Sensors for Environmental Monitoring: Trends and Challenges

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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 like LoRa/LPWAN. 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*—Internet of Things (IoT), Environment, Sensors, Wireless Sensor Networks (WSN), LoRaWAN, Artificial Intelligence of Things (AIoT), Environmental Monitoring.**

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 [29]–[32]. 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 [31], [33]–[35].

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 [36]–[38].

This literature review is structured into five main sections. First, it addresses the sensors and technologies used in environmental monitoring, categorizing them according to their application domains (hydrological, soil, and air quality). Next, the role of Wireless Sensor Networks and associated communication technologies is discussed. Then, the main challenges and current trends in the field of environmental monitoring are presented, focusing on technological innovations. Finally, conclusions and future perspectives are outlined.

Although previous reviews have thoroughly examined sensors for soil monitoring, such as those by [12], [41], [42], or water level measurement techniques as in [3], [4], [39], there is a notable lack of recent studies that comprehensively integrate both sensor technologies and communication infrastructures, presenting emerging concepts in environmental monitoring and going beyond specific applications.

This review aims to fill that gap by offering a broad perspective that covers sensor technologies applied to the monitoring of soil, water, and/or air/chemical compounds, along with an analysis of wireless communication technologies, energy efficiency strategies, artificial intelligence and security challenges in WSN deployments for environmental monitoring. The main contribution of this work is to consolidate multidisciplinary advances, highlight underexplored technologies, and provide a comparative analysis to guide future research and applications in the development of environmental monitoring projects.

II. Sensors and Technologies for Environmental Monitoring

In this work, we chose to group sensors according to the type of environment where they are applied, such as water level sensors, air quality sensors, and soil sensors, in order to better guide research in those environments.

A. Water Level Sensors for Open Environments

Simple methods for monitoring water levels, such as marked rulers or staff gauges, are still widely used in natural environments like rivers and lakes. Other common techniques range from basic visual tools to floating or contact-based sensors, including pressure sensors and limnigraphs, which measure the hydrostatic pressure of the water column. A limnigraph sensor was evaluated in the comparative study by [5], showing accurate readings and resistance to parameters like water turbidity. However, the same study highlights a key limitation: reduced reliability in harsh conditions. In flood scenarios with strong currents and high debris loads, these sensors may become damaged or obstructed. Similarly, float-based systems, where a buoy attached to a rope or cable tracks water height relative to a fixed reference, are simple and effective but can also be affected by floating debris, extreme weather, temperature changes, and corrosion [5], [7]–[9].

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For non-contact monitoring applications, this review highlights three approaches: ultrasonic sensors, LiDAR sensors, and remote monitoring via satellite imagery.

Ultrasonic water level sensors emit sound waves and measure the time it takes for the waves to return to the sensor. These sensors are widely used due to their accuracy and ability to operate in environments with temperature and pressure variations [7], [21]. For example, the ultrasonic sensor model GY-Us42 was tested, showing that the average error of the device is less than 3% [7]. Another model, the HC-SR04, was also evaluated as a technically and economically viable option for water level monitoring [21], and is a good choice for education, citizen science, and research due to its low cost [22].

LiDAR sensors use optical waves to measure distances and are widely used in metrology, environmental monitoring, archaeology, and robotics [6], [23]. These 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 [8]. 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 [20]. 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 [5].

Another method for monitoring water levels in open environments is the use of satellite-based remote sensing. The work [18] 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, [19] 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. Both studies confirm the viability and accuracy of satellite altimetry and image-based techniques for long-term and large-scale water level monitoring, especially in remote or transboundary regions.

B. Water Level Sensors for Controlled Environments

In controlled environments such as tanks and cisterns, where long-range sensing, debris, or extreme weather are not concerns, simpler and more cost-effective sensor technologies can be used. While the same sensors applied in rivers and lakes may still be suitable, simpler methods like resistive and capacitive sensors are commonly employed. Resistive sensors measure electrical resistance between submerged electrodes and are inexpensive and easy to install, though they can suffer from corrosion and scaling. Capacitive sensors, in contrast, detect changes in capacitance due to varying water levels are also great options [3], [5].

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 [26], [27].

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 [28]. While highly accurate, these systems typically have limited measurement ranges and may involve more complex calibration.

C. Water Quality

Recent advancements in sensor technologies have significantly enhanced water quality monitoring. The work by [10] 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, [39] review the application of artificial intelligence (AI) in water quality assessment.

D. Alternative Technologies for Large-Scale Soil Monitoring

Batteryless sensing technologies have emerged as promising alternatives for soil sensing in remote or hard to access locations. [15] introduced an NFC-based soil sensor that harvests energy from the NFC reader's magnetic field, 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, [47] 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, confirming AH-OFDR's superior spatial resolution and its potential for environmental and geotechnical soil moisture monitoring.

While LoRaWAN and traditional wireless sensor networks (WSNs) are widely adopted for monitoring in extensive agricultural fields, alternative architectures have been explored to address limitations in communication infrastructure, energy consumption, and scalability. One such approach is presented by Deng et al. [13], who developed a hybrid monitoring system combining passive RFID soil sensors with mobile data collection using a patrol vehicle. This system benefits from the simplicity, low cost, and low energy requirements of RFID technology, leveraging backscatter communication to transmit environmental data such as soil conditions to a centralized platform via the mobile unit.

Another innovative method involves the use of unmanned aerial vehicles (UAVs) as mobile data collectors. Caruso et al. [46] propose a solution where drones equipped with LoRa radios periodically fly over fields to collect data from distributed ground sensors. This method is particularly suitable for areas lacking fixed infrastructure or where real-time monitoring is not required. The authors present an analytical model to optimize drone path planning, sensor spacing, and flight parameters to ensure reliable data collection. Their model can be adapted to various drone types and communication protocols, offering a flexible and infrastructure-independent alternative for precision agriculture and other remote sensing applications.

E. Air and Chemical Composition Monitoring Review

When thinking of urban environments integrated with IoT under the concept of smart cities, one of the most relevant parameters is air quality, due to its direct impacts on public health, the environment, and the global economy. Atmospheric pollution in urban areas, with non-uniform spatial and temporal distribution, reinforces the need for monitoring systems with high spatiotemporal resolution, something traditional monitoring systems still struggle to provide at scale and with broad data coverage [2].

In this context, the advancement of sensor technologies, such as MEMS and wireless sensor networks (WSNs), has driven the development of the concept of the Next Generation Air Pollution Monitoring System (TNGAPMS). For this type of application, the most concerning gases are carbon monoxide (CO), nitrogen dioxide (NO_2), ground-level ozone (O_3), and sulfur dioxide (SO_2). Currently, the most used and suitable sensors for monitoring these gases in urban and industrial settings are electrochemical sensors and solid-state (semiconductor) sensors, although there are also other low-cost technologies such as catalytic sensors, NDIR, and PID sensors, which are widely applied in various gas detection contexts [2].

F. Chemical Element Detection

The study by [16] 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.

G. Air Pollution and Quality

The work by [17] 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 [2] 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.

III. Challenges and Trends

A. Long Range Communication Technologies

In this context, Wireless Sensor Networks (WSNs) have established themselves as a promising tool, offering significant advantages in terms of deployment flexibility, quick responsiveness, and cost-benefit compared to traditional monitoring infrastructures. WSNs enable dense spatial sampling and continuous data collection—critical aspects for tracking natural phenomena [36], [38].

The need for real-time environmental monitoring has increased the demand for data, highlighting the importance of low-power, long-range technologies such as LoRa. These technologies are particularly suitable for applications in remote areas where communication infrastructure is limited or non-existent [36], [38].

A new emerging technology in this field are beat sensors...

B. Artificial Intelligence with Internet of Things(AIoT)

The integration of Artificial Intelligence (AI) into Internet of Things (IoT) systems, referred to as AIoT, has enabled smarter, more autonomous applications across fields like smart cities, industry, and environmental monitoring. The work [45] describe this evolution as part of a broader shift toward cyber-physical systems, where embedded devices, humans, and the environment interact to form intelligent systems. AI enhances the capability of IoT by enabling real-time analysis, predictive decision-making, and self-adaptive behavior. However, this convergence also raises challenges, including data security, ethical concerns, and the complexity of system integration.

The work of [40] emphasize the growing use of AI-enabled sensors that are context-aware, reliable, and efficient. These sensors reduce energy use, improve response time, and support applications like predictive maintenance and smart routing. In the environmental domain, [10] apply this concept in a wireless sensor node that classifies aquatic pollutants using embedded neural networks and distributed processing. Similarly, [39] review the use of AI in water quality analysis, discussing its potential to improve detection accuracy and response speed while noting limitations related to data availability and transparency.

C. Security and Privacy Challenges

Apostolos and koulamas [**?**] discuss the security and privacy challenges in IoT systems. The authors emphasize the importance of addressing these challenges to enable the widespread adoption of IoT technologies.

IV. Conclusion and Future Perspectives

Acknowledgment

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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