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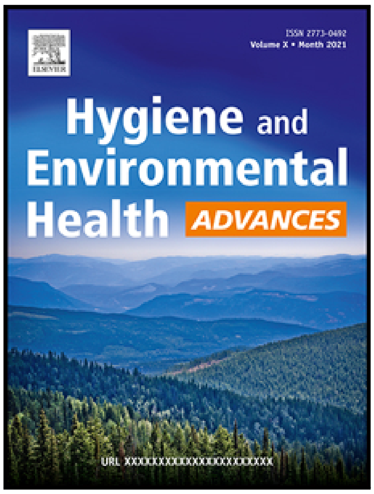

Artificial Intelligence in Environmental Monitoring: Advancements, Challenges, and Future Directions

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PII: S2773-0492(24)00027-8
DOI: https://doi.org/10.1016/j.heha.2024.100114
Reference: HEHA 100114

To appear in: *Hygiene and Environmental Health Advances*

Received date: 25 November 2023
Revised date: 2 August 2024
Accepted date: 17 October 2024

Please cite this article as: David B. Olawade , Ojima Z. Wada , Abimbola O. Ige , Bamise I. Egbewole , Adedayo Olojo , Bankole I. Oladapo , Artificial Intelligence in Environmental Monitoring: Advancements, Challenges, and Future Directions, *Hygiene and Environmental Health Advances* (2024), doi: https://doi.org/10.1016/j.heha.2024.100114

Highlights

- AI-driven pollution detection enhances environmental protection.
- Real-time monitoring facilitates prompt interventions for pollution prevention.
- Accurate air quality forecasting aids in planning pollution-reducing activities.
- AI's role in smart cities fosters sustainable urban development.
- AI algorithms integrate diverse data sources for pollution detection.

Artificial Intelligence in Environmental Monitoring: Advancements, Challenges, and Future Directions

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Abstract

The application of Artificial Intelligence (AI) in environmental monitoring offers accurate disaster forecasts, pollution source detection, and comprehensive air and water quality monitoring. This article provides an overview of the value of environmental monitoring, the challenges of conventional methods, and potential AI-based solutions. Several significant AI applications in environmental monitoring are highlighted, showcasing their contributions to effective environmental management.

AI technologies enhance environmental monitoring by enabling better understanding, prediction, and mitigation of environmental risks. However, realizing the full potential of AI faces hurdles such as a shortage of specialized AI experts in the environmental sector and challenges related to data access, control, and privacy. These issues are more pronounced in regions with developing technological infrastructure. The paper advocates for proactive data governance measures by governments to protect sensitive information. Despite these challenges, the future of AI in environmental monitoring remains promising, with advancements in AI algorithms, data collection techniques, and computing power expected to further improve accuracy and efficiency in pollution monitoring and management.

Keywords: Artificial Intelligence; Environmental monitoring; Pollution detection; Disaster prediction; Air and water quality

Introduction

The essential process of environmental monitoring entails the systematic observation, measurement, and evaluation of the natural environment and all of its components. Monitoring the environment's current condition and identifying any changes that can be harmful to the ecosystem or public health is its main goal (Artiola et al., 2004). Traditional environmental monitoring techniques include statistical analysis, laboratory analysis, and manual sampling (Zhang, 2024). Unfortunately, these approaches have limitations, such as high costs, prolonged procedures, and poor accuracy.

The efficiency of conventional environmental monitoring techniques is constrained by several issues. The expense of using these procedures is one of the biggest obstacles. The costs associated with manual sampling and laboratory analysis are high and include skilled employees, equipment, and chemicals (Dressing et al., 2016; Ditria et al., 2022). As a result, environmental monitoring programs often have a narrow focus, use small sample sizes, and do not provide a comprehensive picture of the state of the environment. The time-intensiveness of traditional methods is another significant problem (Thomson et al., 2011; Ceccato et al., 2014; Dressing et al., 2016). Decision-making and emergency response in the case of natural catastrophes or pollution crises can be delayed by manual sampling and laboratory analysis, which might take weeks or even months to generate results. Additionally, the subjectivity of human observation and the potential for human error limit the accuracy of traditional environmental monitoring techniques (Hameed et al., 2017; Daniele, 2017). Human interpretation required for manual sampling and laboratory analysis can lead to inconsistent data collection and processing.

Furthermore, the utilization of advanced technologies and the presence of adequately trained technical personnel necessary for precise environmental monitoring are frequently impeded by cost limitations and a scarcity of qualified individuals (Cordier et al., 2021). Consequently, achieving regular monitoring becomes an arduous task, particularly in regions with limited resources (Li et al., 2020). This is especially pronounced in areas lacking technological infrastructure and expertise (Li et al., 2020).

Artificial intelligence (AI) has emerged as a crucial integration in environmental monitoring endeavors, seeking to enhance the objectivity of results and improve accessibility to regions suffering from limited resources. AI, a subfield of computer science, focuses on creating algorithms and computer programs that can perform activities like sensing, reasoning, learning, and decision-making that would ordinarily require human intellect (Rodgers, 2020; Sarker, 2021a, 2021b). Large data sets can be analyzed using AI, which has proven useful for identifying patterns and making precise predictions (Duan et al., 2019; UNEP.org, 2022). In environmental monitoring, AI has been applied in various areas, including the prediction of natural disasters, monitoring air and water quality, and identifying pollutants (Subramaniam et al., 2022). Table 1 offers a comparative analysis of AI methods versus traditional approaches in terms of accuracy, speed, cost, scalability, data integration, maintenance, and environmental impact. It underscores the significant advantages of AI in enhancing the efficiency and effectiveness of environmental monitoring while highlighting the potential initial costs and the importance of considering long-term benefits.

For instance, AI models such as Convolutional Neural Networks (CNNs) are used for image-based environmental monitoring tasks like detecting deforestation and identifying wildlife, as seen in the work by Williams et al. (2020). Support Vector Machines (SVMs) have been applied to predict harmful algal blooms in lakes, demonstrating the model's capability to handle high-dimensional data (Li et al., 2017). Recurrent Neural Networks (RNNs) are utilized for time series forecasting, such as predicting flood events based on historical rainfall data (Chen et al., 2021).

In addition, the utilization of advanced technologies and the presence of adequately trained technical personnel necessary for precise environmental monitoring are frequently impeded by cost limitations and a scarcity of qualified individuals. Consequently, the attainment of regular monitoring becomes an arduous task, particularly in regions of the world facing resource constraints, particularly in the global south. Therefore, in recent years, AI has emerged as a crucial integration in environmental monitoring endeavors, seeking to enhance the objectivity of results and improve accessibility to regions suffering from limited resources. This narrative review aims to comprehensively explore and evaluate the current state of AI technologies implemented in key areas of environmental monitoring, shedding light on their efficacy and potential implications for future research and practical applications.

Table 1: AI methods versus traditional approaches in environmental monitoring.

Criteria	AI Methods (Specific Model/Tool)	Traditional Methods	Ref.
Accuracy	- **Deep Learning Models (e.g., Convolutional Neural Networks - CNNs)**: High precision in image and pattern recognition. - **Random Forests**: Effective for handling large datasets and identifying complex patterns. - **Support Vector Machines (SVM)**: Excellent for classification tasks.	- Variable accuracy dependent on human expertise. - Susceptible to human error and biases. - Often limited by the resolution and frequency of manual sampling.	(Masood & Ahmad, 2021; Ullo & Sinha, 2020)
Speed	- **Real-time Data Processing (e.g., TensorFlow, Keras)**: Immediate analysis and anomaly detection. - **Automated Monitoring Systems (e.g., IBM Watson)**: Faster data aggregation and synthesis from multiple sources.	- Time-intensive data collection and analysis. - Delayed results due to lengthy laboratory processes. - Slower response time in emergency situations.	(Bibri et al., 2024; Ranyal et al., 2022)
Cost	- Initial setup can be expensive (equipment, software, training). - Long-term operational costs are lower due to automation and reduced need for human labor. - Scalable with decreasing marginal costs.	- High ongoing costs for labor, equipment, and consumables. - Expensive manual sampling and laboratory analyses. - Costs increase proportionally with the scale of monitoring efforts.	(Asha et al., 2022; Xiang et al., 2021)
Scalability	- **Cloud-based Platforms (e.g., Microsoft Azure, Google Cloud AI)**: Easily scalable to cover large geographic areas.	- Limited scalability due to reliance on human labor and physical sampling. - Expensive and logistically	(Bibri et al., 2024; Fascista, 2022)

	- Capable of integrating data from various sources (e.g., satellites, IoT devices).	challenging to expand coverage.	
Data Integration	- **Big Data Analytics Tools (e.g., Hadoop, Apache Spark)**: Handle and integrate large volumes of diverse data. - Capable of continuous monitoring and real-time updates.	- Limited capacity to integrate diverse data sources. - Manual data entry and slower data updates.	(Boehm et al., 2022; Shi et al., 2020)
Maintenance	- Requires periodic software updates and occasional hardware maintenance. - Lower maintenance cost over time.	- Regular maintenance of equipment and calibration. - High ongoing costs for consumables and replacements.	(Ahmad et al., 2021; Çınar et al., 2020)
Environmental Impact	- Lower environmental impact due to reduced need for physical sampling and travel. - **Energy-efficient Solutions (e.g., AI-powered sensors)**: Minimized carbon footprint.	- Higher environmental impact from frequent physical sampling. - Travel and transportation increase carbon footprint.	(Ye et al., 2020)

AI Models for Environmental Monitoring

When choosing an AI model for environmental monitoring, it is essential to consider factors such as data availability, computational resources, and expertise. Some AI models require large amounts of data and computational power to train, while others can be trained on smaller datasets with less computational expense (Zhou et al., 2020). Support Vector Machines (SVMs) are well-suited for handling high-dimensional data and learning complex relationships between variables (Manikandan & Abirami, 2021). SVMs can be used with various data types, including images and text. For instance, SVMs have been used effectively for image classification tasks, such as detecting deforestation and identifying wildlife (Zagajewski et al., 2021). They are also applied in natural language processing to extract information from environmental reports (Meza et al., 2019). Support Vector Regression (SVR), a variant of SVM, is used for regression problems in environmental monitoring, offering an effective solution for predicting environmental control parameters (Ye et al., 2020).

Decision trees are relatively simple to train and interpret, making them accessible for various data types. They are commonly used for tasks like detecting and monitoring deforestation, monitoring air quality, and water quality (De Bem et al., 2020; Tarazona & Miyasiro-López, 2020). However, decision trees can be prone to overfitting, especially when handling complex, noisy data, and may not perform as well on image recognition or natural language processing tasks (Buntine, 2020).

Random forests are an ensemble learning method that combines the predictions of multiple decision trees. They are more robust to overfitting than individual decision trees and can handle various data types, including images and text (El-Magd et al., 2022). Random forests are commonly used for image classification, natural language processing, and time series forecasting tasks in environmental monitoring. Despite their robustness, random forests can be computationally intensive and require substantial memory and processing power.

Convolutional Neural Networks (CNNs) are well-suited for image classification and tasks involving spatial data. CNNs can learn complex patterns from images without explicit programming, making them ideal for detecting deforestation and identifying wildlife (Zhang et al., 2022). However, CNNs can be computationally expensive to train and require large amounts of labeled data. Training CNN models can be challenging due to the lack of annotated datasets for visual recognition. Pre-training models using data from similar domains can mitigate this issue (Ghorbani & Behzadan, 2021).

Recurrent Neural Networks (RNNs) are suitable for tasks involving sequential data, such as time series forecasting and natural language processing. RNNs can learn long-term dependencies in data, making them effective for predicting extreme weather events and extracting information from environmental reports (Haq et al., 2022). However, RNNs can be computationally expensive to train and require large datasets. Advanced models like CDLSTM (Convolutional Deep Long Short-Term Memory) have been developed for more accurate climate change forecasting and groundwater storage change modeling.

Hybrid models combine the strengths of machine learning and deep learning models, offering high accuracy and robustness. They are used for environmental monitoring tasks that require capturing complex nonlinear interactions between input and output variables (Zaresefat & Derakhshani, 2023). While hybrid models can be more complex to train and interpret, they provide superior performance for high-stakes environmental monitoring tasks. Highly relevant work, such as the development of Synthetic Minority Over-sampling Technique with Deep Neural Networks (SMOTEDNN) for air pollution forecasting and AQI classification, further exemplifies the potential of AI in this field (Zhao et al., 2024).

Table 2 below presents a variety of AI models used for environmental monitoring. Each AI model has its strengths and limitations, making it important to choose the right model for the specific task at hand. SVMs and SVR are effective for high-dimensional data and regression tasks but can be computationally expensive. Decision trees are simple and interpretable but prone to overfitting (Costa & Pedreira, 2023; Wan et al., 2020). Random forests offer robustness and versatility but require significant computational resources (Boateng et al., 2020). CNNs excel in image-based tasks but need large labeled datasets and substantial computational power. RNNs are effective for sequential data but also demand high computational resources and advanced models like CDLSTM for complex forecasting tasks (Li et al., 2024; Wu et al., 2023). Hybrid models provide the highest accuracy and robustness but are complex to train and interpret.

Table 2: AI models used for environmental monitoring

AI Model	Specific Examples/Case Studies	Strengths	Limitations	Ref.
Support Vector Machines (SVMs)	Case Study 1: Using SVMs for predicting harmful algal blooms in lakes. Case Study 2: Using SVM to monitor air quality.	- Can handle high-dimensional data. - Can learn complex relationships between variables. - Can be used with a variety of data types, including images and text.	- Image classification (e.g. detecting deforestation, identifying wildlife). - Natural language processing (e.g. extracting information from environmental reports). - Time series forecasting (e.g. predicting extreme weather events).	(Ananias & Negri, 2021; Castelli et al., 2020; Leong et al., 2020)
Decision Trees	Case Study 1: Using decision trees to predict water quality in rivers. Case Study 2: Using decision trees for water quality assessments.	- Relatively simple to train and interpret - Can be used with a variety of data types.	- Detecting and monitoring deforestation. - Monitoring air quality. - Monitoring water quality.	(Bui et al., 2020; Nasir et al., 2022; Nouraki et al., 2021)
Random Forests	Case Study 1: Employing random forests to model air quality index in urban areas. Case Study 2: Utilizing random forests to predict forest fire adequately.	- Ensemble learning method that combines the predictions of multiple decision trees - More robust to overfitting than individual decision trees.	- Image classification (e.g. detecting deforestation, identifying wildlife). - Natural language processing (e.g. extracting information from environmental reports). - Time series forecasting (e.g. predicting extreme weather events).	(Alsaber et al., 2021; DeCastro et al., 2022; Montorio et al., 2020; B. T. Pham et al., 2020)
Convolutional Neural	Case Study 1: Using CNNs for monitoring coral reef health via	- Well-suited for image classification and other tasks that involve spatial data	- Image classification (e.g. detecting deforestation, identifying wildlife).	(Burns et al., 2022;

Networks (CNNs)	underwater images. Case Study 2: Employing CNN to monitor coaster erosion.	- Can learn complex patterns from images without the need for explicit programming.		Ghimire et al., 2021; Scardino et al., 2022)
Recurrent Neural Networks (RNNs)	Case Study 1: Applying RNNs to predict flood events based on historical rainfall data. Case Study 2: Employing RNN to predict river flow levels.	- Well-suited for tasks that involve sequential data, such as time series forecasting and natural language processing - Can learn long-term dependencies in data.	- Natural language processing (e.g. extracting information from environmental reports). - Time series forecasting (e.g. predicting extreme weather events).	(Liu et al., 2020; Ren et al., 2020)
Hybrid Models	Case Study 1: Combining CNNs and RNNs for accurate prediction of air pollution levels. Case Study 2: Urban Heat Island Effect Analysis Using Combined CNNs and RNNs	- Combine the strengths of machine learning and deep learning models - Can be more accurate and robust than individual models.	- Any environmental monitoring task where high accuracy and robustness are required.	(Li & Zheng, 2023; Tsokov et al., 2022; Zhang et al., 2022)

Principles of AI models

AI modeling is underpinned by a set of guiding principles that form the bedrock of developing intelligent systems (Bommasani et al., 2021; Palakurti & Kolasani, 2024). These principles provide a roadmap for the creation of AI models that can tackle intricate problems, automate tasks, and make informed decisions. At its core, AI modeling relies on the principle of data-driven learning (J. Wang et al., 2022). The pivotal role of data in AI modeling cannot be overstated. AI models learn from extensive datasets, sifting through data to discern patterns, trends, and relationships. For example, in air quality monitoring, AI models analyze data from various sensors to predict pollution levels and identify pollution sources, as demonstrated by the SMOTEDNN model for air pollution forecasting and AQI classification (Goel et al., 2024; Haq, 2022). In another case, AI models are used to monitor water quality by analyzing parameters such as pH, turbidity, and nitrate levels to predict contamination events and ensure safe drinking water (Ahmed et al., 2020; Jayaraman et al., 2024; Liu et al., 2019). Machine learning and deep learning algorithms are prominent in this regard, as they harness the power of data to make predictions and decisions (Rasool et al., 2023; Tabesh, 2022).

Generalization is another cardinal principle of AI modeling. It implies that AI models must be able to extend their learning from specific datasets to make predictions or decisions in a broader context. This flexibility ensures that AI models can handle new, unseen data effectively (Q.-V. Pham et al., 2020; Sarker, 2022). A practical application of this principle can be seen in the CDLSTM model, which generalizes from historical climate data to forecast future climate changes (Stjelja et al., 2022), thereby aiding in environmental monitoring and decision-making. Similarly, in wildlife conservation, AI models trained on data from camera traps can generalize to detect and track species across different habitats, aiding in the protection of endangered species (Curry et al., 2021; Norouzzadeh et al., 2018; Schneider et al., 2019). Feature engineering is a crucial practice that underscores the need to select relevant features or variables from the data. AI models demand meaningful input features to make accurate predictions. Feature engineering encompasses data preprocessing, feature selection, and transformation to enhance model performance (Dong & Liu, 2018). For instance, in water quality monitoring, selecting appropriate features such as pH, turbidity, and dissolved oxygen levels is essential for accurate predictions (Chen et al., 2020; Ouma et al., 2020). In agricultural monitoring, features like soil moisture, temperature, and crop health indices are engineered to predict yield and detect pest infestations (Hassan et al., 2022).

A delicate balance between model complexity and simplicity is essential. AI models must neither be overly complex nor too simplistic. Overly complex models can lead to overfitting, where they perform exceptionally well on training data but fail to generalize to new data (Kernbach & Staartjes, 2022; Teney et al., 2022). Conversely, overly simplistic models may not capture intricate patterns in the data. In practice, achieving this balance can be observed in environmental monitoring models that use random forests, where ensemble methods help avoid overfitting while maintaining robustness in predictions. Similarly, in urban planning, AI models that predict traffic flow and congestion must balance complexity and simplicity to provide reliable forecasts without overfitting to historical traffic patterns (Kernbach & Staartjes, 2022; Sayed et al., 2023). Moreover, AI models should adhere to the principle of continuous learning. They should be designed to adapt and evolve over time, learning from new data to improve their performance and relevance. For example, AI systems used in deforestation monitoring continually learn from satellite images to update their models and provide more accurate assessments (Masolele et al., 2021; Yang et al., 2022). In healthcare, AI models that monitor disease outbreaks evolve with new epidemiological data, enhancing their predictive accuracy and response strategies (Malik et al., 2021; Zeng et al., 2021).

Finally, model interpretability is of paramount importance. Understanding how and why an AI model reaches a specific decision is vital for user trust and addressing ethical concerns (Bedué & Fritzsche, 2022; Omrani et al., 2022). Interpretable models are particularly critical in fields such as healthcare and law. In the context of environmental monitoring, interpretable models help stakeholders understand the factors contributing to pollution, thereby facilitating informed decision-making and policy development. For instance, decision trees used in environmental monitoring can provide clear, interpretable rules that explain how specific environmental conditions lead to certain outcomes (Ryo et al., 2021; D. Wang et al., 2022).

Similarly, in energy management, interpretable AI models can help utilities understand energy consumption patterns and optimize grid operations.

Shortcomings of AI Models

In the realm of AI for environmental monitoring, alongside its numerous advantages, there exist several noteworthy shortcomings and challenges that must be recognized (Shalu & Singh, 2023). An awareness of these limitations is essential for the responsible and informed development of AI models. Data dependency is a prominent limitation. AI models rely heavily on the quality and quantity of data. Insufficient or biased data can result in poor model performance or algorithmic bias, which may perpetuate discrimination. For example, if an AI model for air quality monitoring is trained primarily on data from urban areas, it may not perform well in rural settings, leading to inaccurate predictions and potentially harmful policy decisions (Almalawi et al., 2022; Krupnova et al., 2022; Rowley & Karakuş, 2023).

Overfitting poses a significant challenge in AI modeling. It occurs when a model learns the training data too well, leading to poor generalization to new, unseen data. Striking a balance in model complexity is key to mitigating this issue. In practical terms, an overfitted model might accurately predict water quality in the specific rivers it was trained on but fail to generalize to other rivers with different characteristics (Fernández del Castillo et al., 2022; Malek et al., 2022). Interpretability is another vexing challenge, particularly in the context of deep learning models. These models are often described as "black boxes" due to their lack of transparency (Abdallah et al., 2020). The ability to comprehend how and why an AI model reaches a particular decision is crucial for building user trust, but it remains an ongoing challenge. For instance, stakeholders might be reluctant to act on AI-driven deforestation alerts if they cannot understand the underlying reasons for the model's predictions (Hodel, 2023; Osman, 2024).

Furthermore, resource intensiveness is another constraint. Training and running complex AI models demand substantial computational resources, which can be a barrier for smaller organizations and developing countries (Dwivedi et al., 2021; Kar et al., 2021). This disparity can exacerbate existing inequalities, where only well-resourced entities can leverage advanced AI technologies effectively. Conversely, ethical concerns are a growing issue in AI development. AI models can inadvertently reinforce existing biases present in the training data. Ensuring fairness and addressing ethical concerns is a significant challenge, particularly in applications where fairness and non-discrimination are paramount (Olaoye, 2024; Singh, 2021). For example, if an AI model for disaster response prioritizes areas based on biased historical data, it might unfairly neglect vulnerable communities.

On the other hand, security risks are a real concern. AI models are susceptible to adversarial attacks, where small, carefully crafted changes to input data can deceive the model (Baniecki & Biecek, 2024; Chakraborty et al., 2021). Ensuring security and robustness against such attacks is a pressing concern in AI development (Zhang et al., 2020). A notable example is the manipulation of AI systems in smart grids, where adversarial attacks could disrupt power distribution and cause significant economic damage (Nguyen et al., 2020). Lastly, the environmental impact of AI models is becoming more evident. Large-scale AI training consumes significant energy resources, contributing to environmental concerns (Ahmad et al., 2021). The carbon footprint of AI models and the need for more energy-efficient solutions are increasingly pressing issues. For instance, training a single large AI model can generate as much carbon emissions as five cars over their lifetimes, highlighting the need for sustainable AI practices (Nishant et al., 2020; Wu et al., 2022).

Natural disaster prediction

Natural disasters including hurricanes, earthquakes, and wildfires pose a serious threat to property around the world. Natural disasters can have a devastating effect, destroying large portions of infrastructure, upsetting the economy, and putting human lives in peril (Rongxing, 2021). AI has garnered increasing attention in recent years for its potential to foresee natural disasters and lessen their effects. AI-based solutions can deliver precise, real-time data on natural disasters, assisting authorities in creating efficient response plans and lowering the dangers to public safety (Pyayt et al., 2011; Zhang et al., 2021). Natural disasters including earthquakes, tsunamis, and storms have been predicted using AI. AI is used to anticipate natural disasters by evaluating data from many sources, such as satellite imagery, seismic sensors, and meteorological forecasts, to find patterns and estimate the risk that a disaster will occur (Marcin, 2023). AI-based natural disaster prediction can give communities and emergency responders early warning, enabling them to plan and act appropriately.

AI is used to anticipate natural disasters by analyzing data from a variety of sources, such as satellite images, weather data, and historical records, to find patterns and trends that may point to an imminent natural disaster (Marcin, 2023). The presence of smoke, ash, or other signs of a wildfire are examples of minor changes in the environment that may signal the beginning of a natural disaster (Sebastian and Natalija, 2017). AI algorithms can also learn to recognize changes in temperature, humidity, or wind patterns.

Using AI to predict natural disasters provides a number of advantages over more conventional approaches. In the beginning, AI-based systems have the capacity to analyze enormous volumes of data from numerous sources, giving an accurate picture of the environment in real-time. This enables authorities to plan ahead for potential natural disasters and act quickly to address them (Guo et al., 2022). Additionally, compared to conventional approaches, AI-based systems can collect and analyze data with higher accuracy and precision. This can lower the possibility of mistakes and inconsistent results, increasing the accuracy of forecasts for natural disasters. Inevitably, AI-based systems can offer unique solutions for various natural disaster locales and types. AI algorithms can create tailored interventions, such as evacuations, warning systems, or disaster relief activities, to lower the risks and impact of these disasters by evaluating data from certain areas and types of natural disasters (Chowdhury and Sadek, 2012).

There are numerous uses for AI-based natural disaster prediction across various sectors. Emergency management is one of the key uses. AI systems are able to assess data on natural catastrophes and create specialized plans for emergency responses such as evacuations, search and rescue operations, and disaster relief (Jeff, 2020). Planning and managing urban areas is another application. In order to lower the risks and effects of natural disasters, AI algorithms can analyze data on disasters and create specialized solutions for urban planning and design. For instance, AI algorithms can suggest modifications to zoning regulations, infrastructure development, and construction regulations to lower the likelihood of flooding, earthquakes, or wildfires. The prediction of natural disasters using AI is also useful for risk management and insurance (Jeff, 2020). AI algorithms can create specialized insurance policies and risk management plans to lower the costs and effects of natural disasters by analyzing data on risk factors and disasters (Dailey and Mamane, 2021; Eling et al., 2022).

Notwithstanding the advantages of AI-based natural disaster prediction, a number of issues need to be resolved in order to assure its successful application. The quality of the data used for analysis represents one of the major obstacles. For AI systems to make precise predictions and choices, they need accurate and trustworthy data. Inadequate data quality can result in inaccurate predictions and choices, which could have a negative impact on property and public safety (Cortès et al., 2000; Wei, 2021; Krupnova et al., 2022; Marcin, 2023). The availability of data presents another difficulty. It is challenging to create precise and trustworthy AI-based prediction systems because there are many regions of the world with insufficient data on natural disasters. In addition to technological constraints, political and economic issues can also have an impact on the availability of data. Finally, it is important to think about the ethical implications of AI-based natural disaster prediction. The use of AI to anticipate natural disasters raises concerns regarding privacy, data ownership, and the possibility of data exploitation. To ensure the ethical use of AI for predicting natural disasters, ethical regulations and guidelines must be developed (Coeckelbergh, 2021; Saheb, 2022; Marcin, 2023). Table 3 shows a number of instances where AI was employed in the prediction of natural disasters.

Table 3: Summary of previous studies employing AI for the prediction of different types of natural disaster

Disaster Type	References	Location	Model	Data Source / Study Area	Result Obtained	Recommendation
Wildfire	Jaafari et al., 2019	Iran	Adaptive Neuro-Fizzy Inference System (ANFIS) Genetic Algorithm (GA) Particles Swarm Optimization (PSO) Shuffled Frog Leaping Algorithm (SFLA) Imperialist Competitive Algorithms (ICA)	Minudasht (Hyrcanian ecoregion)	Compared to previous studies, all hybrid models used improved wildfire prediction accuracy by 18%.	Hybrid/Complex model are more effective to predict the disaster than simple single models.
Forest Fire	Piao et al., 2022	Korea	Classification and Regression Tree (CART) Random Forest (RF) Boosted Regression Tree (BRT)	Gangwon-do region	Slope has a substantial impact on forest fire occurrence. RF and BRT gave excellent prediction accuracy	Further study will relate forest fire with other disaster and proper evaluation of the influencing factors.
Earthquake	Marhain et al., 2021	Malaysia	Random Forest Boosted Decision Tree Regression (BDTR) Support Vector Machine Regression	Terengganu (East Coast of Peninsular)	BDTR gave the best performance in acceleration and depth compared to the other algorithms models utilized	Selection of algorithms can be conducted on diverse sample area to obtain a better accuracy for the prediction.

Earthquake	Oktarina et al., 2020	Indonesia	Artificial Neural Network (ANN)	DIBI (Data & Information Disaster in Indonesia)	ANN provide output of prediction close to the actual data value with 0.47% error.	There is a need to advance ANN model in other to give a detailed inter-link between the input and output variables.
Forest Fire	Li et al., 2020	China	Support Vector Machine (SVM) Backpropagation Neural Network (BPNN)	Guangxi Zhuang Autonomous region	Meteorological factors such as sunshine, temperature, humidity etc. are cause of fires in the region. The BPNN provide more prediction accuracy than SVM.	The obtained result can serve as a reference point for future modelling.
Earthquake	Essam et al., 2021	Malaysia	Artificial Neural Network (ANN) Random Forest	Terengganu, Malaysian Meteorological Department	The ANN model showed a good prediction result of the earthquake acceleration, velocity and depth.	There is a need to restructure the ANN model with advanced algorithm in further research to prove it competency for earthquake prediction.

Earthquake	Majhi et al., 2019	USA	Functional Link Artificial Neural Network (FLANN) Least Square Optimization Levenberg-Marquardt Backpropagation Heuristics and Meta-Heuristics Optimization	U.S. Geological Survey, Kaggle	The FLANN model gave the best root mean square error value which denote better exploration and exploitation capability	More research which focus on the seismological and geophysical factors that lead to earthquakes should be conducted.

Air quality monitoring

A significant environmental issue that impacts quality of life, economic growth, and public health is air pollution. Both locally and globally, air pollution negatively affects health, contributing to serious conditions like cancer, cardiovascular disease, and respiratory ailments (Ghorani-Azam, 2016; Manisalidis, 2020). To address this issue, there has been increased interest in using AI for air quality monitoring. Systems powered by AI can deliver precise, real-time data on air quality, assisting authorities in creating efficient policies and interventions to minimize air pollution. AI-based recommendations can guide responses when air quality is hampered, ensuring timely actions to protect public health. Machine learning algorithms analyze data from various sources, including air quality sensors, satellite imaging, and weather data, to provide real-time information on air quality (Duke University, 2021; Tongshu Z et al., 2021). These algorithms can identify pollution sources, estimate pollution levels, and recommend actions to minimize air pollution by learning to recognize patterns and trends in the data.

In recent times, commonly employed AI algorithms for air quality analysis and prediction include Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Support Vector Machines (SVM), and Fuzzy Logic. However, the choice of AI model largely depends on the required information and the nature of air pollutants in the area. For example, a systematic review by Masood & Ahmad (2021) classified AI-based air pollution forecasting tools considering factors such as performance, input parameters, and the relative frequency of application of AI techniques. They concluded that the best-performing tool for AI-based environmental monitoring is the DNN. On the other hand, Dobrea et al. (2020) compared other AI-oriented techniques/models for air pollutants and suggested Support Vector Regression (SVR) and Autoregressive Integrated Moving Average (ARIMA) as the best-performing techniques for time series analysis of Particulate Matter (PM) with a diameter <10m and diameter <2.5m. It is important to note that PM is considered in the study as it significantly affects health.

Another study by Subramaniam et al. (2022) suggested that hybrid models have better performance for environmental monitoring policy and decision-making. Hybrid models combine the properties/advantages of two AI algorithms or methodologies to make informed decisions about future implications of air pollutants. This has also been confirmed by Fu, et al. (2023), who found that hybrid AI models are more dependable for air quality forecasting.

AI for air quality monitoring offers several advantages over conventional techniques. AI-based systems can analyze enormous volumes of data from numerous sources and present a comprehensive picture of air quality in real-time, enabling officials to make informed decisions and act quickly to reduce air pollution (Chowdhury and Sadek, 2012). AI systems can also collect and analyze data with higher accuracy and precision compared to conventional approaches, reducing the possibility of errors and inconsistencies in air quality data. Furthermore, AI algorithms can provide tailored solutions for various pollution sources and regions. By analyzing data from specific places and sources, AI can offer customized air pollution solutions, such as regulating traffic flow, streamlining industrial processes, or altering urban planning (Ortega-Fernández, 2020; Subramaniam, 2022).

AI-based recommendations can play a critical role in air quality monitoring by providing actionable insights to mitigate pollution(Alloghani, 2023; Neo et al., 2023). For example, AI algorithms can recommend changes in traffic patterns during peak pollution hours to reduce emissions, suggest optimal times for industrial operations to minimize environmental impact, and identify green zones where pollution levels are within safe limits (Boukerche et al., 2020; Degas et al., 2022). These recommendations help authorities implement timely interventions, ensuring that air quality remains within acceptable limits and public health is protected.

There are several applications for AI-based air quality monitoring across various industries. Urban management and planning are key applications where AI algorithms analyze data on air quality, traffic patterns, and urban development to create specialized solutions for reducing air pollution in urban areas (Nandini & Fathima, 2019; K Delavar et al., 2019; Jasim et al., 2020). For example, AI can recommend changes to traffic flow patterns to reduce congestion and air pollution or modifications to urban planning to improve air circulation and lower exposure to pollutants. In industrial operations, AI algorithms can analyze emissions data and suggest modifications to lower pollution levels, such as adopting more eco-friendly materials and energy sources or optimizing production processes to minimize waste and emissions (Alpan & Sekeroglu, 2020). Public health can also benefit from AI-based air quality monitoring. By evaluating data on air quality and health outcomes, AI algorithms can identify at-risk groups and create tailored interventions to promote public health (Masood & Ahmad, 2021; Subramaniam et al., 2022). For instance, AI systems can recommend changes to public transit routes to lessen vulnerable groups' exposure to contaminants. Table 4 provides a summary of past studies where AI was employed for air quality monitoring.

Table 4: Summary of previous studies for the prediction of air quality monitoring using AI

Research Aim	References	Location	Model	Data Source / Study Area	Result Obtained	Recommendation
To evaluate waste-to-energy (WTE) capacity and flue gas pollutants using AI-learning-based algorithms	Ma et al., 2022	China	ANN	Continuous Emission Monitoring System (CEMS) Supervisory Emission Monitoring System (SEMS)	With mean square errors ranging from 0.003 to 0.19 within the model validation constraints, artificial neural network models were developed to forecast WTE capacity and FGP EIs at the city level.	This offers information and model support for developing suitable WTE strategies and a pollutant emission control strategy in various economic regions.
To predict O_3, $PM_{2.5}$, NO_x, and CO concentrations at NCT Delhi	Krishan et al., 2019	India	Long Short-term Memory (LSTM)	National Capital Territory (NCT), Delhi	The Nash- Sutcliffe Efficiency (NSE) value range (0.86-0.94) found obtained in the investigation demonstrates that the LSTM models utilized in the study are suitable for forecasting air pollution concentrations.	Due to data availability, the study consider one station; as a result, the LSTM's capacity to capture spatial correlation was not examined.

Pollutant and particle levels prediction, as well as the air quality index (AQI).	Castelli et al., 2020	California	Support Vector Regression (SVR)	US, Environmental and Protection Agency	A 94.1% accuracy rate was attained in modelling pollutant concentrations such O_3, CO, and SO_2.	There is a need to improve SVR forecasting capabilities, look at its use, and compare it to other algorithms.
To determine the pollutants present concentration level, which will be helpful for Real Time Correction (RTC)	Amuthadevi et al., 2021	India	ANN, Neuro-Fuzzy Regression, Deep Learning Long Short-term Memory (DL-LSTM)	Metrological website	In the study, lower error rates and greater correlation with test data make DL-LSTM effective for analysing and forecasting air pollutants with 24h window.	Data can be divided into hourly-based and weakly-based bases for future research to provide a variety of fresh findings.
To scale up the deployment of AirBeam, a smartphone-based particle counter, to measure and simulate street-level urban air quality	Lim et al., 2019	South Korea	Linear Regression (LR) Random Forest (RF) Stacked Ensemble (SE)	Seoul routes	R^2 values of 0.63, 0.73 and 0.80 were obtained respectively. The SE R^2 values suggest designs using mobile sampling in conjunction with numerous inexpensive air quality monitors that could be used to characterize urban street-level air quality with high	The approach taken by the research and methodology may be places without established air monitoring networks, such as developing nations.

					spatial resolution.	

Water quality monitoring

Human survival depends on water, and the quality of that water is crucial for maintaining public health and safety. However, several factors, including pollution, climate change, and population increase, threaten water quality (Ahmed et al., 2020). Conventional methods of water quality monitoring rely on labor-intensive, expensive, and scope-restrictive manual sampling and laboratory analysis. Furthermore, achieving a reliable prediction through conventional methods requires lengthy processing times and large computational efforts, often associated with human error (Hameed et al., 2017). A promising approach to overcoming these limitations and supplying precise, real-time water quality monitoring is AI (Pappu et al., 2017). Machine learning algorithms examine data from various sources, including weather data, historical records, and water quality sensors, to find patterns and trends that may suggest changes in water quality (Marcin, 2023). AI algorithms can be trained to recognize minute changes in water quality, such as variations in temperature, pH, dissolved oxygen levels, and the presence of pollutants, which may indicate pollution or other abnormalities in water quality.

Various studies on water quality using specific AI techniques have proposed artificial neural networks (ANNs) as highly effective with high-performance accuracy in determining different water quality variables in an aquatic environment over a particular period, often referred to as the Water Quality Index (WQI) (Hameed et al., 2017; Gaya et al., 2020). A similar study by Wang et al. (2019) described how future changes in water quality can be accurately predicted, emphasizing understanding the characteristics and point sources of water pollutants. The Long Short-Term Memory (LSTM) AI model was employed and indicated that water quality is affected in different ways and characterized by various point sources of pollutants in the water body. Aldhyani et al. (2020) suggested an artificial neural network model, specifically the nonlinear autoregressive neural network (NARNET) and LSTM, which are advanced AI algorithms for predicting water quality index and classification, and promising AI tools for water management.

The use of AI to assess water quality has several advantages over conventional techniques (Chen, 2020). AI-based systems can continuously and instantly monitor water quality, enabling authorities to immediately identify and address problems with water quality. This can mitigate the dangers that water contamination poses to public health and the environment (Aldhyani, 2020; Chen, 2020). Moreover, AI-based systems can analyze enormous amounts of data from numerous sources, providing a comprehensive picture of changes in water quality (Chowdhury and Sadek, 2012). This capability aids in identifying trends and patterns in water quality, forecasting future issues, and developing targeted interventions to address these problems (Wu, 2019; Liu, P. 2019). AI-based recommendations can also guide timely actions to mitigate water quality issues. For instance, AI can suggest optimal times for water treatment interventions or recommend specific pollutant control measures based on real-time data (Nova, 2023; Rajitha et al., 2024). AI algorithms can create targeted interventions, such as treatment plans or pollution prevention methods, to lower the risks and impacts of these issues by analyzing data from specific regions and types of water quality problems (Khan, 2016; Wagle, 2020; Zhu, 2022).

Monitoring water quality with AI has several applications across various industries. Water management and treatment is one of the key applications. AI algorithms can assess data on water quality and provide specialized solutions for water treatment and management, such as filtration systems or chemical treatment strategies, to reduce the risks and effects of water quality problems. Agriculture and food production also benefit from AI-based water quality monitoring. AI algorithms can assess water quality data and create specialized irrigation and crop management strategies to mitigate water quality issues. For example, irrigation schedules can be optimized, and crops that are less susceptible to water pollution can be chosen. Environmental preservation and conservation can also benefit from AI-based water quality monitoring. AI algorithms can create specialized solutions for pollution control and habitat protection to save aquatic ecosystems and biodiversity by analyzing data on water quality and environmental conditions (Wagle, 2020; Zhu, 2022).

Several studies have investigated the application of AI in surface water quality monitoring and other water quality monitoring tasks. AI models have been employed for various tasks, including parameter prediction, anomaly detection, and classifying water samples. One study, for instance, used deep learning models to forecast water quality variables such as pH, temperature, and dissolved oxygen. Another study categorized water samples according to their quality using a decision tree algorithm.

Many AI models, including deep learning, decision trees, support vector machines, and artificial neural networks, have been utilized in these studies (Ahmed et al., 2019; Aldhyani, 2020). Depending on the purpose and the type of model used, different input parameters are applied. For example, some studies have utilized chemical factors like dissolved oxygen, biochemical oxygen demand, and total nitrogen, while others have employed physical measures like temperature, pH, and turbidity (El-Chaghaby et al., 2020; Lokman et al., 2021). Common metrics used in these studies include accuracy, sensitivity, specificity, and area under the curve, though they vary depending on the task. Data collected through various techniques, including manual sampling and remote sensing, have been used in studies conducted at different sites, including rivers, lakes, and reservoirs (Deng et al., 2020). These reviewed studies indicate that AI models can provide precise and effective solutions for monitoring water quality, with some models achieving higher accuracy than conventional techniques (Ortega-Fernández, 2020; Subramaniam, 2022).

The key contributions of prior studies include the development of new AI models for water quality monitoring, the comparison of AI models with conventional approaches, and the identification of challenges and opportunities for future research. Issues such as the lack of standards in data collection and processing and the limited availability of high-quality data need to be resolved. Future studies should focus on creating more robust AI models capable of handling multiple data sources and delivering precise forecasts for a variety of water quality indicators. Table 5 provides a summary of instances where AI was employed for water quality monitoring.

Table 5: Summary of previous studies for the prediction of water quality monitoring using AI

Research Aim	References	Location	Model	Data Source / Study Area	Result Obtained	Recommendation
Identification of the characteristics and origin of trace pollutant	Wang et al., 2019	China	Cross Section Apiori Long Short Term Memory Network (LSTM)	Shandong Province	LSTM algorithm gave a high prediction accuracy and traced the major industrial point sources of pollutant that will affect water in the future.	This study will improve the ability to control pollutant discharge and improve the water quality.
To create forecasting models that foresee changes in water level	Zakari et al, 2021	Malaysia	Adaptive Neuro-Fuzzy Inference System (ANFIS) Multi-layer Perceptron Neural Network (MLP-NN)	Historical data from Muda river, Kedah state.	The two models are useful for the prediction of changes in water level. Though, MLP-NN performed better in the running time.	To avoid and mitigate the effect of flooding, the MLP-NN model is promising
Evaluate the groundwater potential using the hybrid model	Nguyen et al., 2020	Vietnam	Artificial Neural Network (ANN) RealAda Boost (RAB)	DakNong Province	The RAB model improved the ANN performance and the hybrid model RABANN can be modified for groundwater potential mapping.	This help in addressing the population's water borne disease-related health issues by enhancing the region's groundwater quality.

This research focuses on the application of the ANN technique for the weekly forecasting of groundwater levels	Mohanty et al., 2015	India	ANN	Mahanadi, Delta of Odisha	The study of the modeling results showed reasonably accurate predictions or forecasts of groundwater levels, however the accuracy of the predictions was found to decline with increasing lead times.	The ANN model should be modified by conducting sensitivity analysis and a longer time frame for prediction analysis.
Prediction of monthly rainfall at meteorological stations using ANN and ANFIS models	Abebe and Endalie, 2023	Ethiopia	ANN ANFIS	Ethiopia Meteorological Stations	In every evaluation criteria across all testing stations, the ANFIS model performs better than the ANN model.	ANFIS can be used for predicting monthly rainfall.
To forecast the need for potassium permanganate in a drinking water treatment facility that uses water	Godo et al., 2019	Spain	ANN	Liobregat River, Abrera	In terms of replicative, predictive, and structural performance, the model delivered good results which proved the effectiveness of ANN model.	To enhance and speed up the decision-making process for plant managers and operators, this can be integrated into an environmental decision support system that can be fed by online data.

To evaluate the water quality for drinking using AI-learning-based algorithms.	Panigrahi et al., 2023	India and Vietnam	Logistics Regression Support Vector Machine Decision Tree AdaBoost XGBoost	Odisha, India and Northern Delta, Vietnam	According to prediction findings, Adaboost, XGBoost, and the Polynomial SVM model correctly identified the Water Quality Classes with 92% and 98% accuracy, respectively.	By using them on comparable datasets gathered from different nations, machine learning models' performance can also be evaluated by expanding the scope of the task

Soil Monitoring

The application of AI in soil monitoring represents a significant advancement in agricultural management, environmental conservation, and land-use planning (Abdulraheem et al., 2023). Traditional soil monitoring methods, which involve manual sampling and laboratory analysis, are often time-consuming, labor-intensive, and limited in scope. AI, however, offers innovative solutions that enhance accuracy, efficiency, and scalability, revolutionizing how soil health is monitored and managed (Fuentes-Peñailillo et al., 2024; Jeffrey & Bommu, 2024; Sharma et al., 2023).

Machine learning algorithms such as Random Forests and Decision Trees have proven to be particularly effective in handling complex datasets with numerous variables. These algorithms predict soil properties like moisture content, nutrient levels, and pH by analyzing large volumes of data from various sources (Folorunso et al., 2023; John et al., 2020). For instance, the use of Random Forests in the study of soil organic carbon stocks has shown improved accuracy compared to traditional statistical methods (Wang et al., 2020). Support Vector Machines (SVM) are employed for soil classification tasks, helping categorize soil types based on physical and chemical properties. These machine learning techniques enable more precise soil health assessments and informed decision-making in soil management (Padarian et al., 2020).

Deep learning models also play a crucial role in soil monitoring. Convolutional Neural Networks (CNNs) are used for image-based soil analysis. By processing images from satellites or drones, CNNs can identify patterns related to soil health, erosion, and contamination (Feizizadeh et al., 2021; Hosseini et al., 2023). For example, drones equipped with multispectral and hyperspectral cameras capture high-resolution images of the soil, and AI algorithms process these images to assess soil health and detect issues such as nutrient deficiencies or pest infestations. Recurrent Neural Networks (RNNs) are utilized for time-series analysis of soil data, predicting changes in soil properties over time based on historical data (Bai et al., 2022; Park et al., 2023). These deep learning models offer advanced predictive capabilities that enhance the proactive management of soil health.

The integration of IoT and smart sensors further amplifies the capabilities of AI in soil monitoring (Rajak et al., 2023). IoT-enabled smart sensors deployed in the field continuously monitor soil conditions, including moisture levels, temperature, and nutrient content. These sensors collect real-time data, which AI algorithms analyze to provide actionable insights. Specific examples include platforms like the Arable Mark 2, an IoT device that integrates weather, soil, and crop data to give comprehensive insights into field conditions (Alahmad et al., 2023). Additionally, platforms such as the John Deere Operations Center leverage AI to integrate sensor data and provide real-time recommendations for soil management practices (Ahmad et al., 2023; Nichols et al., 2022).

The benefits of AI in soil monitoring are substantial. AI-powered sensors and IoT devices enable continuous, real-time monitoring of soil conditions, allowing farmers and land managers to make timely decisions based on current soil health data (Fuentes-Peñailillo et al., 2024; Reddy et al., 2024). The precision of AI algorithms significantly reduces human error, leading to more accurate predictions of soil properties. The scalability of AI solutions allows for comprehensive soil health assessments across large agricultural areas or regions, which is particularly beneficial for large-scale farming operations (Chaterji et al., 2020). AI models' predictive insights enable proactive soil management, such as adjusting irrigation schedules, optimizing fertilizer application (Elshaikh et al., 2024; Hassan et al., 2022; Veeramanju, 2024), and implementing erosion control measures, enhancing the sustainability and productivity of agricultural practices (Ruiz et al., 2023; Sachithra & Subhashini, 2023).

Despite these advantages, the application of AI in soil monitoring faces challenges. The effectiveness of AI models heavily relies on the quality and availability of soil data (Grunwald, 2022). Inaccurate or incomplete data can lead to unreliable predictions, highlighting the need for robust data collection methods. Additionally, the integration of AI technologies requires significant initial investments in infrastructure and training (Aldoseri et al., 2023; Whang et al., 2023). However, the long-term operational costs are generally lower than traditional methods due to automation and reduced need for manual labor. Addressing these challenges will be crucial for fully realizing AI's potential in soil monitoring and ensuring its widespread adoption.

Overall, AI's application in soil monitoring exemplifies how advanced technologies can transform traditional agricultural and environmental practices. By leveraging machine learning, deep learning, and IoT technologies, AI provides precise, real-time, and scalable solutions for monitoring soil health (Fuentes-Peñailillo et al., 2024; Shaikh et al., 2022). As the technology continues to evolve, it promises to offer even greater insights and efficiencies, contributing to more sustainable and productive land management practices (Lakshmi & Corbett, 2020; Nishant et al., 2020).

Human Monitoring and Epidemiological Investigation of Environmental Pollutants

The application of AI in human monitoring and epidemiological investigations related to environmental pollutants has shown remarkable promise, offering precise, timely, and actionable insights into the effects of pollutants on human health (Akinosho, 2024; Rane et al., 2024). These advanced technologies facilitate more effective interventions and inform policy decisions, significantly enhancing public health outcomes (Wallace et al., 2020).

AI-powered models are instrumental in predicting disease outbreaks related to environmental pollution by analyzing extensive datasets that include air and water quality measurements, meteorological data, and health records (Adefemi et al., 2023). Machine learning algorithms, such as Random Forests and Gradient Boosting Machines, have been employed to predict respiratory and cardiovascular diseases caused by air pollution (Kothandaraman et al., 2022; Ravindra et al., 2023). For instance, IBM Watson Health has been utilized in various healthcare settings to analyze environmental data and predict health risks, providing early warnings to healthcare providers and the public (Azzi et al., 2020; Computing). These early warning systems enable timely interventions that can prevent disease outbreaks and reduce the burden on healthcare systems.

Moreover, AI tools play a crucial role in assessing human exposure to environmental pollutants and analyzing their health impacts. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can process vast amounts of data from wearable sensors, satellite imagery, and medical records to estimate individual exposure levels and correlate them with health outcomes (Eskandari et al., 2021; Ghosh & Kumar, 2022). The Air Quality Egg project, for example, integrates IoT sensors and AI algorithms to monitor air quality in real-time, offering personalized exposure assessments and health recommendations (Omidvarborna et al., 2021; Tanveer et al., 2024). This level of granular analysis helps identify vulnerable populations and inform targeted public health interventions.

Epidemiological surveillance has also been significantly enhanced by AI through the automation of data collection and analysis processes (Agbehadji et al., 2020; Zeng et al., 2021). This automation makes it possible to detect patterns and trends that might be overlooked by traditional methods. Natural Language Processing (NLP) algorithms can analyze unstructured data from social media, health forums, and news articles to identify potential outbreaks linked to environmental pollution (Al-Garadi et al., 2022; Baclic et al., 2020). Tools like HealthMap utilize NLP and machine learning to track disease outbreaks globally, providing real-time surveillance and early detection of environmental health threats (Choubey & Naman, 2020; Gupta & Katarya, 2020; Jia et al., 2020; Kamel Boulos & Geraghty, 2020). This capability enables rapid response and containment measures, mitigating the impact of pollutants on public health.

In addition to real-time monitoring and surveillance, AI-powered predictive analytics can inform policy and decision-making by forecasting the long-term health impacts of environmental pollutants (Chauhan et al., 2024; Fan et al., 2023). By integrating historical data on pollution levels, health outcomes, and demographic information, AI models can simulate various scenarios and predict future health trends (Masood & Ahmad, 2021). This predictive capability is invaluable for policymakers designing regulations and interventions to reduce pollution and protect public health. The European Air Quality Portal, for example, uses AI to assess the impact of policy measures on air quality and public health (Kaginalkar et al., 2021; Rovira et al., 2020), providing evidence-based recommendations for regulatory actions.

AI-driven health monitoring systems can also provide real-time alerts to individuals about their exposure to harmful environmental pollutants (Popescu et al., 2024). Wearable devices equipped with AI algorithms can continuously monitor physiological parameters such as heart rate, respiratory rate, and skin temperature, correlating these with environmental data to detect early signs of health deterioration due to pollution exposure (Natarajan et al., 2020; van Goor et al., 2022). Devices like Fitbit and Apple Watch have integrated AI capabilities to offer health insights and alerts based on environmental conditions, enabling users to take preventive actions to safeguard their health (Mirmomeni et al., 2021; Yoon et al., 2020).

Despite the numerous benefits, the application of AI in human monitoring and epidemiological investigations faces several challenges and ethical considerations. Data privacy and security are paramount, as the collection and analysis of personal health and environmental data involve sensitive information (Gabriel, 2023). Ensuring robust data protection measures and transparent data usage policies is essential to maintaining public trust. Additionally, the risk of algorithmic bias must be mitigated by using diverse and representative datasets in model training. Establishing ethical frameworks and guidelines to govern the use of AI in public health is crucial, balancing the benefits of technology with the protection of individual rights.

Benefits of AI-based environmental monitoring

When compared to conventional methods, using AI for environmental monitoring has a number of advantages. First, AI-based environmental monitoring systems have the capacity to evaluate enormous volumes of data from numerous sources, giving an accurate picture of the state of the environment in real time (Zhang et al., 2021). This enables authorities to decide wisely and act quickly to protect both the environment and the general population. Furthermore, by automating the processes of data collection and analysis, AI-based environmental monitoring systems can lower the cost of monitoring programs (Chang, 2019; Himeur et al., 2022). This can save significant resources and allow environmental monitoring programs to grow in scope and scale. With less chance of errors and inconsistencies, AI-based environmental monitoring systems can collect and analyze data with better accuracy and precision than conventional approaches.

Notwithstanding the advantages of AI-based environmental monitoring, a number of issues need to be resolved in order to assure its successful adoption. The quality of the data used for analysis represents one of the major obstacles. For AI systems to make precise predictions and choices, they need accurate and trustworthy data (Hameed et al., 2017). Inadequate data quality can result in inaccurate predictions and judgments, which can have a negative impact on the environment and public health. The availability of data presents another difficulty. It is challenging to construct precise and trustworthy AI-based monitoring systems since many regions of the world lack adequate data on environmental factors. In addition to technological constraints, political and economic issues can also have an impact on the availability of data. The ethical implications of AI-based environmental monitoring must also be taken into account. The application of AI for environmental monitoring raises concerns regarding data ownership, privacy, and the possibility of data misuse. To ensure the ethical use of AI for environmental monitoring, ethical standards, and regulations must be developed.

Potential environmental impact of AI models in environmental monitoring

While the benefits of AI models in environmental monitoring are significant, it is essential to look out for unintended environmental consequences. AI technologies, particularly those involving extensive computational processes, can have considerable environmental footprints that must be carefully managed to ensure overall sustainability. One of the primary concerns is the substantial energy consumption associated with training and operating AI models (Bloomfield et al., 2021). Data centres that support AI computations consume vast amounts of electricity, often sourced from non-renewable energy (Rostirolla et al., 2022). This high energy usage can lead to increased carbon emissions, counteracting the positive impacts that AI applications might have in monitoring and mitigating environmental issues. Recent reports from major tech companies underscore this issue. Google's efforts to reduce its climate footprint are being undermined by its increasing reliance on energy-intensive data centres to power its new AI products (Dan Milmo, 2024). According to Google's annual environmental report, its greenhouse gas emissions have surged by 48% over the past five years, with electricity consumption by data centres and supply chain emissions being primary contributors (Google, 2024). In 2023 alone, Google's emissions rose by 13% compared to the previous year, reaching 14.3 million metric tons of CO_2e, up from 9.7 million metric tons in 2019. Similarly, Microsoft's 2024 environmental report highlighted a substantial increase in greenhouse gas emissions, particularly Scope 3 emissions, which grew by over 30% due to the expansion of data centres and increased consumption of hardware components necessary for their AI research (Microsoft, 2024). Although Microsoft managed to reduce its Scope 1 and 2 emissions by 6.3% compared to 2020, the rise in Scope 3 emissions emphasizes the environmental challenges posed by AI infrastructure.

Moreover, the hardware used in AI, including servers and data storage systems, requires manufacturing processes that often involve the extraction of rare earth elements (REE) and other non-renewable resources (Gundeti et al., 2023). For example, rare minerals like Erbium, Holmium, Terbium, Gadolinium, Lanthanum, and Europium are vital in the manufacturing of optical fibre, capacitors, HD drives, and semiconductors, among other materials (Leal Filho et al., 2023). The associated extraction and processing phases can lead to environmental degradation, especially at end-of-life (landfilling, incineration, and open dumping), resulting. into ecological damage, soil and water pollution, and increased carbon footprints (Balaram, 2019). During extraction, the machinery used generates significant dust, emissions, and wastes (such as radioactive elements and other heavy metals), which could easily dissipate, leading to long-term environmental damage (Willenbacher, 2022). For example, it was estimated that 63,000 m^3 of sulfuric and hydrofluoric acid residues and 1.4 tons of radioactive waste were generated from refining one ton of REE oxide in China (Willenbacher, 2022). This has resulted in a push for eco-friendly approaches for mineral extraction and processing, as well as discouraging single use of extracted metals (Nwaila et al., 2022).

In conclusion, while AI models offer significant advancements in environmental monitoring, their potential environmental impacts must be diligently managed. Future research and policy-making should focus on creating frameworks that ensure the sustainable use of AI technologies, maximizing their benefits while minimizing their ecological footprints.

Limitations and Future Scope

While the application of AI in environmental monitoring has demonstrated significant potential, several limitations must be addressed to realize its full benefits. One prominent limitation is the dependency on high-quality and extensive datasets (Olawade et al., 2024a). AI models require large volumes of accurate and representative data to train effectively, and the availability of such data can be a significant constraint. Additionally, data biases can result in skewed predictions and perpetuate existing inequalities, underscoring the need for careful data curation and preprocessing.

Overfitting is another critical challenge, where models perform exceptionally well on training data but fail to generalize to new, unseen data. Balancing model complexity to avoid overfitting while still capturing intricate patterns in the data is an ongoing challenge in AI development. Furthermore, the interpretability of AI models, especially deep learning models, remains a vexing issue (Olawade et al., 2024b). These models often operate as "black boxes," making it difficult to understand and trust their decisions, which is particularly crucial in high-stakes fields like environmental monitoring.

Resource intensiveness is another constraint, as training and deploying sophisticated AI models demand substantial computational resources. This requirement can be a barrier for smaller organizations and developing countries, limiting their ability to leverage AI technologies effectively. Ethical concerns also pose significant challenges, with AI models potentially reinforcing biases present in training data (Olawade et al., 2023). Ensuring fairness and addressing ethical implications is crucial, especially in applications where equitable outcomes are essential.

Security risks, including susceptibility to adversarial attacks, where small, carefully crafted changes to input data can deceive the model, are a growing concern. Ensuring the robustness and security of AI models against such attacks is imperative. Additionally, the environmental impact of large-scale AI training, which consumes significant energy resources and contributes to carbon emissions, is becoming increasingly evident. Developing more energy-efficient AI solutions is necessary to mitigate this impact.

Despite these challenges, the future scope of AI in environmental monitoring is promising. Advancements in AI algorithms, improved data collection techniques, and increased computational power are expected to enhance the accuracy and efficiency of AI models. Future research should focus on developing robust AI models that can handle diverse and complex environmental data, improving model interpretability, and addressing ethical and security concerns. Collaborative efforts between researchers, policymakers, and industry stakeholders will be essential to foster responsible innovation and ensure the equitable application of AI in environmental monitoring.

Strength of this review

This study provides a comprehensive overview of the principles, applications, and limitations of AI models in environmental monitoring, distinguishing itself from other review studies through several key merits. First, it offers a detailed comparative analysis of various AI models, highlighting their specific applications, strengths, and limitations in environmental monitoring. This detailed comparison provides valuable insights for selecting the appropriate AI model for specific tasks, a feature not always covered in other reviews.

Second, the study integrates practical examples and case studies to illustrate the application of AI principles, making the discussion more concrete and engaging. This approach enhances the relevance and applicability of the theoretical concepts discussed, providing readers with a clearer understanding of how AI technologies are implemented in real-world environmental monitoring scenarios.

Third, the study addresses both technological and ethical challenges comprehensively, emphasizing the importance of responsible AI development. By discussing issues such as data dependency, overfitting, interpretability, and security risks, alongside ethical considerations, this review provides a holistic perspective on the challenges and opportunities in the field.

Lastly, the study outlines a clear future scope for AI in environmental monitoring, identifying key areas for future research and development. This forward-looking perspective encourages ongoing innovation and collaboration among researchers, policymakers, and industry stakeholders to enhance the effectiveness and equity of AI applications in environmental monitoring.

In summary, this study stands out by offering a thorough and practical examination of AI in environmental monitoring, addressing both current applications and future directions, and providing a balanced discussion of technological and ethical considerations. These merits make it a valuable resource for academics, practitioners, and policymakers interested in the responsible application of AI in environmental monitoring.

Conclusion

In conclusion, the integration of AI in environmental monitoring offers transformative benefits across various domains, including soil, water, and air quality monitoring, traffic management, and carbon footprint tracking. These advancements contribute significantly to environmental protection, public health, and sustainable development. AI's capability to provide precise predictions and real-time monitoring enhances the efficiency and effectiveness of environmental management practices. However, it is crucial to acknowledge the potential drawbacks associated with the deployment of AI technologies. One significant concern is the substantial energy burden imposed by data centres and the supply chain, leading to increased greenhouse gas emissions. Additionally, the extraction of resources, such as REEs for AI hardware, results in considerable environmental degradation, including habitat destruction, soil and water pollution, and toxic waste generation.

The shortage of skilled professionals in the environmental sector, particularly in the global south, poses another challenge to fully harnessing AI's potential. Data access, control, and privacy issues must be addressed to prevent the misuse of AI systems for personal gain, such as market manipulation or disaster prediction exploitation. Robust data governance frameworks are essential to mitigate these risks and ensure equitable and ethical use of AI technologies. Despite these challenges, the future of AI in environmental monitoring is promising. For future research, there is a critical need to focus on the ethical implications and environmental impact quantification of AI technologies. Developing standardized methods to assess the environmental footprint of AI systems and exploring the ethical dimensions of their deployment will ensure responsible and sustainable use.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the findings reported in this paper.

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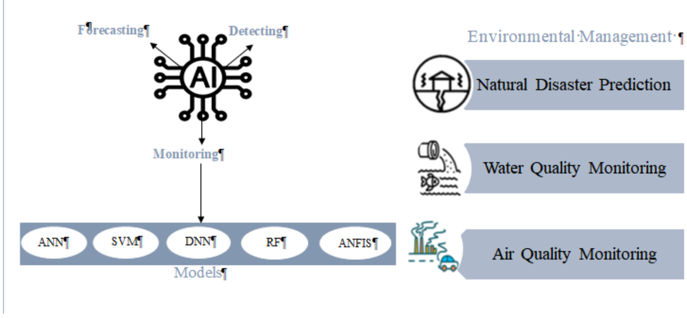
Graphical Abstract



Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: