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Artificial Intelligence for Environmental Monitoring: Recent Advances, Applications, and Future Directions

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Abstract: Artificial intelligence (AI) and machine learning (ML) have emerged as important technologies in modern environmental monitoring as they enable researchers and institutions to analyze huge, complex and continuous environmental datasets. This paper reviews the development of AI-based environmental monitoring up to December 2025, based on recent bibliometric evidence, with a focus on air quality, water quality, climate modelling, biodiversity monitoring, disaster prediction, remote sensing, Internet of Things (IoT) systems and explainable AI. The assessment notes that AI has advanced from experimental modelling to operational decision-support systems, integrating satellite data, ground sensors, meteorological records, camera traps, drones, and real-time IoT networks. However, key remaining issues include uneven data availability, black-box model behavior, insufficient validation in low-resource locations, cybersecurity threats in IoT systems and limited policy integration. The study makes the case that the next phase of AI-based environmental monitoring should emphasize explainability, data fairness, interdisciplinary collaboration and human-centered environmental governance.

Keywords: artificial intelligence; machine learning; environmental monitoring; remote sensing; IoT; air quality; water quality; biodiversity; explainable AI.

1. INTRODUCTION

Climate change, air pollution, water contamination, biodiversity loss and extreme weather events have put growing pressure on ecosystems and public health, making environmental monitoring more vital. Traditional monitoring methods are frequently based on manual sampling, fixed stations and delayed laboratory analysis, which may limit the spatial coverage and real-time decision-making. AI and ML offer a significant enhancement as they are able to spot trends in extensive datasets, forecast future environmental states and allow quicker reactions to environmental threats [1], [2].

In 2024, Alotaibi and Nassif provided a bibliometric study that demonstrated a substantial increase in research on AI and ML for environmental monitoring, notably after 2010. The main research themes found in their investigation were air and water quality monitoring, climate modelling, biodiversity assessment, disaster management, IoT, remote sensing, and explainable AI [1]. Further expansion of this sector was achieved by December 2025, mainly through remote sensing foundation models, IoT-based water-quality monitoring, automated air-quality forecasting, and AI-assisted biodiversity protection [3], [4].

This study seeks to further the subject by providing an overview of the state of AI in environmental monitoring up to December 2025. Instead of replicating the original bibliometric study, it provides a narrative summary of recent applications, methodological improvements, practical problems, and future research priorities. The main point is that AI has been no longer merely a modelling tool but also becoming part of the environmental infrastructure, the success of which depends on transparency, inclusive datasets and responsible implementation [2], [5].

2. METHODOLOGICAL APPROACH

The study is a narrative review based on peer-reviewed literature, review articles, significant environmental reports, and a small number of institutional publications available through December 2025. The review is restricted to research that employed AI, ML, deep learning, remote sensing, IoT, or explainable AI for environmental monitoring. The literature from 2019-2025 was prioritized, with older foundational works included where they remain fundamental to contemporary approaches, e.g. species-distribution modelling and camera-trap picture classification [12], [13].

The collected literature was classified into seven themes: air quality monitoring, water quality monitoring, climate and Earth-system modelling, biodiversity and ecosystem monitoring, disaster management, remote sensing and IoT integration, and explainable/responsible AI. This framework continues the thematic direction of past AI-environmental monitoring work, but updates the debate with information accessible through 2025 [1], [3].

Table 1. Main thematic areas reviewed in this paper

Theme	Main data sources	Typical AI methods
Air quality	Ground stations, satellite AOD, meteorology	Random forest, XGBoost, ensemble learning
Water quality	IoT sensors, water-quality indexes, river records	Neural networks, SVM, XGBoost, anomaly detection
Climate systems	Climate models, satellite data, reanalysis datasets	Deep learning, hybrid/physics-informed models
Biodiversity	Camera traps, UAV imagery, acoustic and ecological records	CNNs, species-distribution models, object detection
Disasters	Remote sensing, weather data, social/environmental signals	Flood susceptibility models, segmentation, early warning models

3. AI AND ML IN AIR QUALITY MONITORING

One important use of artificial intelligence is the monitoring of air quality. Traditional air-quality monitoring stations give accurate findings, but the expense of setting them up is high, and their distribution is patchy, especially in poorer countries. This gap is filled by machine learning algorithms that combine ground-station data with satellite aerosol optical depth, meteorological variables, land-use indicators and chemical transport model outputs [7], [8].

Di et al. developed an ensemble-based PM2.5 model for the United States using several machine learning methods and predictor variables, revealing the capability of ensemble learning to produce high-resolution air pollution estimates over large regions [7]. Similar studies in China have used space-time random forest models to estimate PM2.5 concentrations at a 1 km resolution, which show the potential of random forest techniques to integrate satellite and ground measurements [8]. The findings paved the way for machine learning to become a useful instrument in exposure assessment and environmental health research [7], [8].

This approach has been recently expanded. Yu et al. used deep ensemble machine learning to estimate global daily PM2.5 concentrations at 0.1 degrees x 0.1 degrees resolution and demonstrated differences in exposure patterns among areas and populations [9]. In 2025, Gurtepe et al. developed a regional PM2.5 prediction system for Turkiye using XGBoost to solve monitoring gaps in the Eastern Mediterranean [6]. Yang et al. developed an automated air-quality forecasting system, AI-Air, combining machine learning with atmospheric chemistry modelling for urban predictions [17]. The progress shows that air-quality AI is moving from historical estimation to operational forecasting and early-warning systems [6], [17].

Despite these developments, AI-based air quality monitoring is not without its challenges. Models may not function well during extreme pollution events, dust storms, wildfires, or abrupt changes in emissions. The dependability of the models could be compromised by urban microclimates, unregulated industrial activities and poor monitoring networks. Future air-quality AI should therefore contain uncertainty estimation, explainable modelling, and local calibration before being used for public health decision-making [18], [22].

4. AI IN WATER QUALITY MONITORING

Water quality monitoring has also benefited from AI because conventional sampling is often slow, costly, and unable to provide continuous information. The AI models are able to predict water quality index values, detect contamination, predict dissolved oxygen and classify the water state with the use of sensor data, historical data, satellite images, and IoT networks [4], [5].

The evaluation by Frincu in 2025 highlighted that there is an increased usage of ML and deep learning approaches for the computation and modelling of water quality indexes to allow for a faster assessment of rivers, lakes, groundwater and drinking water systems [5]. Dharmarathne et al. also demonstrated that merging ML with IoT enhances real-time water-quality monitoring with remote tracking and predictive analytics, however sensor fouling, missing data, privacy, network dependability, and cybersecurity remain significant obstacles [4].

The promise of IoT-based systems is clear, notably in continuous measurement of pH, turbidity, temperature, dissolved oxygen, conductivity and total dissolved solids. These sensor streams can be fused with ML models to provide early warning of contamination and assist in managing water resources. However, the long-term operation requires maintenance, calibration, stable communication network, and protection from data tampering [4], [5].

One major challenge is that many AI water-quality models are trained on local datasets and may not transfer well to other river basins, coastal areas or groundwater systems. This implies that the models need to be verified for varied seasons, hydrological conditions and pollution sources. Explainable AI is also vital as regulators and communities need to understand why a model classifies water as safe or harmful [19], [22].

5. CLIMATE MODELLING AND EARTH-SYSTEM SCIENCE

AI is increasingly used in climate and Earth-system science because climate datasets are large, multidimensional, and difficult to analyse using conventional statistical methods alone. Deep learning can identify spatio-temporal patterns in satellite observations, reanalysis datasets, climate simulations, and ecological records [10]. However, AI should not replace physical climate science; instead, it should complement process-based models and improve pattern recognition, downscaling, and uncertainty assessment [10], [11].

Reichstein et al. argued that deep learning can support Earth-system understanding when combined with process knowledge. This is important because purely data-driven models may produce accurate predictions without explaining the physical mechanisms behind them [10]. Rolnick et al. also highlighted that ML can support climate mitigation and adaptation in areas such as disaster response, energy systems, transport, agriculture, and environmental monitoring [11].

The urgency of climate monitoring is reinforced by global climate evidence. The IPCC Sixth Assessment Synthesis Report confirmed widespread and rapid climate change impacts, while the WMO State of the Global Climate 2024 report recorded major climate indicators including global temperature, ocean heat, sea-level rise, and extreme events [20], [21]. These findings increase the need for AI-supported monitoring systems that can process large-scale environmental signals and support early warning, adaptation planning, and climate-risk assessment [20], [21].

Nevertheless, climate AI faces serious risks if it is used without scientific constraints. Climate systems involve nonlinear feedbacks, regional variability, and long-term uncertainty. Therefore, future climate AI should focus on hybrid modelling, physics-informed neural networks, transparent uncertainty reporting, and collaboration between climate scientists, computer scientists, and policymakers [10], [11].

6. BIODIVERSITY AND ECOSYSTEM MONITORING

Biodiversity monitoring is another key area where AI has changed data collection and analysis. Traditional biodiversity surveys are time- and space-limited and labor-intensive. AI can be used for species identification, mapping of habitats, assessment of ecosystem health, and detection of change in biodiversity through camera traps, acoustic sensors, satellite imagery, drones, and datasets based on environmental DNA [13], [14].

Maxent model is still one of the fundamental approaches for species-distribution modelling because it can predict suitable habitats based on presence-only species records and environmental variables [12]. More recently, deep learning has enhanced automated image recognition in ecology. Norouzzadeh et al. showed that convolutional neural networks can detect, count and describe wild animals in camera-trap photos, lowering the time needed for manual classification [13].

By 2025 biodiversity AI has been more tightly coupled with conservation governance. UNDP work on people-centric AI for biodiversity argues that AI may lower the cost and duration of biodiversity surveys but must be structured around local ecological knowledge, institutional capacity and inclusive governance [14]. This is particularly relevant for nations with high biodiversity and insufficient digital infrastructure and tagged ecological datasets [14].

The fundamental issue is that AI systems may perpetuate spatial and taxonomic bias. Species from wealthy locations are more likely to be represented in training datasets, while uncommon species, tropical ecosystems and Indigenous-managed landscapes may be under-represented. Therefore, biodiversity AI should involve community engagement, open datasets, meticulous validation, and ethical data governance [13], [14].

7. DISASTER MANAGEMENT AND ENVIRONMENTAL RISK PREDICTION

AI is commonly utilised in disaster management as it can analyse real-time data from satellites, sensors, weather models, social media, and past disaster records. Applications include flood susceptibility mapping, wildfire detection, landslip prediction, hurricane impact assessment, and drought monitoring [15], [16].

Chapi et al. [15] proposed a hybrid AI approach for flood susceptibility mapping, and showed that ensemble and tree-based learning may improve the spatial prediction of flood-prone locations. Similar technologies are currently applied with remote sensing and geographic information systems in support of disaster preparedness. AI can also detect early environmental signs, such as vegetation dryness, rainfall anomalies, soil moisture changes and river-level patterns [15], [16].

Remote sensing and AI integration are especially critical for disaster response as they offer large-area coverage before, during, and after catastrophes. The 2025 assessment by Kazanskiy et al. showed that remote sensing with AI enhances the interpretation of huge datasets of Earth observation and aids applications in environmental monitoring, agriculture, land-use analysis, and disaster management [3].

But disaster AI has to be treated with caution as false alarms and missed warnings might impact human safety and public trust. Models should therefore be tested under real-world emergency settings, contain uncertainty levels, and remain connected to human decision-makers rather than replacing expert opinion [16], [22].

8. REMOTE SENSING, IOT, AND EMERGING AI SYSTEMS

The most promising advancement by December 2025 is the combination of AI with remote sensing and IoT. Remote sensing offers large-scale spatial coverage, whereas IoT devices offer continuous local data. AI integrates these data streams by finding patterns, spatial gaps, anomalies, and aiding real-time prediction [3], [4].

Remote sensing AI today uses convolutional neural networks, transformers, segmentation models and foundation-model techniques to handle satellite and drone imagery. These strategies enhance land-cover classification, vegetation monitoring, pollution detection, and change detection. Meanwhile, IoT devices are being used for monitoring water quality, air quality, agriculture and smart cities [3], [4].

The next step is probably edge AI, where the models run directly on local devices, rather than sending all data to cloud servers. This can minimize latency, improve privacy and enable environmental monitoring in remote places. However, edge AI also needs low-power hardware, robust sensors, cyber-security protection and maintenance capacity [4], [19].

9. EXPLAINABLE AND RESPONSIBLE AI

Explainable AI is increasingly a necessity for environmental monitoring because many AI models impact decisions on public health, water safety, disaster alerts, conservation priorities and climate adaptation. While black-box models might give correct outputs, they can be hard for policymakers, regulators, and communities to trust [18], [22].

SHAP and other interpretability methods are used to explain which variables influence model predictions [23]. We know from the wider XAI research that explainability is fundamental to responsible AI since it allows for openness, accountability, and stakeholder trust [18]. Samek et al. showed that for deep neural networks, where internal decision processes are not clearly accessible, the explanation approaches become extremely crucial [22].

Explainability must not be a secondary technical feature in environmental monitoring. This should be included in model design, validation and reporting. For example, an air-quality model should make clear if the PM2.5 projections are most influenced by wind speed, temperature, traffic density, satellite aerosol data or industrial activity. A water-quality model should detect if a warning is driven by turbidity, pH, rainfall or upstream discharge. Without such justifications, the defence of AI in regulatory or public settings may be challenging [18], [22], [23].

10. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The first difficulty is data inequality. Many AI models require high-quality monitoring data, but environmental sensors are not distributed evenly across the globe. High environmental risk regions may have the least data coverage. This can result in biased models and poor forecasts in vulnerable communities [1], [14].

The second challenge is generalisability. A model trained in one city, river basin, climate zone, or ecosystem may not function well in another. Future studies should focus on transfer learning, domain adaptation, federated learning, and local validation to improve model reliability across regions [3], [4].

The third problem is explainability and accountability. Environmental AI should be transparent enough for regulators, scientists, and impacted populations to grasp. This is especially relevant when AI informs public warnings, pollution enforcement, biodiversity conservation, or climate adaption funding [18], [22].

Fourth is operational integration. There are still many AI models that are research prototypes that are not linked to government surveillance programs. To be useful, AI techniques need to be integrated with environmental agencies, early-warning systems, urban planning and community-level monitoring programs [2], [17].

Hence, future research should be oriented in five directions: Hybrid AI-physical models, Explainable environmental AI, Low-cost IoT and edge-AI systems, Open and inclusive environmental datasets, Policy-ready decision-support tools. These guidelines would help to shift the field from model development to responsible environmental governance [10], [11], [24].

11. CONCLUSION

AI has become a transformative technology in environmental monitoring. By December 2025, its applications had grown to include air quality, water quality, climate modelling, biodiversity monitoring, disaster prediction, remote sensing and IoT-based environmental systems. The research suggests that AI may be used to improve the accuracy of prediction, extend the spatial and temporal coverage, reduce the manual labour and allow real-time decision making [1], [3], [4].

But the success of AI in environmental monitoring depends on more than technical correctness. Models must be explainable, locally validated, ethically governed and coupled to real-world decision systems. AI for the environment should be used to augment-not replace-human knowledge. The future of this discipline is in responsible, transparent and inclusive AI systems that enable societies to respond more quickly and fairly to climate change, pollution, loss of biodiversity and environmental risk [18], [20], [24].

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