

Artificial Intelligence in Environmental Monitoring and Remediation

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Abstract

Environmental pollution and degradation are currently significant challenges for the whole planet, requiring innovative ways to monitor and clean up environmental pollution. AI (Artificial Intelligence), especially via machine learning and deep learning, provides powerful methods for the analysis of data, prediction of outcomes and making decisions about pollution mitigation efforts. The focus of this review article is how AI is being applied to environmental monitoring and remediation. There are numerous ways in which AI-based methodologies are helping augment traditional methods of monitoring environmental parameters through the use of sensor networks, remote sensing, and large volumes of data. The use of these technologies is enhancing our ability to detect pollutants, predict the trajectory of contaminated sites and assess the environmental risk associated with contaminated areas. In the case of remediation, AI can help optimize the application of remediation strategies (e.g., bioremediation and phytoremediation) by helping to identify the optimal conditions for carrying out these tasks while improving the efficiency of these remediation techniques. In addition, AI models can be used for optimizing processes, detecting faults, and improving resource utilization in water and wastewater treatment processes.

Although the use of AI has many advantages in terms of monitoring and cleaning up pollution, there are some challenges related to using AI in environmental applications, including lack of available data, a lack of transparency in the models developed using AI, and difficulties associated with integrating AI methods with existing frameworks for environmental monitoring and remediation. However, with continued advances in the development of AI technologies, along with a collaborative interdisciplinary approach, there is great potential for sustainable and effective environmental management by utilizing AI. In addition to discussing the current state of AI as applied to environmental monitoring and remediation, this review will also identify major problems that need to be resolved and the future possibilities for implementing AI in this field of study.

Keywords: Environmental monitoring, AI technologies, Air Pollution, weather forecasting, water quality monitoring.

Introduction

The monitoring of the environment is conducted through science-based, systematic observation and measurement and evaluation of the environment, which enables us to assess changes to the environment that may negatively impact ecosystems or public health(Panda et al., 2026). Traditionally, monitoring methods, including statistical analysis, laboratory analysis and manual sampling, all experience substantial limitations as the costs are too high; the time to produce these results is too long; and the level of accuracy is typically low(Hill & Narine, 2026). Because of limited financial resources available to environmental programs, environmental monitoring data collected usually have narrow applications due to small sample sizes and time delays between sample collection and result reporting, which occur in one of two ways: 1) delays cause missed decision opportunities in emergencies, and/or 2) human error and interpretation add an additional layer of inaccuracy to the manual methods(Yun & van Zundert, 2026). Both of these issues greatly reduce the accuracy of the data collected by manual methods(Manono et al., 2026). Budgetary limitations deny local governments from acquiring the advanced technology and trained individuals required for effective environmental monitoring due to lack of resources available, which impact those regions with very few resources(Soesanto et al., 2026).

By enhancing the objectivity and ease of use of environmental monitoring, artificial intelligence (AI) solves many of these problems (S. Singh & Singh, 2026). AI is a subfield of computer science that uses algorithms to simulate human intelligence in the tasks in question herein (i.e., sensing and reasoning) (KARACA et al., 2026). Examples of uses of AI to improve environmental monitoring include the processing of very large data sets, identifying patterns within the data, and using those patterns to make predictions about future events related to the environment such as predicting natural disasters or monitoring levels of pollutants (Samanta et al., 2026). By using AI techniques, organisations are able to collect data regarding the environment that is more accurate, faster, less expensive, more scalable and more integrated than traditional methods of environmental monitoring (Miller et al., 2025). For example, CNNs (Convolutional Neural Networks) are used to detect deforestation; SVMs (Support Vector Machines) are used to predict when harmful algal blooms will occur, and RNNs (Recurrent Neural Networks) can be used to predict flood events from long before any rain would have occurred (Kim et al., 2023).

AI's role in environmental monitoring brings both benefits initially and the potential for high costs initially, with a long-term view (Tetteh, 2026). This narrative review looks into the current status of AI technologies in environmental monitoring and their potential usefulness for future study and application (Magara & Phahlane, 2026).

Methodology

The use of AI in environmental monitoring and conservation has great promise, but also poses several challenges and ethical questions that need to be answered. These issues include: (1) data privacy; (2) algorithmic bias; and (3) transparency, which will be important to developing an equitable way for all areas to benefit from the use of AI by having varying levels of technological capability (min, 2023). Furthermore, AI will impact conservation through methods such as optimization algorithms and predictive modelling to rank/conservate habitats and increase effectiveness in the use of natural resources (Rizavi et al., 2026). AI can help identify threats to species and ecosystems when helping develop better strategies for managing them.

The ability of AI to analyse large amounts of environmental data will aid in predicting future ecological changes and assist in identifying high-value conservation sites (Zuo et al., 2026). While using cutting-edge AI technologies (computer vision, deep learning, machine learning) to complete tasks related to pattern recognition and data analysis in environmental science, AI has revolutionised how we perform research on the environment by providing better and more accurate data collection methods (Devisri & Manjula, 2026a).

Ecosystem conservation and understanding is still reliant on traditional methods (data analysis, remote sensing and field surveys), but these methods are being restricted due to accuracy, scalability and collection efficiencies (Hashmi et al., 2027). Traditional methods of data collection lag behind rapidly changing environmental conditions and do not provide the necessary data in time for effective management (Akpan et al., 2026a). The increasing limitations of older techniques illustrate that we need more advanced and dynamic monitoring and conservation strategies. AI methods will help to provide more accurate and efficient data collection through advanced methods (Dahiya et al., 1 C.E.).

This research presents an expansive assessment of the functionality of AI technology in regards to aiding in environmental protection and monitoring activities (Devisri & Manjula, 2026b). It incorporates methods of collecting data using satellite images, IoT sensors, and existing data sets - then using AI tools for model development to implement usage of AI-based monitoring, resulting in improved conservation efforts (Chimienti et al., 2025). Ethical considerations concerning the application of AI technologies are also discussed throughout the research. For example, raw data (which came from reputable sources) was subjected to a series of processes such as cleaning, normalizing, and aligning before being used in the analyses to ensure quality and consistency in the data sets used in this project (Liu et al., 2026).

The environment is polluted and this leads to various negative impacts on human health including respiratory disease, cardiovascular disease and cancer. If pollution from the environment is detected in a timely manner, it enables responders to take action so as to reduce exposure to hazardous substances or to intervene and treat people adversely affected by pollution (Khanam et al., 2023). By monitoring the levels of pollution in the environment, there is a reduction in health-related issues that are associated with environmental toxins. In addition, monitoring levels of pollution helps to preserve ecosystems and prevent a loss of biodiversity (Sharma, Sharma, et al., 2026). Understanding are the sources of pollutants,

such as emissions from industries, car exhaust; and runoff from agricultural practices, allows for the development and implementation of cleaner technologies and stricter emission laws(Oluwalana-Sanusi et al., 2026). Effective enforcement of environmental laws through proper detection of pollution is necessary to ensure compliance with these laws and foster more sustainable behaviours of both businesses and individuals(Essaid et al., 2026a).

Effective regulatory frameworks allow for appropriate measures to be taken against those causing environmental damage and motivate the adoption of responsible behaviours and more sustainable practices(Essaid et al., 2026b). Educating the community is also important because people who are informed about environmental issues are more likely to participate in activities designed to reduce pollution and improve the environment(Atef & Ramachandran, 2026). Public awareness campaigns are capable of making measurable changes in behaviour, including decreased use of cars and increased participation in clean-up activities, thus creating a healthier environment(Blaisdell, 2026). R and Python provide stakeholders with sophisticated methods for collecting and analyzing data, building models, and engaging with the public in their efforts to reduce pollution using AI(Tsiaras & Tampekis, 2026). By employing sensors (such as Google Nest and hardware created by various manufacturers) and IoT devices (such as smartwatches), AI can provide real-time information about air quality, water quality, and soil quality via data streams(Baby et al., 2026). Python assists with efficiently controlling the data stream; pyserial facilitates the connection of the hardware to collect data and the Pandas package manages the organization and processing of collected data(Kumar, 2026). In addition, R provides capabilities to conduct statistical analysis (e.g., using ggplot2 and dplyr for visualizing pollution trends) and visualize pollution trends through the use of visualization techniques(Naveed et al., 2026).

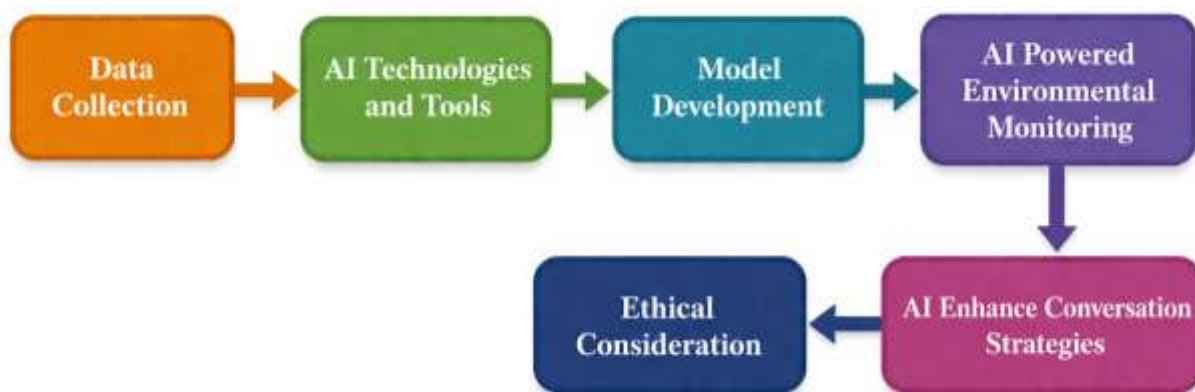


Fig 1. Methodology diagram.

There is empirical evidence of the impact of AI and IoT on monitoring the environment; IoT systems successfully monitor air and water quality, as they compile a substantial amount of information on pollutants (such as particulate matter and ozone) to help inform decision-making about how to manage the environment(Ramírez Díaz et al., 2026). AI has also improved soil quality through optimized agricultural practices, yielding better crops. Additionally, there is evidence that using advanced sensors with machine learning algorithms can detect hazardous materials at a level that balances accuracy and interpretability of the resulting model(Geddis et al., 2026). Various types of pollution analysis as applications of Python can be witnessed through multiple examples. In 2024, for example; Imam et al used machine learning techniques to categorize air quality across various locations using their research(Dawar et al., 2024). Han et al also pursued this approach of using statistical and machine learning methods to further refine their AI model based on contributions from pollution sources around the world(Zhao et al., 2026). Furthermore, Pradhan et al. discovered effective AI methodologies which involved using gradient boosting regression to quantify different air pollutant concentrations; while Carlos-Mancilla et al proposed an innovative smart platform that utilizes web scraping methods to aid in identifying and monitoring all types of environmental pollutants(Hackenberg et al., 2025).

monitoring is being revolutionized through AI-based technologies including devices Pollution that provide real-time alerts to pollution. Examples of the tools that allow for real-time visualisation of this type of data are; Django and Flask from Python, and Shiny from R. As an example of researchers that have incorporated IoT with Deep Learning in

monitoring of air pollution, are Gomathi et al (Gomathi & Malathi, 2026). They created a model that uses Long Short Term Memory (LSTM) networks in combination with the ADAM optimisation method to forecast particulate matter for the next hour (Bennis et al., 2026). Another example of how to monitor both air and noise pollution via the internet is from the research conducted by Prakash et al., who created a wireless Android application that incorporates data visualisation (Anees et al., 2026). According to Srivastava et al. they have developed an Internet of Things (IoT) based air pollution monitoring system which through data analysis is able to provide forecasts of the Air Quality Index (AQI) in real time, while utilising machine learning methods, such as support vector machines (SVM) and random decision forests, for both predictions and emergency notifications (P. Kumar. Dutta et al., 2026). Karkuzhali & Senthilkumar concluded that through AI and IoT, the quality of monitoring the environment relates to public health has greatly improved through effective air quality management (S. Ahmed et al., 2026).

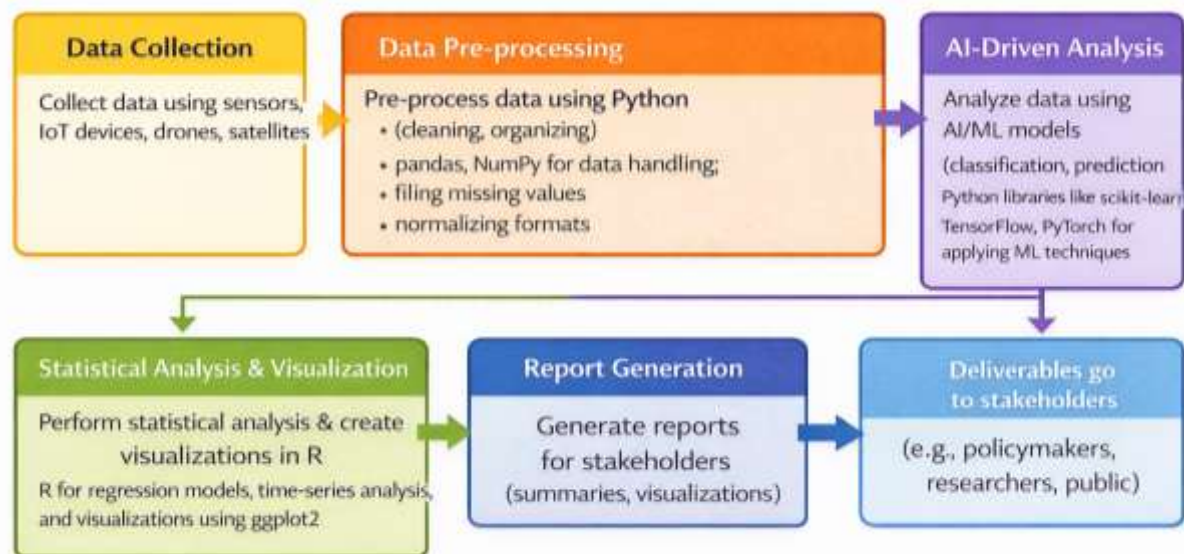


Fig 2. Example data analysis workflow in environmental monitoring using AI, Python, and R.

Fundamentals of Artificial Intelligence in Environmental Sciences

Key considerations include the following factors will help you choose the right AI model for environmental monitoring: data availability, compute resources, and level of expertise available to build the model (Shafik et al., 2026). For example, SVMs (support vector machines) can handle high-dimensional data and complex relationships very well, so they're a good model for image classification and natural language processing; they're also effective at identifying animals in the wild and detecting deforestation (Khare et al., 2026). Support vector regression (SVR), also an extension of SVMs, is highly effective for performing regression tasks within the field. Decision trees are also popular due to their ease of use and ability to explain how they work, which makes them good candidates for monitoring deforestation or assessing water quality; however, they have the disadvantage of increased likelihood of overfitting when used with complex data sets (Mandava & Sravanthi, 2026). A better option may be random forests because they combine decision tree methodologies with some level of robustness against overfitting across multiple data sources, but require higher computational power (Vijaya et al., 2026).

Due to their design specifically for image data, CNNs perform very well at recognizing complex patterns in pictures but require a large amount of labeled data as well as computing resources to build and operate (ElBehairy et al., 2026). Similarly, RNNs are well-suited for modeling sequential or time-series data and performing many types of predictive data analyses (e.g., predicting severe weather, generating environmental reports); however, like CNNs, they require significant amounts of computer processing power (Wen et al., 2026). More advanced models, such as CDLSTMs (convolutional deep long short-term memory), improve climate forecasting and groundwater modeling. Furthermore, hybrid models that incorporate both machine learning methods and deep learning methods will often perform better than either technology alone (Biswakalyani et al., 2026). While some machine learning models can be difficult to train, they can be convenient and powerful when used for many types of complex environmental system interactions. One example

of an innovative way to use AI and machine learning is to forecast air quality using the Synthetic Minority Over-sampling Technique with Deep Neural Networks (SMOTE+DB), which focuses on utilizing various sample data sources to anticipate changes in outdoor air quality (Mane et al., 2025).

Different AI models provide different strengths and weaknesses, emphasizing the need to choose the appropriate model based on the specific environmental applications. For example, support vector machines (SVM) and support vector regression (SVR) can be very effective for high dimensional data, however, these models can require extensive computational resources to implement (Coco-Bassey & Akpama, 2026). Decision trees can be very accessible but may not work as well with more complex data sets. Random forest models provide good flexibility at a cost of processing resources. Convolutional neural networks (CNN) perform very well with image-type data, but require the availability of very large data sets and significant processing power (Samal et al., 2026). Recurrent neural networks (RNN) are most appropriate for sequential applications; however, very detailed modelling approaches may be needed to accurately predict future events with this model type. Hybrid models can offer high levels of accuracy and reliability but can take a lot of time to develop (Qudah, 2026).

Principles

Key principles govern the creation of AI models, which serve as guidelines for intelligent system development, data-driven learning (i.e., how to develop an intelligent system through data), generalization, feature engineering (i.e., how to identify and derive valuable features from a dataset), and balancing model complexity (Dhanka et al., 2025). Data is at the heart of all AI systems. AI models employ large datasets to learn by identifying patterns in the data they are trained on. For example, in the area of environmental monitoring, the SMOTEDNN model has been used to predict air quality using data from numerous sources, as well as to track water quality using common parameters such as pH and turbidity. Generalization allows AI models to apply their learnings from a subset of data to other datasets (i.e., using information from one type of data set to predict the outcome of a different type of data), enabling applications in climate forecasting and wildlife conservation (Gupta & Mahapatra, 2025). Feature engineering involves choosing the most important variables to produce an accurate prediction. When monitoring both water quality and agricultural yield, choosing the appropriate variables is critical to an accurate prediction. A balance between model complexity and model simplicity is required to prevent difficulties such as overfitting. The use of a proper balance is essential when evaluating the performance of models used for environmental monitoring or urban planning (Gao & Zheng, 2024). The application of continuous learning (or the ability of AI systems to continue evolving by adding new data) will further improve the performance of AI models used for deforestation monitoring or healthcare providers' forecasting of disease outbreaks. Finally, building models that are interpretable and easy for users to understand is essential. In many cases, interpretable models are particularly important for building trust and maintaining ethical practices. The use of interpretable models (such as those produced by decision trees) is necessary for developing policies that will help protect the environment (i.e., assist in tracking deforestation). Overall, these best practices provide a foundation upon which AI models can be developed (Jiang et al., 2025).

AI Applications in Environmental Monitoring

Air Quality Monitoring and Forecasting

Air Pollution has become one of the most serious problems facing our planet today. Pollution has been directly linked with poor health outcomes, and economic growth can be affected by the level of air pollution in our communities (Navas-Acien et al., 2026). Today there are many significant health problems related to the air we breathe, including different types of cancer, heart disease, and respiratory illnesses. To help address air pollution (which is an issue we will all continue to face), we are seeing technology such as AI being integrated into air quality monitoring systems as a potential solution to this urgent problem. With the ability to provide real-time, accurate measurements of air quality, AI systems offer valuable data to support decision-making and policy development aimed at reducing air pollution and protecting the public's health (Hoek et al., 2026).

AI technology uses machine learning methods to analyse data from many different sources, including real-time data generated with air quality sensors and satellite imaging, as well as historical data from weather reports, in order to

provide timely information about air quality. Machine learning is able to utilize some of the same types of algorithms to identify the sources of pollution, predict pollution levels, and suggest ways to decrease air quality deterioration by making use of underlying trends and patterns (Janikovičová et al., 2026). The most common AI methods used in assessing air quality include Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Support Vector Machines (SVM), and Fuzzy Logic. Choosing which method/algorithm to use generally depends on the types of information you require and what types of pollutants you are monitoring (S. Wang et al., 2026a).



Fig 3. Role of Artificial Intelligence in Environmental monitoring.

Research has shown differences in the performance of these AI models. A systematic review of the literature done by Masood and Ahmad (2021) suggested that the DNN is the best-performing tool for predicting air quality, while Dobrea et al. (2020) found Support Vector Regression (SVR) and Autoregressive Integrated Moving Average (ARIMA) to be superior for time series analysis of particulate matter (PM) $\leq 10 \mu\text{m}$ and $\leq 2.5 \mu\text{m}$ —two sizes of PM that can significantly affect health (S. Wang et al., 2026b). Additionally, Subramaniam et al. (2022) highlighted the benefits of creating hybrid models by taking the best components of several AI techniques in order to improve decision-making about environmental policy. This type of hybrid AI framework was also validated by Fu et al. (2022), who indicated that hybrid AI models could be used reliably to forecast air quality as a method for improving environmental decision-making (Elabd et al., 2026).

AI monitoring systems are much more efficient than traditional monitoring systems because they can assimilate large amounts of data from numerous location sources of air quality in near real time and provide a comprehensive picture of air quality at any given moment. AI also increases the accuracy and precision of the data analysis process, reducing errors associated with traditional monitoring. AI techniques can develop customised solutions based on the source of the pollution and geographic location, allowing for initiatives such as traffic reform, industrial process adjustments, and urban planning modifications to be undertaken. AI recommendation systems are f(Al-Quhfa et al., n.d.).

AI-enhanced technologies have found uses in many industries for monitoring and improving air quality. One of the most important uses is in urban planning, where AI analyzes both traffic data and urban development data to develop site-specific strategies for reducing air pollution. An example would be using traffic data to propose changes to traffic flows

or using urban development data to suggest modifications to the layout of a city that would allow for improved air circulation(Akpan et al., 2026b). For manufacturers, AI applications can provide insights into the types of materials and energy sources to use by examining emissions data and making suggestions for alternative materials/energy sources to optimize production while reducing waste. Another area of use is related to public health. AI algorithms examine the relationship between air quality and health outcomes, allowing health professionals to locate vulnerable populations and design appropriate health interventions. An example of this would be when AI recommends modifications to public transit routes to facilitate reduced access to environmental pollutants for at-risk populations(Q. R. Wang et al., 2026).

In general, AI provides a new way to approach air quality and managing air quality, and has enormous potential to change public health outcomes and support proactive public policy initiatives related to the environment.

Water Quality Monitoring

The viability of humanity is heavily tied to water quality, which is extremely important for public health. Unfortunately, this valuable resource is being compromised as a result of pollution, climate change and population growth(Mathew et al., 2026). Traditional methods for monitoring water quality are often laborious, expensive and limited in their range; thus, they carry a higher risk for human error and long analysis times. Recently developed machine learning methodologies via artificial intelligence (AI) offer a paradigm shift towards more accurate and timely real-time monitoring of water quality(P. Dutta & Sarma, 2026a).

Machine Learning algorithms can leverage numerous data sources, such as meteorological data, historical records and sensor data to recognize patterns that can be indicators of declining water quality. AI techniques such as Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) models have been found to have very high accuracy rates in determining various water quality indicators; thus, forming the foundation for the Water Quality Index (WQI). There are several advantages to using AI over existing methods: The ability to continuously monitor water quality, which allows immediate detection and reaction to contamination risks to protect human health and the environment(Suman et al., 2025). Fast processing times mean that vast amounts of data can be analyzed quickly to identify patterns, project future water quality problems and recommend specific remediation actions, such as optimal treatment options or pollutant control options.

AI is a tool that can help many industries, including: water resource management, agriculture and environmental protections(M. Singh et al., 2026). When applied to water management (i.e., water treatment), AI applications can develop effective solutions for specific water treatment problems (e.g., filtration system solutions, chemical treatment solutions, etc.) and create a more efficient way to address water quality issues (e.g., through monitoring of irrigation processes, developing optimal cropping schemes). When applied to agriculture, AI applications can assist with developing efficient irrigation processes and cropping schemes to mitigate water quality issues. Similar applications of AI technology can also improve environmental protections through the development of methods to control pollution and to preserve aquatic ecosystems(El-Emam & Shata, 2025).

Numerous studies have demonstrated successful use of AI technology for water quality monitoring activities and water quality testing. Additionally, these studies demonstrate that AI technology improves water quality monitoring tasks compared to traditional methods. Different research studies have employed different methodologies, such as deep learning networks, decision trees and support vector machines, to monitor critical water quality characteristics (i.e., temperature, pH, dissolved oxygen). All of this ongoing research illustrates the need to develop better data standards for water quality and to create better AI-based technologies to utilize multiple data sources for water quality monitoring(P. Dutta & Sarma, 2026b). AI-based water quality monitoring provides a dramatic improvement in addressing many of the shortcomings of traditional water-related monitoring methods and will help advance the process of managing our water resources while protecting the health of our communities as we deal with increasing global environmental challenges.

Soil and Agricultural Monitoring

The use of artificial intelligence (AI) for soil monitoring represents a new paradigm for the management of agriculture, conservation of the environment, and planning for land use. Traditional soil monitoring techniques rely heavily on manual sampling of soil and subsequent laboratory analysis, which is often limited by the time required for these

sampling methods and the effort to analyze the samples(Shi et al., 2026). With the introduction of AI to soil monitoring, there are many innovative new techniques that can improve soil monitoring by providing greater accuracy, more efficiency, and greater scalability.

Machine learning algorithms like Random Forests and Decision Trees are increasingly proving themselves able to handle large volumes of high-dimensional, complex datasets. These algorithms analyze large amounts of data collected from several different sources to predict the physical and/or chemical characteristics of soil, such as moisture, nutrient levels, and pH. For example, estimates of soil organic carbon stocks calculated using Random Forests have been shown to improve accuracy compared with the estimates of soil organic carbon stocks generated from standard statistical methods(X. Wang et al., 2026). The development of support vector machines (SVMs) makes it possible to classify soil based on its physical and chemical characteristics and produce more accurate assessments of soil health.

Soil Monitoring Using Deep Learning Models

Image-based soil analysis with deep learning models, in particular Convolutional Neural Networks (CNNs), has the potential to make a big impact on soil monitoring. Using images taken from satellites or drones, CNNs can use those images to find patterns associated with soil health, erosion, and contamination. Drones equipped with specialized cameras can capture high-resolution images for AI algorithms to evaluate soil health and detect problems such as nutrient deficiencies or pest infestations(Seethapathy et al., 2026). Recurrent Neural Network (RNN) models can help with time-series analysis by predicting soil properties' future value based upon historical values, allowing for better proactive soil management(Teymoori et al., 2026).

AI's capabilities in soil monitoring will further increase with the integration of smart sensors and the Internet of Things (IoT). IoT-enabled smart sensors will be able to continuously monitor soil parameters such as moisture, temperature, and nutrient levels, allowing for near real-time data collection and analysis of soil conditions. This enables AI algorithms to produce actionable soil management insights from the data received(Suthar et al., 2026). An example of this would be the Arable Mark 2 device, which combines weather, soil, and crop data to provide a more comprehensive view of field conditions. Another example of how AI can provide real-time recommendations for soil management is the John Deere Operations Center.

There are many benefits to using AI for soil monitoring. Farmers and land managers can get information on current soil conditions so they will be able to make better choices; this results in fewer mistakes when forecasting. Because AI systems can be scaled up or down to accommodate the size of the agricultural ecosystem, large scale-farming operations will benefit from its expansive reach and ability to provide accurate assessments of large agricultural areas(Yang et al., 2026). The power of AI to predict performance can help farmers schedule irrigation, fertilization and other activities more effectively, as well as ensure they are using sustainable farm practices.

Despite these many advantages, there are challenges involved in implementing AI for soil monitoring. The effectiveness of the AI model will depend on the amount and quality of soil data that is available; if the dataset is only partially completed or contains incorrect amounts of data, the results from the AI will not be reliable. Additionally, implementing an AI technology requires a lot of initial investment and retraining of employees; even though once it is operational, the costs of use are usually less than the manual labour that had to be performed before AI was adopted(Bick et al., 2026). Therefore, it is essential to address these challenges if AI is going to be able to deliver on the promise of transforming soil monitoring and to be widely adopted. Overall, the incorporation of AI into soil monitoring reflects an innovative shift in the way farmers manage and protect the environment. By using machine learning, deep learning technologies and IoT devices, AI provides accurate and timely monitoring of the health of soils on a large scale(Subash et al., 2026).

Climate and Weather Data Analysis

In the 21st century climate change has become a major global challenge impacting all human existence throughout the world. Increased sea temperature and acidification in addition to rising sea levels and extreme weather events represent immense threats to our planet's health. As detailed by Ford et al. (2022), these conditions will continue to have substantial sociological and ecological consequences with future implications expected to be even worse than those occurring now. Average global temperatures have risen by 0.60 C since 1950 contributing to decreased agricultural production, soil

erosion, desertification, environmental degradation, acidification of oceans, depletion of freshwater resources, plant and animal habitat loss, and ozone depletion(Mahbod, 2026).

Due to the complexity and magnitude of consequences associated with climate change, there are numerous multidisciplinary research projects underway around the world to increase the understanding of climate change through gathering scientific data on the Earth's climate system. The Paris Agreement represents an international agreement to limit temperature increases due to global warming to to less than two degree Celsius, although legally binding commitments to reduce greenhouse gas emissions are nonspecific(Arey et al., 2026). Countries across the globe have determined it is necessary to take action to mitigate the effects of climate change; they have committed to reducing their emissions through , and through the development and implementation of new technologies to reduce greenhouse gas emissions.

Earth system models (ESMs) and services have a value to society by providing support for social processes and informing policies on climate change and how to mitigate climate change. Weather models are built from simulations of various interactions between the components of the Earth's system, including the atmosphere, oceans, the land surface, and ice using mathematical models(Volodin et al., 2026). Bala and Pandey (2020) describe ESMs as being important for understanding past climate variability, predicting future climate variability and estimating the impacts of human activities on the climate.

The rapidly increasing amount of data being generated through various forms of Earth system data (e.g., new Earth Observation (EO) satellite technologies and cost-effective crowd-sourced sensors) puts Earth system science in a position to use new deep learning (DL) techniques to analyze their data. The majority of the algorithms and ESMs that are currently used to analyze large amounts of Earth system remain manually built and, therefore, have limited ability to scale their models when processing large data sets(Salehi, 2026). ESMs have been built over many years of climate data collection and require testing to demonstrate that the model produces good representations of real-world climates. Weather models are mathematical equations that predict the atmosphere's state at some time in the future based on the state of known variables at some time in the past(Sartori & Fogt, 2026). To determine the future-state prediction, these equations require numerical methods to solve systems of complex and non-linear equations, typically governed by laws of conservation such as momentum, energy, and water mass. General circulation models (GCMs) simulating the ocean currents and dynamics in conjunction with atmospheric movement and their connections while accounting for hydro-climate interaction variables using a variety of temporal and spatial scales. Regional climate models (RCMs), use global data to achieve finer resolution of local climate by performing dynamic downscaling of the global datasets(Abbas et al., 2026). Validating the performance of complex climate models against recent climate observations is important for validating the accuracy of those models.

As the complexity of the climate models continues to grow and the amount of observational data expands, so too does the use of artificial intelligence (AI) in weather forecasting. AI is being used to increase the accuracy of forecasts, reduce the bias of predictions, and develop new climate models. The main contributor to climate change is the anthropogenic accumulation of CO₂ in the atmosphere(Alagoz et al., 2026). CO₂ can remain in the atmosphere for centuries to thousands of years. Many countries have started to use AI-based techniques (e.g., Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Artificial Neural Networks (ANN)) to produce improved rainfall forecasts, and other types of rainfall and land use forecasts, while accounting for environmental variables. Research has shown that AI-based models are more accurate for summer-month predictions than winter-month predictions, and that AI-based model prediction results are closely aligned to the CMIP6 models' performance metrics(Çiftçi et al., 2025). In addition, machine learning methodologies have been shown to be superior for predicting extreme heat events than traditional methods, providing significant value to communities and decision-makers. In other words, artificial intelligence has been used very successfully in developing and assessing carbon markets because of its ability to create more accurate carbon market concepts and more flexible pricing mechanisms(Bisiotis et al., 2025). This is especially true based on research conducted related to carbon trading programs in several areas including the UK and China.

Human and Epidemiological Monitoring Related to Environmental Pollutants

Artificial intelligence (AI) has shown to be an effective tool for monitoring human health related to environmental pollutants through the use of machine learning algorithms such as Gradient Boosting Machines (GBM) and Random Forests (RF)(Alkharashi et al., 2026). The fast processing of large amounts of data will allow the use of data-driven methods for predicting the occurrence of both cardiovascular and respiratory diseases caused by air pollution through predictive models that use large datasets.

IBM Watson Health is a great example of how AI can be used in the medical field to identify a patient's risk of having a disease before they become symptomatic. AI has also improved our ability to assess people's exposure to pollutants by using deep learning and data collected from a variety of sources including wearable sensors and satellite imagery to correlate the degree of exposure with health status(Afri et al., 2026). An example of a project that has utilized AI for monitoring air quality in real time is the Air Quality Egg, which uses both IoT sensors and AI. AI can also be used for monitoring disease outbreaks through the use of natural language processing techniques to automate the collection and analysis of data. HealthMap is another example of an AI-based tool that monitors disease outbreaks on a global level and enables rapid response to public health emergencies(Sharma, Kumar, et al., 2026).

AI will also continue to be a valuable resource for epidemiological surveillance through automating data collection and analysis as well as for predicting and simulating the health effects of air pollution on population health through tools such as the European Air Quality Portal. AI technology has made substantial improvements; however, there are very serious difficulties with AI tools. These difficulties include security or data privacy issues and algorithmic bias. The development of diverse datasets and the creation of ethical guidelines for AI use in public health are essential to the success of AI technologies(Rabiee, 2026). The benefits that AI offers for environmental monitoring include an improved ability to process large amounts of information quickly, which will allow more rapid action and lower environmental-monitoring costs; however, there are significant challenges in terms of collecting quality data and the availability of quality data(Sultan, 2026).

AI in Environmental Remediation

Soil Remediation Using AI-Assisted Technologies

As a result of swift industrial growth, increased farming intensity, and incorrect disposal methods, soil contamination has developed into one of the greatest concerns regarding the natural environment(Mutinta, 2025). The degradation of soil quality from contaminants such as heavy metals and pesticides has had a negative impact on agricultural productivity and has created potential negative effects on human health and ecosystems. Traditional remediation processes have proven to be inefficient, expensive, and typically time-consuming in addressing the complexities associated with contamination patterns. In this context, the artificial intelligence (AI) technology of machine learning and deep learning are beginning to be relied upon as much more powerful approaches for improving the efficiency and cost-effectiveness of soil remediation solutions(Zhang et al., 2026).

AI technologies have been developed to assist with the analysis of large amounts of complex data about environmental contaminants, such as identifying contamination patterns, predicting how pollutants will move and behave, and designing optimized remediation strategies. A key application of AI in soil remediation is site characterisation and contamination mapping. By using remote sensing data, geographic information systems (GIS) data, and soil sensor data to feed into an AI model, the AI model can accurately identify contaminated sites and produce a remediated contamination map(Madgaocar et al., 2026). An example of this type of AI based model would be to use machine learning methods, such as random forests, to classify different soil types and predict the location of various contaminants (i.e., lead, cadmium, and arsenic) within those soil types.

Predicting the fate of pollutants in the soil environment and their behavior is also a major application of artificial intelligence. In addition to the ability to simulate how pollutants are transported through soils, AI models consider many factors that impact the behavior of these contaminants including the soil texture, pH, moisture content and the presence of microbial activity(Wahid et al., 2026). The prediction capabilities offered by AI provide researchers and environmental managers with the tools to assess the risk of contamination, and to design and implement targeted

remediation strategies. Compared to traditional modeling approaches, AI-based models are able to better accommodate the nonlinear relationships and complex interaction between soil contaminants (Anokye, 2026).

AI plays a critical role in improving remediation technologies, such as bioremediation, phytoremediation, and chemical remediation. In bioremediation, for example, AI can help identify the optimal microbial strains and environmental conditions for degrading pollutants. Similarly, in phytoremediation, AI can provide recommendations for the most suitable plant species to utilize for contaminant uptake and/or degradation. Ultimately, by analyzing field and laboratory data, AI will enable the optimization of all necessary parameters for maximum remediation efficiency (such as nutrient levels, temperature, and moisture) to ensure that remediation is as effective as possible (P. Singh et al., 2026).

AI-driven technologies enable active and adaptive management of cleanup activities in contaminated areas through real-time monitoring and continuous collection of soil property data collection and pollutant concentration measurements using sensors. AI algorithms analyze these continuous measurements to develop real-time insights from the data and dynamically adjust cleanup method(s). Active management of soil cleanup will lead to greater efficiency, reduced costs, and decreased likelihood of adverse effects to the environment from contaminated soil and soils being cleaned up (Basheer et al., 2026).

In addition, AI can serve as a decision support tool for Env. Mgmt. Decision support tools pull information from multiple sources, then synthesize and provide specific recommendations to policy-makers/developers regarding best practices or options available. For example: AI can be utilized in determining when and where to remediate sites through risk assessments, economic feasibility, and potential environmental consequences. The application of AI in decision making will permit the more effective use of scarce financial and physical resources directed towards the protection of environmental quality (Çelik et al., 2026).

While there are many benefits to the use of AI for soil cleanup, there are also many associated challenges such as large, high-quality databases, interpretability of models and the integration of AI with current environmental management systems. Field validation and scalability of AI applications will also be critical to implementation of AI for soil remediation. The rise of AI-supported technologies has revolutionized the process of soil remediation in terms of precision, efficiency, and sustainability (Jana & Bhunia, 2026). advanced data analysis, predictive modeling, and the optimization of remediation methods enable AI to provide new ways to address complex soil contamination issues, making it a promising avenue for future research. Future research should investigate the integration of AI with emerging technologies, including remote sensing and IoT, to expand its capabilities in environmental management even further (Gowda et al., 1 C.E.).

Water and Wastewater Treatment Systems

The increasing need for access to clean drinking water, combined with the rising amount of wastewater created by industries and households, have created a dire need for effective treatment systems in order to support sustainable development. Many traditional methods used to treat both water and wastewater typically use fixed operational parameters and manual processes to monitor performance, which can limit their ability to operate efficiently or respond to changing conditions (Morchid, Qjidaa, et al., 2026). Over the past few years, Artificial Intelligence (AI) as well as Machine Learning and Deep Learning techniques have emerged as game-changing technologies that can help improve the overall performance, automation, and reliability of both types of treatment systems. Currently, AI is being utilized extensively for both the monitoring and predicting of water quality. By utilizing large data sources (such as data collected from sensors, laboratory measurements, or remote sensing), AI can predict key parameters of water based on the use of models that identify and correlate key characteristics of the data (e.g., turbidity, pH, DO, and COD), and the models can also analyze large amounts of real-time data so that machine learning algorithms can identify trends and detect anomalies (Morchid, Elbasri, et al., 2026). This can help improve the safety of drinking water as the opportunity exists to know when water has been contaminated prior to someone consuming said treated water.

AI will also play an important role in optimizing treatment processes in WWTPs (Wastewater Treatment Plants). The treatment of wastewater is a complex process that consists of a combination of biological, chemical, and physical processes, which include the use of activated sludge systems, membrane filtration, and disinfection (W. Ahmed et al.,

2026). AI can analyze operational data so that treatment processes can be optimized by better controlling certain parameters (i.e., aeration rate, sludge retention time, and chemical saturation). The use of AI in treatment will result in higher treatment efficiency and less energy being used, while also providing both lower operation costs. AI control systems can automatically change the aeration of the biological treatment units to help keep the right level of the microbes performing well through its changes in aeration due to better increased treatment systems (Borowska et al., 2026).

AI will also be of major benefit when it comes to the management of predictive maintenance and fault detection through monitoring of the overall operation of the systems for the many failures (equipment failures), membrane fouling and process stability/instability that occur at the wastewater treatment plants (WWTP) and using predictive models that forecast the potential for unwanted failures against maintenance schedules thus assisting in minimizing down time and increasing the reliability and life of the treatment components of the infrastructure (Domaneschi et al., 2026).

AI can assist in helping make decisions regarding the use and management of resources through the use of decision support systems by integrating data from multiple sources and providing recommended solutions to water reuse, sludge management, and process control. AI can also assist in optimizing the water distribution network through the forecasting of demand and the reduction of losses associated with any leaks or inefficiencies. Though there are many benefits of using AI, there are also challenges such as the need for quality data, the need for proper integration related to the existing infrastructure, and concerns related to interpretability (Keshavamurthy et al., 2026). The advancement of sensor technology and the associated data analytics will continue to address these limitations. Water and wastewater treatment procedures are being transformed through intelligent process monitoring, process optimization, and predictive management with the help of AI-based technologies. These methods provide an excellent opportunity to increase efficiency, lower costs, and facilitate sustainable use of water resources in response to growing environmental issues (Daokoru-Olukole et al., 2026).

Challenges, Limitations, and Ethical Considerations

AI's application for monitoring the environment is very promising, but there are some limitations that need to be resolved before it can be fully utilized. One major issue is that AI applications depend on large amounts of quality data to successfully train an AI model. There is not enough reliable evidence, which creates issues with bias in a dataset and subsequently skewed predictions, which will continue to open doors to inequality (Lin, 2026). In addition, when an AI model uses too many parameters (complexity), it will fit the training data but will have issues when it comes to generalizing to new data. This requires that those using AI applications for environmental monitoring strike a balance between the level of detail included in their model and their ability to generalize based on observations of a particular phenomenon.

In an environmental monitoring context, trust in AI outcomes is critical because many times the consequences of those outcomes will have severe implications (Regona et al., 2026). Models that are not interpretable (black box type models, e.g., deep learning) create an issue of trust and interpretation. In many cases, only large organizations and developed countries are capable of utilizing AI due to high levels of resource utilization of sophisticated AI applications. In addition to ethical concerns about bias being perpetuated due to details of training datasets, fairness in AI applications that require equitable outcomes will need to be positive at all stages. Another barrier to AI environmental monitoring applications is that they are highly susceptible to adversarial attacks where input data that are manipulated in a manner that will result in the AI predicting incorrectly (Forouzesh Nejad et al., 2026). Safeguarding against these attacks is critical for environmental monitoring applications. AI also has a large environmental footprint as a result of the high energy costs associated with its widespread application for training AI models.

While these limitations exist today, there is still hope for AI's role in improving the monitoring of the environment. The next few years will continue to see new advancements in algorithm techniques, better ways of collecting data, and new processing hardware that will allow for higher levels of accuracy and processing efficiencies when using AI tools for the environment (Ali et al., 2025). Going forward, researchers should focus on creating more resilient AI models that can analyze complex environmental datasets; ensuring that these models include considerations around their ability to be interpretable and that they do not present ethical or security risks. Researchers, policymakers, and industry need to work

together in order to facilitate responsible innovation and to promote the equitable use of AI in environmental science (Madhura et al., 2027).

Future Prospects and Research Directions

The future use of Artificial Intelligence (AI) to transform Environmental Monitoring and Remediation. Advances in Machine Learning and Deep Learning will create AI systems that will improve data accuracy, efficiency, and capability to interpret complex Environmental Data (Fosso-Wamba et al., 2026). One of the biggest potential advantages of using AI is its ability to integrate with Smart Sensors and IoT (Internet Of Things) to provide real-time monitoring of specialized Environmental Parameters such as air, water, and soil quality. Continuous sources of data will be used by AI algorithms to detect anomalies in Environmental Data Systems (e.g., detecting pollution), as well as providing early warning systems for Environmental Hazards and allowing for timely interventions (Pham et al., 2026). AI will also enhance Predictive Environmental Management in the future by providing highly accurate forecasting models for Pollution rates, Climate Change, and Ecosystem degradation. This will give Policy Makers and Environmental Regulatory agencies the ability to take preventive measures rather than reactive ones, resulting in more sustainable Environmental Management practices.

AI will also increase the efficiency of Environmental Remediation techniques, such as using (but not limited to) Bioremediation and Phytoremediation techniques by allowing AI to analyze Environmental data to develop recommendations for optimal microorganisms to use in combination with the Plant species and Treatment Conditions for pollutant removal (Krishna Raj et al., 2025). Furthermore, AI will support the development of specialized materials and technologies to conduct Targeted Remediation projects. AI enabled drones and robots is also a growing purpose area. They can also be used for environmental monitoring, pollution detection and cleanup of hazardous or inaccessible areas, providing safety for humans and improving operational efficiency (Etim et al., 2026). AI also offers decision support systems that integrate environmental, economic, and social data to provide the information necessary for making sustainable policy and resource management decisions, but there are still challenges to be resolved such as ensuring the quality of data, developing transparent models and integrating with existing government regulations. Overall, the application of AI has the ability to dramatically change the manner in which environmental monitoring and remediation occurs by providing real-time analysis, predictive capabilities and optimized solutions for sustainable environmental protection (Raj & Roy, 2026).

Conclusion

Artificial Intelligence (AI) has become a game-changer in environmental monitoring and remediation by providing an effective method to analyze and manage complex datasets through the use of advanced technologies, such as Machine Learning and Deep Learning. With the ability to predict changes in the environment as well as provide support for developing effective remediation strategies more quickly and accurately than ever before, AI has revolutionized the way we approach environmental monitoring and remediation. AI has been instrumental in revolutionizing the way air, water, and soil quality is monitored in real-time by providing faster data analysis, detection of pollution, and the ability to provide recommendations on how best to prevent further damage. In addition, AI has improved the processes of bioremediation and phytoremediation by allowing researchers to optimize operational parameters and select the most appropriate treatment options for environmental remediation projects. The use of AI in conjunction with emerging technologies such as IoT, remote sensing, and robotics will continue to be an important factor in solving the pressing issues posed to the environment.

There are still some limitations associated with the use of AI, including the need for high-quality datasets, challenges associated with understanding and interpreting model outputs, and challenges with integrating AI systems into existing infrastructure and regulatory frameworks that govern current environmental policies. Addressing these limitations is paramount to the widespread use of AI-based solutions for environmental monitoring and remediation. In closing, AI represents a unique opportunity for the world to move towards a more sustainable way of managing the environment by providing increased efficiency, accuracy, and overall decision-making abilities. Increased research and development, as well as technological advancements will continue to assist in this effort.

References

- Abbas, S. H., Soomro, W. A., & Ali, S. (2026). MACHINE LEARNING-BASED DOWNSCALING OF CLIMATE MODELS USING REMOTE SENSING AND GIS DATA FOR HIGH-RESOLUTION ATMOSPHERIC FORECASTING. *Spectrum of Engineering Sciences*, 4(2), 407–425. <https://doi.org/10.5281/zenodo.18639201>
- Afri, A., Grara, N., Mellouk, F. Z., Bouchaala, L., Alzahrani, K. J., Aslam, A. A., Irfan, M., & Ahmed, M. (2026). Decoding Human Exposure to Toxic Metals: Linking Environmental Distribution to Health Outcomes Through Multivariate Analysis. *Journal of Chemistry*, 2026(1), 4977768. <https://doi.org/10.1155/joch/4977768>
- Ahmed, S., Pasha, A., Kumer, T., Akhtaruzzaman, M., & Hossain, M. (2026). Advancements in Air Quality Monitoring Systems: A Comprehensive Review of Emerging Technologies for Enhancing Environmental Health. *Indoor Air*, 2026(1), 3080684. <https://doi.org/10.1155/ina/3080684>
- Ahmed, W., Kitajima, M., Tandukar, S., & Haramoto, E. (2026). A full-scale Co-located comparison of virus removal by membrane bioreactor and conventional activated sludge systems. *Water Research*, 292, 125352. <https://doi.org/10.1016/j.coesh.2020.02.009>
- Akpan, E. E., Akinlade, O., Alabi, O. O., David, O. A., Afe, O. F., & Ajagbe, S. A. (2026a). Optimizing Traffic Signal Control Using Machine Learning and Environmental Data. *Artificial Intelligence and Applications*, 4(1), 48–56. <https://doi.org/10.47852/bonviewaia52024199>
- Akpan, E. E., Akinlade, O., Alabi, O. O., David, O. A., Afe, O. F., & Ajagbe, S. A. (2026b). Optimizing Traffic Signal Control Using Machine Learning and Environmental Data. *Artificial Intelligence and Applications*, 4(1), 48–56. <https://doi.org/10.47852/bonviewaia52024199>
- Alagoz, B. B., Keles, C., & Baran, B. (2026). A note on effects of fossil fuel reduction policies on atmospheric carbon dioxide buildup and global warming. *Journal of Atmospheric and Solar-Terrestrial Physics*, 279, 106724. <https://doi.org/10.1016/j.jastp.2026.106724>
- Ali, I., Selim, A., & Skender, F. (2025). Leveraging OCR and AI Tools: A Comparative Guide to Enhancing Data Processing and Decision-Making Efficiency in the Digital Age. *Turkish Journal of Engineering*, 10(1), 129–142. <https://doi.org/10.31127/tuje.1796566>
- Alkharashi, A., Al Mazroa, A., M. Alashjaee, A., V, S., M, D. B., S, S., & S, V. (2026). Machine learning models for biogas potential in sustainable aviation: XGBoost, random forest and ridge regression. *Aircraft Engineering and Aerospace Technology*, 98(4), 605–613. <https://doi.org/10.1108/AEAT-12-2024-0369>
- AL-Quhfa, H., Mothana, A., & Song, J. (n.d.). 6992 *A Systematic Review on Data-Driven Traffic Management for Sustainable Urban Transport*. <https://doi.org/10.35444/IJANA.2025.17402>
- Anees, M., Raveesha, L. N., Rakesh, G. K., Muruli, R., & Yashwanth, P. (2026). IoT solutions for environmental monitoring: Current approaches and future directions. *Information and Communication Systems*, 844–851. <https://doi.org/10.1201/9781003650201-134>
- Anokye, A. (2026). Machine Learning–Enhanced PFAS Contaminant Fate and Transport Modeling for Optimized Groundwater Remediation Strategies at Industrial Sites. *Journal of Sustainable Development and Policy*, 5(01), 34–72. <https://doi.org/10.63125/e3x2tt57>
- Arey, J. S., Socolofsky, S. A., Kessler, J. D., Zhao, L., Healy, T. M., Canalizo-Hernandez, M. A., & Nedwed, T. J. (2026). Deep-Ocean Sequestration of Excess Produced Gas to Mitigate Greenhouse Gas Emissions from Offshore Flaring. *Environmental Science & Technology*. <https://doi.org/10.1021/acs.est.5c06770>

Atef, R., & Ramachandran, B. (2026). Promoting Community Engagement and Environmental Awareness Through Educational Initiatives. *Environmental Education and Sustainable Development*, 261–281. https://doi.org/10.1007/978-3-032-05760-0_13

Baby, A., Agboola, O. P., Paul, A. R., & Sunny, S. (2026). AI and IoT Innovations Transforming Industries and Enhancing Urban Sustainability. *Intelligent Mobile and IoT Ecosystems*, 217–235. <https://doi.org/10.1201/9781003608653-12>

Basheer, M. Z., Huang, X., Cai, X., Cui, Y., & Muhammad, M. (2026). Integrating chemical and microbial strategies for heavy metal remediation in contaminated soils: opportunities, challenges, and key factors. *Environmental Science and Pollution Research* 2026 33:1, 33(1), 67–85. <https://doi.org/10.1007/s11356-025-37281-8>

Bennis, M., Youssfi, M., Morabet, R. El, Alsubih, M., & Khan, R. A. (2026). Particulate matter (PM_{2.5} and PM₁₀) prediction using fourier series decomposition in combination with LSTM and SVM. *Scientific Reports* 2026 16:1, 16(1), 7665-. <https://doi.org/10.1038/s41598-026-38436-4>

Bick, A., Blandin, A., & Deming, D. J. (2026). The Rapid Adoption of Generative AI. <https://doi.org/10.1287/Mnsc.2025.02523>. <https://doi.org/10.1287/mnsc.2025.02523>

Bisiotis, K., Christopoulos, D., & Tzougas, G. (2025). Forecasting Carbon Prices: A Literature Review. *Journal of Forecasting*, 45(2), 496–529. <https://doi.org/10.1002/for.70054>

Biswakalyani, C., Samantaray, S., & Satpathy, D. P. (2026). Application of Hybrid Machine Learning for Groundwater Level Prediction: A Comprehensive Review. *Archives of Computational Methods in Engineering* 2026, 1–59. <https://doi.org/10.1007/s11831-025-10447-w>

Blaisdell, R. (2026). *THE COLLECTIVE BINATIONAL PERSPECTIVES OF THE TIJUANA RIVER POLLUTION*.

Borowska, W., Godzieba, M., Ciesielski, S., & Zubrowska-Sudol, M. (2026). Impact of variable aeration on partial nitrification/anammox (PN/A): Insights from batch testing and microbial analysis. *Process Biochemistry*, 162, 62–73. <https://doi.org/10.1016/j.procbio.2026.01.007>

Çelik, M. A., Ağırkaya, M. B., & Gameda, D. O. (2026). Bridging data scarcity with AI methodology: Global research trends in machine and deep learning for air quality prediction. *Journal of Atmospheric and Solar-Terrestrial Physics*, 281, 106777. <https://doi.org/10.1016/j.jastp.2026.106777>

Chimienti, M., Kato, A., Seydi, V., Schoombie, S., Hinke, J. T., Joy, R., Lidgard, D. C., Oosthuizen, W. C., Papastamatiou, Y. P., Ropert-Coudert, Y., Takahashi, A., Thiebot, J. B., Visani, M., Coustaty, M., & Jeanniard-du-Dot, T. (2025). Reviewing seas of data: Integrating image-based bio-logging and artificial intelligence to enhance marine conservation. *Methods in Ecology and Evolution*, 17(2), 272–290. <https://doi.org/10.1111/2041-210X.70063>

Çiftçi, H. Ç., Gümüş, M. G., & Gümüş, K. (2025). National-scale climate forecasting in Türkiye using statistical and artificial intelligence-based machine learning models under CMIP6 scenarios. *Modeling Earth Systems and Environment* 2025 12:1, 12(1), 42-. <https://doi.org/10.1007/s40808-025-02690-8>

Coco-Bassey, M., & Akpama, E. J. (2026). Comparative Evaluation of Support Vector Machines and Random Forest Models in AI-Based Cyber-Physical Systems Control and Security Architectures. *European Journal of Engineering and Technology Research*, 11(2), 1–6. <https://doi.org/10.24018/ejeng.2026.11.2.63306>

Dahiya, R., Kaple, G., Anute, N., Sudheer, P., Selvakumar, P., Manjunath, T. C., & Sharma, M. (1 C.E.). AI Tools for Automating Data Collection and Analysis. <https://services.igi->

- Global.Com/Resolvedoi/Resolve.aspx?Doi=10.4018/979-8-3373-1414-3.Ch016*, 459–486.
<https://doi.org/10.4018/979-8-3373-1414-3.ch016>
- Daokoru-Olukole, C., Jacob, D. E., Izah, S. C., El-Harairy, A., Fayiah, M., Ogwu, M. C., & El-Harairy, A. (2026). *Climate Change and Water Resources: Challenges and Adaptation Strategies*. 25–59.
https://doi.org/10.1007/978-3-032-10602-5_2
- Dawar, I., Singal, M., Singh, V., Lamba, S., & Jain, S. (2024). Predicting air quality index using machine learning: a case study of the Himalayan city of Dehradun. *Natural Hazards* 2024 121:5, 121(5), 5821–5847.
<https://doi.org/10.1007/s11069-024-07027-9>
- Devisri, P., & Manjula, S. (2026a). *A New Era of Environmental Protection: The AI Revolution*. 129–145.
https://doi.org/10.1007/978-3-031-99086-1_8
- Devisri, P., & Manjula, S. (2026b). *A New Era of Environmental Protection: The AI Revolution*. 129–145.
https://doi.org/10.1007/978-3-031-99086-1_8
- Dhanka, S., Sharma, A., Kumar, A., Maini, S., & Vundavilli, H. (2025). Advancements in Hybrid Machine Learning Models for Biomedical Disease Classification Using Integration of Hyperparameter-Tuning and Feature Selection Methodologies: A Comprehensive Review. *Archives of Computational Methods in Engineering* 2025 33:1, 33(1), 289–324. <https://doi.org/10.1007/s11831-025-10309-5>
- Domaneschi, M., Cucuzza, R., Martinelli, L., Noori, M., & Marano, G. C. (2026). A probabilistic framework for the resilience assessment of transport infrastructure systems via structural health monitoring and control based on a cost function approach. *Structure and Infrastructure Engineering*, 22(1), 107–119.
<https://doi.org/10.1080/15732479.2024.2318231>
- Dutta, P. Kumar., Nguyen, Khoa., Gayathri, N. ., Soundarabai, P. Beaulah., & Raj, Pethuru. (2026). *Artificial intelligence (AI) for climate change mitigation : key motivations and combating methods*. 352.
https://books.google.com/books/about/Artificial_Intelligence_AI_for_Climate_C.html?id=ahyyEQAAQBAJ
- Dutta, P., & Sarma, S. (2026a). Smart Water Management: Role of IoT, AI, and Machine Learning in Water Quality Monitoring. *Water Environment Research*, 98(2), e70249. <https://doi.org/10.1002/wer.70249>
- Dutta, P., & Sarma, S. (2026b). Smart Water Management: Role of IoT, AI, and Machine Learning in Water Quality Monitoring. *Water Environment Research*, 98(2), e70249. <https://doi.org/10.1002/wer.70249>
- Elabd, E., Hamouda, H. M., Ali, M. A. M., Hamid, A. S., & Fouad, Y. (2026). Air quality index AQI classification based on hybrid particle swarm and grey wolf optimization with ensemble machine learning model. *Scientific Reports* 2025 16:1, 16(1), 4152-. <https://doi.org/10.1038/s41598-025-34278-8>
- ElBehairy, A., Abu El-Nasr, N. A., Grimberg, P., & Said, L. A. (2026). A comprehensive review of deep learning methods in damage classification, detection, and segmentation of cultural heritage sites. *Journal of Cultural Heritage*, 78, 228–237. <https://doi.org/10.1016/j.culher.2026.01.015>
- El-Emam, D. A., & Shata, M. A. (2025). Aquatic Ecosystem Preservation Using Artificial Intelligence. *Handbook of Artificial Intelligence in Water Management*, 249–268. <https://doi.org/10.1201/9781003547099-15>
- Essaid, T., Abir, E. A., & Abderrazak, O. (2026a). Environmental Ethics and Behavioral Change: Legal Rule vs. Education. *Environmental Education and Sustainable Development*, 197–225.
https://doi.org/10.1007/978-3-032-05760-0_10

Essaid, T., Abir, E. A., & Abderrazak, O. (2026b). Environmental Ethics and Behavioral Change: Legal Rule vs. Education. *Environmental Education and Sustainable Development*, 197–225. https://doi.org/10.1007/978-3-032-05760-0_10

Etim, E. E., Humphrey, ·, Samuel, S., David, ·, Undie, A., Oluwakemi, ·, Akinpelu, O., Francis, ·, Ibekwe, A., Onimisi, ·, Onotu, P., & Samuel, H. S. (2026). Environmental management practices in the oil and gas industry moving beyond conventional perceptions of harm. *Discover Environment* 2026 4:1, 4(1), 8-. <https://doi.org/10.1007/s44274-025-00505-2>

ForouzeshNejad, A. A., Arabikhan, F., & Taheri, R. (2026). The Role of Explainable AI (XAI) in Enhancing the Security of Machine Learning Systems Against Adversarial Attacks. *Adversarial Example Detection and Mitigation Using Machine Learning*, 153–170. https://doi.org/10.1007/978-3-031-99447-0_11

Fosso-Wamba, S., Guthrie, C., Queiroz, M. M., & Oyedijo, A. (2026). Building AI-enabled capabilities for improved environmental and manufacturing performance: evidence from the US and the UK. *International Journal of Production Research*, 64(2), 545–564. <https://doi.org/10.1080/00207543.2024.2428427>

Gao, Y., & Zheng, Z. (2024). Using Multi-objective Optimization Algorithms to Balance Landscape Design of Historic and Cultural Districts with Urban Development Needs. <https://doi.org/10.1142/S0129156425402268>, 35(02). <https://doi.org/10.1142/s0129156425402268>

Geddis, A., Williams, H., Bashir, S., Malenfant, J., Dubois, C., Hamlet, L., & Masson, J. F. (2026). Artificial intelligence and machine learning for plasmonic and surface-enhanced sensing. *Chemical Society Reviews*, 55(6), 3599–3644. <https://doi.org/10.1039/d5cs01522g>

Gomathi, C., & Malathi, S. (2026). A Systematic Review and Meta-Analysis on Diagnosis of Osteoporosis Risk in Real Time Using Machine Learning and Deep Learning Techniques. <https://doi.org/10.1142/S0219649225300037>. <https://doi.org/10.1142/S0219649225300037>

Gowda, V. D., Saranya, R., Ramanan, S. V., Kumar, N. M. G., & Jadhav, P. S. A. C. H. I. N. (1 C.E.). AI-Based Solutions for Future Trends in IoT and Remote Sensing Integration for Precision Agriculture. <https://doi.org/10.4018/979-8-3693-7994-3.ch002>, 19–44. <https://doi.org/10.4018/979-8-3693-7994-3.ch002>

Gupta, D., & Mahapatra, S. (2025). Beyond Prediction: Adaptive AI as a Catalyst for Climate Change Mitigation and Understanding. *Adaptive Artificial Intelligence: Fundamentals, Challenges and Applications*, 45–71. <https://doi.org/10.1002/9781394389070.ch3>

Hackenberger, B. K., Djerdj, T., Hackenberger, D. K., Hackenberger, B. K., Djerdj, T., & Hackenberger, D. K. (2025). *Advancing Environmental Monitoring through AI: Applications of R and Python*. <https://doi.org/10.5772/intechopen.1007683>

Hashmi, H., Kumar, A., & Rizvi, D. R. (2027). AI for Biodiversity and Ecosystem Conservation. *Artificial Intelligence and Biodiversity*, 261–290. <https://doi.org/10.1002/9781394384990.ch15>

Hill, P. A., & Narine, L. K. (2026). Large language models for agricultural and rural development: An application of foundational models in extension. *Advancements in Agricultural Development*, 7(2), 23–34. <https://doi.org/10.37433/aad.v7i2.603>

Hoek, G., van Tongeren, M., Rösli, M., Jochems, S. H. J., Vilahur, N., Albin, M., Baldi, I., Crowley, Q., Fervers, B., Greinert, R., Consonni, D., Feliu, A., Zeeb, H., Schüz, J., D'Souza, E., Ritchie, D., Espina, C., & Kromhout, H. (2026). European Code Against Cancer, 5th edition - outdoor and indoor air pollution and cancer. *Molecular Oncology*, 20(1), 81–95. <https://doi.org/10.1002/1878-0261.70184>

Jana, A. K., & Bhunia, G. S. (2026). *Innovative Solutions for Soil Conservation and Land Rehabilitation: Tackling Climate Change, Land Degradation, and Advancing Sustainability*. 467–495. https://doi.org/10.1007/978-3-032-00704-9_20

Janikovičová, S., Pártlová, P., & Pollák, F. (2026). Comparative analysis of Road Safety, Air Pollution, Public Transport and Noise Disturbance Policies in the V4 countries. *Transportation Research Procedia*, 93(15), 57–70. <https://doi.org/10.1016/j.trpro.2025.11.010>

Jiang, F., Pan, C., Dong, L., Wang, K., Debbah, M., Niyato, D., & Han, Z. (2025). *A Comprehensive Survey of Large AI Models for Future Communications: Foundations, Applications and Challenges*. <https://doi.org/10.1109/COMST.2026.3660844>

KARACA, Y., BALEANU, D., ZHANG, Y.-D., GERVASI, O., & MOONIS, M. (2026). EDITORIAL ARTICLE OF SPECIAL ISSUE: PART I-A SERIES MATHEMATICAL MODELING OF COMPLEX SYSTEMS: FRACTALS-FRACTIONAL-ITÔ-DEs-WAVELET-ENTROPY-AI-BASED THEORIES, ANALYSES AND APPLICATIONS. <https://doi.org/10.1142/S0218348X26020020>

Keshavamurthy, D., Kumar, M., Tsaramirsis, G., & Oroumchian, F. (2026). An AI-Based Framework for Secure and Transparent Banking: Integrating Adversarial Robustness, Interpretability, and Organizational Modeling. *Security and Privacy*, 9(1), e70153. <https://doi.org/10.1002/spy2.70153>

Khanam, Z., Sultana, F. M., & Mushtaq, F. (2023). Environmental Pollution Control Measures and Strategies: An Overview of Recent Developments. *Geospatial Analytics for Environmental Pollution Modeling: Analysis, Control and Management*, 385–414. https://doi.org/10.1007/978-3-031-45300-7_15

Khare, S., Singh, A., Khare, R., Hazra, S., & Mellal, M. A. (2026). AI-Machine Learning Techniques in the Management of Environmental Issues. *Studies in Computational Intelligence*, 1240, 127–152. https://doi.org/10.1007/978-3-032-06732-6_8

Kim, T. H., Shin, J., & Cha, Y. K. (2023). Incorporation of feature engineering and attention mechanisms into deep learning models to develop an early warning system for harmful algal blooms. *Journal of Cleaner Production*, 414, 137564. <https://doi.org/10.1016/j.jclepro.2023.137564>

Krishna Raj, C., Siranjeevi, R., Susmitha, R., Sameera Shabnum, S., Saravanan, A., Vickram, A. S., & Chopra, H. (2025). Bioremediation in action: recent progress, challenges, and future directions for environmental restoration. *Biodegradation* 2025 37:1, 37(1), 9-. <https://doi.org/10.1007/s10532-025-10232-3>

Kumar, Abhishek. (2026). *Smart Chips for Smart Devices : VLSI Design for Next-Generation IoT Solutions*. 373.

Lin, R. (2026). *Discovering the Hidden Role of Gini Index In Prompt-based Classification*. <http://arxiv.org/abs/2603.15654>

Liu, C., Wang, X., Zhang, Z., Wang, W., Wang, T., Zhao, Y., Wang, M., & Chen, W.-H. (2026). GMrepo v3: a curated human gut microbiome database with expanded disease coverage and enhanced cross-dataset biomarker analysis. *Nucleic Acids Research*, 54(D1), D734–D742. <https://doi.org/10.1093/nar/gkaf1190>

Madgaocar, D., Fernandes, C. A., & Lakshmaiah, V. V. (2026). *Application of Machine Learning in Bioremediation and Detection of Pollutants*. 85–100. https://doi.org/10.1007/978-3-032-11426-6_5

Madhura, S., Sridhar, P., Karthikeyan, R., Mounica, P., Reddy, R. A., & Lihore, U. K. (2027). Shaping a Sustainable Future. *Artificial Intelligence and Biodiversity*, 213–229. <https://doi.org/10.1002/9781394384990.ch13>

Magara, T., & Phahlane, M. (2026). Unlocking IIoT Potential: A Systematic Review of AI Applications, Adoption Drivers, and Implementation Barriers. *Applied AI Letters*, 7(1), e70017. <https://doi.org/10.1002/ail2.70017>

Mahbod, M. (2026). *Pollution, Ecosystem Degradation, Human Vulnerability and Projection*. 1–20. https://doi.org/10.1007/978-3-031-95524-2_1

Mandava, R., & Sravanthi, G. L. (2026). Quantum Machine Learning Algorithms for Optimizing Complex Data Classification Tasks. *Journal of Transactions in Systems Engineering*, 4(1), 538–559. <https://doi.org/10.1515/JTSE.2026.4.1.538-559>

Mane, M. V., Kumar, D., & Agarwal, K. (2025). Intelligent Forecasting of Urban Air Pollution Using Machine Learning Models. *2025 4th OPJU International Technology Conference on Smart Computing for Innovation and Advancement in Industry 5.0, OTCON 2025*. <https://doi.org/10.1109/OTCON65728.2025.11071117>

Manono, B. O., Mwami, B., Mutavi, S., & Nzilu, F. (2026). Precision Farming with Smart Sensors: Current State, Challenges and Future Outlook. *Sensors 2026, Vol. 26, Page 882, 26(3)*, 882. <https://doi.org/10.3390/s26030882>

Mathew, J. T., Hussaini, J., Inobeme, A., Azeh, Y., Musah, M., Shaba, E. Y., Etsuyankpa, M. B., Tanko, E., Adetunji, C. O., Ibrahim, M. A., Tanko, M. S., & Mamman, A. (2026). Environmental Toxicology and Climate Change. *Coresource 4*, 315–328. <https://doi.org/10.1201/9781003500452-19>

Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokolowska, S., & Nowy, A. (2025). Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data. *Electronics 2025, Vol. 14, Page 696, 14(4)*, 696. <https://doi.org/10.3390/electronics14040696>

min, A. (2023). Artificial Intelligence and Bias: Challenges, Implications, and Remedies. *Journal of Social Research*, 2(11), 3808–3817. <https://doi.org/10.55324/josr.v2i11.1477>

Morchid, A., Elbasri, A., Qjidaa, H., El Alami, R., Bossoufi, B., Mobayen, S., & Skruch, P. (2026). Intelligent fire detection in agriculture using machine learning and embedded systems for risk prevention and improved sustainability. *Scientific Reports 2026 16:1, 16(1)*, 9773-. <https://doi.org/10.1038/s41598-026-40378-w>

Morchid, A., Qjidaa, H., Alami, R. El, Mobayen, S., Skruch, P., & Bossoufi, B. (2026). Smart irrigation-based internet of things and cloud computing technologies for sustainable farming. *Scientific Reports 2026 16:1, 16(1)*, 5293-. <https://doi.org/10.1038/s41598-026-35810-0>

Mutinta, G. (2025). Environmental Challenges in Africa. *An African Perspective on Environmental Communication*, 29–49. https://doi.org/10.1007/978-3-032-05052-6_2

Navas-Acien, A., Kaufman, J. D., Khatana, S. A. M., Parks, R. M., Rajagopalan, S., Smith, C. M., & Foraker, R. (2026). JAHA at Scientific Sessions 2024: Climate Change-Related Cardiovascular Health Effects in the Global South. *Journal of the American Heart Association*, 15(1), e044079. <https://doi.org/10.1161/JAHA.125.044079>

Naveed, M., Satti, Z., Tahir, M. M., Yasir, Q. M., Li, H., & Wang, F. (2026). Characterizing global air pollution seasonality and trends through integrated satellite and meteorological analytics. *Environmental Pollution*, 393, 127728. <https://doi.org/10.1016/j.envpol.2026.127728>

Oluwalana-Sanusi, A. E., Jombo, S., Hlatywayo, J., Munzeiwa, W. A., Mafame, T., Obagbuwa, I. C., Speek, D., Sefadi, J. S., Gwenzi, W., & Chaukura, N. (2026). Dusty Streets: The Challenge of Dust-Borne Pollutants in Low-Income Countries. *Clean - Soil, Air, Water*, 54(2), e70121. <https://doi.org/10.1002/clen.70121>

Panda, U. S., Pradhan, U., Naik, S., Kumaresan, D., Pradhan, S., Sahoo, R. K., & Ramanamurthy, M. V. (2026). Comprehensive Framework for Monitoring of Seas and Coastal Ecosystems Under Changing Environments. *Monitoring Coastal Marine Ecosystems Under Climate Change*, 81–139. https://doi.org/10.1007/978-3-032-09137-6_5

Pham, C. T., Nguyen, H. T., Le, H. H. T. C., Tran, N. Q. L., Do, K. Q., Bui, V., Phung, H., Phung, D., & Chu, C. (2026). Challenges and Strategies for the Development and Implementation of Climate-Informed Early Warning Systems for Vector-Borne Diseases: A Systematic Review. *Tropical Medicine and International Health*, 31(1), 10–21. <https://doi.org/10.1111/tmi.70045>

Qudah, H. (2026). Tracing the development of environmental, social and governance (ESG) performs: a systematic review and bibliometric analysis. *Future Business Journal 2025* 12:1, 12(1), 1-. <https://doi.org/10.1186/s43093-025-00705-5>

Rabiee, P. (2026). *Artificial Intelligence in Healthcare Systems of Low- and Middle-Income Countries: Opportunities, Challenges, and Pathways to Ethical Integration*. 157–170. https://doi.org/10.1007/978-3-032-06520-9_9

Raj, Y., & Roy, D. B. (2026). Intelligent Analytics for Environmental Sustainability and Energy Optimization. *Data Science*, 69–89. <https://doi.org/10.1201/9781003628569-3>

Ramírez Díaz, K. I., Espinoza, J. C., Espinosa Fuerte, E., & Picazzo Palencia, E. (2026). Effects of pollution on health in the monterrey metropolitan area 2016–2023. *Air Quality, Atmosphere & Health* 2026 19:4, 19(4), 70-. <https://doi.org/10.1007/s11869-026-01941-6>

Regona, M., Yigitcanlar, T., Hon, C., & Teo, M. (2026). Building Trust in Artificial Intelligence: A Systematic Review through the Lens of Trust Theory. *ACM Computing Surveys*. <https://doi.org/10.1145/3789256>

Rizavi, S. S., Amir, M., Siddique, M., Ali, K., & Umal Banin, S. (2026). Greening the path to firms' success: unveiling “Going Green” strategies through natural resource orchestration for sustainable development. *Asia-Pacific Journal of Business Administration*, 18(2), 356–386. <https://doi.org/10.1108/APJBA-02-2024-0073>

Salehi, V. (2026). A holistic and systematic approach for generation of synthetic data sets from CAD data related CNC-production environment. *AIP Conference Proceedings*, 3381(1), 070006. <https://doi.org/10.1063/5.0308429>

Samal, S., Sunder, S., Gadekellu, T. R., Yagin, F. H., Shawi, R. El, & Ahmed, N. (2026). A manta ray-bayesian optimization approach for hyperparameter-tuned convolutional neural networks in lung cancer classification. *Scientific Reports* 2026. <https://doi.org/10.1038/s41598-026-42506-y>

Samanta, R., Singh, V., Bajpai, R., Lodh, A., Routray, A., & Srivastava, A. (2026). Advances in the monitoring and forecasting of urban extreme meteorological events: a bibliometric review. *Natural Hazards* 2026 122:5, 122(5), 186-. <https://doi.org/10.1007/s11069-025-07933-6>

Sartori, N. C., & Fogt, R. L. (2026). Investigating a potential new Antarctic sea ice state during 2021–2023 using an atmosphere-based reconstruction. *Climate Dynamics* 2026 64:3, 64(3), 86-. <https://doi.org/10.1007/s00382-026-08070-x>

Seethapathy, P., Kannan, M., & Manalil, S. (2026). AI-Enabled Early Anomaly Detection of Crop Diseases at Real-Field Environments. *Harnessing AI to Reshape the Future of Agriculture*, 281–308. https://doi.org/10.1007/978-3-032-12118-9_13

Shafik, W., Hidayatullah, A. F., Kalinaki, K., Gul, H., Zakari, R. Y., & Tufail, A. (2026). A systematic literature review on transparency and interpretability of AI models in healthcare: taxonomies, tools, techniques, datasets, open research challenges, and future trends. *Health and Technology* 2026 16:2, 16(2), 209–230. <https://doi.org/10.1007/s12553-025-01051-w>

Sharma, A., Kumar, A., Dhanka, S., Maini, S., Rautela, K., Kant, S., Kaur, A., & Palta, A. (2026). Artificial Intelligence in Epidemic Modeling and Pandemic Preparedness: A Comprehensive Review. *Archives of Computational Methods in Engineering* 2026, 1–31. <https://doi.org/10.1007/s11831-026-10525-7>

Sharma, A., Sharma, S., Sharma, S., Pangtu, S., Thalyari, J., & Sharma, I. (2026). Biodiversity and public health. *One Planet, One Health, One Future: Charting a Course for Global Wellness, Environmental Resilience, and Sustainable Food Systems*, 33–52. <https://doi.org/10.1016/B978-0-443-38325-0.00003-4>

Shi, K., Fu, H., De-la-Torre, G. E., & Okoffo, E. D. (2026). Sampling and Sample Preparation Techniques for Micro- and Nanoplastics. *Microplastics and Nanoplastics in the Environment*, 15–47. <https://doi.org/10.1039/9781837678235-00015>

Singh, M., Mishra, K., Chowdhuri, S. R., Radhapyari, K., Pandey, M., & Singh, S. K. (2026). Artificial Intelligence for Sustainable Water Resource Management. *Artificial Intelligence Enabled Real Time Environmental Monitoring*, 43–79. https://doi.org/10.1007/978-981-95-3767-9_3

Singh, P., Singh, S., & Singh, M. (2026). *Exploring the Effectiveness of Biological Remediation Techniques in the Cleanup of Crude Oil Spill Sites*. 247–273. https://doi.org/10.1007/978-981-96-9128-9_11

Singh, S., & Singh, S. (2026). *Role of Artificial Intelligence for Environment Protection: An Analysis*. <https://doi.org/10.20944/preprints202602.1991.v1>

Soesanto, H., Rumbekwan, M., Soesanto, H., & Rumbekwan, M. (2026). FACTORS RELATED TO DIGITAL TRANSFORMATION IN LOCAL GOVERNMENT: A SCOPING REVIEW. *JWP (Jurnal Wacana Politik)*, 11(1), 14. <https://journal.unpad.ac.id/wacanapolitik/vol11/iss1/14>

Subash, A., Ganeshan, S. A., Nandakumar, V., & Gowthaman, N. (2026). An AI-Powered Crop Health Monitoring System Using NDVI and Predictive Soil-Climate Modeling. *2026 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, 1–6. <https://doi.org/10.1109/IITCEE67948.2026.11393979>

Sultan, A. A. (2026). Blockchain technology adoption in food supply chains: key factors, impacts and challenges. *International Journal of Organizational Analysis*, 34(1), 185–210. <https://doi.org/10.1108/IJOA-09-2024-4790>

Suman, T. Y., Rajendiran, K., & Kwak, I. S. (2025). Microplastics and nanoplastics in human health: a comprehensive review of exposure pathways, cellular mechanisms, and toxicological implications. *Archives of Toxicology* 2025 100:3, 100(3), 811–836. <https://doi.org/10.1007/s00204-025-04233-7>

Suthar, O. P., Parihar, V., Kumar, M., Verma, N. K., & Kashyap, A. K. (2026). Digital Twins and AI: Synergizing Intelligence for Sustainable Farm Management. *Digital Twin Technology for Sustainable Agriculture: Applications, Implementation and Future Trends*, 347–372. https://doi.org/10.1007/978-981-95-5915-2_19

Tetteh, A. A. (2026). *Optimizing AI Integration in Households: Strategies for Enhancing Benefits While Minimizing Risks*. 153–170. https://doi.org/10.1007/978-3-032-02260-8_8

Teymoori, S., Ilchi Ghazaan, M., & Malekitabar, H. (2026). Developing a probabilistic risk assessment framework for construction projects based on Dynamic Bayesian Network. *Reliability Engineering & System Safety*, 267, 111897. <https://doi.org/10.1016/j.ress.2025.111897>

Tsiaras, E., & Tampekis, S. (2026). Integrating AI in Energy Efficiency, Natural Hazards and Ecological Resilience: A Python Case Study. *Engineering Science & Technology*, 72–91. <https://doi.org/10.37256/est.7120268711>

Vijaya, J., Sai Vikas, B., Jaya Surya, J., Nitheesh Kumar, K., & Shriya, B. (2026). A combined voting mechanism in KNN and random forest algorithms to enhance the diabetic retinopathy eye disease detection. *Advances in Computational Intelligence 2026 6:1*, 6(1), 1-. <https://doi.org/10.1007/s43674-025-00086-w>

Volodin, E., Chernenkov, A., Tarasevich, M., Bragina, V., Kostykin, S., Blagodatskikh, D., & Gritsun, A. (2026). *Earth system model ARTS-ESM-L: basic properties, simulation of present climate and historical climate changes*. <https://doi.org/10.21203/rs.3.rs-8969494/v1>

Wahid, N., Wahab, S., Tooba, Assad, N., Khan, M. N., Kaplan, A., Fahad, S., Adnan, M., Hassan, M. N. U., & Hafsa. (2026). Anion dynamics of nitrogen, phosphorus, and sulfur in soil chemistry. *Sustainable Soil Chemistry and Plant Nutrition: Innovations and Applications*, 137–172. <https://doi.org/10.1016/B978-0-443-40584-6.00002-4>

Wang, Q. R., Bell, M. L., & Zhang, Y. (2026). Integrating mobility data into air pollution research for public health. *Nature Health 2026 1:3*, 1(3), 280–289. <https://doi.org/10.1038/s44360-026-00056-7>

Wang, S., Dai, W., Wang, L.-C., & Li, G. Y. (2026a). *Robust Processing and Learning: Principles, Methods, and Wireless Applications*. <http://arxiv.org/abs/2602.09848>

Wang, S., Dai, W., Wang, L.-C., & Li, G. Y. (2026b). *Robust Processing and Learning: Principles, Methods, and Wireless Applications*. <http://arxiv.org/abs/2602.09848>

Wang, X., Wang, X., Zhang, X., Zhou, T., Wang, Y., Duan, W., Zhao, Y., Cheng, Z., Liu, Y., & Zhao, L. (2026). Divergent spatial distributions, carbon stocks, and climatic threshold responses of soil inorganic and organic carbon in the Tibet Plateau. *Soil and Tillage Research*, 260, 107145. <https://doi.org/10.1016/j.still.2026.107145>

Wen, W., Xie, R., Tang, Q., Xiong, Z., Xie, G., & Huang, T. (2026). Green Orchestra: Joint Spatiotemporal Task Scheduling and Hybrid Energy Coordination in Computing Power Networks. *IEEE Transactions on Cognitive Communications and Networking*, 1–1. <https://doi.org/10.1109/tccn.2026.3656279>

Yang, Z., Wu, S., Ji, Y., & Tan, L. (2026). Can large-scale farms lead smallholder agricultural digitalization? Evidence from intelligent machinery use in China. *Applied Economics*, 58(3), 397–412. <https://doi.org/10.1080/00036846.2025.2590625>

Yun, S. M., & van Zundert, A. (2026). Beyond Human Error: Building Intelligent Resilience for Medication Safety in the ICU. *Healthcare 2026, Vol. 14, Page 619, 14(5)*, 619. <https://doi.org/10.3390/healthcare14050619>

Zhang, S., Cui, C., Huang, S., Wang, Z., & Wu, S. (2026). Application and mechanisms of biochar-immobilized enzymes in environmental remediation: a review. *Biochar 2026 8:1*, 8(1), 4-. <https://doi.org/10.1007/s42773-025-00515-6>

Zhao, Y., Yu, X., Song, X., Zhang, Y., Wang, D., & Wei, Y. (2026). Optimization of agricultural non-point source nitrogen pollution control in reservoir watersheds: a machine learning-driven spatially integrated governance framework. *Journal of Cleaner Production*, 544, 147674. <https://doi.org/10.1016/j.jclepro.2026.147674>

Zuo, J., Zhang, L., Chen, B., Hu, Y., Zhang, B., Raza, S. A., Zhang, S., & Ruan, L. (2026). A cost–benefit synergistic framework for balancing ecological importance and vulnerability in island conservation. *International Journal of Digital Earth*, 19(1). <https://doi.org/10.1080/17538947.2026.2625557>