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Artificial Intelligence Models as a Tool for Environmental Monitoring: Review and Analysis

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The application of artificial intelligence (AI) for environmental monitoring enables accurate forecasts of natural disasters, identification of pollution sources, and comprehensive monitoring of air and water quality. This article provides an overview of the challenges associated with monitoring using traditional methods, as well as the potential for implementing AI-based solutions. The article discusses several models that apply artificial intelligence in the implementation of environmental monitoring, demonstrating case studies of environmental research. However, realizing the full potential of AI faces obstacles such as the lack of specialized AI experts in the environmental sector and the problem of data access, control and privacy. The above challenges are more acute in regions with developing technological infrastructure.

Keywords: Artificial intelligence, environmental monitoring, pollution detection, disaster forecasting, air and water quality.

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Introduction

The essential process of environmental monitoring involves the systematic observation, measurement and assessment of the state of the natural environment and all its components in order to detect any changes that may harm the ecosystem or public health [*Baryshnikova and Kolodina*, 2019]. Traditional methods of environmental monitoring include manual sampling, laboratory tests and statistical analysis [*Dobrinskaya et al.*, 2025]. The listed approaches have limitations in the form of high cost, large time expenditures for the procedures (payment for the labor of qualified employees, purchase or lease of equipment and purchase of chemicals) and low accuracy of the results obtained, which significantly reduces the effectiveness of traditional methods of environmental monitoring. As a result, environmental monitoring programs often have a narrow focus, use small sample sizes and do not provide a complete picture of the state of the environment. In addition, a serious problem of traditional methods is their labor intensity due to the need for lengthy procedures of manual sampling and laboratory analysis to obtain results [*Novgorodov*, 2024], which does not allow prompt response and decision-making in case of natural disasters or crisis situations related to environmental pollution. The subjectivity of human observation and the possibility of human error in data interpretation limit the accuracy of traditional environmental monitoring methods [*Dzhumabaev*, 2023]. Consequently, providing regular monitoring becomes a challenging task, especially in regions with limited resources, lacking technological infrastructure and staff expertise.

Artificial intelligence (AI), which as a field of computer science, focuses on creating algorithms and computer programs that perform actions such as perception, reasoning, learning, and decision making similar to human intelligence, is becoming a crucial element of environmental monitoring to improve the objectivity of results and accessibility for regions suffering from limited resources [*Dovgal*, 2022]. Artificial intelligence, which has proven its usefulness in identifying patterns and making accurate predictions, allows analyzing large data sets [*Dovgal and Kuizheva*, 2021]. In the field of environmental monitoring, artificial intelligence has been applied in various areas including predicting natural disasters, monitoring air and water quality, and detecting pollutants [*Sharavina and Molchanova*, 2024]. The comparative analysis of AI techniques and traditional approaches in terms of accuracy, speed, cost, scalability, data integration, maintenance, and environmental impact presented in Table 1 demonstrates the significant benefits of AI in improving the effectiveness of environmental monitoring, given the potential initial costs and the importance of considering long-term benefits.

For example, artificial intelligence models such as Convolutional Neural Networks (CNNS) are used for image-based environmental monitoring tasks such as deforestation detection and wildlife identification [*Medvedkov*, 2024]. Support Vector Machines (SVM), which is a category of universal feed forward networks that demonstrates the model's ability to handle multivariate data, have been applied to predict harmful algal blooms in lakes [*Razveeva and Rakhimbaeva*, 2022]. Recurrent Neural Networks (RNNS) are used for time series forecasting, such as flood forecasting based on historical rainfall data [*Pak and Jong*, 2017].

In addition, the use of advanced technologies and the availability of properly trained technical personnel required for accurate environmental monitoring are often hindered by cost constraints and lack of skilled professionals. Consequently, providing regular monitoring becomes a difficult task, especially in resource-poor regions of the world, especially in the global south. Thus, in recent years, artificial intelligence has become a crucial element of environmental monitoring to improve the objectivity of results and accessibility for resource-constrained regions. The purpose of this article is to comprehensively explore and evaluate the current status of artificial intelligence technologies applied in key areas of environmental monitoring, identifying their effective utilization and potential implications for future research and practical applications.

Artificial intelligence models for environmental monitoring

When selecting an artificial intelligence model for environmental monitoring, it is important to consider factors such as data availability, computational resources, and expertise. Some artificial intelligence models require large amounts of data and computational power for training, while others can be trained on small datasets with less computational effort [*Valero-Carreras et al.*, 2021]. SVMs are believed to be well suited for handling multivariate data and learning complex relationships between variables [*Demidova and Sokolova*, 2017] and can be used with various types of data including images and text. For example, SVMs have been effectively used for image classification tasks such as deforestation detection and wildlife identification [*Kolegov*, 2023]. They have also been applied in natural language processing to extract information from environmental reports [*Krivosheev and Spitsyn*, 2019]. A variant of SVM, the Support Vector Regression (SVR) method, is used for regression problems in environmental monitoring, offering an efficient solution for predicting environmental monitoring parameters [*Ye et al.*, 2020].

Decision trees are relatively easy to train and interpret, making them available for different types of data. They are commonly used for tasks such as deforestation detection and monitoring, air and water quality monitoring [*Popova et al.*, 2018]. However, decision trees can be prone to overtraining, especially when processing complex, noisy data, and may not perform as well in image recognition or natural language processing tasks [*Minkin and Nikolaeva*, 2024].

Table 1. Comparison of AI techniques with traditional approaches in environmental monitoring

Criteria	Artificial intelligence methods (specific model/tool)	Traditional methods
Accuracy	• Deep learning models (e.g., convolutional neural networks – CNNS): high accuracy in image and pattern recognition; • random forests: effective for processing large datasets and detecting complex patterns; • support vector machines (SVMs): excellent for classification tasks.	• Accuracy depends on human expertise; • subject to human error and distortion; • often limited by the resolution and frequency of manual sampling.
Speed	• Real-time data processing (e.g., TensorFlow, Keras): direct analysis and anomaly detection; • automated monitoring systems (e.g., IBM Watson): accelerate aggregation and synthesis of data from multiple sources.	• Data collection and analysis are time-consuming; • delay in obtaining results due to lengthy laboratory processes; • slower response times in emergency situations.
Cost	• Initial setup can be expensive (hardware, software, training); • long-term operating costs are reduced due to automation and reduced need for human labor; • scalability with decreasing marginal costs.	• High ongoing costs for labor, equipment, and consumables. • costly manual sampling and laboratory analyses. • costs increase in proportion to the scale of the monitoring effort.
Scalability	• Cloud platforms (e.g., Microsoft Azure, Google Cloud AI): easily scalable to cover large geographic areas; • Ability to integrate data from different sources (e.g., satellites, Internet of Things devices).	• Limited scalability due to the use of human labor and physical sampling; • scaling up coverage is costly and logistically challenging.
Data integration	• Big data analytics tools (e.g., Hadoop, Apache Spark): process and integrate large amounts of diverse data; • ability to continuously monitor and update in real time.	• Limited ability to integrate different data sources; • manual data entry and slower data updates.
Maintenance	• Requirement for periodic software updates and periodic equipment maintenance; • lower maintenance costs over time.	• Regular equipment maintenance and calibration; • high ongoing costs for consumables and their replacement.
Environmental impact	• Reduced environmental impact by reducing the need for physical sampling and travel. • Energy-efficient solutions (e.g., artificial intelligence-based sensors): Minimizing carbon dioxide emissions.	• Higher environmental impact due to frequent physical sampling; • travel and transportation increase carbon dioxide emissions

Random forests are a collective learning method that combines the predictions of multiple decision trees. They are more robust to overtraining than individual decision trees and can handle a variety of data types, including images and text 18]. Random forests are commonly used for image classification, natural language processing, and time series prediction in environmental monitoring tasks. Despite their robustness, random forests can be computationally intensive and require significant memory resources and computational power.

CNNs are well suited for image classification and spatial data related tasks. CNNs can learn complex patterns in images without explicit programming, making them ideal for deforestation detection and wildlife identification [*Chernousova et al.*, 2024]. However, training CNNs can be computationally expensive and require large amounts of labeled data. Training CNN models can be challenging due to the lack of annotated datasets for visual recognition. Pre-trained models that utilize data from similar domains can mitigate this problem [*Naberezhnyeh*, 2023].

Recurrent neural network (RNN) is suitable for tasks involving sequential data (e.g., time series prediction and natural language processing). RNNs can learn long-term dependencies in data, which makes them effective for predicting extreme weather events and extracting information from environmental reports [*Bykov and Tsaralov*, 2022]. However, training such networks can be computationally expensive and require large datasets. Advanced models, such as Convolutional Deep Long Short-Term Memory (CDLSTM) [*Liu et al.*, 2021], have been developed to better predict climate change and simulate changes in groundwater storage.

Hybrid models, combining the advantages of machine learning and deep learning models, provide high accuracy and reliability and can be used for environmental monitoring tasks that require consideration of complex nonlinear interactions between input and output variables [*Stepanov et al.*, 2024]. Hybrid models, while being more difficult to train and interpret, provide high performance in complex environmental monitoring tasks. There are studies (e.g., the development of Synthetic Minority Over-sampling Technique with Deep Neural Networks (SMOTEDNN) for predicting air pollution and determining Air Quality Index (AQI), further demonstrates the potential of AI in this field [*Zhao et al.*, 2024].

Table 2 summarizes the different AI models used for environmental monitoring.

Each of the models presented in the table has its own advantages and limitations, so it is important to choose the appropriate model for a particular task. SVM and SVR are effective for handling multivariate data and regression tasks, but can be computationally expensive. Decision trees are simple and interpretable, but are prone to overfitting. Random forests provide robustness and versatility but require significant computational resources. CNNs are excellent for image-based tasks, but they require large labeled datasets and significant computational power. RNNs are efficient for sequential data, but also require large computational resources and advanced models such as CDLSTM for complex prediction tasks. Hybrid models provide the highest accuracy and reliability, but are difficult to train and interpret.

Advantages of AI-based environmental monitoring

Compared to traditional methods, using artificial intelligence for environmental monitoring has several advantages:

1. AI-based environmental monitoring systems are capable of evaluating vast amounts of data from multiple sources, creating an accurate picture of the environment in real time [*Razveeva and Rakhimbaeva*, 2022] and enabling informed and rapid decision-making in protecting the environment and the public;
2. reducing the cost of software for environmental monitoring systems based on artificial intelligence by automating the processes of data collection and analysis, thus saving significant resources and expanding the scope of environmental monitoring programs [*Orlov*, 2021].

Disadvantages of artificial intelligence models

In the field of AI for environmental monitoring, along with its many advantages, there are several quite important disadvantages and challenges that affect the competent and valid AI model development [*Skatkov et al.*, 2020]:

1. quality of the data used for analysis, on which the accuracy of predictions and decisions made by the AI system depends – unreliable data can lead to inaccurate predictions

Table 2. AI models used for environmental monitoring

Artificial intelligence models	Specific examples/case studies	Strengths	Limitations
Support vector methods (SVMS)	• Using SVMS to predict harmful algal blooms in lakes. • Use of SVMs for air quality monitoring.	• Handles multivariate data; • explores complex relationships between variables; • is used with a variety of data types, including images and text.	• mage classification (e.g., for deforestation detection, wildlife identification); • natural language processing (e.g., extracting information from environmental reports); • time series forecasting (e.g., predicting extreme weather events).
Decision trees	• Using decision trees to predict water quality in rivers; • Using decision trees for water quality assessment.	• relatively easy to train and interpret; • can be used with different types of data.	• Deforestation detection and monitoring; • air quality monitoring; • water quality monitoring.
Randomized decision trees	• Using random forests to model air quality index in urban areas; • Using random forests to adequately predict forest fires.	• A collective learning method that combines the predictions of multiple decision trees; • greater robustness to overestimation than individual decision trees.	• Image classification (e.g., deforestation detection, wildlife object identification); • natural language processing (e.g., extracting information from environmental reports); • time series forecasting (e.g., predicting extreme weather events).
Converged neural networks (CNNS)	• Using CNNs to monitor coral reef health using underwater imagery. • Using CNNs to monitor coastal pavement erosion.	• Is well suited for image classification and other tasks involving spatial data; • allows learning complex patterns in images without the need for explicit programming.	• Image classification (e.g., deforestation detection, wildlife identification).
Recurrent Neural Networks (RNNs)	• Application of RNNSs for flood forecasting based on historical rainfall data; • Using RNNs to predict river flow levels.	• Is well suited for tasks involving sequential data (time series forecasting and natural language processing); • explores long-term dependencies in the data.	• Natural language processing (e.g., extracting information from environmental reports); • time series forecasting (e.g., for predicting extreme weather events).
Hybrid models	• Combining CNNs and RNNs to accurately predict air pollution levels; • Analyzing the heat island effect in cities using combined CNNs and RNNs.	• Combines the advantages of machine learning and deep learning models; • can be more accurate and reliable than individual.	• any environmental monitoring task where high accuracy and reliability are required.

and judgments, poor model performance or algorithmic error, which can have negative impacts on the environment and public health;

2. overfitting – high degree of learning data assimilation by the model leads to poor generalization of new, previously unknown environmental parameters (to overcome this disadvantage, it is recommended to maintain a balance in model complexity);
3. interpretability – the ability to understand the ways of finding this or that solution by the model (this is especially relevant for deep learning models, which are often called ”black boxes” due to their opacity) [*Fishcheva et al.*, 2021]. For example, stakeholders

may be reluctant to respond to AI-based deforestation alerts if they cannot understand the reasons behind the model's predictions.

4. resource-intensive – requiring significant computational resources to train and run complex AI models (especially for small organizations and developing countries) [*Shcherbakov*, 2023]. Only organizations with sufficient resources can effectively use advanced AI technologies, which can exacerbate existing inequalities;
5. ethical aspects of AI development – AI models may inadvertently reinforce existing distortions present in training data [*Cheremisova*, 2024]. For example, for disaster response, an AI model prioritizes areas based on biased historical data and may unfairly overlook vulnerable communities.
6. information security risks: AI models – susceptible to hostile attacks, a model can be misled by small, carefully considered changes in input data [*Artamonov et al.*, 2022] (which requires the design of artificial intelligence to be secure and resilient to malicious attacks). For example: manipulation by hostile attacks of AI systems in smart grids can disrupt power distribution and cause significant economic damage.
7. the increasingly obvious environmental impact of AI models – large-scale AI training consumes significant energy resources, exacerbating global environmental problems (the emergence of a carbon footprint and the need for more energy-efficient solutions).

Conclusions

The analysis presented in this article on the implementation of AI-based solutions for environmental monitoring tasks shows that the integration of artificial intelligence will provide significant benefits in various areas of environmental research, including soil, water and air quality monitoring, traffic flow management and carbon footprint tracking, contributing significantly to environmental protection, public health and sustainable development. The ability of artificial intelligence to provide accurate predictions and real-time monitoring increases the effectiveness of environmental management techniques.

However, it is critical to recognize the potential drawbacks associated with the adoption of artificial intelligence technologies:

- increased greenhouse gas emissions due to the significant energy burden on data centers and supply chains;
- extraction of resources (e.g., rare earth elements) to create AI hardware, leads to significant environmental degradation, including habitat destruction, soil and water contamination, and toxic waste generation;
- ensuring secure data access, control and privacy to prevent the misuse of AI systems for personal purposes (such as market manipulation or the use of natural disaster forecasts).

In addition, it is only possible to fully exploit the potential of AI in the environmental sector if there is a sufficient number of skilled professionals (which is a challenge for countries in the global south).

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