

Sensors for Environmental Monitoring: Trends and Challenges

1st Klaus Dieter Kupper

dept. name of organization (of Aff.)

name of organization (of Aff.)

City, Country

email address or ORCID

2nd Jordan

dept. name of organization (of Aff.)

name of organization (of Aff.)

City, Country

email address or ORCID

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—Internet of Things (IoT), Environment, Sensors, Wireless Sensor Networks (WSN), Soil, Water L, 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. LEVEL AND RANGE SENSORS

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.

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

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 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 and 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.

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 [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.

B. 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.

C. 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.

D. 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 ($\text{PM}_{2.5}$). 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.

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.” This method eliminates the need for

conventional sensing circuitry and enables the use of ultra-low-power, compact, and cost-effective devices suitable for scalable deployments in smart environments. Applications include power monitoring systems such as Power Beat and DC Current Beat sensors, aimed at energy reduction in residential and commercial buildings [49].

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 [50]. 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 [48].

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

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 [51]. As embedded systems now support safety-critical applications, ensuring reliability and resilience becomes essential [52]. 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 [43].

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 [53]. 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 [51], [53].

V. CONCLUSION AND FUTURE PERSPECTIVES

The conclusion is at least two paragraphs long. The first paragraph should summarize the main findings of the paper, while the second paragraph should discuss the implications of these findings and suggest directions for future research.

The conclusion is at least two paragraphs long. The first paragraph should summarize the main findings of the paper, while the second paragraph should discuss the implications of these findings and suggest directions for future research.

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.

REFERENCES

- [1] M. Javaid, A. Haleem, S. Rab, R. P. Singh, and R. Suman, “Sensors for daily life: A review,” *Sensors International*, vol. 2, p. 100121, 2021. doi: 10.1016/j.sintl.2021.100121.
- [2] W. Yi, K. Lo, T. Mak, K. Leung, Y. Leung, and M. Meng, “A survey of wireless sensor network based air pollution monitoring systems,” *Sensors*, vol. 15, pp. 31392–31427, Dec. 2015. doi: 10.3390
- [3] P. Mohindru, “Development of liquid level measurement technology: A review,” *Flow Measurement and Instrumentation*, vol. 89, p. 102295, Mar. 2023. doi: 10.1016/j.flowmeasinst.2022.102295.
- [4] Z. Wu, Y. Huang, K. Huang, K. Yan, and H. Chen, “A Review of Non-Contact Water Level Measurement Based on Computer Vision and Radar Technology,” *Water*, vol. 15, p. 3233, Jan. 2023. doi: 10.3390/w15183233.
- [5] V. Santana, R. E. Salustiano, and R. Tiezzi, “Development and Calibration of a Low-Cost LIDAR Sensor for Water Level Measurements,” *Flow Measurement and Instrumentation*, vol. 2024, pp. 102729–102729, Oct. 2024. doi: 10.1016/j.flowmeasinst.2024.102729.
- [6] N. Li, C. P. Ho, J. Xue, L. W. Lim, G. Chen, Y. H. Fu, and L. Y. T. Lee, “A Progress Review on Solid-State LiDAR and Nanophotonics-Based LiDAR Sensors,” *Laser and Photonics Reviews*, vol. 16, p. 2100511, Aug. 2022. doi: 10.1002/lpor.202100511.
- [7] M. MasoudiMoghaddam, J. Yazdi, and M. Shahsavandi, “A Low-Cost Ultrasonic Sensor for Online Monitoring of Water Levels in Rivers and Channels,” *Flow Measurement and Instrumentation*, vol. 102, p. 102777, Dec. 2024. Elsevier BV. doi: 10.1016/j.flowmeasinst.2024.102777.
- [8] J. D. Paul, W. Buytaert, and N. Sah, “A Technical Evaluation of Lidar-Based Measurement of River Water Levels,” *Water Resources Research*, vol. 56, Apr. 2020. doi: 10.1029/2019wr026810.
- [9] C. Yukawa, T. Oda, T. Sato, M. Hirota, K. Katayama, and L. Barolli, “An Intelligent Water Level Estimation System Considering Water Level Device Gauge Image Recognition and Wireless Sensor Networks,” *Journal of Sensor and Actuator Networks*, vol. 14, p. 13, Jan. 2025. doi: 10.3390/jsan14010013.
- [10] Y. Ferreira, C. Silvério, and J. Viana, “Conception and Design of WSN Sensor Nodes Based on Machine Learning, Embedded Systems and IoT Approaches for Pollutant Detection in Aquatic Environments,” *IEEE Access*, vol. 11, pp. 117040–117052, Jan. 2023. doi: 10.1109/access.2023.3325760.
- [11] R. A. Viscarra Rossel and J. Bouma, “Soil sensing: A new paradigm for agriculture,” *Agricultural Systems*, vol. 148, pp. 71–74, Oct. 2016. doi: 10.1016/j.agsy.2016.07.001.
- [12] H. Yin, Y. Cao, B. Marelli, X. Zeng, A. J. Mason, and C. Cao, “Smart Agriculture Systems: Soil Sensors and Plant Wearables for Smart and Precision Agriculture (Adv. Mater. 20/2021),” *Advanced Materials*, vol. 33, p. 2170156, May 2021. doi: 10.1002/adma.202170156.
- [13] F. Deng, P. Zuo, K. Wen, and X. Wu, “Novel soil environment monitoring system based on RFID sensor and LoRa,” *Computers and Electronics in Agriculture*, vol. 169, p. 105169, Feb. 2020. doi: 10.1016/j.compag.2019.105169.
- [14] A. Nagpure, G. Reddy, and S. Naidu, “Water Level Controller Using Ultrasonic Sensor,” *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, pp. 242–257, Dec. 2022. doi: 10.22214/ijraset.2022.47856.
- [15] M. Boada, A. Lazaro, R. Villarino, and D. Girbau, “Battery-Less Soil Moisture Measurement System Based on a NFC Device With Energy Harvesting Capability,” *IEEE Sensors Journal*, vol. 18, pp. 5541–5549, Jul. 2018. doi: 10.1109/jsen.2018.2837388.
- [16] J. Devkota, P. Ohodnicki, and D. Greve, “SAW Sensors for Chemical Vapors and Gases,” *Sensors*, vol. 17, p. 801, Apr. 2017. doi: 10.3390/s17040801.
- [17] F. Karagulian, M. Barbiere, A. Kotsev, L. Spinelle, M. Gerboles, F. Lagler, N. Redon, S. Crunaire, and A. Borowiak, “Review of the Performance of Low-Cost Sensors for Air Quality Monitoring,” *Atmosphere*, vol. 10, p. 506, Aug. 2019. doi: 10.3390/atmos10090506.
- [18] Z. Jiang and L. Hong, “Monitoring of Surface Water Area and Water Level Changes in Nine Plateau Lakes in Yunnan and Analysis of Influencing Factors,” in **Proc. 2024 IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conf. (IMCEC)**, pp. 1027–1031, May 2024. doi: 10.1109/imcecs9810.2024.10575197.
- [19] T. Ali, A. Zaidi, J. Rehman, F. Noor, F. Naz, and S. Jamali, “Satellite Radar Altimetry Insights into Dam-Induced Changes and Accuracy of Water Level Estimation for the Mekong River,” in **Proc. IGARSS 2022 - IEEE Int. Geosci. Remote Sens. Symp.**, vol. 570, pp. 5063–5066, Jul. 2024. doi: 10.1109/igarss53475.2024.10642418.
- [20] S. Tamari and V. Guerrero-Meza, “Flash Flood Monitoring with an Inclined Lidar Installed at a River Bank: Proof of Concept,” *Remote Sensing*, vol. 8, p. 834, Oct. 2016. doi: 10.3390/rs8100834.
- [21] T. S. R. Pereira, T. P. de Carvalho, T. A. Mendes, and K. T. M. Formiga, “Evaluation of Water Level in Flowing Channels Using Ultrasonic Sensors,” *Sustainability*, vol. 14, p. 5512, May 2022. doi: 10.3390/su14095512.
- [22] P. Bresnahan, E. Briggs, B. Davis, A. Rodriguez, L. Edwards, C. Peach, N. Renner, H. Helling, and M. Merrifield, “A Low-Cost, DIY Ultrasonic Water Level Sensor for Education, Citizen Science, and Research,” *Oceanography*, vol. 36, 2023. doi: 10.5670/oceanog.2023.101.
- [23] B. Behroozpour, P. A. M. Sandborn, M. C. Wu, and B. E. Boser, “Lidar System Architectures and Circuits,” *IEEE Communications Magazine*, vol. 55, pp. 135–142, Oct. 2017. doi: 10.1109/mcom.2017.1700030.
- [24] J. C. Fernandez-Diaz, C. L. Glennie, W. E. Carter, R. L. Shrestha, M. P. Sartori, A. Singhania, C. J. Legleiter, and B. T. Overstreet, “Early Results of Simultaneous Terrain and Shallow Water Bathymetry Mapping Using a Single-Wavelength Airborne LiDAR Sensor,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, pp. 623–635, Feb. 2014. doi: 10.1109/jstars.2013.2265255.
- [25] G. Smart, J. Bind, and M. Duncan, “River bathymetry from conventional LiDAR using water surface returns,” in **Proc. 18th World IMACS / MODSIM Congress**, 2009. [Online]. Available: <https://mssanz.org.au/modsim09/F13/smart.pdf>
- [26] S. F. Ali, N. Mandal, P. Maurya, and A. Lata, “SAW Sensor Based a Novel Hydrostatic Liquid Level Measurement,” in **Proc. IECON 2020 - 46th Annual Conf. IEEE Industrial Electronics Society**, pp. 724–729, Oct. 2020. doi: 10.1109/iecon43393.2020.9254540.
- [27] V. S. Sreejith and H. Zhang, “Modeling and Testing of a Highly Sensitive Surface Acoustic Wave Pressure Sensor for Liquid Depth Measurements,” *Sensors and Actuators A: Physical*, vol. 372, p. 115377, Jul. 2024. doi: 10.1016/j.sna.2024.115377.

- [28] C. C. Ramos, J. Preizal, X. Hu, C. Caucheteur, G. Woyessa, O. Bang, A. M. Rocha, and R. Oliveira, "High Resolution Liquid Level Sensor Based on Archimedes' Law of Buoyancy Using Polymer Optical Fiber Bragg Gratings," *Measurement*, vol. 252, p. 117368, Mar. 2025. Elsevier BV. doi: 10.1016/j.measurement.2025.117368.
- [29] S. N. Jonkman, "Global Perspectives on Loss of Human Life Caused by Floods," *Natural Hazards*, vol. 34, pp. 151–175, Feb. 2005. doi: 10.1007/s11069-004-8891-3.
- [30] M. Borgia, M. Stoffel, L. Marchi, F. Marra, and M. Jakob, "Hydrogeomorphic Response to Extreme Rainfall in Headwater Systems: Flash Floods and Debris Flows," *Journal of Hydrology*, vol. 518, pp. 194–205, Oct. 2014. doi: 10.1016/j.jhydrol.2014.05.022.
- [31] J. Hall *et al.*, "Understanding Flood Regime Changes in Europe: A State-of-the-Art Assessment," *Hydrology and Earth System Sciences*, vol. 18, pp. 2735–2772, Jul. 2014. doi: 10.5194/hess-18-2735-2014.
- [32] C. G. J. F. N. Bragança, "Análise da Influência dos Fenômenos El Niño e La Niña na Ocorrência de Eventos Climáticos de Seca e Enchente," *Dissertação de Mestrado*, 2024.
- [33] U. Iqbal, P. Perez, W. Li, and J. Barthelemy, "How Computer Vision Can Facilitate Flood Management: A Systematic Review," *International Journal of Disaster Risk Reduction*, vol. 53, p. 102030, Feb. 2021. doi: 10.1016/j.ijdr.2020.102030.
- [34] F. Lin, Z. Yu, Q. Jin, and A. You, "Semantic Segmentation and Scale Recognition-Based Water-Level Monitoring Algorithm," *Journal of Coastal Research*, vol. 105, 2020. doi: 10.2112/jcr-si105-039.1.
- [35] S.-W. Lo, J.-H. Wu, F.-P. Lin, and C.-H. Hsu, "Visual Sensing for Urban Flood Monitoring," *Sensors*, vol. 15, pp. 20006–20029, Aug. 2015. doi: 10.3390/s150820006.
- [36] D. Chen, Z. Liu, L. Wang, M. Dou, J. Chen, and H. Li, "Natural Disaster Monitoring with Wireless Sensor Networks: A Case Study of Data-Intensive Applications upon Low-Cost Scalable Systems," *Mobile Networks and Applications*, vol. 18, pp. 651–663, Aug. 2013. doi: 10.1007/s11036-013-0456-9.
- [37] S. Yellampalli, Ed., "Wireless Sensor Networks - Design, Deployment and Applications", IntechOpen, Sep. 2021. doi: 10.5772/intechopen.77917. [Online]. Available: <https://www.intechopen.com/books/8086>
- [38] M. Pule, A. Yahya, and J. Chuma, "Wireless Sensor Networks: A Survey on Monitoring Water Quality," *Journal of Applied Research and Technology*, vol. 15, pp. 562–570, Dec. 2017. doi: 10.1016/j.jart.2017.07.004.
- [39] W. B. N.R., S. Palarimath, H. Gunasekaran, S. W. Haidar, S. G. S. Subitha, and J. Sarmila, "AI Modeling and Water Quality Sensing Technique Proffers Water Security: An Open Review," in *Proc. 2022 Int. Conf. Electronics and Renewable Systems (ICEARS)*, pp. 1028–1034, Feb. 2025. doi: 10.1109/icears64219.2025.10940077.
- [40] S. C. Mukhopadhyay, S. K. S. Tyagi, N. K. Suryadevara, V. Piuri, F. Scotti, and S. Zeadally, "Artificial Intelligence-Based Sensing for Next Generation IoT Applications: A Review," *IEEE Sensors Journal*, vol. 21, pp. 1–1, 2021. doi: 10.1109/jsen.2021.3055618.
- [41] Y. Teng, J. Wu, S. Lu, Y. Wang, X. Jiao, and L. Song, "Soil and Soil Environmental Quality Monitoring in China: A Review," *Environment International*, vol. 69, pp. 177–199, Aug. 2014. doi: 10.1016/j.envint.2014.04.014.
- [42] D. M. de Queiroz, A. L. de F. Coelho, D. S. M. Valente, and J. K. Schueller, "Sensors Applied to Digital Agriculture: A Review," *Revista Ciência Agrônômica*, vol. 51, 2020. doi: 10.5935/1806-6690.20200086.
- [43] J. M. Tien, "Internet of Things, Real-Time Decision Making, and Artificial Intelligence," *Annals of Data Science*, vol. 4, pp. 149–178, May 2017.
- [44] A. Haroun, X. Le, S. Gao, B. Dong, T. He, Z. Zhang, F. Wen, S. Xu, and C. Lee, "Progress in Micro/Nano Sensors and Nanoenergy for Future AIoT-Based Smart Home Applications," *Nano Express*, vol. 2, p. 022005, Apr. 2021. doi: 10.1088/2632-959x/abf3d4.
- [45] A. Ghosh, D. Chakraborty, and A. Law, "Artificial Intelligence in Internet of Things," *CAAI Transactions on Intelligence Technology*, vol. 3, pp. 208–218, Dec. 2018. doi: 10.1049/trit.2018.1008. [Online]. Available: <https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/trit.2018.1008>
- [46] A. Caruso, S. Chessa, S. Escobar, J. Barba, and J. C. Lopez, "Collection of Data with Drones in Precision Agriculture: Analytical Model and LoRa Case Study," *IEEE Internet of Things Journal*, vol. 2021, pp. 1–1, 2021. doi: 10.1109/IJOT.2021.3075561.
- [47] C. Sun, C.-S. Tang, F. Vahedifard, Q. Cheng, A. Dong, T.-F. Gao, and B. Shi, "High-resolution monitoring of soil infiltration using distributed fiber optic," *J. Hydrol.*, vol. 640, p. 131691, Jul. 2024. doi: 10.1016/j.jhydrol.2024.131691.
- [48] M.-H. Dao, K. Ishibashi, T.-A. Nguyen, D.-H. Bui, H. Hirayama, T.-A. Tran, and X.-T. Tran, "Low-cost, high accuracy, and long communication range energy-harvesting Beat Sensor with LoRa and Ω -antenna for water-level monitoring," *IEEE Sensors Journal*, vol. 25, pp. 1–1, Jan. 2025. doi: 10.1109/jsen.2025.3533014.
- [49] K. Ishibashi, R. Takitoge, and S. Ishigaki, "Beat sensors IoT technology suitable for energy saving," in *Proc. 2017 7th Int. Conf. on Integrated Circuits, Design, and Verification (ICDV)*, pp. 52–55, Oct. 2017. doi: 10.1109/icdv.2017.8188637.
- [50] K. Ishibashi, R. Takitoge, D. Manyone, N. Ono, and S. Yamaguchi, "Long battery life IoT sensing by Beat Sensors," in *Proc. 2019 IEEE Int. Conf. on Industrial Cyber Physical Systems (ICPS)*, pp. 430–435, May 2019. doi: 10.1109/icphys.2019.8780159.
- [51] Pimentel, A. D. (2017). Exploring exploration: A tutorial introduction to embedded systems design space exploration. *IEEE Design & Test*, 1, 77–90. doi:10.1109/MDAT.2016.2626445.
- [52] Koulamas, C., & Lazarescu, M. (2018). Real-time embedded systems: Present and future. *Electronics*, 9, 205. doi:10.3390/electronics7090205.
- [53] Fournaris, A., Pocero Fraile, L., & Koufopavlou, O. (2017). Exploiting hardware vulnerabilities to attack embedded system devices: A survey of potent microarchitectural attacks. *Electronics*, 3, 52. doi:10.3390/electronics6030052.

IS REF VALID? — C. G. J. F. N. Bragança, "Análise da Influência dos Fenômenos El Niño e La Niña na Ocorrência de Eventos Climáticos de Seca e Enchente," *Dissertação de Mestrado*, 2024.