Emerging 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 state-of-the-art, 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), LiDAR, Beat sensors, LoRaWAN, soil sensors, air quality, Artificial Intelligence of Things (AIoT), embedded systems, security.**

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], [2]. These phenomena highlight the need for effective 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 [17], [20].

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. Level and Range Sensors

A. Water Level Sensors for Open Environments

Traditional water level monitoring methods, like staff gauges and limnigraphs, remain common in natural environments. Limnigraph sensors, which measure hydrostatic pressure, showed accurate readings in [3], but their reliability drops in flood conditions due to damage or obstruction risks.

Ultrasonic water level sensors are widely used due to their accuracy and ability to operate in environments with temperature and pressure variations [4], [6]. For example, the ultrasonic sensor model GY-Us42 was tested, showing that the average error of the device is less than 3% [4]. Another model, the HC-SR04, was also evaluated as a technically and economically viable option for water level monitoring in short ranges [6], and is a good choice for education, citizen science, and research due to its low cost [5].

LiDAR sensors have been explored as a low-cost alternative for measuring water levels from bridges, with lab and field tests showing good accuracy (error around 0.1%), though subject to variations due to sensor temperature and water surface roughness [7]. LiDAR sensors installed on riverbanks for flood monitoring were also tested with good results, the study showed that suspended particles in the water positively affected reading accuracy and that the sensor could also be used to detect suspended particle concentration [8]. Another study compared the TF-mini LiDAR sensor with limnigraph pressure sensors, highlighting the benefits of LiDAR's non-contact measurement method over the contact-based limnigraph method and validating LiDAR as an excellent choice among fluid level measurement technologies [3].

Another method for monitoring water levels in open environments is the use of satellite-based remote sensing. The work [11] 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, [12] 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.

B. 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. Emerging technologies show promise for these scenarios. For example, surface acoustic wave (SAW) sensors can passively detect water level changes by measuring strain or pressure variations on tank walls, converting them into frequency shifts or response signals [14], [15].

Another promising approach involves optical fiber-based sensors. These rely on the hydrostatic principle of Archimedes, where a floating element alters light transmission through a fiber to reflect changes in water level. This principle has been demonstrated in recent developments [16]. While highly accurate, these systems typically have limited measurement ranges and may involve more complex calibration.

III. Sensor Systems for Detecting Chemicals and Pollutants

A. Water Quality

Recent advancements in sensor technologies have significantly enhanced water quality monitoring. The work by [9] 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, [22] 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 [13], 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.

To address the need for continuous, high-resolution monitoring of soil infiltration, [24] proposed Active Heating Optical Frequency Domain Reflectometry (AH-OFDR). This method combines improved active heating fiber optics with OFDR technology to track water infiltration continuously across soil profiles, leveraging the principle that wetter soils change temperature more efficiently. Laboratory tests validated the method against traditional distributed temperature sensing (DTS) and infrared thermography.

C. 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. Deng et al. [10] 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. [23] 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.

D. Chemical Element Detection

The study by [18] investigates 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.

E. Air Pollution and Quality

The work by [19] 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.

The study by [21] presents 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. 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 [26].

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 [27]. 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 [25].

B. 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 [29], 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 [28]. In environmental monitoring, [9] developed a sensor node using embedded neural networks for pollutant classification, while [22] reviewed AI's role in water quality analysis, noting its potential benefits and data-related limitations.

C. 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 [31]. As embedded systems now support safety-critical applications, ensuring reliability and resilience becomes essential [32]. 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 [30].

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 [33]. 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 [31], [33].

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 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.

By connecting innovations in sensor technologies, low-power communication, AI-driven processing, and secure architectures, this review provides an integrated perspective on the future of environmental monitoring. The convergence of these areas enables more scalable, autonomous, and resilient systems capable of meeting the demands of climate adaptation, resource management, and urban sustainability.

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