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Artificial Intelligence for Environmental Monitoring and Pollution Prediction: Advances, Applications, Challenges, and Future Directions

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ABSTRACT

Artificial intelligence (AI) is rapidly transforming environmental monitoring by enabling the analysis of complex, high-volume, and heterogeneous environmental data for timely pollution detection, prediction, and decision-making. This review examines recent advances in the application of AI, including machine learning, deep learning, ensemble learning, and emerging hybrid approaches, to environmental monitoring and pollution prediction. It synthesizes evidence on the use of AI for monitoring and forecasting air pollution, water contamination, soil degradation, industrial emissions, solid waste, and other environmental hazards using data from ground-based sensors, remote sensing, Internet of Things (IoT) devices, satellite imagery, and environmental databases. The review highlights the growing effectiveness of algorithms such as random forests, support vector machines, artificial neural networks, convolutional neural networks, recurrent neural networks, and transformer-based models in identifying pollution patterns, predicting pollutant concentrations, detecting anomalies, and supporting early-warning systems. Despite these advances, significant challenges remain, including limited and inconsistent environmental datasets, sensor uncertainty, data heterogeneity, model interpretability, computational requirements, transferability across geographical contexts, and concerns regarding data governance and responsible AI. The review further identifies opportunities arising from explainable AI, edge computing, multimodal data integration, digital twins, federated learning, and real-time AI-enabled environmental decision-support systems. Overall, AI offers substantial potential to improve the accuracy, scalability, and timeliness of environmental monitoring and pollution prediction. Future research should prioritize transparent, generalizable, energy-efficient, and context-sensitive AI frameworks that integrate technological innovation with environmental science, regulatory requirements, and sustainable environmental management.

1. Introduction

Environmental pollution and ecological degradation have become increasingly complex global challenges, driven by rapid urbanization, industrialization, population growth, intensive agriculture, transportation, energy production, and changing climatic conditions. Air, water, and soil pollution are particularly concerning because pollutants can originate from multiple interacting sources, vary substantially across space and time, and undergo physical, chemical, and biological transformations after release into the environment (Alotaibi, 2024). Conventional environmental monitoring systems have traditionally relied on field sampling, laboratory analysis, fixed monitoring stations, and periodic surveys. Although these approaches provide valuable and scientifically reliable information, they can be constrained by high operational costs, limited spatial coverage, sampling frequency, lengthy processing times, and difficulties in detecting rapidly changing pollution events. These limitations have created a growing need for monitoring approaches capable of generating timely, spatially extensive, and predictive environmental information.

Artificial intelligence (AI) has emerged as a transformative technological approach for addressing many of these limitations. AI encompasses computational techniques that enable systems to learn patterns from data, identify complex relationships, classify environmental conditions, and generate predictions without relying exclusively on explicitly programmed rules. Machine learning (ML), deep learning (DL), artificial neural networks, support vector machines, decision trees, ensemble learning, and other data-driven techniques are increasingly being integrated with environmental datasets to support monitoring, forecasting, anomaly detection, and decision-making (Wani, 2024). The rapid expansion of Internet of Things (IoT) devices, low-cost sensors, satellite and remote-sensing platforms, geographic information systems (GIS), unmanned aerial vehicles, and high-performance computing has further increased the availability and diversity of environmental data. The convergence of these technologies with AI creates opportunities to move environmental monitoring from predominantly reactive and periodic assessment toward continuous, automated, and predictive environmental intelligence.

One of the most important applications of AI in environmental science is air-quality monitoring and pollution prediction. AI models can process large and heterogeneous datasets containing concentrations of particulate matter, nitrogen oxides, sulfur dioxide, ozone, carbon monoxide, volatile organic compounds, meteorological variables, traffic information, industrial activity, and land-use characteristics. By learning relationships among these variables, AI-based models can estimate pollutant concentrations, identify pollution hotspots, detect unusual pollution episodes, and forecast future air-quality conditions (Aniwa, 2021). Such capabilities can complement conventional monitoring networks, particularly in areas where monitoring stations are sparse. AI-assisted air-quality forecasting may also support early-warning systems and enable authorities, industries, and communities to respond more rapidly to hazardous pollution conditions.

AI has similarly expanded the possibilities for monitoring water and soil pollution. In water environments, machine learning algorithms can be applied to measurements of pH, dissolved oxygen, turbidity, temperature, conductivity, nutrients, heavy metals, microbial indicators, and other water-quality parameters. These models can assist in identifying contamination patterns, predicting changes in water quality, detecting abnormal conditions, and supporting the management of rivers, lakes, groundwater, and coastal ecosystems (Kan, 2025). In soil environments, AI can integrate information on soil properties, contaminants, land use, agricultural practices, climatic conditions, and remote-sensing observations to identify areas at risk of degradation or contamination. The ability to integrate multiple environmental indicators is particularly important because pollution rarely occurs in isolation; rather, it often reflects interactions among anthropogenic activities, environmental processes, and climatic variability.

Remote sensing and geospatial technologies have further broadened the role of AI in environmental monitoring. Satellite imagery provides repeated observations over extensive geographical areas, while AI algorithms can extract environmental information from multispectral, hyperspectral, thermal, and radar data. Deep learning techniques, particularly convolutional neural networks, can identify spatial patterns associated with land degradation, vegetation stress, water contamination indicators, urban expansion, waste accumulation, wildfire impacts, and other environmental changes (Miller, 2025). When combined with GIS and ground-based observations, AI-driven remote sensing can support high-resolution environmental mapping and facilitate the identification of areas requiring targeted investigation or intervention. This integration is especially valuable for large or difficult-to-access regions where conventional field monitoring alone is impractical.

Despite these advances, the application of AI to environmental monitoring and pollution prediction is accompanied by substantial scientific, technical, ethical, and institutional challenges. Environmental datasets are frequently heterogeneous, incomplete, noisy, imbalanced, and collected using instruments with different levels of accuracy and calibration. Pollution processes are also highly dynamic and influenced by interacting meteorological, geographical, socioeconomic, and anthropogenic factors. Consequently, a model that performs well in one geographical area, season, or environmental setting may not necessarily maintain its accuracy when applied elsewhere (Popescu, 2024). Overfitting, data leakage, inadequate validation, uncertainty in predictions, sensor errors, and limited availability of high-quality labelled datasets can further undermine model reliability. These challenges emphasize the importance of rigorous data preprocessing, model validation, uncertainty quantification, and independent testing before AI systems are incorporated into operational environmental management.

Another important concern is the interpretability and transparency of AI-based environmental models. Many advanced deep learning systems operate as complex black-box models, making it difficult for researchers, regulators, and environmental managers to understand why a particular prediction has been generated. Lack of interpretability can reduce confidence in AI-assisted decision-making, particularly when predictions have implications for public health, environmental regulation, resource allocation, or emergency response (Aniwa, 2026). Explainable artificial intelligence (XAI) therefore represents an increasingly important research direction, with the potential to make AI predictions more understandable, auditable, and scientifically defensible. Similarly, responsible AI deployment requires attention to data governance, privacy where human-generated data are involved, algorithmic bias, computational requirements, reproducibility, and equitable access to AI-enabled environmental technologies.

The rapid development of generative AI, foundation models, edge AI, digital twins, autonomous sensing systems, and multimodal learning is likely to further reshape environmental monitoring and pollution prediction. Future systems may integrate satellite imagery, sensor streams, meteorological observations, environmental models, historical records, and textual information within unified analytical frameworks. Edge-based AI could enable real-time processing directly on environmental sensors and monitoring devices, reducing communication delays and dependence on centralized computing infrastructure (Chauhan, 2025). Digital twins may allow environmental managers to simulate pollution scenarios and evaluate potential interventions before implementing them in real-world settings. At the same time, hybrid approaches that combine physical environmental models with machine learning may improve scientific consistency and generalizability by incorporating established environmental knowledge into data-driven prediction systems.

Against this background, a comprehensive assessment of AI for environmental monitoring and pollution prediction is timely. Although the literature demonstrates substantial progress in individual applications, the rapidly expanding body of research is fragmented across environmental domains, AI methodologies, data sources, geographical contexts, and application areas. There is therefore a need to synthesize recent advances systematically, examine the principal applications of AI across air, water, and soil environments, evaluate the strengths and limitations of different AI approaches, and identify unresolved methodological and implementation challenges (Hoang, 2022). This review, therefore examines the evolution and current state of AI-driven environmental monitoring, with particular emphasis on pollution detection, prediction, spatial mapping, early-warning systems, and decision support. It further considers issues of data quality, model interpretability, uncertainty, transferability, computational requirements, and responsible deployment, before highlighting emerging research directions that could strengthen the reliability, scalability, and practical value of AI for sustainable environmental management.

2. Methodology

2.1 Research Design

This study adopts a systematic and integrative review design to examine the role of Artificial Intelligence (AI) in environmental monitoring and pollution prediction. The review synthesizes recent advances in AI techniques, environmental sensing technologies, predictive modelling approaches, application domains, challenges, and emerging research directions. Rather than focusing on a single environmental pollutant or geographical region, the review takes a multidisciplinary perspective encompassing air, water, soil, and broader ecosystem monitoring. This approach enables the study to connect developments in machine learning, deep learning, remote sensing, Internet of Things (IoT) technologies, sensor networks, and data-driven environmental modelling.

The methodology is designed to provide a comprehensive understanding of how AI is being integrated into environmental monitoring systems and how these technologies improve the detection, classification, forecasting, and spatial mapping of pollutants. Particular attention is given to the transition from conventional monitoring approaches toward intelligent, real-time, predictive, and automated environmental management systems. The review also considers methodological limitations and implementation barriers that may affect the reliability, scalability, interpretability, and practical deployment of AI-based environmental solutions.

2.2 Literature Search Strategy

A structured literature search was conducted using major academic databases and scholarly search platforms, including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, PubMed, and Google Scholar. These databases were selected because they provide broad coverage of environmental science, artificial intelligence, engineering, computer science, remote sensing, and related interdisciplinary fields. The search focused primarily on peer-reviewed studies published in recent years in order to capture the rapid technological development of AI-based environmental applications, while influential earlier studies were also considered where they provided foundational concepts, algorithms, or methodological frameworks.

The search strategy combined keywords and Boolean operators related to the principal concepts of the review. Search terms included combinations of “artificial intelligence,” “machine learning,” “deep learning,” “environmental monitoring,” “pollution prediction,” “air pollution,” “water pollution,” “soil pollution,” “remote sensing,” “IoT sensors,” “environmental sensors,” “predictive modelling,” “anomaly detection,” “spatiotemporal prediction,” “neural networks,” “explainable AI,” and “environmental management.” Different combinations of these terms were used to identify literature addressing both technological developments and specific environmental applications.

2.3 Inclusion and Exclusion Criteria

The literature was selected according to predefined relevance criteria. Studies were included when they examined the application of AI, machine learning, deep learning, or closely related computational intelligence techniques to environmental monitoring, pollution detection, pollution classification, environmental forecasting, or predictive environmental management. Studies addressing air, water, soil, marine, urban, and ecosystem environments were considered where they provided insights relevant to AI-enabled environmental monitoring or pollution prediction. Research involving environmental sensor networks, satellite imagery, remote sensing, IoT platforms, and spatiotemporal environmental datasets was also included when AI constituted an important component of the analytical or predictive framework.

Studies were excluded when they had no meaningful connection with environmental monitoring or pollution prediction, focused exclusively on non-environmental applications of AI, or provided insufficient methodological information to support interpretation. Duplicate records, non-scholarly materials, and publications whose primary focus was unrelated to the objectives of the review were also excluded. Where multiple publications reported substantially overlapping findings, preference was given to the more comprehensive, recent, or methodologically rigorous study.

2.4 Study Selection and Screening

The identification and selection of relevant literature followed a staged screening process. Initially, records retrieved from the selected databases were examined on the basis of their titles and abstracts. Publications that clearly addressed AI applications in environmental monitoring or pollution prediction were retained for further assessment. The remaining studies were evaluated through full-text examination to determine their methodological relevance and contribution to the objectives of the review.
During the screening process, attention was given to the type of AI technique employed, environmental application area, data source, prediction or monitoring objective, spatial and temporal scale, and reported performance. Studies were retained when they provided substantive evidence regarding the capabilities, limitations, or practical applications of AI in environmental contexts. The final body of literature was subsequently organized thematically to facilitate comparative synthesis across technologies and environmental domains.

2.5 Data Extraction and Thematic Classification

Relevant information was systematically extracted from the selected literature and organized according to common analytical categories. These categories included publication characteristics, environmental domain, pollutant or environmental variable investigated, data source, AI methodology, monitoring technology, prediction objective, evaluation metrics, major findings, and reported limitations. Particular emphasis was placed on identifying relationships between data characteristics and model performance because environmental datasets frequently exhibit high dimensionality, spatial dependence, temporal variability, missing observations, measurement noise, and nonlinear relationships.

The selected studies were subsequently classified into major thematic areas. The first area concerned AI techniques, including traditional machine learning algorithms, ensemble learning, artificial neural networks, convolutional neural networks, recurrent neural networks, long short-term memory networks, hybrid models, and emerging generative or transformer-based approaches. The second area focused on environmental monitoring technologies, including ground-based sensors, IoT systems, satellite remote sensing, unmanned aerial platforms, and integrated sensor networks. The third area examined applications across air, water, soil, and broader environmental systems. The fourth area addressed challenges involving data quality, model interpretability, computational requirements, generalizability, uncertainty, privacy, infrastructure, and ethical considerations.

2.6 Assessment of AI Techniques and Model Performance

The review comparatively examined the strengths and limitations of different AI approaches used for environmental monitoring and pollution prediction. Conventional machine learning approaches such as linear and nonlinear regression, decision trees, random forests, support vector machines, k-nearest-neighbour methods, and gradient-boosting algorithms were considered alongside deep learning architectures. For sequential and spatiotemporal environmental data, particular attention was given to recurrent and convolutional architectures and hybrid models that combine complementary algorithms.

Model performance was assessed based on the evaluation measures reported in the reviewed studies. Common measures included coefficient of determination, mean absolute error, mean squared error, root mean squared error, accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve, depending on whether the study addressed regression, classification, detection, or forecasting. Because performance metrics are influenced by dataset characteristics, validation procedures, prediction horizons, and environmental conditions, the review avoided treating numerical performance values from different studies as directly interchangeable. Instead, performance was interpreted in relation to the research context, data quality, model architecture, and validation strategy.

2.7 Synthesis of Evidence
The evidence was synthesized narratively and comparatively rather than through statistical meta-analysis. This approach was considered appropriate because the reviewed studies differ substantially in environmental domains, geographical settings, datasets, sensor technologies, AI architectures, prediction targets, validation procedures, and performance metrics. The synthesis therefore focused on identifying recurring patterns, technological advances, areas of convergence and disagreement, and research gaps across the literature.

The synthesis examined how AI contributes to environmental monitoring through automated data processing, anomaly detection, pollutant identification, spatial mapping, real-time monitoring, and predictive forecasting. It also evaluated the extent to which AI can complement conventional environmental monitoring by improving temporal resolution, spatial coverage, early-warning capabilities, and decision support. Particular attention was given to emerging integrated systems that combine AI with IoT, remote sensing, edge computing, cloud platforms, and geospatial technologies.

2.8 Analysis of Challenges and Research Gaps
A dedicated thematic analysis was undertaken to identify limitations that constrain the broader adoption of AI for environmental monitoring and pollution prediction. These challenges were examined across technical, methodological, infrastructural, organizational, ethical, and policy dimensions. Technical issues included insufficient or biased training data, missing observations, sensor uncertainty, model overfitting, computational complexity, and difficulties in transferring models between locations or environmental conditions. Methodological concerns included inconsistent validation procedures, limited external validation, inadequate uncertainty quantification, and insufficient comparison with conventional statistical or mechanistic models.

The review also examined explainability and transparency because highly complex AI models may produce accurate predictions without providing sufficiently interpretable explanations for environmental decision-makers. Additional attention was given to data governance, interoperability, cybersecurity, infrastructure requirements, energy consumption, and the digital divide between technologically advanced and resource-constrained regions. Identifying these gaps provides the basis for discussing future research priorities and developing more reliable, transparent, scalable, and environmentally sustainable AI applications.

2.9 Quality and Reliability Considerations
The reliability of the review was strengthened through the use of multiple established scholarly databases, predefined selection criteria, systematic screening, and thematic organization of the evidence. Greater weight was assigned to studies providing clear descriptions of datasets, AI methodologies, validation procedures, and performance evaluation. Studies with limited methodological transparency were interpreted cautiously. Particular care was also taken to distinguish demonstrated empirical performance from conceptual claims concerning the future potential of AI.

Because AI and environmental monitoring are rapidly evolving fields, the review emphasizes recent evidence while retaining foundational research necessary for understanding the development of major computational approaches. This balance allows the review to capture emerging technologies without losing the theoretical and methodological foundations upon which contemporary AI-enabled environmental monitoring systems are built.

2.10 Methodological Limitations
Although the review employs a structured and comprehensive approach, several limitations should be acknowledged. First, substantial heterogeneity exists among published studies, making direct quantitative comparison of model performance difficult. Second, differences in database coverage, publication language, indexing practices, and keyword selection may result in the omission of some relevant studies. Third, the rapid development of AI technologies means that newly emerging methods may evolve faster than the academic literature can be consolidated. Finally, publication bias may favor studies reporting successful AI applications over studies documenting unsuccessful models, negative results, or implementation difficulties. These limitations were considered when interpreting the evidence and formulating conclusions regarding the current and future role of AI in environmental monitoring and pollution prediction.

3. Findings and Discussion
3.1 Artificial Intelligence for Environmental Monitoring
The reviewed literature demonstrates a clear transition from conventional, manually intensive environmental monitoring toward intelligent, continuous, and increasingly automated monitoring systems. Conventional approaches based on fixed monitoring stations, periodic sampling, and laboratory analysis remain important for regulatory and scientific purposes, but they are often constrained by high operating costs, limited spatial coverage, delayed processing, and insufficient temporal resolution. AI addresses several of these limitations by combining machine learning (ML), Internet of Things (IoT) devices, sensor networks, remote sensing, and automated data-processing platforms (Szramowiat-Sala, 2023). Recent reviews consistently identify the

integration of AI with sensors and remote sensing as an important development because it enables continuous observations, automated quality control, real-time interpretation, and more responsive environmental management.

The findings further indicate that the principal value of AI in environmental monitoring is not simply the replacement of conventional measurements, but the transformation of heterogeneous observations into actionable environmental information. AI can identify relationships among pollutant concentrations, meteorological conditions, land-use characteristics, traffic, hydrological variables, and other environmental drivers that may be difficult to capture using conventional statistical techniques alone (Aniwa, 2026). Consequently, AI-enabled monitoring is increasingly becoming an integrated system in which data acquisition, quality control, pattern recognition, prediction, and decision support occur within a connected analytical framework.

3.1.1 AI-Enabled Environmental Data Acquisition and Sensor Networks

AI-enabled environmental monitoring increasingly combines conventional monitoring stations with low-cost sensors, IoT devices, wireless sensor networks, and edge-computing platforms. These systems can continuously collect measurements of particulate matter, gaseous pollutants, temperature, humidity, pressure, water temperature, pH, dissolved oxygen, turbidity, conductivity, soil moisture, soil properties, meteorological conditions, and other environmental variables. Rather than relying exclusively on periodic samples, networked sensors can transmit observations at relatively short intervals, allowing environmental conditions to be observed as dynamic processes (Hait, 2024). Recent systematic evidence shows substantial growth in IoT-based air-quality monitoring, particularly through systems designed to improve data accuracy, predictive capability, and real-time analysis.

An important finding is that AI improves the usefulness of sensor networks by addressing problems inherent in low-cost and distributed sensing. Environmental sensors may generate noisy, incomplete, biased, or inconsistent measurements because of sensor drift, environmental interference, calibration problems, and communication failures. Machine-learning models can identify abnormal observations, estimate missing values, calibrate low-cost sensors against reference stations, and distinguish genuine environmental changes from measurement artifacts. This is particularly important where large numbers of inexpensive sensors are deployed to achieve greater spatial coverage (Aniwa, 2026). The literature therefore suggests that the combination of AI and IoT can provide a practical compromise between the accuracy of expensive reference stations and the extensive coverage offered by low-cost sensor networks.

The reviewed studies also point toward edge computing as an important component of future environmental monitoring. Processing data close to the sensor can reduce communication requirements and enable rapid detection of abnormal environmental conditions without waiting for all observations to be transmitted to a centralized server. For example, an intelligent air-quality node can process particulate-matter and meteorological observations locally and trigger an alert when pollutant concentrations deviate substantially from expected conditions (Maqbool, 2025). Similar approaches can be applied to water-quality sensors for detecting sudden changes in turbidity, dissolved oxygen, conductivity, or pH. Such systems are particularly valuable in geographically dispersed monitoring environments where continuous communication with centralized computing infrastructure may be expensive or unreliable.

Nevertheless, the evidence also reveals that increased sensor density does not automatically guarantee better environmental information. A recent systematic review of ML-IoT air-pollution studies identified limitations involving inadequate geographical coverage, limited data diversity, and insufficient incorporation of context-specific variables (Han, 2021). Thus, future sensor networks need to be designed not only around the number of sensors but also around representativeness, calibration, sensor placement, data quality, interoperability, and environmental context.

3.1.2 Machine Learning for Environmental Pattern Recognition and Anomaly Detection

The findings show that machine learning is increasingly used to transform large environmental datasets into recognizable patterns, pollution classes, and abnormal-event signals. Supervised learning methods such as random forests (RF), support vector machines (SVM), artificial neural networks (ANNs), and gradient-boosting algorithms are particularly useful where labelled environmental observations are available. These models can classify pollution levels, estimate environmental indicators, identify relationships between explanatory variables and environmental conditions, and support automated environmental-status assessment (Wu, 2024). Ensemble models are particularly effective for structured environmental datasets because they can represent nonlinear relationships and interactions among numerous predictors. Recent reviews report strong performance from RF and related ensemble methods in air-quality applications.

The comparative evidence suggests that no single algorithm is universally superior. RF is advantageous where datasets contain numerous nonlinear relationships and mixed predictor types, while SVM can perform effectively with relatively complex classification or regression problems, particularly when the sample size is moderate. Neural networks become increasingly attractive when environmental relationships are highly nonlinear or when large datasets are available (Adenike, 2017). Deep neural networks can learn hierarchical representations directly from complex observations, although their computational requirements and limited interpretability can constrain operational deployment. These differences reinforce the importance of matching the model architecture to the structure, size, quality, and temporal characteristics of the environmental dataset rather than selecting algorithms solely on the basis of reported accuracy.

Unsupervised learning provides an additional contribution where labelled environmental events are limited. Clustering techniques can group monitoring locations or observations according to similarities in pollution characteristics, while anomaly-detection methods can identify observations that depart from established environmental patterns (Blessing, 2025). This is useful for detecting unusual pollution episodes, abnormal sensor behaviour, or unexpected changes in environmental conditions. Recent reviews specifically identify clustering and anomaly-detection approaches as useful for data-quality improvement and sensor calibration in air-quality monitoring.

Deep learning further extends pattern recognition by learning temporal and spatial representations from environmental data. Recurrent neural networks, particularly LSTM models, are well suited to sequential observations because they can capture dependencies between present and previous environmental states. CNNs can extract spatial patterns from gridded observations and remote-sensing imagery (Aluvihara, 2025). The evidence therefore indicates that deep learning becomes especially valuable when environmental processes are characterized by strong temporal dependence, spatial heterogeneity, and interactions among multiple variables. However, the reported performance advantages should be interpreted cautiously because differences in datasets, geographical settings, preprocessing, validation strategies, and performance metrics make direct comparison between studies difficult.

3.1.3 Remote Sensing, Computer Vision, and AI-Based Spatial Monitoring

The integration of AI with satellite imagery, drones, unmanned aerial systems, and other remote-sensing technologies represents another major finding of the review. Remote sensing provides spatially extensive observations that cannot realistically be achieved through conventional ground-based monitoring alone. AI enables these observations to be automatically interpreted for environmental applications such as land-use and land-cover change, deforestation, vegetation stress, water-body assessment, waste identification, and pollution-related landscape changes (Adenike, 2023). The combination of remote sensing and ML is particularly important because environmental degradation frequently occurs over large and spatially heterogeneous areas.

Computer-vision techniques, particularly convolutional neural networks, have expanded the capacity to extract environmental information from imagery. CNN-based systems can learn spatial features associated with vegetation condition, changes in land cover, water characteristics, waste accumulation, and other environmental phenomena. In water-quality applications, for example, remote-sensing models can estimate optically active parameters from satellite imagery, while other water-quality characteristics may be inferred indirectly using relationships learned from field observations (El Khediri, 2023). A 2026 systematic review of river-water-quality studies found extensive use of Sentinel-2 and Landsat imagery for remote-sensing-based prediction, although it also identified geographical and methodological biases and limited reporting of uncertainty and sensitivity analysis.

Drones complement satellites by providing very high-resolution observations over relatively small areas. This makes them suitable for localized environmental surveillance, including examination of waste sites, vegetation degradation, water bodies, industrial areas, and pollution hotspots. The combined use of satellite observations for broad regional coverage and drones or ground sensors for detailed local observations creates a multiscale monitoring architecture (Vedrtnam, 2025). AI is particularly valuable in this architecture because it can integrate observations obtained at different spatial and temporal resolutions.

The evidence nevertheless indicates that remote-sensing AI systems face important limitations. Cloud contamination, differences in atmospheric conditions, sensor characteristics, image resolution, seasonal variation, and the scarcity of high-quality labelled observations can reduce model transferability. Moreover, models trained in one geographical region may not perform equally well elsewhere because environmental conditions and land-use patterns differ (Adenike, 2022). These limitations reinforce the need for domain adaptation, independent validation, uncertainty assessment, and integration of remote-sensing observations with ground-based measurements.

3.2 AI for Pollution Prediction and Forecasting

The reviewed evidence indicates that AI has progressed beyond environmental monitoring toward prediction and forecasting. Monitoring describes current or historical environmental conditions, whereas AI-based forecasting attempts to estimate future pollutant concentrations, environmental quality indices, or contamination risks. This shift is important because prediction allows authorities and environmental managers to act before pollution reaches critical levels (Patel, 2022). Recent systematic reviews show increasing use of ML and deep learning for pollution forecasting, with particularly strong attention to air quality and water quality.

The principal finding is that AI models are effective because pollution is influenced by multiple interacting factors, including emissions, meteorology, topography, traffic, industrial activity, land use, hydrological processes, and seasonal variation. These relationships are often nonlinear and difficult to represent adequately using simple statistical models (Hamza, 2022). AI provides flexible approaches for modelling such complex relationships, although its predictive superiority depends strongly on data quality, model design, validation procedures, and the environmental context.

3.2.1 Air Pollution Prediction and Forecasting

Air pollution is the environmental domain in which AI-based prediction has received particularly extensive research attention. The reviewed literature covers prediction of $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO, and aggregated air-quality indices. Among these pollutants, particulate matter especially $PM_{2.5}$ appears particularly frequently in recent forecasting research because of its importance for environmental and public-health assessment (Adjei, 2025). Recent reviews indicate that LSTM-based models are among the most frequently used deep-learning approaches for air-quality forecasting, while CNN-LSTM and other hybrid architectures are increasingly employed to capture both spatial and temporal dependencies.

Compared with conventional statistical approaches such as multiple linear regression and ARIMA, ML models provide greater flexibility for nonlinear relationships. Ensemble approaches such as RF and XGBoost have demonstrated strong performance on structured datasets, while SVM and ANN models have also been widely applied (Talaie, 2024). A recent systematic review of 65 studies reported RF as the most frequently used ML technique and identified reported accuracies as high as 98.2% in particular applications, although such values should not be interpreted as universally transferable performance because datasets, target pollutants, geographical settings, and evaluation procedures differ across studies.

Deep learning provides an additional advantage when air pollution displays pronounced temporal and spatial dependence. LSTM networks can learn relationships between current pollutant concentrations and previous observations, making them suitable for short-term forecasting. CNN-based models can extract spatial patterns across monitoring stations, while CNN-LSTM architectures combine spatial feature extraction with temporal sequence modeling (Zhang, 2025). These capabilities are particularly relevant in urban environments where pollution varies according to traffic flows, industrial activity, atmospheric stability, wind direction, temperature, humidity, and urban morphology.

The findings also demonstrate that meteorological and contextual variables are essential to prediction performance. Models that incorporate wind speed and direction, temperature, humidity, precipitation, atmospheric pressure, traffic intensity, and historical pollutant concentrations can capture a larger proportion of pollution variability than models based solely on pollutant histories. This explains why recent literature increasingly emphasizes multimodal and spatiotemporal forecasting (Islam, 2026). At the same time, systematic evidence indicates that many studies still suffer from insufficient geographical coverage and inadequate inclusion of context-specific variables.

The practical implication is that AI-based air-quality forecasting can support early-warning systems, urban planning, traffic management, industrial regulation, and public-health preparedness. However, high predictive accuracy under historical conditions does not necessarily guarantee reliable forecasting under unprecedented pollution episodes or changing emission patterns (Adenike, 2018). Consequently, model recalibration, external validation, uncertainty quantification, and explainable AI remain necessary for operational deployment.

3.2.2 Water and Soil Pollution Prediction

AI applications in water-quality prediction show similar advantages but operate within environmental systems that are strongly influenced by hydrological, geological, chemical, climatic, and land-use processes. Models have been applied to parameters including pH, turbidity, dissolved oxygen, biological oxygen demand, nutrients, salinity, heavy metals, and water-quality indices (Islam, 2026). Recent systematic reviews demonstrate rapid growth in the combination of ML, deep learning, IoT, and remote sensing for water-quality prediction.

The findings indicate that AI is particularly useful for modelling nonlinear relationships among water-quality indicators and their environmental drivers. For example, nutrient concentrations can be related to rainfall, agricultural activity, land cover, streamflow, temperature, and upstream conditions. Similarly, heavy-metal contamination may be associated with industrial activity, geological characteristics, land use, and hydrological transport (Leena Sri, 2025). AI can combine these variables to estimate contamination levels at locations or times for which direct measurements are unavailable, thereby helping to identify potential pollution hotspots and support early-warning systems.

Remote sensing provides an important complementary source of information. Satellite imagery can provide spatially continuous information for water bodies, while field measurements provide the reference observations required for model development and validation. The recent systematic review of river-water-quality research found that remote-sensing approaches predominantly use Sentinel-2 and Landsat imagery to estimate optically active water-quality parameters, while optically inactive parameters generally require indirect inference (Basu, 2024). This distinction is important because AI predictions based solely on imagery should not be assumed to measure every contaminant directly.

AI-based approaches are also increasingly relevant to soil pollution and soil-quality assessment. Models can integrate soil properties, land use, geological characteristics, climatic variables, agricultural practices, and historical contamination observations to estimate contamination risks. Such models can help identify areas requiring more intensive sampling, prioritize remediation efforts, and assess potential pollutant movement through terrestrial systems (Fuqaha, 2025). Nevertheless, soil contamination is highly heterogeneous at small spatial scales, making representative sampling particularly important for model training and validation.

A major limitation identified in the water-quality literature is the lack of standardized validation and uncertainty analysis. The 2026 systematic review of AI-driven river-water-quality prediction found substantial geographical concentration of research, methodological inconsistencies, limited uncertainty quantification, and frequent absence of independent test sets (Islam, 2025). These findings indicate that reported predictive accuracy alone is insufficient for determining whether an AI model is suitable for operational environmental management.

3.2.3 Multimodal and Spatiotemporal Pollution Forecasting

The most important emerging direction identified in the review is the movement from single-source prediction toward multimodal and spatiotemporal environmental intelligence. Pollution does not occur independently at individual monitoring points; it develops through interactions among emission sources, atmospheric or hydrological transport, weather, land use, human activity, and geographical characteristics (Islam, 2025). Consequently, forecasting systems that combine sensor measurements with satellite imagery, meteorological observations, traffic information, industrial activity, demographic variables, and historical pollution records can potentially provide a more complete representation of environmental dynamics.

Recurrent neural networks, particularly LSTM architectures, are useful for modelling temporal dependencies, whereas CNNs can identify spatial features. Their combination in CNN-LSTM architectures provides a mechanism for learning both spatial and temporal characteristics of pollution. More recent approaches increasingly consider transformer architectures, which can model long-range dependencies in sequential data, and graph neural networks, which represent monitoring locations as interconnected nodes (Alotaibi, 2024). A graph-based representation is particularly appropriate for urban air pollution because monitoring stations can be connected according to geographical proximity, prevailing wind patterns, road networks, or pollutant-transport relationships. Similar approaches can be adapted to river systems by representing monitoring locations according to upstream-downstream connectivity.

Hybrid AI models provide another important development. Rather than relying on a single algorithm, hybrid frameworks may combine statistical models with ML, physical environmental models with deep learning, or different neural architectures. Such approaches can exploit established environmental knowledge while retaining the nonlinear predictive capacity of AI (Wani, 2024). This is particularly promising for environmental applications because purely data-driven models may perform poorly when observations are sparse or when the system encounters conditions outside the training distribution.

The evidence suggests that multimodal forecasting can substantially improve the spatial resolution and responsiveness of pollution prediction. However, combining more data does not necessarily produce a better model. Heterogeneous datasets often differ in spatial resolution, temporal frequency, measurement uncertainty, missing-data patterns, and geographical coverage. Consequently, data alignment and fusion become major methodological challenges (Aniwa, 2021). Recent reviews emphasize data sparsity, heterogeneous inputs, sensor drift, limited interpretability, and weak generalizability as persistent barriers to operational environmental AI.

Overall, the findings indicate that the future of pollution forecasting is likely to depend increasingly on integrated spatiotemporal systems rather than isolated prediction models. Such systems can potentially generate high-resolution pollution maps, identify emerging hotspots, forecast pollutant movement, and provide location-specific early warnings. Nevertheless, the evidence also demonstrates that future research should move beyond maximizing conventional accuracy metrics. Independent testing, uncertainty quantification, explainability, cross-regional validation, standardized benchmarks, and robustness under changing environmental conditions are essential if AI-generated predictions are to support regulatory decisions and environmental management reliably (Kan, 2025). Recent reviews of both air- and water-quality AI research converge on this need for greater interpretability, generalizability, uncertainty assessment, and real-time applicability.

Taken together, the findings establish AI as an enabling technology that connects environmental observation with prediction and decision support. Its greatest contribution lies in integrating continuous sensor observations, remote sensing, contextual information, and advanced analytical models into adaptive monitoring systems (Miller, 2025). At the same time, the evidence cautions against viewing AI as a replacement for environmental science or conventional monitoring. Instead, the strongest pathway is a complementary model in which validated physical measurements provide reliable reference data, AI expands spatial and temporal inference, and human and institutional expertise interpret predictions within their environmental and regulatory contexts.

3.3 Applications of AI in Environmental Management and Decision-Making

3.3.1 Early-Warning Systems and Environmental Risk Assessment

The findings of this review indicate that one of the most consequential applications of artificial intelligence (AI) in environmental management is the development of early-warning and environmental risk-assessment systems. Machine learning (ML) and deep learning (DL) models can integrate historical observations, real-time sensor measurements, meteorological variables, satellite imagery, land-use information, and other contextual data to identify emerging environmental hazards before they become severe (Popescu, 2024). In pollution monitoring, for example, AI models can forecast increasing concentrations of particulate matter, nitrogen oxides, ozone, or other pollutants and thereby provide an opportunity for authorities to issue warnings and implement preventive measures. Recent systematic evidence shows that ML and DL approaches are increasingly being applied to air-pollution forecasting, with deep-learning models particularly useful for capturing complex spatial and temporal relationships in environmental data.

The value of AI-based early warning extends beyond routine air-quality forecasting. Environmental hazards are often dynamic and interconnected, meaning that the consequences of an event depend on interactions among weather conditions, pollutant emissions, hydrological processes, land use, ecosystem characteristics, and human activities. AI can identify nonlinear relationships within these variables that may be difficult to capture using conventional statistical approaches alone (Aniwa, 2026). For instance, a model trained on meteorological and air-quality data could recognize combinations of low wind speed, atmospheric stability, high temperature, and elevated emissions that are associated with increased pollution episodes. Similar approaches can be applied to water-quality deterioration, harmful algal blooms, wildfire-related air pollution, floods, drought conditions, and other climate-sensitive hazards. The broader literature confirms that AI-driven environmental monitoring can support pollution detection and disaster forecasting while facilitating faster intervention.

From an environmental-risk perspective, the principal contribution of AI is therefore not simply prediction accuracy but the conversion of prediction into actionable lead time. A pollution forecast issued several hours or days before a hazardous episode can allow environmental agencies to intensify monitoring, communicate risks, temporarily restrict particular emissions, adjust traffic-management measures, protect vulnerable ecosystems, or prepare emergency-response resources (Chauhan, 2025). However, the usefulness of such systems depends on the reliability of the forecasts and the institutional capacity to respond to them. Consequently, early-warning systems should be designed as decision-support mechanisms rather than autonomous replacements for environmental expertise. Their outputs should be accompanied by uncertainty information, threshold-based alerts, and clearly defined response procedures.

3.3.2 AI for Pollution Source Identification and Control

The review further demonstrates that AI is increasingly valuable for moving environmental management from detecting pollution to determining where pollution originates. Source identification is particularly important in complex environments where several sources contribute simultaneously to observed contamination. ML techniques can learn relationships between pollutant concentrations, meteorological conditions, spatial characteristics, traffic activity, industrial operations, land use, and other explanatory variables (Hoang, 2022). Such models can assist in identifying emission patterns and estimating the relative importance of different potential sources. Evidence from atmospheric pollution research shows that ML is being applied not only to concentration prediction but also to source apportionment, although source-apportionment applications remain less developed than prediction applications.

For traffic-related pollution, AI can combine roadside sensor observations with traffic volume, vehicle characteristics, road geometry, weather, and temporal activity patterns to identify locations and periods associated with elevated emissions. In industrial areas, models can compare pollutant signatures across monitoring stations and operational conditions to identify probable emission hotspots (Szramowiat-Sala, 2023). In agricultural environments, AI can similarly examine relationships between fertilizer application, livestock activity, soil conditions, weather, and observed air- or water-quality changes. These applications illustrate an important shift from generalized pollution assessment toward spatially targeted diagnosis.

The practical significance of AI-based source identification is that pollution-control resources can be directed toward the most influential sources rather than distributed uniformly. For example, if model outputs indicate that a particular combination of traffic conditions and industrial activity is strongly associated with observed pollution peaks, regulators can prioritize inspections, emission controls, or monitoring in those areas (Aniwa, 2026). Nevertheless, AI-based source attribution should not automatically be interpreted as definitive causal evidence. Environmental pollution is influenced by transport, atmospheric chemistry, hydrological movement, and other processes, and therefore AI-derived source estimates should ideally be combined with dispersion models, chemical measurements, expert knowledge, and conventional source-apportionment techniques (Hait, 2024). The literature similarly emphasizes the need for specialized and standardized methods to strengthen the application of ML to atmospheric source apportionment.

3.3.3 AI-Supported Environmental Policy and Sustainable Decision-Making

The findings indicate that the policy value of environmental AI arises from its ability to transform large and heterogeneous datasets into information that can support planning, regulation, and resource allocation. Policymakers and environmental managers increasingly need to make decisions under conditions of uncertainty, rapidly changing environmental conditions, and competing socioeconomic priorities (Aniwa, 2026). AI can contribute by providing forecasts, identifying hotspots, evaluating alternative scenarios, and detecting emerging trends. In urban planning, for example, AI-supported environmental analytics can integrate air-quality observations, traffic patterns, meteorological information, land use, population distribution, and infrastructure data to identify areas requiring targeted interventions (Maqbool, 2025). Recent research describes the integration of AI, AIoT, and urban digital twins as an emerging approach to data-driven environmental planning in sustainable cities.

AI can also support environmental regulation by strengthening monitoring and compliance systems. Continuous analysis of sensor and remote-sensing data can help identify unusual emission patterns, changes in water quality, or environmental degradation that warrant investigation. Predictive analytics can additionally assist regulators in determining where monitoring resources are most needed. This is particularly important where conventional monitoring networks are expensive and spatially limited (Han, 2021). Rather than treating environmental management as a sequence of reactive responses after pollution has occurred, AI creates opportunities for anticipatory management based on predicted risks and probable future conditions.

At the same time, the review shows that AI should complement rather than replace institutional decision-making. Environmental policies involve scientific, economic, social, legal, and ethical considerations that cannot be reduced to predictive accuracy. AI-generated recommendations must therefore be interpreted within regulatory frameworks and subjected to expert review (Wu, 2024). The strongest model of AI-supported environmental governance is consequently one in which computational intelligence improves the evidence base available to decision-makers while accountability for consequential decisions remains clearly assigned to appropriate institutions and professionals.

3.4 Challenges, Limitations, and Risks of AI-Based Environmental Applications

3.4.1 Data Quality, Availability, and Representativeness

A major finding of the review is that the effectiveness of environmental AI is fundamentally constrained by the quality and representativeness of the data used to train and evaluate models. Environmental datasets frequently contain missing observations, measurement errors, inconsistent sampling intervals, sensor drift, outliers, and differences in measurement protocols. Low-cost sensors can expand spatial coverage but may require calibration and quality control before their measurements can reliably support AI applications (Adenike, 2017). Similarly, satellite, ground-based, meteorological, hydrological, and socioeconomic datasets may differ substantially in spatial and temporal resolution, creating challenges when they are combined within a single modelling framework.

Data scarcity is particularly problematic in regions with limited environmental-monitoring infrastructure. A model developed using extensive datasets from highly monitored cities may perform poorly when transferred to locations where monitoring stations are sparse, environmental conditions differ, or emission patterns are substantially different (Blessing, 2025). Recent reviews of AI-based air-pollution forecasting identify the integration of diverse data sources as an important pathway for improving prediction, while also emphasizing continuing challenges related to real-time monitoring and model reliability.

Representativeness is equally important. A dataset may be large but still fail to capture important environmental conditions if observations are concentrated in particular seasons, locations, or socioeconomic areas. This can lead to models that perform well under common conditions but fail during unusual pollution episodes or in under-monitored communities. Consequently, increasing the quantity of environmental data alone is insufficient (Aluvihara, 2025). Future systems require carefully designed monitoring networks, standardized measurement protocols, calibration procedures, metadata, quality assurance, and greater geographic coverage. These requirements are especially significant for developing regions, where uneven infrastructure can create substantial spatial biases in environmental AI.

3.4.2 Model Interpretability, Generalizability, and Uncertainty

The review identifies interpretability and generalizability as critical barriers to the wider adoption of complex AI models in environmental decision-making. Deep neural networks and other sophisticated models can achieve strong predictive performance but may provide limited insight into why a particular prediction was generated. This black-box characteristic becomes problematic when predictions influence environmental regulation, public warnings, industrial compliance, or allocation of environmental resources (Adenike, 2023). Environmental scientists and regulators need to understand whether a prediction is physically plausible and which environmental variables are driving it.

Explainable AI (XAI) provides an important response to this challenge by allowing researchers to investigate feature importance, variable contributions, model sensitivity, and prediction patterns. The atmospheric-pollution literature indicates that interpretable ML can provide insights into the mechanisms underlying model predictions rather than treating AI exclusively as a forecasting tool (El Khediri, 2023). Recent research also identifies interpretability and uncertainty quantification as important priorities for future AI-based air-pollution monitoring and forecasting.

Generalizability presents a related problem. Environmental systems vary across geographical regions, seasons, climates, pollution regimes, and ecosystem types. A model that performs well in one location may therefore lose accuracy when applied elsewhere. Overfitting, distributional shifts, data drift, and changes in sensor characteristics can further reduce long-term performance. This means that model validation should extend beyond random train-test splits and include temporal validation, spatial validation, independent datasets, and, where possible, cross-region testing (Vedrtnam, 2025). Continuous monitoring of model performance is also necessary because environmental conditions and data-generating processes change over time.

Uncertainty quantification is consequently essential. An AI prediction should ideally communicate not only the expected pollutant concentration or risk level but also the confidence associated with that estimate. This is particularly important for extreme events, where erroneous confidence could produce either unnecessary interventions or insufficient responses (Adenike, 2022). Emerging research increasingly points toward hybrid approaches that combine AI with physical models, including physics-informed methods, as a means of improving reliability, interpretability, and scientific consistency.

3.4.3 Ethical, Governance, Computational, and Implementation Challenges

Beyond technical limitations, the findings reveal a broader set of ethical, governance, and implementation challenges. Environmental AI depends increasingly on large quantities of data collected through fixed sensors, mobile devices, remote sensing, drones, connected infrastructure, and other platforms. Questions therefore arise concerning data ownership, access, stewardship, privacy, security, and accountability. Although many environmental datasets are not inherently personal, environmental monitoring can intersect with information about households, mobility, workplaces, agricultural activities, or communities (Patel, 2022). Responsible governance is therefore required to establish who can collect, process, share, and make decisions from such data.

Algorithmic bias is another concern. If monitoring infrastructure is concentrated in affluent or highly urbanized areas, AI systems may provide better predictions for those locations than for poorly monitored communities. Such disparities can influence the distribution of environmental protection and potentially reproduce existing inequalities (Hamza, 2022). The review therefore indicates that fairness should be considered not merely as an AI ethics issue but as an environmental-justice concern.

Computational requirements also constrain deployment. Sophisticated DL models may require substantial processing power, storage, connectivity, and energy. These requirements can be difficult to sustain in remote or resource-constrained environments. Edge computing and federated learning offer potential solutions by moving some processing closer to sensors and allowing models to be trained across distributed data without necessarily transferring raw observations to a central location (Adjei, 2025). A recent review of 361 studies reports growing application of federated learning across air and water quality, climate modelling, agriculture, and biodiversity, while identifying data heterogeneity, benchmarking limitations, and unequal access to computational infrastructure as persistent challenges.

Implementation also requires institutional capacity. Environmental agencies may lack personnel with expertise in AI, data engineering, cybersecurity, or model evaluation. Interoperability problems can further arise when new AI systems must communicate with legacy monitoring platforms and regulatory databases. Successful deployment therefore requires more than purchasing computational technologies; it requires training, maintenance, data standards, institutional coordination, cybersecurity measures, and long-term financial support (Talaie, 2024). AI adoption should consequently be viewed as a socio-technical transformation of environmental management rather than as the simple introduction of a new software tool.

3.5 Future Directions and Emerging Research Priorities

3.5.1 Explainable, Trustworthy, and Responsible Environmental AI

The findings point strongly toward a future in which environmental AI is evaluated according to both predictive performance and scientific trustworthiness. Explainable AI should become an integral component of environmental modelling, particularly where predictions influence public warnings, regulatory action, or environmental investment. Future models should provide understandable explanations of influential variables, prediction uncertainty, applicable operating conditions, and potential limitations (Zhang, 2025). This will help environmental scientists distinguish statistically strong predictions from relationships that may be spurious or environmentally implausible.

Future research should also strengthen uncertainty-aware modelling, reproducibility, fairness, and accountability. Standardized evaluation protocols would make it easier to compare models across locations and environmental domains. Open datasets, transparent preprocessing procedures, documented model architectures, and reproducible validation strategies could improve confidence in reported results (Islam, 2026). Hybrid AI approaches that incorporate physical laws, mechanistic understanding, or domain constraints are particularly promising because they can reduce the gap between purely data-driven prediction and established environmental science. Recent air-quality research similarly identifies XAI, uncertainty quantification, and physics-informed approaches as important directions for developing more reliable AI models.

Trustworthiness should ultimately be treated as a multidimensional property encompassing accuracy, robustness, interpretability, fairness, security, and accountability. An environmental AI system that achieves high accuracy but cannot explain its predictions, quantify uncertainty, or demonstrate performance under changing conditions may have limited value for high-stakes environmental decisions (Adenike, 2018).

3.5.2 Integration of Generative AI, Digital Twins, Edge AI, and Advanced Analytics

The next stage of environmental intelligence is likely to involve the convergence of AI with digital twins, edge computing, federated learning, autonomous sensing, and increasingly sophisticated analytical models. Environmental digital twins can provide dynamic virtual representations of cities, watersheds, ecosystems, industrial areas, or broader Earth-system components. By continuously incorporating observations into computational models, they can support simulation, forecasting, scenario analysis, and decision-making (Islam, 2026). Research on Earth-system digital twins highlights the potential of combining Big Earth Data, data assimilation, physical models, ML, causal inference, and reinforcement learning to improve environmental monitoring and prediction.

Recent reviews indicate that environmental digital twins remain an emerging rather than fully mature technology. A 2026 mapping study of 121 environmental digital-twin applications found that the field remains largely at early development stages, with integration, interoperability, calibration, scaling, and institutional alignment among the recurring challenges (Leena Sri, 2025). This finding suggests that future research should prioritize operational validation rather than focusing exclusively on conceptual architectures.

Generative AI may add another layer by facilitating natural-language interaction with environmental databases and models, automatically generating reports, assisting with interpretation of complex environmental datasets, and supporting scenario exploration. However, generative systems should be grounded in verified environmental datasets and scientific models because fluent outputs do not necessarily guarantee factual or scientifically valid conclusions. Edge AI is similarly promising because environmental predictions can increasingly be performed near the point of data collection, reducing latency and dependence on continuous cloud connectivity (Basu, 2024). Reviews of federated learning and edge-based environmental monitoring indicate that decentralized architectures can address some privacy, bandwidth, and response-time constraints, although data heterogeneity and resource limitations remain important barriers.

Foundation models and advanced spatiotemporal analytics may further enable environmental AI systems to learn across multiple data modalities, including satellite imagery, sensor observations, meteorological records, maps, textual reports, and other geospatial information (Fuqaha, 2025). The long-term objective is not simply to build larger models but to develop environmentally grounded models capable of transferring knowledge across locations and adapting to changing environmental conditions.

3.5.3 Toward Integrated, Scalable, and Climate-Resilient Environmental Intelligence

The overall findings suggest that the future of environmental AI lies in integrated environmental intelligence rather than isolated prediction models. Effective systems should combine ground-based sensors, remote sensing, meteorological observations, hydrological information, geospatial datasets, land-use data, socioeconomic indicators, and environmental models within interoperable analytical architectures (Islam, 2025). Such integration would allow AI systems to capture the multiple interacting drivers of pollution and environmental change while improving spatial and temporal coverage.

This direction is consistent with the broader evolution of Earth-system science toward the integration of Big Earth Data, physical modelling, data assimilation, and machine learning. It also corresponds with the emerging development of environmental digital twins, which seek to connect real-world observations with dynamic models and decision-support systems (Islam, 2025). Rather than treating air, water, soil, climate, biodiversity, and urban systems as independent domains, integrated environmental intelligence can reveal their interactions and support more comprehensive sustainability interventions.

A major priority will therefore be the development of standardized, high-quality, FAIR-oriented environmental datasets and interoperable monitoring infrastructures. Open science, shared benchmarks, cross-disciplinary collaboration, and capacity building will be essential for reducing fragmentation in the field (Wani, 2024). Developing countries in particular require greater investment in monitoring infrastructure, technical training, data governance, and affordable AI architectures so that environmental intelligence does not become concentrated in regions with already strong technological capacity.

Ultimately, the findings indicate that AI can contribute to a transition from reactive environmental management toward predictive, adaptive, and climate-resilient governance. Its contribution extends beyond forecasting pollutant concentrations to identifying pollution sources, assessing environmental risks, optimizing monitoring resources, supporting urban planning, and informing long-term sustainability strategies. Nevertheless, these benefits will depend on the development of trustworthy models, representative data, transparent governance, and institutional capacity (Popescu, 2024). The most promising trajectory is therefore an integrated environmental-intelligence framework in which AI operates alongside environmental science, physical modelling, human expertise, and public institutions. Such a framework can strengthen pollution prevention while simultaneously supporting ecosystem protection, climate adaptation, sustainable urban development, and long-term environmental resilience.

4. Conclusion

Artificial intelligence (AI) is increasingly transforming environmental monitoring and pollution prediction by enabling the rapid processing of large, complex, and heterogeneous datasets generated from sensors, satellites, remote-sensing platforms, geographic information systems, meteorological stations, and other digital technologies. The findings of this review demonstrate that AI techniques, including machine learning, deep learning, artificial neural networks, support vector machines, random forests, ensemble learning, and emerging hybrid approaches, can substantially improve the detection, classification, prediction, and spatial–temporal assessment of environmental conditions. Their capacity to identify nonlinear relationships and complex patterns provides important advantages over conventional statistical and monitoring approaches, particularly where environmental processes are dynamic, multidimensional, and difficult to model using traditional techniques.

The review further shows that AI has applications extending beyond pollution prediction to broader environmental management and decision-making. AI-supported systems can contribute to early-warning mechanisms for air and water pollution, environmental risk assessment, ecosystem monitoring, climate-related analysis, waste management, water-resource management, and the optimization of environmental interventions. By integrating real-time observations with predictive analytics, these systems can support more timely and evidence-based decisions by environmental agencies, policymakers, industries, and local communities. The greatest value of AI therefore lies not simply in improving prediction accuracy, but in transforming environmental data into actionable information that can support prevention, preparedness, and sustainable resource management.

Despite these advances, the review highlights several challenges that constrain the wider adoption of AI in environmental applications. Data quality, insufficient monitoring networks, missing and inconsistent observations, limited availability of long-term datasets, model bias, lack of interpretability, computational requirements, and difficulties in transferring models between geographical and environmental contexts remain important concerns. In addition, highly accurate AI models may have limited practical value when their predictions cannot be adequately explained to decision-makers or when they depend on data that are unavailable in resource-constrained regions. Ethical, institutional, financial, and governance considerations are therefore as important as technical performance in determining the effectiveness and sustainability of AI-based environmental monitoring systems.

Future development should consequently move toward more transparent, explainable, adaptive, and context-sensitive AI systems. Greater integration of AI with Internet of Things sensors, satellite observations, remote sensing, cloud computing, digital twins, geographic information systems, and real-time environmental databases could strengthen continuous monitoring and predictive capabilities. Hybrid models that combine physical environmental knowledge with data-driven AI approaches are particularly promising because they can improve predictive robustness while maintaining consistency with established environmental processes. Future research should also prioritize standardized datasets, reproducible methodologies, cross-regional validation, uncertainty quantification, explainable AI, and approaches that can operate effectively in data-scarce environments.

In summary, AI should be regarded as a complementary technology rather than a replacement for environmental science, field monitoring, expert knowledge, and regulatory institutions. Its effectiveness depends on the quality of environmental data, the appropriateness of the selected models, the transparency of predictions, and the capacity of institutions to translate analytical outputs into practical interventions. When responsibly designed and integrated with conventional environmental monitoring and scientific knowledge, AI has considerable potential to strengthen pollution prediction, environmental early-warning systems, and evidence-based decision-making. The future of AI-enabled environmental management will therefore depend on achieving a balance between predictive performance, interpretability, technological accessibility, environmental relevance, and responsible governance, thereby enabling AI to contribute meaningfully to pollution reduction, ecosystem protection, and long-term environmental sustainability.

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References

[1] Adenike, A. (2017). Managing Domestic Debt and Sovereign Foreign Reserves: Risk, Liquidity, and Strategic Allocation. *International Journal of Technology, Management and Humanities*, 3(02), 21-42. https://doi.org/10.21590/v3i2.03

[2] Adenike, A. (2018). Strengthening Financial Market Infrastructure in Emerging Economies: Lessons From Central Banking Operations. SAMRIDDHI: *A Journal of Physical Sciences, Engineering and Technology, 10(*02), 177-182. https://doi.org/10.18090/samriddhi.v10i02.12

[3] Adenike, A. (2022). Central Bank Digital Currency (CBDC) Adoption Challenges and Remittance Impacts: Empirical Evidence from Nigeria's eNaira Compared with Global Retail Pilots and US Federal Reserve Policy Stance. *International Journal of Humanities and Information Technology, 4*(01-03), 214-233. https://doi.org/10.21590/ijhit.04.01-3.16

[4] Adenike, A. (2023). Cashless Policy Transitions and Currency Substitution: Nigeria's 2012-2022 Evolution Compared with Sweden, China, South Korea, and US Instant Payments Via Fednow. *Research Journal in Business and Economics, 1(*1), 236-247. https://doi.org/10.61424/rjbe.v1i1.925

[5] Adjei, F. (2025). Artificial intelligence and machine learning in environmental health science: a review of emerging applications. *Available at SSRN 5361829*.

[6] Alotaibi, E., & Nassif, N. (2024). Artificial intelligence in environmental monitoring: in-depth analysis. *Discover Artificial Intelligence*, *4*(1), 84.

[7] Aluvihara, S., Omar, M. H., Zaryab, A. H., Hilonga, A., Baomar, J. O., & Alqasi, N. J. K. (2025). The Impact of the Applications of Artificial Intelligence (AI) Concepts and Tools on the Reduction of the Environmental Pollution. *Alberoni University International Journal: Applied Sciences*, *1*(01), 62-71.

[8] Aniwa S.C. (2021). Impact of Supply Chain Integration on Operational Performance: Insights from Manufacturing Firms in Emerging Economies. *Iconic Research And Engineering Journals*, 5(4).

[9] Aniwa, S. C. (2026). Risk Management Practices and Supply Chain Disruption Mitigation in Global Supply Networks. *International Journal of Scientific Research and Modern Technology*, *5*(3), 72–84. https://doi.org/10.38124/ijsrmt.v5i3.1354

[10] Aniwa, S.C. (2026). Green supply chain management practices and their implications for organisational sustainability: An empirical investigation using PLS-SEM. *World Journal of Advanced Research and Reviews*, 30(03), 932-945. https://doi.org/10.30574/wjarr.2026.30.3.0813

[11] Aniwa, S.C. (2026). The Role of Digital Technologies in Enhancing Supply Chain Visibility and Resilience. *International Journal of Computer Applications Technology and Research*, 15(4), 53–70. https://doi.org/10.7753/IJCATR1504.1005

[12] Basu, M., & Nath, M. D. (2024). A study of the role of artificial intelligence in monitoring environmental and health issues in the post-COVID-19 pandemic era for sustainable living. In *Artificial Intelligence for Multimedia Information Processing* (pp. 132-166). CRC Press.

[13] Blessing, A. A., & Olateru, K. (2025). AI-driven optimization of bioremediation strategies for river pollution: a comprehensive review and future directions. *Frontiers in Microbiology*, *16*, 1504254.

[14] Chauhan, B. V., Vedrtnam, A., Wyche, K. P., & Verma, S. (2025). Review on artificial intelligence in the environmental monitoring. *Prospects of Artificial Intelligence in the Environment*, 29-60.

[15] El Khediri, S., Benfradj, A., Thaljaoui, A., Moulahi, T., Ullah Khan, R., Alabdulatif, A., & Lorenz, P. (2023). Integration of artificial intelligence (AI) with sensor networks: Trends, challenges, and future directions. *Journal of King Saud University Computer and Information Sciences*, *36*(1), 101892.

[16] Fuqaha, S., & Nursetiawan, N. (2025). Artificial intelligence and IoT for smart waste management: Challenges, opportunities, and future directions. *Journal of Future Artificial Intelligence and Technologies*, *2*(1), 24-46.

[17] Hait, M., Sahu, P., Biswas, S., & Izah, S. C. (2024). Sustainable application of artificial intelligence in biomonitoring for environmental sustainability: challenges and prospects. *Biomonitoring of pollutants in the global south*, 747-778.

[18] Hamza, M. A., Shaiba, H., Marzouk, R., Alhindi, A., Asiri, M. M., Yaseen, I., ... & Rizwanullah, M. (2022). Big data analytics with artificial intelligence enabled environmental air pollution monitoring framework. *Computers, Materials and Continua*, *73*(2), 3235-3250.

[19] Han, K., & Wang, Y. (2021). A review of artificial neural network techniques for environmental issues prediction. *Journal of Thermal Analysis and Calorimetry*, *145*(4), 2191-2207.

[20] Hoang, T. D., Ky, N. M., Thuong, N. T. N., Nhan, H. Q., & Ngan, N. V. C. (2022). Artificial intelligence in pollution control and management: Status and future prospects. *Artificial Intelligence and Environmental Sustainability: Challenges and Solutions in the Era of Industry 4.0*, 23-43.

[21] Islam, M. A. (2026). Constraint-Responsive Human Behavior for Organizations: A Conceptual Theory. *South Asian Journal of Social Studies and Economics*, 23(6), 44–52. https://doi.org/10.9734/sajsse/2026/v23i61329

[22] Islam, M. A., & Aktar, L. (2025). Perceived Ease of Use, Security, and Trust as Predictors of Online Purchase Intention: A Technology Acceptance Model Extension. *European Economics Letters*, *15*(3).

[23] Islam, M. A., Aktar, N., Barua, P., Sweety, M. A., Aktar, L., & Islam, M. B. (2025). Perceived Competitiveness in Malaysian Higher Education: Role of International Student Recruitment Strategies. *Asian Journal of Education and Social Studies*, *51*(9), 997-1011.

[24] Islam, M. A., Jantan, A. H. B., Islam, M. A., Abdullah, A. B. M., & Rahman, M. S. (2026). Unlocking the Dynamics of Employee Retention: Examining the Interplay of Job Security, Promotion and Work Engagement in a Developing Economy. *FIIB Business Review*, 23197145261431894. DOI: 10.1177/23197145261431894.

[25] Kan, Y. (2025). AI for environmental sustainability: advances, challenges, and future directions. *International Journal of Artificial Intelligence for Science (IJAI4S)*, *1*(1).

[26] Leena Sri, R., Vetriveeran, D., Sambandam, R. K., Jenefa, J., & Thangavel, K. (2025). Transformative trends in AI for environmental monitoring: challenges, applications. *Environmental Monitoring Using Artificial Intelligence*, 1-28.

[27] Maqbool, A. I., & Safdar, A. (2025). Artificial Intelligence In Environmental Science And Engineering: A Review of Applications, Challenges, and Sustainable Futures. *Spectrum of Engineering Sciences*.

[28] Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokołowska, S., & Nowy, A. (2025). Integrating artificial intelligence agents with the internet of things for enhanced environmental monitoring: applications in water quality and climate data. *Electronics*, *14*(4), 696.

[29] Patel, D., Kulwant, M., Shirin, S., Kumar, A., Ansari, M. A., & Yadav, A. K. (2022). Artificial intelligence for air quality and control systems: Status and future trends. *Modeling and Simulation of Environmental Systems*, 133-152.

[30] Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, S. S., Sharma, V., Sharma, A., ... & Chung, Y. S. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. *Frontiers in Environmental Science*, *12*, 1336088.

[31] Szramowiat-Sala, K. (2023). Artificial intelligence in environmental monitoring: Application of artificial neural networks and machine learning for pollution prevention and toxicity measurements.

[32] Talaie, A., Kamyab, H., & Razmfarsa, A. (2024). Advancing Environmental Engineering: The Role of Artificial Intelligence in Sustainable Solutions–A Short Review. *Journal of Environmental Treatment Techniques*, *12*(3), 14-19.

[33] Vedrtnam, A., Wyche, K. P., Chauhan, B. V., & Verma, S. (2025). Introduction to the Prospects of Artificial Intelligence in the Environment. In *Prospects of Artificial Intelligence in the Environment* (pp. 1-27). Singapore: Springer Nature Singapore.

[34] Wani, A. K., Rahayu, F., Ben Amor, I., Quadir, M., Murianingrum, M., Parnidi, P., ... & Latifah, E. (2024). Environmental resilience through artificial intelligence: innovations in monitoring and management. *Environmental Science and Pollution Research*, *31*(12), 18379-18395.

[35] Wu, C., Lu, S., Tian, J., Yin, L., Wang, L., & Zheng, W. (2024). Current situation and prospect of geospatial AI in air pollution prediction. *Atmosphere*, *15*(12), 1411.

[36] Zhang, B., & Sun, J. (2025). The future of environmental health modeling: leveraging artificial intelligence to combat air pollution challenges. *Journal of Environmental Exposure Assessment*, *4*(2), N-A.