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Application of Artificial Intelligence in Detection and Remediation of Heavy Metals in Contaminated Water and Soils in Africa -A Systematic Review

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Abstract
Heavy metal poisoning of water and soils remains a serious environmental and public health issue in Africa, fuelled by growing industrialisation, mining operations, urban growth, and insufficient waste management systems. Although artificial intelligence has been widely regarded as a transformative tool for global environmental monitoring, existing research rarely addresses Africa-specific constraints, rarely integrates detection and remediation, and offers limited guidance for policy implementation in data- and resource-constrained contexts. This study conducts a systematic review using a structured literature synthesis guided by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) screening principles to investigate artificial intelligence-based approaches for heavy metal detection, prediction, mapping, and remediation in African water and soil systems. The evaluation assesses the performance, data needs, and contextual applicability of machine learning, deep learning, adaptive neuro-fuzzy inference systems, Internet of Things-enabled sensing, and geospatial artificial intelligence in comparison to worldwide applications. The synthesis shows that remote sensing-artificial intelligence frameworks and Internet of Things-integrated systems enable scalable monitoring and early-warning capabilities, whereas artificial neural networks and adaptive neuro-fuzzy inference systems achieve high predictive accuracy (coefficient of determination frequently > 0.90) under limited data conditions. Despite showing potential, adoption is hampered by fragmented datasets, poor digital infrastructure, talent gaps, and insufficient integration with regulatory frameworks. To address these issues, the report suggests an Africa-focused artificial intelligence-environment policy framework to promote sustainable heavy metal management and increase environmental governance.

Introduction

Heavy metal contamination of soil and water remains one of the most serious environmental and public health issues of the twenty-first century. Toxic metals such as lead (Pb), cadmium (Cd), arsenic (As), chromium (Cr), and mercury (Hg) are non-biodegradable, accumulate in ecosystems, and pose long-term threats to human health, food security, and ecosystem integrity (Wani et al., 2024). Rapid industrialisation, mining activities, urban expansion, and inadequate waste management have all contributed to global heavy metal pollution, while traditional monitoring and remediation approaches remain expensive, labour-intensive, time-consuming, and difficult to implement at large spatial scales (Singh et al., 2024). These limits impede prompt detection and successful intervention, especially in low- and middle-income countries.

By enabling the analysis of complex, nonlinear, and high-dimensional datasets beyond the scope of conventional statistical techniques, recent developments in artificial intelligence (AI) have revolutionised environmental monitoring. Predictive modelling, anomaly detection, and spatial risk mapping across various environmental media are currently supported by machine learning (ML), deep learning (DL), Internet of Things (IoT)-enabled sensing, and geospatial artificial intelligence (Zhong et al., 2021). Globally, proactive, data-driven environmental management systems with near-real-time surveillance and early-warning capabilities have replaced reactive, laboratory-based monitoring, thanks to AI-driven frameworks.

Increasing research shows that AI-based models can effectively evaluate and forecast heavy metal contamination in soil and water systems. Metal concentrations, water quality indices, and spatial contamination patterns have all been estimated using artificial neural networks (ANNs), convolutional neural networks (CNNs), long short-term memory (LSTM) networks, adaptive neuro-fuzzy inference systems (ANFIS), and hybrid geostatistical–machine learning models (Padarian et al., 2020; Dawood et al., 2021; Trach et al., 2022; Kouadri et al., 2022). Complementary advancements in IoT-enabled sensors and AI-assisted remote sensing have further improved large-area monitoring capabilities, enabling the identification of contamination hotspots that are challenging to detect with traditional sampling alone (Gupte & Pradeep, 2022; DeMedeiros et al., 2023).

Due to widespread mining operations, rapid urbanisation, industrial discharges, and inadequate waste treatment infrastructure, heavy metal contamination is particularly severe in Africa. Reports of elevated concentrations of toxic metals in rivers, agricultural soils, and urban areas in several nations have raised concerns about food safety, drinking water quality, and long-term ecological degradation (Tarekegn et al., 2022; Folorunso et al., 2023; Murphy et al., 2025). Despite many African countries having water and soil protection regulations, enforcement is frequently hampered by a lack of laboratory capacity, disjointed monitoring programmes, insufficient funding, and infrastructure challenges (Pouyanfar et al., 2022). These drawbacks limit the efficacy of traditional analytical techniques and emphasise the need for scalable, affordable substitutes.

Applications in African contexts remain dispersed, mostly pilot-based, and unevenly distributed across regions, despite significant global advancements in AI-driven environmental assessment (Chang et al., 2025). Reviews that do exist typically take a broad, global approach and seldom consider the limitations unique to Africa in terms of data accessibility, digital infrastructure, technical capability, and regulatory integration. Additionally, the majority of research treats heavy metal detection and remediation as distinct fields, offering little insight into integrated AI-enabled frameworks that connect contamination assessment with remediation planning and decision support in resource-constrained settings.

This work fills these gaps by providing a systematic evaluation of artificial intelligence applications for detecting, predicting, spatial mapping, and remediating heavy metal contamination in African soil and water. The review assesses model performance, data needs, scalability, and contextual relevance by combining information from machine learning, deep learning, neuro-fuzzy systems, IoT-enabled sensing, and geospatial artificial intelligence. The goal is to provide an Africa-focused analytical foundation that facilitates research translation, promotes environmental governance, and guides the creation of long-term, AI-driven heavy metal management plans.

Methodology

With an emphasis on African contexts, this study conducted a systematic review to examine applications of artificial intelligence (AI) for the detection and remediation of heavy metal contamination in soil and water systems. While acknowledging that the review is not a fully systematic review, the literature selection approach was guided by PRISMA 2020 screening criteria to improve transparency and reproducibility in research identification and screening (Moher et al., 2009; Sarkis-Onofre et al., 2021).

Scopus, Web of Science, ScienceDirect, PubMed, and Google Scholar were all used in an organised literature search. Publications from the last 7 years were included in the search, which reflects the time frame during which AI-based environmental applications have significantly matured. Artificial intelligence, machine learning, deep learning, neuro-fuzzy systems, Internet of Things, remote sensing, heavy metals, soil, water, and Africa were all included in search strings along with Boolean operators. To identify additional pertinent studies, the reference lists of key reviews and empirical publications were also manually searched.

The selection of research was done in two steps: first, duplicates, irrelevant records, and studies unrelated to heavy metal evaluation or remediation were eliminated through title and abstract screening. After that, full-text screening was conducted according to predetermined eligibility criteria. The included studies reported quantitative performance metrics (e.g., R^2, RMSE, or accuracy), showed applicability under real-world or resource-constrained environmental conditions, and explicitly applied AI-based techniques (e.g., machine learning, deep learning, neuro-fuzzy systems, geospatial-AI, or IoT-integrated models) to heavy metal detection, prediction, spatial modelling, or remediation in soil or water systems. Excluded were studies that presented only conceptual frameworks, concentrated on non-metal contaminants, lacked an AI component, or provided insufficient methodological detail.

Before screening, [N_2] duplicates were removed from the [N_1] records generated by the database search. [N_3] records were omitted from title and abstract screening, mainly because they had nothing to do with heavy metals or lacked AI-based techniques. After [N_4] papers underwent full-text evaluation, [N_5] studies that satisfied the inclusion criteria were kept for qualitative synthesis. Supplementary Figure S1 presents a PRISMA flow diagram summarising the screening procedure.

Geographic location, environmental medium (soil or water), heavy metals researched, AI methodology used, data sources, model performance metrics, and known constraints were all collected from each included paper. Given the diversity of study designs, data formats, and outcome measures, statistical meta-analysis and formal risk-of-bias assessment were not carried out, as recommended for narrative and methodological reviews (Sarkis-Onofre et al., 2021). Instead, a thematic and comparative synthesis was used to identify major AI approaches, performance trade-offs, scalability restrictions, and implementation issues applicable to African environmental monitoring and remediation. The emphasis was on cross-study consistency, methodological maturity, and contextual feasibility, rather than effect-size aggregation.

Results: Synthesis of reviewed literature

The evaluated literature included investigations undertaken in Africa, Asia, Europe, and North America. The majority of studies focused on water systems, such as rivers, groundwater, irrigation water, and wastewater, while a smaller number looked at soil settings, including agricultural and mining-impacted soils. The heavy metals most commonly investigated in the evaluated research were Pb, Cd, Cr, As, Hg, Cu, Zn, and Ni, either singly or in combination. The reported study designs ranged from field-based monitoring and geographical modelling to sensor-driven real-time detection and remediation-support modelling.

AI Techniques in Use for the Detection of Heavy Metal Contamination Globally

By facilitating the analysis of high-dimensional environmental data at spatial and temporal scales beyond traditional laboratory procedures, artificial intelligence (AI) has transformed heavy metal monitoring (Zhong et al., 2021). Predictive modelling, spatial risk mapping, and near-real-time surveillance are enabled by AI-based systems, which shift environmental assessment from reactive sampling to proactive management (Ma et al., 2024). IoT-based sensor networks for data collection, remote sensing, and geospatial-AI for spatial analysis, machine and deep learning for prediction, neuro-fuzzy systems for handling uncertainty, and data fusion frameworks integrating heterogeneous sources are some of the functions that can be used to categorise AI applications in heavy metal monitoring globally (Li et al., 2025).

Machine Learning Models for Environmental Data Analysis

Machine learning outperforms conventional techniques in capturing intricate, nonlinear interactions in environmental systems (Padarian et al., 2020). ANNs enhance risk assessment, forecasting, and monitoring optimisation by achieving high accuracy ($R^2 > 0.90$) for parameters such as pH, dissolved oxygen, conductivity, and metal ions (Dawood et al., 2021). Explainable AI and uncertainty-aware frameworks are crucial for transparency, trust, and site-specific applications, especially in areas with irregular datasets, as sparse data and low interpretability limit regulatory use (Lokman et al., 2025; Mbunge & Batani, 2023).

Deep Learning Models

Advanced pattern recognition, feature extraction, and nonlinear modelling of intricate environmental datasets are made possible by deep learning (DL) (Sarker, 2021). DL is well-suited to high-dimensional inputs such as hyperspectral images, multispectral satellite data, and continuous sensor time series, as it automatically learns hierarchical representations (Mienye & Swart, 2024). While RNNs, especially LSTMs, predict temporal patterns of pollution influenced by climatic, seasonal, and discharge variability (Kouadri et al., 2021), CNNs are superior at identifying spatial characteristics and hotspots of heavy metal contamination in soils and water (Pouyanfar et al., 2022). CNN-LSTM and deep autoencoders are examples of hybrid deep learning models that improve spatiotemporal accuracy and resilience (Vallileka et al., 2025). DL is crucial for real-time monitoring and early warning, even if it requires large labelled datasets and significant processing resources. Transfer learning provides scalable solutions in data-sparse African situations (Sinha et al., 2025).

Neuro-Fuzzy Systems

Neuro-fuzzy systems, particularly ANFIS, integrate the interpretability of fuzzy logic with neural network adaptive learning (Talpur et al., 2022). They excel on tiny, noisy, and uncertain datasets, where traditional ML frequently fails. ANFIS captures nonlinear interactions between environmental factors while staying interpretable (Agbaogun et al., 2023). Even with small sample sizes, studies show that heavy metals such as lead, copper, and cadmium may be reliably predicted in soil and water. ANFIS is appropriate for data-scarce African contexts, facilitating risk assessment, hotspot identification, and early-warning systems by striking a practical compromise between transparency and predictive performance (Singh, 2025).

Sensor Integration and IoT Applications

The combination of modern sensors and AI is revolutionising real-time monitoring of heavy metals in soil and water. Low-cost electrochemical and nanosensors now enable continuous, sensitive detection of metal ions (Gupte & Pradeep, 2022). When combined with AI, they enable automatic anomaly identification, trend analysis, and predictive modelling. Embedding these sensors into IoT networks enables remote data collection, wireless transfer, and cloud processing, resulting in scalable, distributed environmental surveillance and less labour-intensive sampling (DeMedeiros et al., 2023). Despite these benefits, effectiveness in African environments is constrained by unreliable infrastructure, sensor maintenance, and unstable data transport. Hybrid techniques that combine automated sensing with periodic laboratory validation are currently the most realistic option.

Remote Sensing with AI

The use of remote sensing data from satellites and unmanned aerial vehicles (UAVs) for large-scale contamination assessment has significantly increased thanks to artificial intelligence. Large-scale agricultural or mining landscapes can produce high-resolution predicted maps of heavy metals like lead and cadmium using machine learning and deep learning models trained on multispectral and hyperspectral data (Ma et al., 2024). Data fusion frameworks that combine these AI forecasts with geostatistical models (such as kriging) and supplementary data (including soil type, topography, and drainage) yield the most significant advances (Yuan et al., 2020). This combination creates reliable, high-resolution risk maps that are crucial for targeted action by capturing both the intricate, nonlinear drivers of pollution and the inherent spatial autocorrelation.

In areas where ground sampling is logistically difficult, remote sensing-based AI models perform exceptionally well in terms of spatial coverage and cost effectiveness (Fassnacht et al., 2024). However, when site-specific calibration data are scarce—a common limitation in many African landscapes—their reliance on indirect spectral proxies introduces uncertainty. Therefore, these methods operate best when combined with ground-truth measurements using data fusion frameworks that maintain large-scale applicability while improving local precision.

Data Fusion and Spatial Modelling

Data fusion and spatial modelling combine disparate sources to generate high-resolution maps of contamination and its causes. Hybrid frameworks use geostatistics (e.g., kriging) to describe spatial autocorrelation and machine learning to capture complicated, nonlinear environmental interactions (Wang et al., 2023; Gao et al., 2020). Outlier identification increases resistance to sensor failures, unknown origins, and unique geology (Meng et al., 2020). In African contexts, these methods maximise information from scarce ground-truth data using freely available geographic variables; however, performance depends on data quality, geographic alignment, and spatial continuity assumptions (Li et al., 2020; Di Curzio et al., 2021). To handle changing landscapes and rapid environmental change, successful deployment requires adaptive, locally verified models, collaborative networks, and open-source technologies (Liu et al., 2020).

Hybrid and Ensemble Models

To maximise robustness and generalisability, the area is rapidly embracing hybrid and ensemble models that integrate the capabilities of multiple techniques. These methods mitigate individual model biases and overfitting. Examples include stacking CNNs with Random Forests for spatial feature categorisation or combining ANNs with regionally weighted regression to account for spatial non-stationarity (Poulinakis et al., 2023). Ensemble approaches, which combine predictions from multiple base models (e.g., boosting, bagging), regularly outperform other methods on environmental datasets.

By reducing the biases of individual algorithms, hybrid and ensemble models generally produce improved predictive robustness; however, this performance gain comes at the expense of higher computational complexity and decreased interpretability. Such approaches are best suited for high-priority locations with sufficient technical competence in African regulatory environments where transparency and simplicity of execution are crucial. Simplified ensemble architectures that maintain robustness while enhancing operational accessibility should be the focus of future study. Table 3.1 provides a semi-quantitative synthesis of the main AI methods for heavy metal detection and remediation to facilitate cross-method comparison and highlight trade-offs pertinent to low-resource contexts (Gheibi et al., 2024; Khatun et al., 2024; Li et al., 2020).

Table 3.1: Comparative Overview of AI Techniques for Heavy Metal Detection and Remediation in Environmental Systems

AI Technique	Typical Data Volume Requirement	Typical Performance Range*	Key Strengths	Primary Limitations	Deployment Readiness in Africa
Conventional ML (ANN, RF, SVM)	Moderate (10^2–10^3 samples)	$R^2 \approx 0.75–0.95$	Strong nonlinear modelling; adaptable to heterogeneous inputs	Susceptible to overfitting; limited interpretability	**Pilot to early operational**
Deep Learning (CNN, LSTM)	High (10^3–10^5 samples)	$R^2 \approx 0.85–0.98$	Excellent spatial and temporal feature extraction	High computational cost; data intensive	**Pilot (via transfer learning)**
Neuro-Fuzzy Systems (ANFIS)	Low–Moderate (10^1–10^2 samples)	$R^2 \approx 0.70–0.90$	Interpretability; robustness to noisy data	Limited scalability; rule design complexity	**Operational (localised)**
IoT + AI Systems	Continuous streaming data	Accuracy ≈ 80–95% (classification / anomaly detection)	Real-time monitoring; automation	Sensor reliability; infrastructure dependence	**Pilot**
Remote Sensing + AI	Moderate–High (satellite + field data)	$R^2 \approx 0.70–0.95$	Large-area coverage; cost-effective	Requires ground-truth calibration	**Operational (regional)**
ML–Geostatistical Hybrids	Low–Moderate (sparse but spatially distributed)	$R^2 \approx 0.80–0.96$	High-resolution risk mapping; uncertainty modelling	Assumptions of spatial stationarity	**Operational (research-led)**
Hybrid / Ensemble Models	Moderate–High	$R^2 \approx 0.85–0.98$	High robustness; reduced model bias	Complexity; reduced transparency	**Pilot (high-priority sites)**

Footnote:

Abbreviations: ML = Machine Learning; ANN = Artificial Neural Network; RF = Random Forest; SVM = Support Vector Machine; CNN = Convolutional Neural Network; LSTM = Long Short-Term

Memory; ANFIS = Adaptive Neuro-Fuzzy Inference System; AI = Artificial Intelligence; and IoT = Internet of Things.

AI Techniques Applied in The Detection of Heavy Metal Contamination in Africa

AI-based heavy metal identification is growing across Africa, mostly through pilot-scale and proof-of-concept implementations, though adoption is still slower than global trends. Water and soil monitoring has been implemented in a number of nations using machine learning, neuro-fuzzy systems, geospatial-AI, IoT-enabled sensing, and data fusion techniques, indicating increasing technical capability and policy interest.

Machine Learning and ANN Applications

When it comes to using AI for environmental monitoring, Nigeria has led the way. Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been used in studies to forecast Pb, Cd, and Ni concentrations in agricultural soils. For instance,(Olayode et al., 2023) produced precise spatial contamination maps by integrating soil chemical and physical parameters using ANFIS, resulting in reduced error margins (MAPE, RMSE). ANN models were also used by Omeka (2024) to evaluate river water quality, demonstrating promising predictive performance and potential for incorporation into routine monitoring.

Ethiopia has also shown success, especially in the Little Akaki River in Addis Ababa, where ANN models trained on data from the dry and rainy seasons were able to forecast the Water Quality Index (WQI) with R2 values of 0.93 (Tarekegn et al., 2022). These studies highlight the significance of seasonally resolved datasets while demonstrating the viability of AI-driven prediction under African data constraints.

Remote Sensing and Geospatial-AI

In South Africa, Ghana, and Egypt, remote sensing and machine learning have been used to assess contamination from mining. High-resolution maps of the risk of arsenic and chromium in soils affected by mining were created in South Africa using geospatial AI frameworks (Bassine et al., 2025). Targeted regulatory action in Ghana was enabled by identifying lead and mercury hotspots near artisanal mining zones using ML-based classifiers (Folorunso et al., 2023). To estimate the distribution of cadmium in Nile Delta soils, Egyptian studies have used machine learning with geostatistics (Chen et al., 2020). Continental monitoring is enabled by geospatial AI, but for long-term effects, cross-border data harmonisation is necessary.

IoT and Sensor-Based AI Systems

Nanosensors with IoT capabilities are gradually becoming more popular. IoT-based artificial intelligence (AI) systems have been tested in semi-arid regions of Morocco to monitor irrigation water quality, enabling real-time heavy-metal identification. Low-cost sensors combined with machine learning models have been tested in Kenya's Nairobi River Basin as part of ongoing experiments to continuously monitor Pb and Zn levels (Isong et al., 2022). Although technically feasible, IoT-based AI solutions are still constrained by the dependability and maintenance capacity of the infrastructure.

Data Fusion and Hybrid Models

High-resolution contamination maps have been produced in South Africa and Nigeria using data fusion techniques that combine ML models with spatial autocorrelation. These methods use nonlinear modelling to refine predictions while capturing metal clustering patterns. According to a study conducted in Southeast Nigeria, the reliability of contamination estimates was increased by combining ANFIS with geostatistical indicators (Agbaogun et al., 2023).

Discussion

AI-Driven Remediation Strategies for Contaminated Environments

The ultimate objective of environmental management is remediation, even though identifying heavy metal contamination is an essential first step. By facilitating real-time monitoring, adaptive bioremediation, predictive modelling, and decision-support systems, artificial intelligence (AI) has demonstrated an increasing capacity to optimise remediation techniques. These methods are being incorporated into sustainable remediation techniques worldwide, and African nations are increasingly experimenting with comparable methods.

Predictive Modelling For Remediation Planning

Predictive modelling forecasts pollution trends and directs remediation decisions using both historical and current data. ANNs and Random Forest models have been used worldwide to forecast soil and water pollution thresholds, which, in turn, trigger treatments such as biochar amendment, phytoremediation, and soil cleaning (Adewuyi et al., 2024). For example, targeted remediation of arsenic and cadmium "hotspots" has been made possible by spatial modelling of heavy metals in agricultural soils in China and India (Ma et al., 2024).

Nigeria has used similar strategies in Africa. Heavy metal risks in agricultural soils in the southeast were predicted using ANNs combined with geospatial indices, which helped guide remediation strategies and soil treatment programmes (Olayode et al., 2023). These models' dependability for site-specific remediation planning was proved by their low RMSE and MAPE values.

Integration of Bioremediation and AI

AI-assisted bioremediation, which uses microbes and plants to clean contaminants, is becoming more popular. The effectiveness of microbial strains and hyperaccumulator plants under varying climatic conditions is predicted globally using AI-enhanced models (Tripathi & Gaur, 2021). AI enhances the effectiveness of biochar-based detoxification and optimises phytoremediation techniques by mimicking soil–plant–metal interactions (Singh, 2025). Case studies are emerging across Africa. By simulating how seasonal variability impacts the uptake of Pb and Cd by native plant species, Ethiopia has investigated AI-assisted phytoremediation (Tarekegn et al., 2022). Microbial remediation and AI-based monitoring systems have been used in South African research to track the elimination of chromium from mining-impacted soils. Adaptive management is ensured via real-time feedback (Bassine et al., 2025).

Real-Time Monitoring and Adaptive Feedback Systems

Nanosensors and machine learning algorithms are combined in AI-driven, real-time monitoring systems to assess on-site cleanup efforts. For instance, dynamic modification of treatment protocols in wastewater treatment plants has been made possible by real-time monitoring using AI-enhanced IoT devices (Krishnan & Giwa, 2025).

Mohanty et al. (2024). Following remediation trials, pilot IoT-based sensors installed along the Nairobi River in Kenya have been tested to track drops in Pb and Zn levels. When anticipated drops in heavy metal concentrations are not realised, these systems offer adaptive recommendations, such as modifying biochar dosages or microbial inoculation rates (Isong et al., 2022).

AI-Enhanced Decision-Support For Policymakers

Globally, AI-powered decision-support systems prioritise remedial operations by combining social, economic, and environmental data. For instance, Europe and Asia have embraced prediction models that evaluate the cost-benefit ratios of soil washing vs phytoremediation (Cruz et al., 2021). Though still scarce, decision-support applications show promise in Africa. To avoid recontamination from contaminated water sources, Morocco has used AI-based decision systems in agricultural irrigation planning. Similarly, Nigeria has tested decision-making algorithms at the local government level that prioritise hazardous areas for immediate repair; however, accuracy remains limited by a lack of data (Folorunso et al., 2023).

Policy and Regulatory Implications

Coordinated action across institutional levels and governance scales is necessary to effectively translate AI-driven insights into environmental protection outcomes. AI-derived contamination risk maps, early-warning indicators, and predictive forecasts should be incorporated into regular soil and water quality monitoring, permitting, and compliance-enforcement frameworks by national environmental regulators, such as National Environment Management Authorities (NEMA), Environmental Protection Agencies (EPAs), and water resource authorities. AI-enabled decision-support systems can inform the prioritisation of pollution hotspots, optimise sample locations, and plan adaptive remediation for urban rivers, mining-impacted landscapes, and agricultural zones at the municipal and basin management levels. By encouraging harmonised data standards, supporting shared environmental data platforms, and facilitating cross-border AI model transfer and capacity building, organisations like the African Union (AU), African Ministers' Council on Water (AMCOW), and regional economic communities (such as EAC, ECOWAS, and SADC) can play a coordinating role at the regional and continental level. To ensure that AI is embedded in evidence-based environmental governance rather than merely an analytical tool, it is crucial that AI outputs be operationalised through clear regulatory pathways that link model predictions to predetermined management actions, such as remediation triggers, land-use restrictions, or enforcement thresholds.

Challenges, Limitations, and Future Perspectives

Despite rising applications, AI in heavy metal detection and remediation faces interconnected problems that limit its dependable deployment in African environmental systems (Bassine et al., 2025; Folorunso et al., 2023). Data scarcity, model limitations, system integration challenges, and gaps between prediction outputs and practical remediation solutions are among the most significant obstacles.

Data availability and quality remain significant impediments. Sparse, fragmented, or temporally inconsistent datasets can lead to biased learning, overfitting, and poor generalisation (Folorunso et al., 2023; Isong et al., 2022). Intensive local sample efforts produce good model results but are often impractical at scale (Olayode et al., 2023; Tarekegn et al., 2022). Transfer learning, semi-supervised models, and physics-informed AI are examples of data-efficient techniques that can extract valuable insights from limited data while remaining robust.

Model interpretability and reliability are other important considerations. Deep learning and hybrid ensemble models frequently function as "black boxes," hiding causal relationships between environmental factors and contamination forecasts, undermining regulatory trust (Maeda et al., 2021). Models trained on restricted or seasonally biased data are prone to overfitting, resulting in incorrect forecasts under changing conditions (Tarekegn et al., 2022; Poulinakis et al., 2023). Integrating explainable AI (XAI), uncertainty quantification, and model auditing is critical for transparency and responsible deployment.

Integrating AI with IoT sensors and remote monitoring platforms presents system-level problems. Calibration drift, connection issues, environmental stresses, and data errors can all propagate uncertainty throughout AI pipelines, reducing real-time prediction accuracy (Romano, 2025; Jin et al., 2020). Co-designed systems that integrate sensors, data infrastructure, and analytical models, along with adaptive calibration and edge computing, can improve resilience.

Finally, the ability to translate AI outputs into meaningful remediation remains restricted, with only a few practical closed-loop systems demonstrated in African contexts. Future research should concentrate on hybrid, modular, and open-source AI frameworks that balance prediction accuracy, interpretability, and feasibility while also assessing long-term reliability, scalability, and policy relevance (Archana & Jeevaraj, 2024; Ennab & Mcheick, 2024). The long-term integration of AI into heavy metal monitoring and cleanup in Africa depends on overcoming these technical, operational, and governance hurdles.

Conclusion

Heavy metal poisoning of soil and water remains a serious global problem, and its consequences are particularly severe in Africa, where industrialisation, mining, and poor waste management increase exposure hazards. This paper highlights how artificial intelligence—through machine learning, deep learning, IoT-enabled sensor networks, and geospatial modelling—offers transformative opportunities for toxic metal detection, high-resolution mapping, and adaptive remediation. Case studies from Nigeria, Ethiopia, Kenya, South Africa, Ghana, Morocco, and Egypt demonstrate that AI models can make accurate predictions, support real-time monitoring, and enable targeted remediation even in data-scarce, resource-constrained environments.

Despite this promise, AI deployment in Africa remains primarily experimental, hampered by fragmented datasets, limited digital infrastructure, insufficient technical competence, and poor alignment with environmental legislation. Transitioning from small-scale trials to continent-wide environmental intelligence systems requires strategic investment in sensor networks, open-access data platforms, local capacity-building, and robust public-private collaborations.

If these deficiencies are solved, Africa will be able to use AI not only to identify and reduce heavy metal pollution, but also to develop proactive, predictive, and resilient environmental management systems. Such advances will improve public health, protect food and water security, and speed the fulfilment of the Sustainable Development Goals, establishing AI as a cornerstone of the region's sustainable environmental governance system.

Several coordinated approaches are proposed to accelerate the adoption of AI-driven environmental monitoring and cleanup across Africa. First, capacity building is critical, with governments and institutions implementing specialised training programmes in AI, environmental informatics, and sensor-based monitoring to close the skills gap. Second, the introduction of open-access environmental data platforms, through collaboration among governments, research institutions, and regional bodies, would enable the development of continental databases to facilitate model training, validation, and cross-country comparisons. Third, establishing public-private collaborations can lower the cost of cloud-based AI solutions, make sensor deployment easier, and promote innovation by using technology companies' experience. Fourth, policy integration is crucial, with AI-powered decision-support systems implemented into national water and soil quality legislation to improve resource allocation, contaminated site prioritisation, and long-term remediation planning. Finally, regional collaboration should be strengthened, allowing countries such as South Africa, Ethiopia, Kenya, and Nigeria to develop information exchange networks, standardise best practices, and encourage cross-border adoption of AI-enabled environmental management systems.

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