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Novel artificial intelligence-based approaches for rapid environmental health assessment in crisis situations: A narrative review

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Abstract

The increasing frequency of natural disasters and environmental contamination events in recent decades has posed significant challenges to crisis management and public health. Traditional environmental monitoring methods based on manual sampling lack sufficient efficiency due to time and cost constraints. This narrative review examines the role of novel technologies based on artificial intelligence (AI), the Internet of Things, and remote sensing in enhancing the speed and accuracy of environmental health assessments under crisis conditions. Research sources included the international databases Scopus, PubMed, Web of Science, and Science Direct from 2018 to 2025. Textual analysis indicated that the convergence of AI and environmental sensors has shifted the monitoring paradigm from a reactive to a proactive approach. Fluorescent sensor arrays combined with machine learning algorithms identify toxic arsenic species with over 96% accuracy, while unmanned aerial vehicles equipped with multispectral sensors and convolutional neural networks achieve more than 85% accuracy in building damage assessment after earthquakes and reduce hazard mapping time by up to 80%. Furthermore, deep learning-based super-resolution techniques have improved the resolution of satellite images for monitoring urban groundwater aquifers. The findings demonstrate that intelligent technologies, through real-time monitoring and reduction of human error, significantly enhance the resilience of environmental health systems, although the development of integrated platforms and global standard protocols is essential to address data and cybersecurity challenges.

Keywords: Artificial Intelligence (AI), Internet of Things, Risk Assessment, Crisis Management, Environmental Health

Introduction

In the present era, human societies face increasing environmental challenges and complex natural disasters that pose serious threats to public health, ecosystem sustainability, and critical infrastructure (1). The intensification of climate change, contamination of water resources, and sudden events such as floods, earthquakes, and landslides have made crisis management one of the primary global concerns (2). In emergency situations and post-disaster contexts, time is a critical factor, and rapid and accurate assessment of environmental health components—such as the identification of chemical pollutants in drinking water sources or the evaluation of structural integrity for emergency shelter—plays a decisive role in reducing casualties and financial losses (3).

However, traditional environmental monitoring methods, which largely rely on manual sampling, time-consuming laboratory analyses, and field observations, have demonstrated inefficiency when confronted with the volume, speed, and scale of modern events (4). These methods are often constrained by spatial limitations, high costs, and delays in data processing, and they lack the capacity to support real-time decision-making (5, 6). For instance, in water contamination events, conventional methods are unable to rapidly differentiate and identify hazardous chemical species such as arsenic at the incident site, posing significant challenges to emergency response strategies (7, 8). Therefore, transitioning from traditional approaches to intelligent, data-driven systems is an unavoidable necessity to fill this technological gap and enhance resilience against environmental hazards.

Recent research indicates that the convergence of novel technologies, particularly the integration of artificial intelligence (AI) with the Internet of Things and Remote Sensing, has opened new horizons in disaster management and environmental monitoring (9). This emerging paradigm, sometimes referred to as sixth-generation sensors (6GS) or AI of Things (AIoT), enables continuous monitoring, predictive analytics, and automated decision-making (5, 10, 11). A review of previous studies shows that the application of these technologies has expanded significantly across various dimensions of environmental health (12-14).

In the domain of water resource monitoring, recent investigations have focused on the use of deep learning (DL) to enhance the resolution of remote sensing imagery, allowing for more accurate assessment of groundwater quality and detection of environmental changes in urban areas (15-17). Additionally, the development of fluorescent sensor arrays based on machine learning (ML) has enabled rapid and simultaneous differentiation of various arsenic species (AsIII and AsV) in contaminated water sources, representing a major advancement in the management of chemical disasters (7, 18, 19).

Beyond water resources, natural disaster management and physical damage assessment have also benefited from these innovations (20, 21). The use of unmanned aerial vehicles (UAVs) equipped with advanced sensors and Light Detection and Ranging (LiDAR) technology provides safe access to difficult-to-reach areas and high-resolution data collection during events such as floods and earthquakes (22). In parallel, computer vision algorithms and convolutional neural network (CNN) models have been applied for rapid and automated assessment of building damage post-disaster, substantially increasing the speed and accuracy of relief and shelter operations (23-26).

Furthermore, AI, through the analysis of environmental big data, has introduced novel capabilities in predicting disease outbreaks, monitoring air pollution, and optimizing waste management under emergency conditions, functioning as a decision support system (DSS) (27, 28). Despite these advancements, existing literature highlights challenges such as data heterogeneity, model uncertainty, and the need for integrated frameworks to interpret complex datasets, which remain primary barriers to the full-scale implementation of these systems (29-31).

This narrative review aims to provide a comprehensive and coherent overview of AI applications in rapid environmental health assessment, consolidating fragmented previous findings and illuminating future research directions. The primary objectives of this study include reviewing and categorizing novel AI- and IoT-based methods for pollutant monitoring, analyzing the role of remote sensing technologies in real-time hazard assessment, and identifying gaps in the operational implementation of these technologies. Based on the reviewed evidence, this research hypothesizes that the integration of deep learning algorithms with sensor data significantly enhances the accuracy and speed of critical environmental parameter assessments compared to conventional methods. It also assumes that the use of intelligent predictive models enables early intervention in environmental incidents, and that the development of autonomous systems reduces reliance on human personnel in high-risk areas while improving the efficiency of recovery operations.

Materials and Methods

In this narrative review, to collect relevant and up-to-date scientific sources, the international databases Scopus, PubMed, Web of Science, and Science Direct were searched for the period from January 2018 to 24 November 2025. To ensure comprehensiveness, the Google Scholar search engine was also examined for tracking gray literature and supplementary studies, but it was not considered a primary database.

The search employed the following Persian and English keywords and their logical combinations (using the operators AND, OR): Artificial Intelligence (AI), Internet of Things, Remote Sensing, Environmental Health, Disaster Management, Water Quality Monitoring, Risk Assessment, Deep Learning (DL), Unmanned Aerial Vehicle (UAV), and Emergency Response.

Inclusion criteria comprised original research articles, review studies, and technical reports that directly addressed the operational application of intelligent algorithms in the identification of environmental pollutants (such as arsenic and heavy metals), monitoring floods and earthquakes, or assessing infrastructure damage. Studies that only addressed theoretical aspects of data processing without field application in environmental health, or for which full-text access was unavailable, were excluded. Key information from eligible sources was extracted, thematically categorized, and analytically presented in various sections of the article. After completing the search and screening based on inclusion and exclusion criteria, a total of 37 sources including research articles, review studies, and technical reports—were deemed eligible and utilized in the final synthesis of this study.

Results

The findings of the present study indicate that the application of artificial intelligence (AI) in environmental health and crisis management has progressed beyond theoretical exploration and has been translated into high-precision operational solutions. The results of this research are categorized into three main domains: water quality monitoring and pollutant identification, physical damage assessment in natural disasters, and the convergence of Internet of Things and AI (AIoT).

1. Efficiency of Artificial Intelligence in Water Quality Monitoring and Chemical Species Identification

Analysis of the reviewed studies demonstrates that machine learning (ML) and deep learning (DL) algorithms have successfully addressed the limitations of conventional methods, such as time consumption and reliance on heavy laboratory equipment (32-34). Specifically, the study by Wei et al. (2025) reported that a fluorescent sensor array based on metal-organic frameworks (MOFs), coupled with a support vector machine (SVM) algorithm, could identify four different arsenic species (AsIII, AsV, MMAV, and DMAV) with an average accuracy of 96.88% in test sets. The limit of detection (LOD) for arsenite (AsIII) in this method was approximately 0.33 µg/mL, which is highly suitable for emergency conditions (7).

Furthermore, findings from Zou et al. (2025) indicate that deep learning-based super-resolution techniques applied to remote sensing satellite imagery significantly enhanced spatial resolution. In a case study in Lahore, this method improved the peak signal-to-noise ratio (PSNR) by 32.4 dB and the structural similarity index (SSIM) to 0.91, enabling more precise monitoring of groundwater contamination in densely populated urban areas (15). Table 1 presents a summary of the performance metrics of these methods compared with other techniques examined.

It is noteworthy that the performance metrics presented in Table 1 cover diverse aspects of efficiency, including classification accuracy, image reconstruction quality, and operational speed. These metrics were selected based on the nature of each technology, and their presentation aims to demonstrate the capabilities of each method within its specialized domain, rather than providing a direct numerical comparison between heterogeneous indicators.

Table 1. Comparing the performance of artificial intelligence models in assessing water and environmental quality parameters (Synthesis of findings 2023-2025)

Evaluation Axes	Technology / Algorithm	Key Performance Indicators / Achievements	Application in critical situations	References
Arsenic Identification	Fluorescent Sensor + SVM	Detection accuracy: 96.88% (for 4 arsenic species)	Rapid and in-situ separation of toxic species in drinking water sources	(7)
Groundwater Quality	Remote Sensing + CNN (SR)	Improved image resolution (SSIM: 0.91)	Monitoring pollution penetration in dense urban areas with high resolution	(15)
Earthquake Damage Assessment	UAV + Transfer Learning	Identification accuracy: 85%	Rapid mapping of damaged buildings with low data	(23)
Flood Warning	UAV + Remote Sensing	Reduced hazard mapping time by up to 80%	Access to inaccessible areas and emergency evacuation of residents	(22)
Quality Anomaly Monitoring	Internet of Things (AIoT)	False positive rate: less than 5%	Automatic and real-time monitoring of water reservoirs and issuing early warnings	(28)
Structural Damage Detection	Convolutional Neural Network (CNN)	Accurate assessment under operational conditions	Identifying the safety of structures after disasters for resettlement	(25)
Infrastructure Crack Detection	Machine Vision (Vision-based)	Full automation of the inspection process	Monitoring the health of critical structures (bridges and dams) after an incident	(26)
Water Resource Management	Satellite Remote Sensing	High correlation with ground data	Monitoring drought and floods in areas without ground stations	(17)
Intelligent Agents (AI Agents)	Integration of AI and IoT	Optimized energy and data consumption	Managing water quality and climate data at the edge of the network	(6)
Emergency Management	Big Data + AI	Improved response time and resource allocation	Predicting environmental health risks and hospital management	(27)

2. Intelligent Assessment of Damage in Natural Disasters

Findings from a review of 370 articles by Al Shafian & Hu (2024) indicate that over the past decade, the use of computer vision-based methods for assessing building damage following earthquakes and floods has grown exponentially. Analyses show that convolutional neural networks (CNNs), accounting for more than 60% of the studies, have been the most commonly applied algorithm for structural damage detection (23).

According to Chen (2024), unmanned aerial vehicles (UAVs) equipped with multispectral sensors and Light Detection and Ranging (LiDAR) technology can generate three-dimensional models of affected areas with centimeter-level spatial accuracy. This technology has reduced the time required for hazard mapping compared to traditional ground-based surveying methods by up to 80% in events such as earthquakes and flash floods (22).

Moreover, the use of transfer learning has enabled AI models to achieve over 85% accuracy in identifying collapsed buildings, even when trained on limited datasets, which are common during the early hours of a crisis (23). The comparative performance of these models across different environmental applications is illustrated in Figure 1.

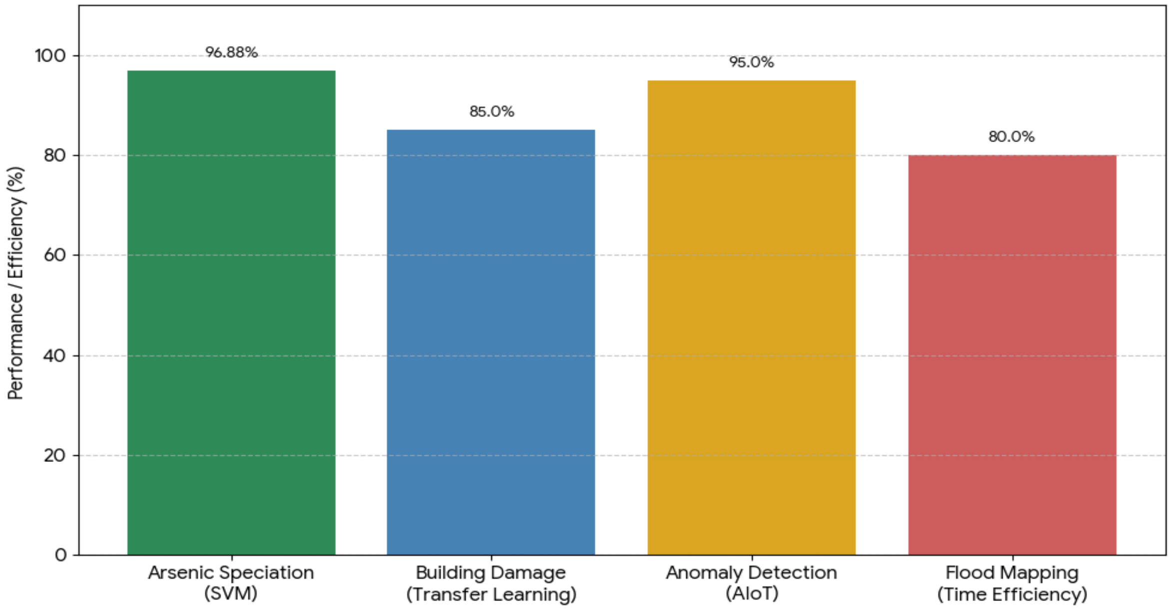

Figure 1. Comparison of performance indicators and efficiency of artificial intelligence models in various environmental health applications (7, 23, 28)

A review of the quantitative data from the articles shows that the research focus has shifted from purely satellite remote sensing methods to the integration of drone data and artificial intelligence. As can be seen in Figure 2, while in 2014 less than 10% of papers dealt with deep learning, this figure has increased to more than 70% in 2024, indicating a paradigm shift towards automated analytics (23).

3. Convergence of IoT and AI in Integrated Data Management

Findings related to system integration indicate that the combination of artificial intelligence (AI) and the Internet of Things (AIoT) has significantly enhanced data reliability (35, 36). According to Miller et al. (2025), the use of intelligent algorithms at the network edge (Edge AI) for sensor data preprocessing has reduced the volume of transmitted data and optimized energy consumption in sensor nodes (6).

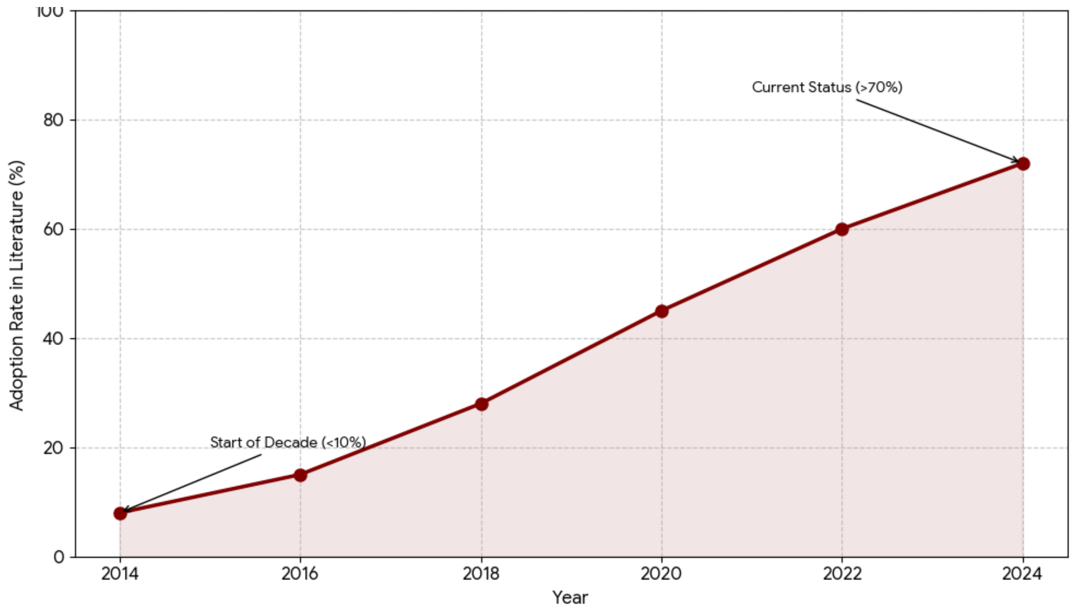

Figure 2. Evolution and increasing share of the use of deep learning in disaster management studies (2014-2024) (23)

Additionally, Rahaman (2025) reports that AIoT-based environmental monitoring systems can automatically detect anomalies in air and water quality and issue early warnings with a false-positive rate of less than 5% (28). Analyses by Bari et al. (2023) further confirm that the integration of big data and AI in the disaster response phase optimizes the allocation of relief resources and improves response times to events such as floods and earthquakes (27).

However, Mishra et al. (2025) emphasize that challenges related to data heterogeneity and the opacity of black-box models remain primary barriers to the full adoption of these systems by decision-makers (29).

In summary, the research findings demonstrate that these novel technologies not only increase the accuracy of environmental health parameter measurements but also transform crisis management capacity by reducing data processing time from hours or days to minutes or seconds (6, 7).

Discussion

A comprehensive review of the scientific literature in this study indicates that the paradigm of environmental health management and crisis response is undergoing a fundamental shift under the influence of the convergence of artificial intelligence (AI), the Internet of Things, and Remote Sensing. This transition moves practices from reactive, manual sampling-based approaches toward proactive, automated, and data-driven systems. This technological evolution, referred to in recent literature as AIoT or sixth-generation sensors (6GS), has created unprecedented capabilities in speed, accuracy, and scalability of environmental assessments that were unattainable with traditional methods (5, 6). Analyses suggest that these technologies function not only as data collection tools but also as intelligent agents in critical decision-making processes (10).

1. Transformation in Water Quality Monitoring and Precise Pollutant Identification

One of the most prominent discussion points in the reviewed literature is the remarkable improvement in the efficiency of machine learning models for rapid, on-site identification of chemical and biological pollutants. Unlike conventional laboratory methods, which require prolonged microbial culturing or spectroscopic analyses, modern systems such as fluorescent sensor arrays based on machine learning enable real-time differentiation and identification of toxic species like arsenic (AsIII and AsV) (Wei et al., 2025). This capability is critical in emergencies where there is a risk of mass contamination of water sources. Furthermore, the use of deep learning (DL) techniques for satellite image super-resolution overcomes previous remote sensing limitations in monitoring groundwater quality and allows for more precise tracking of hydrogeological changes and pollutant infiltration in complex urban environments (15). These findings align closely with research emphasizing the role of AI in predictive modeling of water quality and reduction of health hazards (37, 38).

2. Enhancement of Disaster Management and Intelligent Damage Assessment

In the field of natural disaster management, text analyses indicate that unmanned technologies (UAVs) and remote sensing have revolutionized damage detection and assessment operations. AI-equipped UAVs can access high-risk and hard-to-reach areas during events such as floods, earthquakes, and landslides, transmitting visual and thermal data in real time (22). Integrating these data with advanced computer vision algorithms and convolutional neural networks (CNNs) significantly accelerates the evaluation of structural and infrastructural damage while reducing human error caused by fatigue or stress in post-disaster conditions (23). Additionally, AI-driven analysis of environmental big data enables more accurate prediction of natural events such as earthquakes and wildfires, providing critical opportunities for early warning and evacuation that directly contribute to reducing human casualties (27, 29).

3. Synergy of Technologies and Decision Support Systems

Discussions on technology integration highlight that the combination of IoT with AI (AIoT) has created dynamic, autonomous systems capable of responding to environmental changes. For example, the application of reinforcement learning algorithms in wireless sensor networks enables energy optimization and prolongs network lifetime in long-term environmental monitoring (28). These systems, utilizing edge computing, minimize data transfer latency and provide crisis managers with the capability for immediate, on-site decision-making (6).

4. Implementation Challenges and Existing Limitations

Despite clear advantages, critical analysis of the literature reveals that operational deployment of these systems faces significant technical and structural challenges. Data heterogeneity from diverse sources (IoT sensors, satellite imagery, UAVs) and the lack of global standard protocols for synchronization and integration (data fusion) represent major barriers to creating comprehensive and unified systems (30). Additional ly, high computational costs for training deep learning models, the need for powerful hardware infrastructure, and serious cybersecurity and data privacy concerns in IoT networks are among the challenges that researchers emphasize must be addressed for broad adoption of these technologies (28, 39). Furthermore, the performance of AI models depends heavily on the quality and quantity of training data, which can lead to predictive uncertainty when sufficient historical data are unavailable (29). Table 2 summarizes the identified technical and structural challenges along with proposed technological solutions to address them, providing a comprehensive overview of current barriers and pathways for overcoming them.

Beyond technical challenges, ethical considerations are also critical in applying these technologies. Sole reliance on algorithms without human oversight may introduce biases in the allocation of relief resources. Therefore, a human-in-the-loop approach, in which AI acts as an assistant and final decisions are made by experts, is recognized as the safest strategy in the response phase. Additionally, cybersecurity in AIoT networks presents another critical challenge, as neglecting it could expose vital water and electricity infrastructure to cyberattacks during crises.

Table 2. The main challenges of implementing artificial intelligence in critical situations and proposed technological solutions

Identified challenges	Problem Description	Proposed Technology-Based Solution	References
Data heterogeneity	Different data formats of satellite, drone and ground sensors that hinder integrated analysis.	Development of Data Fusion Algorithms and Protocol Synchronization	(29, 30)
Model uncertainty	The “black box” nature of deep learning models and lack of transparency in how they make decisions.	Development of Interpretable Artificial Intelligence (XAI) to Clarify Decision-Making Logic	(29, 31)
Computational latency and cost	The large volume of image data and bandwidth and energy limitations during a crisis.	Use of Edge Computing to Process Data at the Sensor Site	(6, 28)
Lack of training data	The lack of sufficient labeled data from rare events to accurately train models in the early hours.	Use of Transfer Learning Techniques with Limited Data	(23)
Cybersecurity	The vulnerability of IoT networks to cyberattacks and manipulation of critical data.	Integration of Advanced Security Protocols in AIoT Network Layers	(35, 39)

5. Future Perspectives and Recommendations for Research

Based on the gaps identified in this review, the following avenues are suggested for future research:

Development of Explainable AI (XAI) Models: Future studies should focus on developing models that are not only accurate but also provide explanations for hazard alerts, thereby enhancing the trust of operational managers.

Standardization of Communication Protocols: Establishing global protocols for interoperability between IoT sensors and satellite systems is essential to overcome the problem of data silos.

Green AI: Considering the high energy consumption of intensive deep learning processes, the development of lightweight, energy-efficient algorithms for deployment on UAVs and battery-powered sensors is recommended.

Integration of Social and Physical Data: Combining environmental sensor data with social network or crowdsourced data can enhance the accuracy of crisis assessment during the early moments of an event.

Conclusion

This narrative review, synthesizing the recent scientific literature, demonstrates that the integration of artificial intelligence (AI) with Internet of Things and Remote Sensing technologies has created a novel and transformative paradigm in environmental health assessment and crisis management. The findings confirm that the transition from traditional, manual approaches to intelligent, data-driven systems is not merely a technological choice but a vital necessity for enhancing societal resilience against natural and anthropogenic hazards.

Specifically, the results of this study can be summarized in three main domains:

1. Monitoring of Critical Resources and Water Quality: Modern technologies have eliminated previous spatial and temporal limitations. The use of sixth-generation sensors (6GS) and machine learning algorithms enables real-time, on-site detection of hazardous pollutants such as arsenic and heavy metals, playing a key role in preventing mass poisoning during emergencies. Additionally, advanced image processing techniques, such as deep learning-based super-resolution, have

substantially improved satellite imagery resolution for groundwater monitoring, enabling more precise management of water resources in densely populated urban areas.

2. Disaster Management and Physical Damage Assessment: The use of automated systems and AI-equipped UAVs has transformed the efficiency of response operations. Evidence indicates that integrating remote sensing data with computer vision models accelerates the evaluation of structural damage following earthquakes and floods, providing precise hazard maps that ensure the safety of relief teams and residents. These technologies also enable early-warning systems for events such as wildfires and landslides, increasing the lead time between prediction and incident occurrence and providing critical opportunities for preventive actions.

3. Facilitation of Strategic Decision-Making: AI's role as a facilitator of high-level decision-making in emergency health is increasingly evident. AI agents, by analyzing environmental and climatic big data, identify hidden patterns of environmental change and assist crisis managers in optimal resource allocation and adaptive strategy formulation.

However, this review highlights that the path to full-scale implementation of these technologies is not straightforward. Challenges related to data heterogeneity, high computational costs, and cybersecurity issues in IoT networks require continued attention. Moreover, the lack of global standard protocols for multi-source data integration limits the scalability of these systems internationally.

Finally, the future outlook in this domain depends on the development of explainable AI (XAI) models, edge computing for faster data processing, and the creation of interdisciplinary collaborative platforms. Future research should focus on addressing operational barriers and developing ethical and security frameworks for the use of these technologies in crisis situations, thereby leveraging the full potential of AI to ensure sustainable environmental health and safety.

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