

Role of New Technologies in the Management of Environmental Pollution: A Review

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Abstract

Environmental pollution across air, water, and soil continues to threaten human health and ecosystem stability worldwide, even as regulatory frameworks and conventional abatement methods struggle to keep pace with the scale and complexity of contemporary contamination sources. This paper reviews recent, peer-reviewed evidence on the role of emerging technologies in environmental pollution management, organised around eleven interconnected domains: sensor- and artificial-intelligence-driven air-quality monitoring and calibration, satellite and remote-sensing observation networks, unmanned aerial vehicle (UAV)-based monitoring, nanotechnology-based water and wastewater treatment, photocatalytic degradation of organic pollutants, biosensors and bioremediation, phytoremediation of contaminated soils, microplastic detection technologies, blockchain-enabled environmental data governance, artificial-intelligence-driven solid-waste management and e-waste recovery, and carbon capture, utilisation, and storage. Across these domains, the reviewed literature shows that digital, biological, and materials-science technologies are markedly improving the resolution, speed, and reliability with which pollution is detected, characterised, and, in many cases, removed, often at a lower chemical and energy intensity than conventional methods. At the same time, recurring constraints, including sensor calibration drift, nanomaterial toxicity and scale-up costs, computational and connectivity requirements, regulatory fragmentation, and uneven geographic validation, continue to limit real-world deployment, particularly in low-resource settings. The review concludes that maximising the environmental benefit of these technologies will depend less on further isolated technical refinement and more on their integration into interoperable monitoring-to-remediation systems, supported by harmonised standards and equitable access.

Keywords: *environmental pollution, pollution monitoring, artificial intelligence, Internet of Things, nanotechnology, remote sensing, biosensors, wastewater treatment, phytoremediation, microplastics, carbon capture, environmental management*

1. Introduction

Air, water, and soil pollution includes one of the most persistent environmental problems in today's world, contributing to early deaths, loss of biodiversity, and damage to the ecological processes on which food and water systems depends. For decades, management of pollution meant to occasional hand collections of samples, laboratory testing, and preparing reports through centralized regulatory channels. That method was designed for a slower, more industrial age, and it struggles to keep pace with how pollution actually moves today — from patchy urban traffic exhaust to industrial plumes crossing national borders, alongside newly recognized contaminants such as microplastics. Over the past few years, a broad mix of digital, biological, and materials-science innovations has shifted to practical use for monitoring and removing pollution. Drawing on more than eighty peer-reviewed and technical sources — most published between 2017 and 2026 across environmental science, engineering, chemistry, and computing — this review asks two connected questions: what do these technologies actually offer that older methods could not, and what still stands in the way of turning them into everyday practice, particularly outside wealthier nations? The remainder of the paper is organized as follows. Section 2 looks at AI- and IoT-based air-quality sensing and calibration. Section 3 covers satellite remote sensing, and Section 4 covers drone-based monitoring. Section 5 discusses nanotechnology applied to water and wastewater treatment, and Section 6 covers photocatalytic degradation of organic pollutants. Section 7 addresses biosensing and bioremediation, and Section 8 covers soil phytoremediation. Section 9 reviews microplastic-detection technology, Section 10 examines blockchain's role in environmental data governance, and Section 11 covers AI applications in waste management and e-waste recovery. Section 12 discusses carbon capture, utilization, and storage; Section 13 covers noise-pollution monitoring; Section 14 pulls together barriers to adoption and their policy implications; and Section 15 concludes.

2. AI and IoT for Air-Quality Monitoring and Calibration

Merging artificial intelligence with networks of Internet-of-Things sensors has become the most actively studied path toward real-time pollution tracking. A wide-ranging review of AI- and IoT-based environmental technologies notes that AI-powered sensor systems are now commonly deployed to identify and characterize pollutants across air, water, and soil (Popescu et al., 2024). Combining low-cost sensors with LoRaWAN networking and machine-learning-based calibration has been shown to extend reliable monitoring into areas that reference-grade instruments historically never reached (Ali et al., 2021), and edge-computing architectures have been proposed as a route to lowering both cost and latency for monitoring at scale (Idrees et al., 2018).

Calibration continues to be the toughest technical problem in this space. A review synthesizing more than ninety peer-reviewed studies concluded that machine-learning calibration substantially improves the accuracy of low-cost optical, electrochemical, metal-oxide, and infrared sensors relative to their out-of-the-box settings — but how well those calibration models generalize across different locations, seasons, or fixed-versus-mobile setups is still hard to predict. Comparative tests of calibration approaches for nitrogen-oxide sensors reach a similar conclusion: machine-learning approaches outperform simple linear

correction, though results depend heavily on how diverse the co-location training data are (Bigi et al., 2018; De Vito et al., 2018; Nowack et al., 2021). Recent experimental work confirms that a model built for one location often loses accuracy when applied somewhere else (Abu-Hani et al., 2024).

Guidance on monitor deployment, co-location duration, and data selection is essential to producing exposure estimates usable for health research, as emphasised by systematic reviews of low-cost sensor performance (Bi et al., 2022; Karagulian et al., 2019), while in-situ calibration algorithms and participatory monitoring frameworks have extended low-cost networks into citizen-science and smart-city contexts (Delaine et al., 2019; Chen et al., 2017; Concas et al., 2021). Other studies connect sensor data more directly to health outcomes like longitudinal work using digital health-monitoring devices linked with air-pollution exposure to respiratory symptoms (Su et al., 2024). Also, land-use regression models have been increasingly incorporating low-cost sensor networks to capture fine spatial information about different pollution levels (Ma, X. et al., 2024). Indoor air quality has become an emerging sub-field in its own right, with digital-twin platforms and indoor-specific IoT systems, which are now being used to track and manage pollutants inside the buildings (Qian, 2024; Gautam, 2021; Khan et al., 2026), and indoor low-cost sensor readings have also been used to trace combustion by-products, other pollutants, back to their sources (Higgins et al., 2024).

3. Satellite and Remote-Sensing Networks

Satellite remote sensing has emerged into an essential complement to ground-based monitoring, offering spatial coverage and temporal consistency that sparse sensor networks cannot achieve alone. The instruments launched in 2024 illustrate how fast this field is emerging, as for an example, NASA's Tropospheric Emissions Monitoring of Pollution (TEMPO) mission provides hourly and high-resolution measurements of nitrogen dioxide, formaldehyde, and ozone over North America, and resolves pollution differences down to the neighborhood scale. TEMPO is part of a larger international network — including geostationary satellites over East Asia and Europe — that collectively enables near-continuous tracking of pollution events that cross national boundaries.

Regulatory bodies now increasingly incorporate satellite data formally into national emissions-inventory checks and public-health assessments (Holloway, Bratburd, et al., 2025), building on an established research base linking satellite observation to air-quality and health outcomes (Holloway, Miller, et al., 2021). Hyperspectral instruments such as PRISMA have demonstrated the ability to track urban air quality at fine spectral resolution (De Santis et al., 2024), while methane-detecting satellites now allow point-source leaks from oil and gas facilities to be identified at a level of detail that ground-based methods cannot match on their own (De Gouw et al., 2020). Satellite tracking of landfill sites has also emerged as a lower-cost alternative to the expensive and logistically demanding ground surveys traditionally relied on for monitoring waste-disposal locations (Sharma & Rajendra, 2025).

4. UAV and Drone-Based Monitoring

Drones occupy a useful middle ground between fixed ground sensors and satellites, delivering three-dimensional, targeted data close to pollution sources at a fraction of what crewed aircraft cost. Sensor-equipped UAVs have been used to map how particulate matter spreads along highway corridors (Li et al., 2022) and to track dust storms in arid regions (Zhou et al., 2022), while gas-sensor-equipped drone swarms have been proposed as a tool for spotting industrial leaks (Tosato et al., 2019). A systematic review and meta-analysis covering both satellite- and drone-based air-pollution observation found that drones fill a genuine resolution gap between satellite and ground-level monitoring, especially for characterizing plumes close to their source (Javan et al., 2025); reviews of UAV applications for community-level and indoor-adjacent pollutant tracking highlight their value specifically for environmental-justice-oriented monitoring efforts (Bakirci, 2024).

A newer "lab-on-a-drone" concept makes it possible to sample and perform preliminary analysis of pollutants at remote or hazardous sites without transportation of samples to any external laboratory (Silva-Neto et al., 2025). That said, reviews in this area consistently point to short flight times, payload limits that constrain how advanced onboard sensors can be, and inconsistent international drone regulations as ongoing barriers to fully integrating UAVs into the broader satellite-and-ground monitoring system.

5. Nanotechnology in Water and Wastewater Treatment

Nanotechnology has become one of the most active areas of research in pollution remediation, particularly for water and wastewater treatment. A review of nanoparticle- and nanocomposite-based treatment methods catalogues a wide range of engineered materials — metal nanoparticles, carbon-based nanomaterials, and hybrid nanocomposites — that remove contaminants through adsorption, catalytic breakdown, and membrane filtration (Tripathy et al., 2024). Nanocomposite membranes incorporating engineered nanomaterials have outperformed conventional polymer membranes on both throughput and resistance to fouling (Ismail et al., 2023), and a broader survey of nanotechnology's role in water security covers applications ranging from desalination to trace-level contaminant sensing (Alvarez et al., 2018).

Biochar treated with sulfuric acid and loaded with manganese dioxide has proven to be effective at removing toxic organic pollutants across a wide ranges of pH (Zhang, L. et al., 2023); in addition, nanocomposites based on hydrous cerium oxide shows improved selectivity for removals of lead and cadmium (Yang et al., 2025); and reviews nanomaterials in water treatment point to rise interest in recovering and reusing spent nanomaterials as part of a more circular treatment model (Nyabadza et al., 2024). A broader annual survey of nanomaterials used in water remediation identifies scale-up difficulties, uncertain long-term ecological toxicities, and the challenge of moving from bench-scale results to pilot-scale operation as the main hurdle that still limits the wider adoption (Klink et al., 2026).

6. Photocatalytic Degradation of Organic Pollutants

Photocatalysis refers to the breakdown of organic pollutants into carbon dioxide and water using light energy, and has become a promising advanced oxidation technique for treating dyes, pharmaceuticals, and other persistent organic contaminants that resist conventional treatment methods. Reviews of the underlying chemistry have noted that semiconductor photocatalysts, especially titanium dioxide and related metal oxides, degrade pollutants through the production of reactive oxygen species when exposed to UV, visible, or solar light (Zhu & Zhou, 2019); cerium-oxide-based photocatalysts are known for their versatility, and are useful in breakdown of pollutants and conversion of carbon dioxide (Tran et al., 2022; Han et al., 2025).

Recent efforts have focused on making photocatalysts recoverable and reusable, including magnetic nanocomposites that combine graphene oxide's electron-transport capability with easy magnetic separation, along with metal-organic-framework photocatalysts such as ZIF-8 and UiO-66, which have shown effectiveness against dyes, pesticides, and pharmaceutical residues (Çalık et al., 2022). Despite encouraging lab-scale degradation rates, rapid recombination of charge carriers and reactor-design limitations continue to hold back full-scale deployment (He & Qu, 2025); phthalocyanine-based photosensitizers also explored as a way to extend photocatalytic activity into the visible-light range, making these systems better suitable for solar-powered treatment setups (Gamelas et al., 2023).

7. Biosensors and Bioremediation

A distinct line of research turns to biological rather than purely chemical or physical systems for detecting and removing pollutants, particularly heavy metals. Whole-cell microbial biosensors engineered with transcription factors responsive to heavy metals enable real-time, on-site detection of contaminants such as lead, copper, mercury, and cadmium even at low concentrations. Whole-cell biosensors that can be read by eye or optically have been designed specifically for low-cost, field-deployable mercury screening (Ma et al., 2024), and deoxyviolacein-based whole-cell biosensors have shown selective detection of cadmium in biological samples (Zhang, J. et al., 2024), extending environmental biosensing techniques into human-exposure monitoring as well.

Electrochemical and optical biosensors, together with molecularly imprinted polymer sensors, are described as outperforming conventional laboratory analysis on portability, reproducibility, and suitability for ongoing field use — particularly for tracking heavy metals and pesticide residues in wastewater (O'Hara & Singh, 2021; Talukder et al., 2024). Newer water-quality biosensor platforms increasingly aim to detect chemical contaminants and microbial pathogens at the same time (Fdez-Sanromán et al., 2025), and advances in kinetics-based surface-enhanced Raman spectroscopy are sharpening the ability to distinguish structurally similar pollutants right at the point of detection (Zhou, T. et al., 2025). Low-cost chemosensor platforms and paper-based electrochemical biosensors using conductive inks are also being explored as affordable options for field or resource-limited settings (Albu et al.,

2025; Gupta et al., 2025) — though some reviews caution that abiotic stressors, such as co-occurring antibiotic contamination, can complicate the interpretation of microbial biosensor signals in real-world soil and water samples (Rasheela et al., 2024).

8. Phytoremediation of Contaminated Soils

Phytoremediation — using plants to extract, contain, or break down soil contaminants — is widely cited as a low-cost, environmentally friendly alternative to engineered physical and chemical remediation for heavy-metal-contaminated soils. One comprehensive review underscores the growing need for new remediation methods as industrial soil contamination rises, and surveys a range of hyperaccumulator plant species used for detoxification purposes. Reviews focused specifically on cadmium contamination describe enhanced phytoextraction using hyperaccumulator species, while noting long cleanup timelines and low removal efficiency per growing cycle as persistent shortcomings of the method.

To address these limitations, researchers mostly favour "phyto-combined" strategies that combines plant-based remediation with chelating agents, beneficial soil organisms like mycorrhizal fungi and plant-growth-promoting bacteria, and soil amendments like biochar and compost, which have been shown to increase the uptake of metals and improve plant stress tolerance. Techno-economic analysis suggests that while phytoremediation's running costs are well below those of engineered alternatives, the long timeframes needed to fully clean a site remain an obstacle wherever regulatory deadlines or redevelopment plans apply (Wang & Delavar, 2023); a case study from Bangladesh illustrates how combining phytoremediation with bioenergy production from harvested hyperaccumulator biomass can strengthen its economic viability. A synthesis editorial on this body of work concludes that the scientific understanding, efficiency, and practical implementation pathways for phytoremediation have advanced considerably, even as field-scale, regulatory, and economic obstacles continue to slow its broader uptake (Wang, Liang, & Liu, 2024).

9. Microplastic Detection Technologies

Microplastics — now detected across aquatic, terrestrial, and atmospheric environments — have driven rapid development of dedicated detection tools over the last three years. Electrochemical sensors lead this field, offering high sensitivity, low cost, and real-time on-site detection compared with the more established but slower and more expensive spectroscopic techniques; sensors built with biochar and graphene electrodes have demonstrated selective electrochemical detection of polystyrene and other common microplastic polymers (Kim et al., 2024; Du et al., 2023). Portable, field-ready formats — including triboelectric microfluidic sensors — are moving microplastic detection out of the lab and into the field (Motalebizadeh et al., 2023), and systematic reviews of in-situ aquatic detection methods report substantial recent growth in this research area (Abimbola et al., 2024).

Beyond electrochemical approaches, nanomaterial-enhanced optical methods — including surface-enhanced Raman spectroscopy using gold and iron-oxide nanoparticles — and biosensor-based detection are described as complementary options, each balancing sensitivity, cost, and field portability differently (Jebril et al., 2024; Islam et al., 2024). Terahertz spectroscopy has been proposed as a fast, broadly applicable method to quantify microplastics in soil (Zhao et al., 2022), and broader reviews of microplastic detection and characterization catalogue an expanding toolkit based on vision, spectral, and thermal-analysis techniques (Randhawa, 2023). Apart from this, AI-based image analysis is increasingly proposed as a way to automate microplastic identification from field imageries.

10. Blockchain and Distributed-Ledger Technologies for Environmental Data Governance

The research examines blockchain and related distributed-ledger technologies as a governance layer for environmental data. As blockchain records cannot be manipulated once entered, reviews conclude that this technology can help in ensuring the accuracy and trustworthiness of pollution and emissions data, supporting more reliable regulatory report preparations and reducing the potential for data manipulation in compliance monitoring, emissions-credit tradings, and fine collections. Pairing the blockchain with IoT sensor networks has been reported to improve authenticity of data, transparency, and traceability beyond what IoT monitoring. Also, systematic reviews of combined IoT-blockchain pollution-monitoring systems finds that heavy computing demands and gaps in sensor coverage remains major hurdles in scaling these systems up.

An empirical economic study of blockchain-based environmental monitoring in China finds that while adopting blockchain can reduce local industrial pollution, it may also encourage businesses to relocate to less-regulated jurisdictions — a reminder that governance technologies on their own cannot substitute for coordinated regional or international regulation, and can even create pollution-leakage effects if adoption is uneven (Cong et al., 2025).

11. AI in Solid-Waste Management and E-Waste Recovery

AI and machine learning are reshaping solid-waste management, a field closely tied to pollution prevention through source reduction and material recovery. Deep-learning image classifiers are now widely used to automate waste sorting, separating recyclable from non-recyclable material streams with far greater throughput and consistency than manual sorting allows; deep-learning object classifiers have specifically been applied to improve e-waste collection planning (Nowakowski & Pamuła, 2020), and cloud-connected IoT systems have been proposed to optimize collection logistics more broadly (Misra et al., 2018). A narrative review of AI-driven circular-economy applications in waste management finds that intelligent sorting systems and predictive models are improving resource-recovery efficiency throughout the waste-management lifecycle, while cautioning that scaling these gains depends on

overcoming technical, economic, and systemic obstacles rather than on algorithmic performance alone (Olawade et al., 2026).

Institutional and firm-level studies find that regulatory pressure and market incentives — rather than technology availability alone — are the strongest drivers of circular-economy adoption in waste-intensive industries (Arranz et al., 2022), and smart-circular-economy frameworks argue that AI-enabled waste systems need to be embedded within wider product-design and material-flow strategies to realize their full environmental benefit (Bressanelli et al., 2022). Machine-learning applications targeting municipal solid-waste circularity in Latin America and the Caribbean demonstrate how these methods can be adapted to resource-constrained regional contexts (Bijos et al., 2022).

E-waste recovery, also known as urban mining, is a rapidly growing branch of this literature, includes goals of reducing hazardous-material release and recovering valuable raw materials like gold, copper, and cobalt from the discarded electronics. Reviews of e-waste recycling techniques describe a range of mechanical, chemical, and biohydrometallurgical extraction methods, which use microorganisms to extract metals, a more sustainable alternative compared to conventional smelting-based recovery. Critical reviews of cobalt recovery from recycled lithium-ion batteries highlights the increasing economic and strategic significance of urban mining as global battery demand accelerates (Botelho Junior et al., 2021), and comparative digestion-method studies quantify the heavy-metal, precious-metal, and rare-earth content recoverable from different e-waste streams (Tunali et al., 2021). Despite this progress, systematic reviews of urban-mining research consistently identify weak reverse-logistics infrastructure, the dominant role of informal-sector actors in many regions, and inconsistent international regulation as the main reasons e-waste recovery rates continue to lag behind e-waste generation (Abdelbasir et al., 2018).

14. Adoption Barriers and Policy Implications

A consistent pattern emerges across every technology domain covered in this review: strong performance in controlled or pilot settings does not automatically translate into widespread real-world adoption. Four recurring barriers stand out. First, cost and infrastructure requirements, reliable connectivity, computing capacity, and specialized technical expertise, keep advanced monitoring and remediation technologies concentrated in well-resourced regions. Second, problems with calibration, standardization, and interoperability persist both within individual technologies, as shown by the site-transferability limits documented throughout the low-cost air-quality sensor calibration literature, and across technologies, since AI, satellite, UAV, biosensor, and blockchain systems have mostly been developed and tested separately rather than as interoperable components of a single monitoring-to-remediation pipeline.

Third, regulatory frameworks for several of these technologies, nanomaterial safety assessment, engineered-organism biosafety, drone airspace access, blockchain-based emissions verification remain fragmented across jurisdictions, creating uncertainty for

developers and adopters and slowing the transition from pilot projects to routine regulatory use. Fourth, and most fundamentally, most of the literature reviewed here originates from, and has been validated in, high- and upper-middle-income countries, even though the health and ecological burden of pollution falls disproportionately on lower-income and rapidly urbanizing regions precisely the places with the least monitoring infrastructure and the greatest reliance on informal-sector labor for waste and e-waste handling. Closing this gap between where evidence is generated and where deployment is most needed will likely require targeted investment in low-cost, locally adaptable sensor and remediation technologies, together with capacity-building in local data science, biosafety, and environmental-engineering expertise, rather than further high-end technical refinement concentrated in places that are already well monitored.

15. Conclusion

New technologies are visibly reshaping how pollution is managed at every stage of the monitoring-to-remediation pipeline: extending the reach and resolution of detection through AI-enabled sensor networks, satellite observation, and UAV platforms; opening lower-impact remediation pathways through nanotechnology, photocatalysis, bioremediation, and phytoremediation; addressing emerging contaminants such as microplastics through purpose-built sensing tools; and strengthening data integrity and material recovery through blockchain governance and AI-driven circular-economy and e-waste systems. Even so, the evidence gathered here suggests that the main constraint on achieving real-world environmental benefit is not the further refinement of any single technology in isolation, but the fragmented and unevenly resourced way these technologies are currently being rolled out. Future research and investment would be better directed toward integrated monitoring-to-remediation systems that combine sensing, forecasting, and treatment within interoperable, standardized frameworks; toward extending field validation to low-resource, high-burden regions that remain underrepresented in the current literature; and toward building harmonized international regulatory standards, particularly for nanomaterial safety, engineered-organism biosafety, drone operation, and blockchain-based emissions verification capable of keeping pace with how quickly this field continues to innovate.

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