible degradation from sediment presence, reinforcing robustness for tropical river conditions [5].

From a systems engineering perspective, LiDAR offers non-contact operation, electromagnetic interference immunity, high precision (typical repeatability $<0.1\%$ full scale), and enhanced safety for flood-prone or debris-laden channels. Trade-offs include higher capital cost , susceptibility to adverse meteorological factors (dense fog, heavy rain), and thermal drift requiring compensation. Comparative surveys of liquid level technologies position optical (LiDAR and related) approaches as superior in accuracy and maintenance profile relative to many conventional contact methods, while acknowledging cost and environmental vulnerability constraints [12].

D. Satellite-Based Remote Sensing

Another method for monitoring water levels in open environments is the use of satellite-based remote sensing. The work [13] employed a multi-source remote sensing data fusion method via Google Earth Engine to estimate surface water area and water level changes in nine plateau lakes in Yunnan, China, between 2003 and 2022. Their results showed high consistency with in-situ measurements, with deviations under 0.3 meters, and highlighted the influence of climate variability and human activities on lake dynamics.

Similarly, [14] used Sentinel-3A radar altimetry to assess the impact of dam operations on water levels in the Mekong River basin, validating satellite-derived levels with in-situ telemetry data and achieving a correlation of 0.98.

Advantages of this method include wide area coverage, long-term consistency, and accessibility to remote regions. Disadvantages include limited spatial resolution, high initial infrastructure costs, and dependency on satellite availability.

E. Water Level Sensors for Controlled Environments

While the same sensors applied in rivers and lakes may still be suitable, simpler methods like resistive and capacitive sensors are commonly employed for monitoring water levels in tanks and cisterns. Resistive sensors operate by measuring electrical resistance changes as water level varies, typically using conductive materials with power consumption in the micro-watt range.

Surface acoustic wave (SAW) sensors represent emerging passive technologies that can detect water level changes by measuring strain or pressure variations on tank walls, converting them into frequency shifts or response signals [15], [16]. These sensors operate without active power supply, harvesting energy from the interrogating RF signal, making them ideal for IoT and Industry 5.0 applications requiring minimal maintenance.

Another promising approach involves optical fiber-based sensors. Optical fiber-based sensors rely on the hydrostatic principle of Archimedes, where a floating element alters light transmission through a fiber to reflect changes in water level [17]. While highly accurate (±1mm resolution), these systems typically have limited measurement ranges and involve more complex calibration procedures, requiring specialized optical components and signal processing units.

III. Sensor Systems for Detecting Chemicals and Pollutants

A. Water Quality Sensors

Recent advancements in sensor technologies have significantly enhanced water quality monitoring. The work by Ferreira *et al.* [18] presents the development of a wireless sensor network (WSN) node capable of detecting pH, turbidity, and electrical conductivity (EC) sensors and classifying pollutants in aquatic environments using embedded systems, IoT, and machine learning. The system demonstrated promising results in controlled tests with seawater samples containing oil derivatives, offering low power consumption and effective pollutant classification through distributed processing and embedded neural networks. Complementing this work, in [19] the authors review the application of artificial intelligence (AI) in water quality assessment.

B. Alternative Technologies for Soil Monitoring

Batteryless sensing technologies have emerged as promising alternatives for soil sensing in remote or hard to access locations. A NFC-based soil sensor that harvests energy from the NFC reader's magnetic field was introduced by Boada *et al.* [20], enabling measurements of temperature, humidity, and soil moisture without relying on batteries. The system integrates a microcontroller and stores data in NDEF format for later retrieval.

For continuous, high-resolution monitoring applications, Active Heating Optical Frequency Domain Reflectometry (AH-OFDR) provides distributed sensing capabilities along fiber optic cables [21]. This technology combines heated fiber optic cables with OFDR systems, leveraging the principle that soil thermal conductivity varies with moisture content. The system operates by actively heating sections of optical fiber while monitoring temperature changes. Tests validated the method against traditional distributed temperature sensing (DTS) and infrared thermography [21].

C. Chemical Element Detection and Gas Sensing

In [22], the authors investigate SAW sensors for passive detection of gases and chemical vapors in the air, based on the interaction of the compounds with the antenna, which alters the received acoustic signal. SAW sensors are shown to be viable for detecting inorganic gases such as NH_3, NO_2, SO_2, CO, organic vapors such as toluene, ethanol, acetone, and even chemical warfare agents.

The study highlights the importance of material stability in extreme environments, the use of antennas for wireless operation, and low energy consumption, pointing to future research directions in sensitive materials, flexible sensors, and multi-element arrays for simultaneous gas monitoring. Advantages include passive wireless operation, low power consumption (no power required for sensing), and rapid response times (seconds). Disadvantages include temperature sensitivity, selectivity limitations, and drift over long-term operation due to substrate saturation.

D. Air Pollution and Quality Monitoring

Karagulian *et al.* [23] analyzes the performance of low-cost sensors (LCS) for monitoring various air pollutants, including carbon monoxide (CO), nitrogen oxides (NO and NO_2), ozone (O_3), and particulate matter ($PM_{2.5}$). The review highlights the potential of these sensors to expand spatial coverage in both urban and remote areas and assesses different calibration methods such as MLR, ANN, SVR, and RF, considering factors like relative humidity, which significantly affects particulate measurement.

In [24], the authors present a review of air pollution monitoring systems based on wireless sensor networks (WSNs), classifying them into three main categories: Static Sensor Networks (SSN), Community Sensor Networks (CSN), and Vehicular Sensor Networks (VSN), based on the types of sensor carriers. The analysis shows that many current solutions are already viable in terms of spatiotemporal resolution, cost, energy efficiency, ease of deployment, maintenance, and public data accessibility. However, challenges remain, such as the lack of 3D data acquisition, limitations in active monitoring capability, and the use of uncontrolled or semi-controlled carrier, factors that should be improved in the next generations of air pollution monitoring systems.

IV. Challenges and Trends

A. Energy-Efficient Communication and System Architecture

The maturation of wireless sensor networks for environmental monitoring has shifted design priorities toward long range, low maintenance, and multi-year autonomy [25]. Low Power Wide Area Network (LPWAN) paradigms, like Sigfox, LoRa/LoRaWAN, and NB-IoT, compete to service hydrological, soil, and air-quality deployments by offering kilometer-scale coverage at low bitrates [26]. Comparative analyses show strategic differentiation: Sigfox leverages narrowband frames and strict duty cycle limits to minimize energy per uplink for tiny, infrequent payloads, but imposes downlink and payload size constraints. LoRaWAN provides adaptive data rates and multiple device classes: Class A (uplink-initiated, lowest energy), optional Class B (scheduled receive slots), and Class C (near-continuous listening for low bidirectional latency) at elevated power cost. NB-IoT, integrated with cellular infrastructure, offers improved QoS, managed mobility, and lower latency, yet synchronization overhead, attach procedures, and OFDM/FDMA waveforms drive higher peak and average currents, shortening lifetime versus Sigfox or Class A LoRa for identical reporting intervals [26].

Energy efficiency is the primary bottleneck for sustainable environmental WSNs: communication dominates lifetime energy, batteries are expensive to service at scale, and remote nodes must remain operational for years [27]. LPWAN technologies mitigate range–energy trade-offs but still require minimizing uplink frequency through local feature extraction and adaptive sampling [26]. Harvesting (solar plus auxiliary micro-sources) plus predictive power budgeting enables energy neutrality (harvested $\geq$ consumed) despite environmental variability [27].

B. Large Area Monitoring With Vehicles

Although LoRaWAN and traditional WSNs are common in large agricultural fields, alternative architectures have emerged to overcome infrastructure, energy, and scalability challenges [4]. Deng *et al.* [28] developed a hybrid system using passive

RFID soil sensors and a patrol vehicle for mobile data collection. This approach offers low cost and energy efficiency by leveraging backscatter communication to send environmental data to a central platform.

Caruso *et al.* [29] introduced a drone-based system where UAVs with LoRa radios periodically collect data from ground sensors. Ideal for areas without fixed infrastructure or where real-time updates aren't essential, the method includes an adaptable model for optimizing flight paths and sensor layout, supporting various drone types and communication protocols.

C. Beat Sensors

Beat sensors represent an innovative approach in the field of IoT, designed specifically to minimize power consumption and cost. Introduced in 2017, these sensors operate by transmitting only ID codes wirelessly; the receiving unit (RX) decodes sensor data based on the time intervals between transmissions, referred to as "beats." Applications include power monitoring systems such as Power Beat and DC Current Beat sensors, aimed at energy reduction in residential and commercial buildings [30].

Subsequent studies have demonstrated the long-term efficiency of beat sensors in energy-critical IoT scenarios. A 2019 evaluation showed that a Beat sensor powered by a CR2032 coin battery could transmit over 3.8 million ID signals, translating to more than seven years of operation, significantly outperforming conventional IoT sensors with intermittent duty cycles [31]. More recently, a 2025 study applied the beat sensing concept to water-level monitoring, proposing a solar-powered system using a \$ 72.5 BoM sensor node with LoRa communication and a quasi-isotropic Ω-antenna. The device operated continuously for 21 days without a battery, achieving a 2 km communication range and consuming less than 100 μW [32].

D. Artificial Intelligence with Internet of Things (AIoT)

The integration of Artificial Intelligence into IoT systems, known as AIoT, enables smarter, autonomous applications in areas like smart cities, industry, and environmental monitoring. As described by [33], this marks a shift toward cyber-physical systems that combine embedded devices, human interaction, and real-time analytics. While AI enhances predictive and adaptive capabilities, it also introduces challenges such as data security and system complexity.

AI-enabled sensors are becoming more context-aware and energy-efficient, supporting applications like predictive maintenance and smart routing [34]. In environmental monitoring, [18] developed a sensor node using embedded neural networks for pollutant classification, while [19] reviewed AI's role in water quality analysis, noting its potential benefits and data-related limitations.

E. Security and Privacy Challenges

The widespread integration of embedded systems in IoT architectures introduces critical security challenges, particularly as these systems perform real-time sensing and decision-making in sensitive contexts. Their constrained nature and the tendency to treat security as secondary in design make them vulnerable to attacks [35]. As embedded systems now support safety-critical applications, ensuring reliability and resilience becomes essential [36]. A compromised device can threaten the entire IoT network, highlighting the need for robust, integrated security, especially in edge processing, where minimizing data transfer also reduces the attack surface [37].

In addition to software risks, hardware-level threats such as microarchitectural attacks are gaining attention. These stealthy exploits bypass traditional protections and compromise trust mechanisms [38]. Middleware connecting heterogeneous systems is particularly exposed if hardware is not adequately secured. Manufacturers must adopt secure-by-design principles and deliver timely patches, while architects must understand the full attack taxonomy to implement end-to-end protections [35], [38].

V. Conclusion and Future Perspectives

Environmental monitoring technologies are evolving rapidly to meet the challenges posed by climate change, urbanization, and resource management. This review presented the current landscape and emerging directions in sensor development, ranging from conventional water level and air pollution sensors to more advanced, energy-efficient, and batteryless alternatives.

The integration of Power Electronics and Control systems with environmental sensing represents a paradigm shift toward sustainable and energy-efficient monitoring solutions. Low-power design strategies are achieving power consumption below 100 μW, while energy harvesting technologies enable perpetual operation without battery replacement. These advances are particularly relevant for applications requiring minimal maintenance and environmental impact.

The review also helps identify the most suitable sensing technologies based on context. For water level monitoring, ultrasonic sensors are ideal for short ranges (under 5 meters), while LiDAR offers better performance for longer distances. Satellite-based remote sensing is well-suited for large areas or hard-to-access regions. Soil monitoring benefits from technologies like NFC-powered sensors and optical fiber, while large-scale deployments can rely on mobile data collection using vehicles or UAVs.

In air quality monitoring, and to a certain extent in other domains, sensor affordability and maturity are no longer the main limitations. The current challenges lie in expanding data acquisition, maximizing the value of collected data, and securing communication in increasingly distributed sensor networks.

There is significant potential in combining the innovations discussed throughout this review. For example, AIoT can improve pollutant classification, Beat sensors enable long-term monitoring in remote areas, and applying security by design is critical as networks scale. Notably, Artificial Intelligence can be a powerful tool for prediction, anomaly detection, and autonomous response, but its effectiveness depends on the availability of high-quality, large-scale data. This creates a natural synergy with the broader push for denser and more distributed sensor deployments in smart cities, agriculture, and environmental systems.

As sensor networks scale in size and complexity, ensuring data security and integrity becomes increasingly critical. Security threats can undermine not only data accuracy but also the reliability of decision-making systems in critical scenarios, potentially triggering false alerts or skewing AI-driven analyses. Security must therefore be treated as a foundational component of system design, not an afterthought.

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