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Artificial Intelligence in Environmental Research: Applications, Challenges and Future Directions: A Narrative Review

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ABSTRACT
Climate change, biodiversity loss, and pollution are producing environmental data whose volume, velocity, and complexity increasingly surpass the capabilities of conventional analytical methods. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), is being rapidly adopted to analyse these data; however, evidence regarding its performance remains dispersed across disciplines. This narrative review synthesises peer-reviewed literature identified through structured searches of Scopus, Web of Science, and Google Scholar (1997–2026), selected according to explicit inclusion criteria and organized thematically. The review examines AI applications in four domains: climate science (model emulation, downscaling, precipitation nowcasting, and methane detection); ecology and biodiversity conservation (species identification, habitat mapping, and wildlife-trade surveillance); pollution and waste management (air-quality forecasting, plastic detection, and materials design); and water resources (water-quality, streamflow, and flood forecasting). Across these domains, the most robust evidence is found in data-rich settings where AI models have been benchmarked against established physical or statistical methods. Conversely, many other applications, particularly in the Global South, remain at the proof-of-concept or simulation stage. Persistent limitations include scarce and spatially biased training data, limited interpretability, weak transferability between regions, and the energy and carbon costs associated with training large models. Additionally, concerns regarding equity, privacy, and human rights are emerging. This review concludes that AI is most valuable as a complement to, rather than a replacement for, process-based understanding and field observation. It identifies local data infrastructure, independent validation, interpretable and energy-efficient models, and equitable research partnerships as key priorities.

Keywords: Artificial intelligence, Machine learning, Deep learning, Environmental monitoring, Climate change, Biodiversity conservation, Remote sensing, Sustainability

INTRODUCTION

The twenty-first century is characterised by closely interrelated environmental challenges. The global assessment by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) estimated that approximately one million animal and plant species are threatened with extinction (IPBES, 2019). Concurrently, the Intergovernmental Panel on Climate Change (IPCC) has concluded that human-induced climate change has already resulted in widespread adverse impacts and that the opportunity to secure a liveable and sustainable future is rapidly diminishing (IPCC, 2022). Addressing these interconnected crises requires enhanced capacity to observe, understand, and predict the behaviour of complex Earth systems. Environmental science has become increasingly data-intensive: Earth-observation programmes such as the European Space Agency's Copernicus Sentinel missions generate substantial volumes of imagery daily, sensor networks continuously monitor air, water, and soil, and citizen-science platforms contribute millions of species observations (Hampton et al., 2013). Nevertheless, the volume, velocity, and heterogeneity of these data frequently surpass the processing capabilities of conventional statistical and computational approaches.

Artificial intelligence (AI), particularly its sub-fields of machine learning (ML) and deep learning (DL), consists of algorithms that learn patterns from data and use these patterns to make predictions or decisions without explicit programming for each scenario (LeCun et al., 2015). This capability renders AI particularly suitable for addressing the non-linear, high-dimensional problems prevalent in environmental research. Bibliometric analyses indicate that research in this area has expanded rapidly over the past decade across climate science, ecology, environmental chemistry, and public health (Alotaibi & Nassif, 2024; Z. Chen et al., 2026; Rawat & Yadav, 2025). Furthermore, Guo et al. (2025) observe that AI is increasingly applied not only to environmental monitoring but also to the assessment of environment–health relationships, including exposure modelling and risk prediction.

Several reviews have documented this growth; however, most are bibliometric mappings of publication trends (Alotaibi & Nassif, 2024; Rawat & Yadav, 2025), syntheses limited to a single domain such as climate change mitigation and adaptation (Rolnick et al., 2022), or reviews focused on pollution chemistry and environmental health (Guo et al., 2025). Relatively little attention has been devoted, across the climate, biodiversity, pollution, and water domains collectively, to evaluating the strength of evidence for AI performance, assessing whether reported gains transfer from data-rich to data-poor regions such as much of the Global South, or examining how methodological, environmental, and ethical limitations constrain deployment. Demonstrated, benchmarked applications are also rarely distinguished explicitly from proposed or simulation-based ones. This review seeks to address these gaps. Section 2 describes the

review methodology; Section 3.1 introduces the main AI methods; Sections 3.2–3.5 examine applications in climate science, ecology and biodiversity, pollution and waste management, and water resources (Figure 1); Section 3.6 comparatively appraises the strength of the evidence; Section 3.7 discusses challenges and ethical issues; Section 3.8 outlines future directions; and Section 4 presents the conclusion and recommendations.

Figure 1. Overview of AI application domains in environmental research

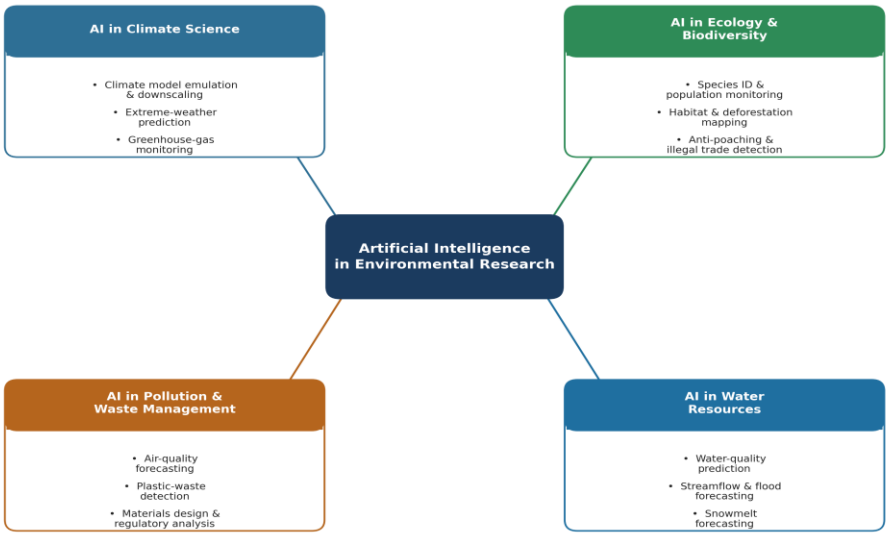


Figure 1: The Four Environmental Research Domains Examined in this Review and the Principal AI Applications Discussed Under Each

Aim of the Review

The objective of this review is to critically synthesise evidence regarding the application of artificial intelligence in four principal domains of environmental research: climate science, ecology and biodiversity, pollution and waste management, and water resources. Particular attention is given to the strength and transferability of the evidence, its main limitations, and its implications for research and policy in data-scarce regions.

Review Methodology

This study adopts a narrative review approach rather than a systematic review or meta-analysis and does not adhere to the full PRISMA protocol. However, a structured search-and-selection procedure was implemented, as described below, to ensure that the process can be followed and replicated by other researchers.

Information Sources and Search Strategy

Literature was retrieved from Scopus, the Web of Science Core Collection, and Google Scholar. Searches were conducted between 2 January 2026 and 9 September 2026, covering publications from January 1997 to December 2026. An initial core search string combined artificial intelligence terms with general environmental terms, which was then further refined with domain-specific terms. In Scopus, the core string was applied to titles, abstracts, and keywords (TITLE-ABS-KEY): ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*") AND ("environmental research" OR "environmental monitoring" OR "environmental science" OR "environmental sustainability"). The artificial intelligence block was subsequently combined, in separate searches, with each of the following domain blocks: ("climate model*" OR downscaling OR "extreme weather" OR nowcasting OR "greenhouse gas*" OR methane); (biodiversity OR "species identification" OR "camera trap*" OR "habitat mapping" OR "wildlife trade"); ("air quality" OR "air pollution" OR "plastic pollution" OR "waste management" OR "source apportionment"); and ("water quality" OR streamflow OR "flood forecast*" OR "algal bloom*"). Equivalent search strings were applied to the Web of Science using the topic field (TS=). Because Google Scholar does not support complex Boolean syntax, simplified combinations of the same terms were used, and the results of each query, sorted by relevance, were screened. Reference lists of key reviews and included articles were also examined to identify additional relevant studies through backward citation searching.

Eligibility Criteria

Eligible sources included peer-reviewed journal articles, book chapters, conference proceedings, and authoritative technical reports from international organizations such as the IPCC, IPBES, the World Health Organization, and the European Commission's Joint Research Centre. Studies were included if they reported, evaluated, or proposed a specific application of artificial intelligence, machine learning, or deep learning methods to an environmental problem, or if they constituted foundational methodological works (for example, those introducing convolutional or recurrent neural networks) upon which such applications depend. Foundational works were included regardless of publication date due to their ongoing technical significance. Studies were excluded if they were purely theoretical computer science papers without environmental application, fell outside the scope of environmental science, were not written in English, or if the full text was inaccessible. Preference was given to work published within the most recent decade to ensure the synthesis reflects the current Records retrieved from the three databases were exported, and duplicates were removed by matching DOIs and titles. Titles and abstracts were screened according to the eligibility criteria, followed by full-text

assessment of potentially relevant records. Both authors independently screened and assessed full texts, resolving disagreements through discussion. In total, 312 records were identified; 267 remained after duplicate removal, 45 full texts were assessed, and 49 sources were retained and cited in this review.

Appraisal and Synthesis of Evidence

No formal risk-of-bias tool was applied, consistent with standard practice for narrative reviews. Instead, each included empirical study was qualitatively appraised based on five criteria: peer-review status; clarity in reporting data, study area, and validation design (such as independent test data or cross-validation); comparison with established baseline methods; reporting of performance measures; and examination of transferability beyond the original study area. Studies were classified as (i) benchmarked or operationally evaluated, (ii) empirical case studies, or (iii) proposed frameworks, perspectives, or simulation-based studies. Evidence was synthesised thematically by environmental domain, and a comparative appraisal of representative studies is provided in Section 3.6 (Table 2). The limitations of this approach are discussed in Section 3.7.5.

RESULTS AND DISCUSSION

Overview of AI Methods Used in Env

A foundational understanding of the artificial intelligence methods most frequently employed in environmental science is essential prior to examining specific applications. Environmental chemistry and related disciplines have become increasingly data-intensive and interdisciplinary (Hrytsulyak & Yevnika, 2025), which has contributed to the adoption of AI-based approaches. While a comprehensive technical discussion of these methods is beyond the scope of this review, the main categories are introduced below and summarized in Table 1.

Machine Learning

Machine learning encompasses algorithms that improve their performance on a given task as they are exposed to increasing amounts of data. Among conventional machine learning models, random forests—ensembles of decision trees are widely used for classification and regression tasks due to their ability to handle non-linear relationships and mixed predictor types, as demonstrated in habitat-suitability modelling. Support vector machines (SVMs) are effective in classification problems with relatively small training sets, such as land-cover mapping from satellite imagery. Gradient-boosting machines, such as XGBoost, are frequently among the strongest performers on structured, tabular data, for example, when predicting air-quality indices from meteorological variables. These methods typically require less training data and computational resources than deep neural networks and are generally easier to interpret, making them particularly suitable for data-scarce settings.

Deep Learning

Deep learning employs artificial neural networks with multiple layers and is particularly effective for unstructured data such as images, audio, and text. Convolutional neural networks (CNNs), which gained widespread adoption following the success of deep image classifiers (Krizhevsky et al., 2012), form the basis of most environmental image-analysis applications, including species identification in camera-trap photographs, coral-reef mapping, and deforestation detection. Recurrent neural networks, especially long short-term memory (LSTM) networks (Hochreiter & Schmidhuber, 1997), are designed for sequential data and are widely used to forecast time series such as streamflow and pollutant concentrations. Autoencoders learn compressed representations of data and are applied for dimensionality reduction and anomaly detection, for example, to identify malfunctioning environmental sensors. However, this flexibility requires greater amounts of labelled data and computational resources and results in reduced interpretability (Section 3.7).

Other Relevant Techniques

In reinforcement learning (RL), an agent learns a decision policy by taking actions and receiving rewards. RL is being explored for operational problems such as smart-grid energy management and reservoir operation, although most environmental applications remain experimental. Transfer learning enables a model pretrained on a large, general dataset to adapt to a specific environmental task, such as identifying a rare species with relatively few labelled examples, thereby reducing both data requirements and computational cost (Weiss et al., 2016). This approach is particularly relevant to data-scarce regions.

Table 1: Main Categories of AI/ML Techniques and their Primary Environmental Applications

Category	Technique	Core strength	Representative environmental application
Machine learning	Random forests	Robust to non-linear relationships; handles mixed data types	Habitat-suitability modelling
Machine learning	Support vector machines (SVMs)	Strong classification performance with modest training data	Land-cover classification from satellite imagery
Machine learning	Gradient boosting (e.g., XGBoost)	Often among the strongest performers on tabular data	Predicting air-quality indices from meteorological data
Deep learning	Convolutional neural networks (CNNs)	Image and spatial-pattern analysis	Species identification from camera traps; deforestation and reef mapping
Deep learning	RNNs / LSTM networks	Captures temporal dependence in sequential data	Streamflow, flood and air-pollutant forecasting
Deep learning	Autoencoders	Dimensionality reduction and anomaly detection	Detecting faulty sensors; anomalies in monitoring data
Other techniques	Reinforcement learning (RL)	Learns sequential decisions through reward	Smart-grid energy optimisation; reservoir operation

Category	Technique	Core strength	Representative environmental application
Other techniques	Transfer learning	Adapts pretrained models with limited new data	Identifying rare or data-scarce species

AI in Climate Science

Climate science relies on physically based models that are computationally demanding. AI is increasingly used to complement these models, to accelerate selected components and to extract information from observational data.

Improving Climate Models and Projections

Global climate models (GCMs) are the principal tools for projecting future climate, but they typically operate at coarse spatial resolution (about 100–200 km) and are computationally expensive. ML 'emulators' approximate selected model outputs at a fraction of this cost. (Watson-Parris et al., 2022) provides a standardised benchmark in which ML emulators including Gaussian processes, random forests and neural networks are trained on Earth system model simulations to predict temperature and precipitation responses to emission scenarios. Such emulators allow rapid exploration of scenarios, but their skill is bounded by the single Earth system model and the limited set of scenarios used for training. ML is also used for statistical downscaling: Vandal et al. (2017) adapted image super-resolution CNNs (DeepSD) to generate high-resolution precipitation projections from coarse GCM output. A common caveat is that models trained on historical or simulated data may not extrapolate reliably to climate states outside their training range, which is one motivation for the physics-informed approaches discussed in Section 3.8.

Predicting Extreme Weather Events

Short-term precipitation forecasting is currently the most mature application in this area. Ravuri et al. (2021) developed a deep generative model of radar data that produced precipitation nowcasts up to 90 minutes ahead; in a blind evaluation by expert Met Office forecasters it was preferred to competing methods in most cases. Sønderby et al. (2020) developed MetNet, a neural weather model that uses radar and satellite inputs to forecast precipitation up to eight hours ahead over the continental United States, and reported that it outperformed an operational numerical weather prediction model (HRRR) at lead times of up to about seven to eight hours. Both systems, however, were evaluated in regions with dense radar coverage, and their transferability to radar-sparse regions such as much of sub-Saharan Africa has not been demonstrated. For tropical cyclones, ML has been applied to the prediction of genesis, track and intensity, but a review of this work concluded that existing techniques are not yet mature enough to improve numerical forecast models comprehensively, and that hybrid ML–dynamical approaches are the most promising (R. Chen et al., 2020). For drought, satellite observations of soil moisture, precipitation and vegetation condition provide the inputs to early-warning systems (AghaKouchak et al., 2015); ML is increasingly used to combine these inputs, although validation against ground observations remains limited in many drought-prone regions.

Monitoring Greenhouse Gas Emissions

Satellite remote sensing increasingly supports the independent verification of methane emissions. The TROPOMI instrument on board Sentinel-5P provides near-daily global coverage of methane, and Schuit et al. (2023) combined a CNN with a support-vector classifier to detect plumes from large point sources ('super-emitters') in TROPOMI data automatically, identifying thousands of plumes in a single year that were associated mainly with oil and gas facilities, coal mines and landfills. Higher-resolution imaging spectroscopy can then attribute emissions to individual facilities: Irakulis-Loitxate et al. (2021) used such observations to detect and quantify very large methane point sources in the Permian Basin of the United States. These tools can help regulators and operators prioritise inspections and repairs, but detection is restricted to large emitters, is affected by cloud cover and surface conditions, and must be confirmed on the ground before regulatory action is taken.

AI in Ecology and Biodiversity Conservation

The scale of the biodiversity crisis demands monitoring methods that can be applied over large areas and long periods, and AI is increasingly used to automate data-intensive ecological tasks.

Automated Species Identification and Population Monitoring

Camera traps and acoustic recorders produce more data than can be analysed manually. Platforms such as Wildlife Insights apply CNN classifiers to very large collections of camera-trap images, enabling ecologists to track species distribution, abundance and activity over time (Ahumada et al., 2020). Classification accuracy is, however, typically highest for common species that are well represented in training data and lower for rare or cryptic species, so expert verification remains necessary. In bioacoustics, Sethi et al. (2020) showed that a general-purpose acoustic feature set derived from a pretrained CNN could characterise soundscapes across diverse ecosystems and detect anomalous acoustic events, supporting ecosystem-level monitoring. For aerial surveys, Torney et al. (2019) compared deep learning with citizen-science counts of wildebeest in Serengeti survey images and found that automated counts achieved comparable accuracy while processing images far more quickly, indicating a cost-effective complement to manual counting.

Habitat Mapping and Deforestation Monitoring

Satellite imagery is central to monitoring land-cover change. Hansen et al. (2013) produced global 30-m resolution maps of forest loss and gain from Landsat data using decision-tree classification; this product underpins the Global Forest Watch platform, which provides near-real-time deforestation alerts to governments and civil-society organisations. Beyond forests, Li et al. (2020) used CNNs to generate a global probability map of coral-reef extent from satellite imagery, establishing a baseline against which change can be assessed. Devisri and Manjula (2026) similarly describe AI-enabled 'smart forestry' systems that integrate remote sensing, predictive analytics and automated monitoring into forest management. A limitation common to these applications is that map accuracy varies between regions and depends on ground-truth data, which are often sparse in tropical and dryland ecosystems.

Combating Illegal Wildlife Trade

Illegal wildlife trade is a major driver of population decline in species such as elephants, rhinoceroses and pangolins, and an increasing share of this trade is advertised online. Di Minin et al. (2018) proposed a framework in which ML methods for

image, text and metadata analysis would screen social-media content for wildlife products and flag suspicious posts for enforcement agencies. This contribution is a perspective rather than an evaluated system, and published data on the operational performance of such tools remain scarce; the approach also raises questions about false positives, access to platform data and privacy. Drones equipped with automated video analytics are likewise being trialled for anti-poaching patrols, but peer-reviewed evaluations are limited, and such surveillance must respect the rights of local communities (Section 3.7.4).

AI in Pollution Control and Waste Management

Air, water and plastic pollution are major threats to human and ecosystem health, and AI is being applied to their monitoring, forecasting and management.

Air-Quality Forecasting and Source Apportionment

The World Health Organization (WHO) estimates that exposure to air pollution causes around seven million premature deaths each year (WHO, 2021). ML models, particularly LSTM networks and gradient-boosting methods, are widely used to forecast concentrations of pollutants such as $PM_{2.5}$ and NO_2 hours to days in advance from historical pollution, meteorological and traffic data, which can inform public-health warnings and short-term interventions such as traffic restrictions (Alotaibi & Nassif, 2024; Guo et al., 2025). Forecasting skill, however, depends strongly on the density and quality of monitoring data. For source apportionment, receptor models such as positive matrix factorisation (PMF) remain the reference approach for estimating the contributions of sources such as traffic, industry and dust from monitoring-station data (Belis et al., 2019); ML is increasingly being combined with these models, but such hybrid approaches are still developing and require the same careful evaluation as conventional receptor models.

Plastic Waste Detection and Cleanup

Tackling plastic pollution requires knowledge of where plastic waste travels and accumulates. Biermann et al. (2020) showed that floating plastic aggregations in coastal waters could be detected in Sentinel-2 optical imagery and distinguished from natural floating material such as seaweed and driftwood using a Naïve Bayes classifier, although detection was limited to relatively large, dense patches. ML analysis of drone and aerial imagery is also used to quantify debris in rivers and the open ocean and to plan cleanup operations, and computer-vision systems are used in recycling facilities to sort plastics by type, with potential gains in sorting efficiency and material purity. Independent, peer-reviewed performance data for many such operational and commercial systems remain limited.

Air Pollution and Waste-to-Energy Management in the Global South

Much of the early literature on AI and pollution draws on dense monitoring networks in North America, Europe and East Asia; more recent studies have begun to address the data and infrastructure constraints of rapidly urbanising cities in the Global South. Islam (2025b) reviewed air pollution in Dhaka, Bangladesh, and argued that AI and ML techniques can be adapted to improve pollution management and forecasting even where monitoring infrastructure is sparse and heterogeneous. In a related study, Islam (2025a) proposed an AI-driven smart waste-to-energy framework for Dhaka that combines AI optimisation, life-cycle modelling and digital-twin simulation, and reported projected gains in material recovery and reductions in emissions. Because these results derive from simulation and scenario analysis rather than field implementation, they indicate potential rather than demonstrated performance; nonetheless, they illustrate how municipal waste management could become an integral part of urban climate-adaptation planning rather than a purely logistical task.

AI-Assisted Environmental Chemistry, Materials Design and Regulatory Analysis

AI is also being applied to the chemistry that underpins pollution mitigation. Gu et al. (2025) reviewed the ML-guided design of electrocatalysts and showed how data-driven materials discovery can shorten the search for catalysts relevant to emissions reduction and clean-energy conversion, thereby complementing monitoring-focused applications by addressing pollution at its source. AI tools are also being applied to the regulatory dimensions of hazard management: Croce et al. (2025) assessed the strengths and weaknesses of AI tools for reconstructing the regulatory history of asbestos across countries and concluded that, although such tools can rapidly synthesise fragmented legal and historical records, their outputs require careful expert verification given the high stakes of hazardous-materials governance.

AI in Water Resources Management

Sustainable water management is central to food security, ecosystem health and human well-being, and AI is being applied in both hydrology and operational water management.

Water-Quality Monitoring and Prediction

Conventional water-quality monitoring is labour-intensive and intermittent. AI supports a shift towards continuous and predictive monitoring, in which variables measured in real time by sensors (for example, temperature, turbidity, chlorophyll-a or phycocyanin fluorescence) are used to forecast variables that are harder or costlier to measure, such as harmful algal blooms. Fournier et al. (2024) compared linear regression, random forest and LSTM models using six years of incomplete high-frequency data from multiparametric probes; the multivariate LSTM performed best and predicted cyanobacterial alert levels with accuracies of up to 90% at forecast horizons of 4–28 days. These results are encouraging, but they were obtained in a limited number of water bodies, and transferability to systems with different trophic states and climates has yet to be demonstrated.

Streamflow and Flood Forecasting

Accurate streamflow prediction underpins flood warning, hydropower generation and irrigation planning. Physically based hydrological models are complex and require extensive parameterisation, whereas LSTM networks can learn rainfall–runoff relationships directly from data. Kratzert et al. (2018) showed that LSTM models trained on data from 241 catchments in the CAMELS data set achieved performance comparable to that of a well-established conceptual model (SAC-SMA coupled with Snow-17). The approach has since been extended to the global scale: Nearing et al. (2024) showed that an LSTM-based model could forecast extreme riverine floods in ungauged catchments with reliability at five-day lead times similar to, or better than, that of a leading global forecasting system at same-day lead times. This model underpins Google's Flood Hub, which provides flood forecasts in more than 80 countries. Data-driven methods are also being used to forecast snowmelt-driven runoff by combining satellite snow-cover data with meteorological forecasts, which is important in arid regions that depend on

mountain water supplies. Nonetheless, the skill of data-driven hydrological models remains dependent on the availability of gauging records for training and evaluation, which are sparse in many of the regions where flood early warning is most needed.

Comparative Appraisal of the Evidence

Table 2 compares representative studies discussed above in terms of AI approach, data and setting, main evaluation result and level of evidence. Three patterns emerge. First, the strongest evidence comes from tasks for which large, well-curated datasets and clear benchmarks exist—precipitation nowcasting, rainfall–runoff modelling, methane-plume detection and large-scale image classification—where AI models have been compared directly with operational or established methods. Second, a substantial share of the applications reported in the literature, including several focused on the Global South, are proposals, perspectives or simulation-based frameworks whose performance has not been independently evaluated in the field. Third, transferability is rarely tested: models are usually trained and evaluated within the same region, so reported accuracies cannot be assumed to hold elsewhere. Claims that AI 'outperforms' traditional methods should therefore be read as specific to particular tasks, datasets and regions rather than as general conclusions.

Table 2: Comparative Appraisal of Representative AI Applications Reviewed

Domain and study	AI approach	Data and setting	Main evaluation result	Evidence level and key limitation
Climate emulation – Watson-Parris et al. (2022)	Gaussian process, random forest and neural-network emulators	Earth system model simulations under emission scenarios	Standardised benchmark of emulator skill for temperature and precipitation	Benchmarked; based on one Earth system model and few scenarios
Precipitation nowcasting – Ravuri et al. (2021)	Deep generative model	Radar data, United Kingdom	0–90 min nowcasts preferred by expert forecasters in blind evaluation	Operationally evaluated; short lead time, radar-dense region
Precipitation forecasting – Sønderby et al. (2020)	Neural weather model (MetNet)	Radar and satellite data, continental United States	Outperformed HRRR up to about 7–8 h lead time	Benchmarked (preprint); single region and variable
Methane detection – Schuit et al. (2023)	CNN with support-vector classifier	TROPOMI satellite data, global	Automated detection of thousands of super-emitter plumes in one year	Operational; large emitters only; cloud and surface effects
Wildlife counting – Torney et al. (2019)	CNN-based object detection	Aerial survey images, Serengeti	Accuracy comparable to manual counts, much faster	Empirical case study; single species and ecosystem
Wildlife trade – Di Minin et al. (2018)	Proposed ML (image, text, metadata)	Social-media content	Conceptual framework	Perspective; not yet evaluated
Plastic detection – Biermann et al. (2020)	Naïve Bayes classifier	Sentinel-2 imagery, coastal waters	Plastics distinguished from natural floating debris	Empirical; large, dense patches only
Algal blooms – Fournier et al. (2024)	LSTM vs. linear regression and random forest	High-frequency probe data	Up to 90% accuracy for alert levels at 4–28-day horizons	Empirical; limited number of water bodies
Streamflow – Kratzert et al. (2018)	LSTM	241 CAMELS catchments, United States	Comparable to SAC-SMA + Snow-17	Benchmarked; data-rich catchments
Floods – Nearing et al. (2024; ODUMO & Epelle,2026; Dangiwa & Ndawayo, 2026)	LSTM	Global, including ungauged catchments	5-day reliability similar to or better than a global system's same-day reliability	Benchmarked and operational; skill depends on gauge records
Waste-to-energy – Islam (2025a)	AI optimisation with digital twin	Dhaka, Bangladesh	Projected gains in recovery and emissions reduction	Simulation-based; not field-validated

Challenges, Limitations and Ethical Considerations

Although AI offers considerable opportunities, its use in environmental science involves important methodological, environmental and ethical difficulties.

The Black-Box Problem and Explainable AI

Many high-performing AI models, especially deep neural networks, are regarded as 'black boxes' because it is difficult to understand how they arrive at a particular prediction. In consequential environmental decisions, such as conservation policy or the issuing of flood warnings, understanding why a model produces a given output is essential for building trust and for ensuring that decisions rest on sound science rather than on spurious correlations in the data. Explainable AI (XAI) techniques for interpreting model outputs are developing rapidly, but Rudin (2019) argues that, for high-stakes decisions, inherently interpretable models should be preferred to post hoc explanations of black-box models wherever they achieve comparable accuracy.

Data Scarcity and Bias

AI models require large amounts of data. Many environmentally critical regions, particularly in the Global South, lack high-quality, labelled training data, so models that perform well in North America or Europe may perform poorly when applied to tropical ecosystems or to cities in developing countries. Islam (2025c) similarly argues that realising the potential of AI for environmental monitoring and sustainable development will depend on closing this infrastructure and data gap, particularly in low- and middle-income countries. Datasets can also contain inherent biases: citizen-science data from platforms such as iNaturalist are biased towards easily accessible areas and charismatic species, which can propagate into model predictions (Ball-Damerow et al., 2019). Possible responses include targeted investment in data collection in under-represented regions and techniques such as transfer learning that reduce dependence on large labelled datasets.

Computational Cost and Environmental Footprint

Training large AI models requires substantial computing resources and energy and therefore has a carbon footprint. Strubell et al. (2019) estimated that training one large natural-language-processing model, including an extensive neural architecture search, could emit around 284,000 kg of CO_2-equivalent—roughly five times the lifetime emissions of an average American car, including fuel. This figure represents an upper-bound scenario, and actual emissions depend strongly on hardware efficiency, training duration and the carbon intensity of the electricity used. Most environmental applications rely on far smaller models, but the trend towards very large pretrained models makes systematic energy and emissions accounting increasingly important if tools used to address environmental problems are not to add materially to them.

Ethical Deployment, Equity and Human Rights

The benefits of AI should be shared fairly. An 'AI divide' could exacerbate existing global inequalities if wealthier countries and corporations gain a greater capacity to manage their environments and resources while poorer nations are left behind. Malik et al. (2024) note that the broader Industry 4.0 transition, which includes environmental applications of AI, raises similar questions of equity regarding which regions and sectors benefit from productivity and sustainability gains. Developing AI tools that are open, accessible and co-designed with local communities and scientists in the Global South is therefore an ethical priority (Rolnick et al., 2022). Conservation applications, such as drone-based anti-poaching surveillance, must likewise be designed and implemented with due regard for the rights and privacy of local and Indigenous communities. More broadly, Chan and Lo (2025) argue that the rapid advance of AI across sectors, including environmental governance, requires sustained attention to its human-rights implications, from data privacy to due process in decisions informed by algorithmic systems.

Limitations of This Review

As a narrative review, this study is subject to selection bias: although the search and selection procedure is reported in Section 2, the final choice of sources involved the authors' judgement, and the restriction to English-language publications may have excluded relevant work, including studies from non-English-speaking parts of the Global South. Google Scholar searches are not fully reproducible, and the field is evolving so rapidly that some recent developments may not be captured. No quantitative meta-analysis of performance was attempted, because the included studies differ widely in their tasks, datasets and evaluation measures. The review should therefore be read as a critical overview of the main applications and evidence rather than as an exhaustive account of all published studies.

Future Directions

The integration of AI into environmental research is still at a relatively early stage, and several developments are likely to shape it in the coming years. The first is the development of physics-informed neural networks (PINNs), which incorporate governing physical equations such as conservation laws for mass, momentum and energy directly into the training of neural networks (Raissi et al., 2019). By combining the flexibility of data-driven learning with the physical consistency of process-based models, such hybrid approaches may improve generalisation beyond the training data, which is a central weakness of purely data-driven emulators (Section 3.2.1).

A second development is the emergence of large 'foundation models' for Earth science, which are pretrained on very large and diverse Earth-observation, weather-station and climate-model datasets and can then be adapted to specific tasks, such as crop-yield prediction or wildfire-risk assessment, with relatively little additional labelled data. If made openly available, such models could substantially lower the data barrier faced by researchers in data-scarce regions, although their energy demands (Section 3.7.3) and their behaviour in under-represented regions will require careful evaluation. A third development is edge AI, in which lightweight models run directly on sensors, drones or satellites, allowing data to be analysed and acted upon in real time without transmission delays; this is particularly relevant to the early detection of wildfires and to real-time bycatch avoidance in fisheries.

Environmental AI is also expanding into adjacent sustainability domains. Jadhav et al. (2025) examine AI-powered sustainable mobility in public transport, Sourek (2025) discusses the growing role of AI in architecture and the built environment, and Malik et al. (2024) situate these developments within the broader Industry 4.0 transition. Taken together with the equity concerns raised in Section 3.7.4, these trends suggest that environmental AI is becoming integrated with urban planning, transport and infrastructure design within a wider sustainability agenda. Finally, the most robust applications are likely to come from sustained collaboration among computer scientists, environmental scientists, social scientists and policymakers, so that tools are not only technically advanced but also scientifically valid, locally relevant and socially acceptable.

CONCLUSION

This review shows that AI is already making useful contributions to environmental research, from precipitation nowcasting and flood forecasting to the automated detection of methane super-emitters, wildlife and plastic debris. The strongest evidence, however, comes from data-rich settings in which models have been benchmarked against established methods, whereas many applications—particularly in the Global South remain at the stage of proposals, case studies or simulations whose transferability has not been tested. AI is therefore best regarded as a complement to, rather than a substitute for, process-based understanding, field observation and expert judgement. Its value depends on the quality and representativeness of the data on which it is trained, on rigorous and independent validation, and on governance that addresses transparency, bias, computational sustainability and human rights.

RECOMMENDATIONS

Four priorities follow directly from the evidence reviewed. First, governments, research institutions and international funders should invest in environmental monitoring networks, open datasets and computing infrastructure in data-poor regions, including Nigeria and other parts of sub-Saharan Africa, so that AI models can be trained and evaluated on representative local data. Second, AI models intended for operational use should be validated independently in the regions where they will be deployed, compared with established baseline methods, and used alongside expert judgement and field evidence rather than as definitive sources of decisions. Third, researchers should favour interpretable and energy-efficient models where these perform comparably, and should report the computational and energy costs of their models. Fourth, equitable research partnerships, capacity building and, where privacy and security permit, open sharing of tools and data should be promoted, together with clear institutional guidelines on bias, accountability, privacy and human oversight, so that the benefits of environmental AI are shared fairly.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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