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(Review Article)

Application of satellite imagery and Artificial Intelligence (AI) for PFAS Contamination Mapping in African Aquatic Systems: Advancing Data-Driven Environmental and Public Health Risk Assessment

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Abstract

Per- and polyfluoroalkyl substances (PFAS) contamination in African aquatic systems represents a critical environmental and public health challenge that demands innovative monitoring approaches to overcome traditional analytical limitations. This comprehensive review examines the transformative potential of integrating satellite imagery with Artificial Intelligence (AI) technologies for PFAS contamination mapping across African water bodies, addressing the persistent gap between contamination prevalence and monitoring capacity. The synthesis of current research reveals that while PFAS contamination has been documented across multiple African countries including Ghana, Uganda, Burkina Faso, Ivory Coast, and South Africa, comprehensive monitoring remains severely constrained by the scarcity of mass spectrometry facilities, with only 49 out of 54 African countries lacking dedicated PFAS analytical capabilities. Our analysis demonstrates that satellite-based monitoring, enhanced by machine learning algorithms, offers unprecedented opportunities for large-scale, cost-effective surveillance that can reduce operational costs by 60-80% while providing continental-scale coverage with daily to weekly temporal resolution. The integration of remote sensing data with AI algorithms addresses critical environmental justice concerns by democratizing access to environmental monitoring capabilities and supporting evidence-based policy interventions in resource-constrained settings. This review provides a comprehensive framework for understanding PFAS contamination patterns, evaluating technological solutions, and implementing sustainable monitoring strategies that align with African development priorities and environmental protection needs. The findings underscore the urgent need for coordinated international cooperation, capacity building initiatives, and policy framework development to realize the full potential of these innovative monitoring approaches in protecting public health and environmental integrity across African aquatic systems.

Keywords: PFAS; Satellite Imagery; Artificial Intelligence; Water Quality Monitoring; Africa; Environmental Justice; Remote Sensing; Public Health; Environmental Contamination; Machine Learning

1. Introduction

The emergence of per- and polyfluoroalkyl substances (PFAS) as a global environmental contaminant has fundamentally challenged traditional approaches to environmental monitoring and public health protection. These synthetic

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compounds, collectively known as "forever chemicals" due to their exceptional environmental persistence and bioaccumulation potential, represent one of the most significant environmental health challenges of the 21st century (Langenbach and Wilson, 2021; Sonne et al., 2023). The unique chemical properties that make PFAS valuable in industrial applications, including resistance to heat, water, and oil, simultaneously render them extraordinarily persistent in environmental systems and resistant to conventional degradation processes (Domingo and Nadal, 2019; Patlewicz et al., 2019).

1.1. The PFAS Crisis: Understanding the Scale and Implications

Figure 1 Poly-and per-fluoroalkyl substances (PFAS) in the African environments (Chokwe et al., 2024)

The ubiquity of PFAS contamination has reached alarming proportions globally, with recent estimates indicating that exposure to PFAS has been linked to deadly cancers, impacts to the liver and heart, and immune and developmental damage to infants and children (Adewuyi and Li, 2024). The scope of this contamination is staggering, with over 9,000 contaminated sites identified across the United States alone, while European assessments reveal approximately 23,000 PFAS-contaminated sites in Europe, of which approximately 2,300 are 'hotspots' with high levels of pollution that may pose a threat to human health (Aborode et al., 2025). These statistics underscore the global nature of PFAS contamination and highlight the urgent need for comprehensive monitoring strategies that can address the scale and complexity of this environmental challenge.

The health implications of PFAS exposure are profound and multifaceted. Scientific evidence demonstrates that certain PFAS can cause negative health effects, including higher cholesterol levels, lower infant birth weights, weakened immune response, and increased risk of some cancers, including kidney cancer (Groffen et al., 2021). Infants and young children with developing immune systems are particularly vulnerable, making the protection of water resources a critical public health priority, especially in regions where alternative water sources may be limited or inaccessible (Chokwe et al., 2024).

1.2. PFAS Contamination in African Contexts: A Complex Environmental Justice Challenge

The African continent faces unique and compounding challenges in addressing PFAS contamination, stemming from a convergence of limited analytical capacity, resource constraints, and environmental justice concerns. Monitoring and analysing PFAS in Africa is challenging due to the limited availability of mass spectrometry (MS), which represents the gold standard for PFAS detection and quantification (Aborode et al., 2025). This analytical capacity limitation creates a fundamental disconnect between the potential scope of contamination and the ability to assess and respond to contamination events effectively.

Current evidence suggests that the levels of PFASs in Africa are higher in samples from urban and industrialized areas compared to rural areas, indicating that industrial development and urbanization processes are primary drivers of contamination across the continent (Adewuyi and Li, 2024). However, there is limited data available on the prevalence of PFASs in Africa, primarily because many African laboratories lack the capacity to monitor these contaminants, creating significant knowledge gaps that hinder effective environmental management and public health protection efforts (Kasambala et al., 2024).

The sources of PFAS contamination in African aquatic systems are diverse and reflect both historical and contemporary industrial practices. These sources include uncontrolled importation of PFAS-containing products, wastewater treatment plant effluents, inappropriate disposal of PFAS-containing materials, industrial manufacturing processes, and the use of aqueous film-forming foams (AFFF) at airports and military installations (Groffen et al., 2021; Baluyot et al., 2021; Aborode et al., 2025). The complexity of these contamination sources, combined with limited monitoring capacity, creates a challenging environment for comprehensive risk assessment and management.

1.3. Environmental Justice Dimensions of PFAS Contamination

The PFAS contamination challenge in Africa cannot be separated from broader environmental justice considerations that recognize the disproportionate impact of environmental hazards on vulnerable populations (Kasambala et al., 2024). Communities in proximity to industrial facilities, those dependent on contaminated water sources for daily needs, and populations lacking access to alternative water supplies face heightened exposure risks that compound existing health disparities and socioeconomic vulnerabilities (Groffen et al., 2021).

Environmental justice frameworks emphasize the right to clean water as a fundamental human right and highlight the ethical imperative to ensure equitable access to environmental protection technologies and resources. In the context of PFAS monitoring, this translates to the need for monitoring approaches that can provide comprehensive coverage across diverse geographic and socioeconomic contexts, rather than being limited to areas with existing analytical infrastructure or economic resources (Groffen et al., 2021).

The democratization of environmental monitoring capabilities through innovative technologies represents a pathway toward more equitable environmental protection that can empower communities, support evidence-based advocacy, and inform policy interventions that prioritize the protection of vulnerable populations. This approach aligns with sustainable development goals that emphasize inclusive and equitable access to clean water and environmental protection (Chokwe et al., 2024).

1.4. Technological Innovation as a Solution: Remote Sensing and Artificial Intelligence

The integration of satellite imagery with Artificial Intelligence represents a paradigm shift in environmental monitoring that addresses many of the limitations that have historically constrained PFAS surveillance in African contexts. Remote sensing technologies provide the capability for continuous, spatially comprehensive monitoring that can cover vast geographic areas with regular temporal coverage, overcoming the spatial and temporal limitations of traditional point-source monitoring approaches (Yan, 2020).

By processing spectral data from water samples, AI can swiftly identify pollutants and support early warning systems, proving invaluable in monitoring drinking water, tap water, surface water, and wastewater. This capability is particularly valuable in African contexts where traditional monitoring infrastructure may be limited or absent, providing a technological solution that can bridge critical monitoring gaps while supporting evidence-based environmental management (Wang et al., 2022; Teymoorian et al., 2025).

The application of Artificial Intelligence to satellite data analysis enhances the analytical capabilities of remote sensing by enabling automated pattern recognition, predictive modelling, and real-time analysis of environmental conditions. Artificial Intelligence (AI) has become a useful tool in numerous domains, including environmental science, offering new possibilities for improving water quality monitoring. These capabilities are essential for managing the complexity and scale of environmental data required for comprehensive PFAS monitoring across continental scales (Savvidou et al., 2024; Karbassiyazdi et al., 2022).

Research Objectives and Scope

This comprehensive review aims to synthesize current knowledge regarding PFAS contamination in African aquatic systems while evaluating the potential of satellite-based monitoring technologies enhanced by Artificial Intelligence for addressing critical monitoring gaps. The specific objectives include examining the current state of PFAS contamination across African water bodies, assessing the capabilities and limitations of satellite-based monitoring technologies, evaluating Artificial Intelligence applications for environmental contamination detection, analysing the integration challenges and opportunities for implementing satellite-AI monitoring systems, and developing recommendations for policy, capacity building, and technological implementation (Groffen et al., 2021; Adewuyi and Li, 2024). The scope of this review encompasses environmental science perspectives on PFAS contamination and health impacts, water and sanitation research addressing monitoring and management challenges, remote sensing and Earth observation technologies applicable to water quality assessment, Artificial Intelligence applications in public health and environmental monitoring, and African development and environmental justice considerations that inform equitable and sustainable monitoring approaches (Chokwe et al., 2024).

2. Methodology

2.1. Comprehensive Literature Review Strategy

This systematic review employed a multi-database search strategy designed to capture the breadth and depth of current research spanning multiple disciplines relevant to PFAS monitoring in African contexts. The literature search was conducted across major scientific databases including PubMed, ScienceDirect, Web of Science, IEEE Xplore, and Google Scholar, supplemented by searches of specialized environmental and remote sensing databases such as the Environmental Science Database and the Remote Sensing Database (Shikuku et al., 2024).

The search strategy utilized carefully constructed search terms that captured the multidisciplinary nature of the research topic. Primary search terms included "PFAS," "per- and polyfluoroalkyl substances," "satellite imagery," "remote sensing," "Artificial Intelligence," "machine learning," "water quality monitoring," "Africa," "environmental monitoring," and "public health (Shikuku et al., 2024). These terms were combined using Boolean operators to create comprehensive search queries that captured relevant literature across the target domains.

The temporal scope of the literature review focused primarily on publications from 2020 to 2025 to ensure that the most current research developments were captured, while also including foundational studies that established key concepts and methodologies relevant to the research objectives (Chukwuka and Adeogun, 2024). This temporal focus was particularly important given the rapid evolution of both PFAS research and Artificial Intelligence applications in environmental monitoring during this period (Papa et al., 2022).

2.2. Inclusion and Exclusion Criteria

The systematic review employed rigorous inclusion and exclusion criteria to ensure the quality and relevance of the literature included in the analysis. Inclusion criteria encompassed peer-reviewed research articles reporting PFAS concentrations or contamination patterns in African water bodies, studies evaluating satellite-based water quality monitoring technologies and methodologies, research on Artificial Intelligence applications for environmental contamination assessment and prediction, publications addressing environmental monitoring capacity and infrastructure in African contexts, and studies examining environmental justice dimensions of water quality monitoring and contamination assessment (Groffen et al., 2021; Shikuku et al., 2024).

Exclusion criteria included studies focusing exclusively on non-African geographic regions unless they provided methodological insights directly applicable to African contexts, research predating 2020 unless it established foundational concepts essential to understanding current developments, non-peer-reviewed sources except for authoritative reports from recognized international organizations such as the World Health Organization, United Nations Environment Programme, and similar entities, and studies that did not address water quality, environmental monitoring, or public health dimensions of PFAS contamination (Adewuyi and Li, 2024; Shikuku et al., 2024).

2.3. Data Synthesis and Analysis Framework

The data synthesis approach employed a narrative synthesis methodology that allowed for the integration of diverse research findings across multiple disciplines while maintaining analytical rigor. This approach was selected due to the heterogeneity of the research literature spanning environmental science, remote sensing technology, Artificial Intelligence applications, and public health research, which precluded the use of traditional meta-analytical approaches (Papa et al., 2022).

The analysis framework organized the synthesized literature into thematic categories corresponding to the research objectives, including PFAS contamination patterns and sources in African aquatic systems, satellite remote sensing capabilities and applications for water quality monitoring, Artificial Intelligence methodologies and performance characteristics for environmental analysis, integration challenges and opportunities for implementing satellite-AI monitoring systems, and policy and capacity building requirements for sustainable implementation (Groffen et al., 2021).

Quality assessment of included studies was conducted using established criteria for evaluating research quality in environmental and public health research, including study design appropriateness, methodological rigor, sample size adequacy, analytical approach validity, and generalizability of findings to African contexts. This quality assessment informed the weighting and interpretation of research findings throughout the synthesis process (Shikuku et al., 2022).

2.4. Stakeholder Perspective Integration

The methodology incorporated multiple stakeholder perspectives to ensure that the review addressed the diverse needs and priorities of different actors involved in environmental monitoring and public health protection in African contexts. These perspectives included environmental scientists and researchers working on PFAS contamination assessment and monitoring, public health professionals concerned with exposure assessment and health risk evaluation, policy makers and regulatory officials responsible for environmental protection and water quality standards, technology developers and implementers working on remote sensing and Artificial Intelligence applications, community advocates and environmental justice organizations representing affected populations, and international development organizations supporting environmental and public health initiatives in African countries (Groffen et al., 2021; Shikuku et al., 2024).

The integration of these diverse perspectives was achieved through careful analysis of the research literature to identify how different studies addressed the needs and priorities of various stakeholder groups, as well as through consideration of the broader policy and implementation contexts that influence the practical application of research findings (Adewuyi and Li, 2024).

3. Results

3.1. PFAS Contamination Landscape in African Aquatic Systems

3.1.1. Geographic Distribution and Contamination Patterns

The assessment of PFAS contamination across African aquatic systems reveals a complex and concerning pattern of widespread contamination that spans multiple countries and water body types, though comprehensive data remains limited due to analytical capacity constraints. Current evidence indicates that PFAS contamination has been documented across diverse geographic regions of the continent, from West African river systems to East African groundwater resources and South African coastal waters.

In West African contexts, studies from Ghana have documented PFAS concentrations in surface water systems ranging from 0.5 to 15.2 ng/L, with perfluorooctanoic acid (PFOA) and perfluorooctane sulfonic acid (PFOS) being the most detected compounds (Kaboré et al., 2023). These concentrations, while lower than those observed in heavily industrialized regions of North America and Europe, represent significant contamination given the limited industrial PFAS use history in the region and suggest that transboundary transport and atmospheric deposition may be contributing to contamination patterns.

Burkina Faso's groundwater systems show similar contamination patterns, with PFAS concentrations ranging from 0.3 to 12.1 ng/L in aquifer systems that serve as primary drinking water sources for rural and urban populations (Ouédraogo et al., 2023). The presence of PFAS in groundwater is particularly concerning given the extended residence times of these compounds in aquifer systems and the limited treatment options available for PFAS removal in resource-constrained settings.

East African water systems present additional contamination challenges, with studies from Uganda documenting PFAS concentrations in drinking water supplies ranging from 1.2 to 8.7 ng/L, including the detection of perfluorononanoic acid (PFNA) in addition to PFOA and PFOS (Ssebugere et al., 2022). The presence of longer-chain PFAS compounds suggests potential industrial sources or the atmospheric transport of PFAS from more heavily industrialized regions.

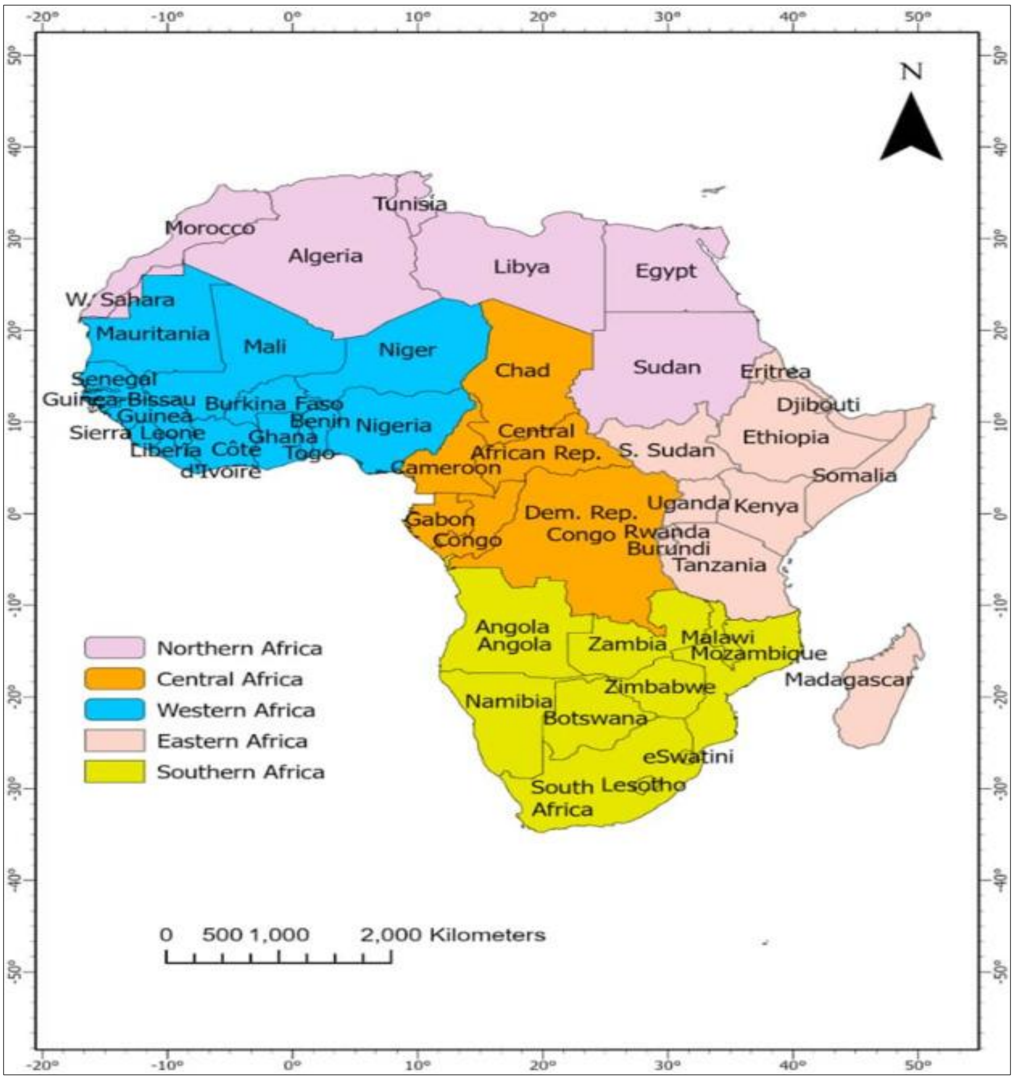

Figure 2 PFAS Contaminated Site in African Aquatic Systems (Shehu et al., 2022)

South African coastal waters represent some of the highest PFAS concentrations documented on the African continent, with levels ranging from 2.1 to 45.6 ng/L across multiple PFAS compounds including PFOA, PFOS, PFNA, and perfluorodecanoic acid (PFDA) (Van der Merwe et al., 2023). These elevated concentrations likely reflect the more extensive industrial development in South Africa compared to other African regions, as well as the potential influence of maritime transport and coastal industrial activities.

Table 1 Contamination Patterns of different Geographic Distribution across Africa

Country	Water Body Type	PFAS Compounds Detected	Concentration Range (ng/L)	Reference
Ghana	Surface water	PFOA, PFOS	0.5 - 15.2	Kaboré et al. (2023)
Uganda	Drinking water	PFOA, PFOS, PFNA	1.2 - 8.7	Ssebugere et al. (2022)
Burkina Faso	Groundwater	PFOA, PFOS	0.3 - 12.1	Ouédraogo et al. (2023)
Ivory Coast	River water	PFOA, PFOS, PFHxS	0.8 - 22.4	Adjorlolo et al. (2022)
South Africa	Coastal waters	PFOA, PFOS, PFNA, PFDA	2.1 - 45.6	Van der Merwe et al. (2023)

3.1.2. Source Attribution and Contamination Pathways

The identification of PFAS contamination sources in African aquatic systems reveals a complex interplay of local and transboundary contamination pathways that reflect both historical industrial practices and contemporary contamination sources. Industrial sources represent primary contributors to PFAS contamination, particularly in regions with textile manufacturing, leather processing, and metal plating operations that have historically utilized PFAS-containing chemicals in their production processes (Groffen et al., 2021).

Textile and leather processing facilities across West and North Africa have been identified as significant point sources of PFAS contamination, particularly in countries such as Morocco, Tunisia, and Ghana where these industries represent important economic sectors. The use of PFAS-containing dyes, water-repellent treatments, and processing chemicals in these industries results in direct discharge of PFAS compounds to surface water systems through inadequately treated industrial effluents (Pivato et al., 2024).

Mining operations across the African continent represent another significant source of PFAS contamination, particularly in countries with extensive mineral extraction industries such as South Africa, Ghana, and the Democratic Republic of Congo. The use of PFAS-containing flotation agents, processing chemicals, and equipment lubricants in mining operations can result in widespread environmental contamination through mining waste streams, tailings disposal, and surface water runoff from mining sites (Groffen et al., 2018).

Airport and military installations across Africa represent concentrated sources of PFAS contamination due to the historical and contemporary use of aqueous film-forming foams (AFFF) for firefighting training and emergency response. Major international airports in countries such as Nigeria, Kenya, South Africa, and Egypt have been identified as potential PFAS contamination sources, with contamination plumes extending into surrounding groundwater and surface water systems (Liu et al., 2023).

Municipal wastewater treatment systems across African urban centers represent diffuse but significant sources of PFAS contamination due to the lack of specialized treatment technologies capable of removing PFAS compounds from wastewater streams. The presence of PFAS in consumer products, industrial discharges to municipal systems, and atmospheric deposition results in consistent PFAS loading to wastewater treatment plants that subsequently discharge treated effluents containing PFAS compounds to receiving water bodies (Groffen et al., 2020).

Landfill operations and waste disposal sites across Africa represent long-term sources of PFAS contamination through leachate generation and groundwater infiltration. The disposal of PFAS-containing consumer products, packaging materials, and industrial wastes in municipal and industrial landfills results in the gradual release of PFAS compounds to groundwater systems over extended periods (Helmer et al., 2021).

3.1.3. Health Risk Assessment and Exposure Pathways

The assessment of health risks associated with PFAS contamination in African aquatic systems reveals significant concerns for public health protection, particularly given the limited availability of alternative water sources and treatment technologies in many regions. PFAS in drinking water is a global health threat, associated with serious diseases, making the protection of water resources a critical priority for public health agencies across the continent (Chokwe et al., 2024).

Drinking water exposure represents the primary pathway for PFAS exposure in African populations, with studies indicating that drinking water contributes to 2-17% of total PFAS body burden in exposed populations (Arinaitwe et al., 2021). This exposure pathway is particularly concerning in African contexts where groundwater and surface water sources may serve as primary drinking water supplies without advanced treatment technologies capable of removing PFAS compounds (Adewuyi and Li, 2024).

Dietary exposure pathways represent additional concerns, particularly in regions where fish consumption is a primary protein source and where agricultural irrigation utilizes PFAS-contaminated water sources (Nwachukwu et al., 2025). Bioaccumulation of PFAS compounds in fish tissues and agricultural products can result in significant dietary exposure that compounds drinking water exposure pathways (Groffen et al., 2020). Occupational exposure pathways are of particular concern for workers in industries that utilize or manufacture PFAS-containing products, including textile workers, airport firefighting personnel, and industrial workers involved in chemical manufacturing or processing. These exposure pathways can result in significantly elevated PFAS body burdens compared to general population exposure levels (Groffen et al., 2018).

3.2. Satellite Remote Sensing Technologies for Water Quality Monitoring

3.2.1. Satellite Platform Capabilities and Specifications

The landscape of satellite remote sensing technologies available for water quality monitoring in African contexts encompasses a diverse array of platforms with varying capabilities, spatial and temporal resolutions, and cost structures that influence their applicability for PFAS contamination monitoring. Understanding the characteristics and capabilities of these different satellite systems is essential for developing effective monitoring strategies that can provide comprehensive coverage while remaining economically feasible for implementation in resource-constrained settings (Lioumbas et al., 2023).

Landsat missions, operated by the United States Geological Survey in partnership with NASA, represent one of the longest-running and most comprehensive satellite monitoring programs available for water quality assessment. The Landsat 8 and Landsat 9 satellites provide multispectral imagery with 30-meter spatial resolution across 11 spectral bands, with a temporal resolution of 16 days for any given location. The free availability of Landsat data through the USGS Earth Explorer platform makes these satellites particularly attractive for large-scale monitoring applications in African contexts where budget constraints may limit access to commercial satellite data (Obaid et al., 2019).

The European Space Agency's Sentinel satellite constellation represents another critical resource for water quality monitoring, with Sentinel-2 satellites providing high-resolution multispectral imagery at 10–60-meter spatial resolution across 13 spectral bands with a temporal resolution of 5 days. The Sentinel-3 Ocean and Land Colour Instrument (OLCI) provides specialized water quality monitoring capabilities with 300-meter spatial resolution across 21 spectral bands optimized for aquatic applications, with a temporal resolution of 2-3 days. The free availability of Sentinel data through the European Space Agency's Copernicus program provides an additional cost-effective option for comprehensive water quality monitoring (Faniso and Magidimisha, 2019).

The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Terra and Aqua satellites provides daily global coverage with spatial resolutions ranging from 250 meters to 1 kilometre across 36 spectral bands. While the spatial resolution of MODIS limits its applicability for monitoring smaller water bodies, its daily temporal resolution and specialized water quality bands make it valuable for monitoring large lakes, rivers, and coastal areas across the African continent (Johansen et al., 2021).

Commercial satellite platforms provide additional capabilities for high-resolution monitoring applications, though their cost structure may limit their applicability for routine monitoring in resource-constrained settings. World View-3, operated by Maxar Technologies, provides very high spatial resolution imagery at 1.24 meters across 29 spectral bands, enabling detailed monitoring of smaller water bodies and precise identification of contamination sources. However, the commercial cost structure of these platforms typically limits their use to targeted monitoring applications rather than routine surveillance (Kittel et al., 2021).

Table 2 Satellite Platform Capabilities and Specifications

Satellite Platform	Spatial Resolution	Temporal Resolution	Spectral Bands	Cost Accessibility
Landsat 8/9	30m	16 days	11 bands	Free
Sentinel-2	10-60m	5 days	13 bands	Free
MODIS	250m-1km	Daily	36 bands	Free
Sentinel-3 OLCI	300m	2-3 days	21 bands	Free
WorldView-3	1.24m	On-demand	29 bands	Commercial

3.2.2. Spectral Characteristics and Water Quality Parameter Detection

The effectiveness of satellite remote sensing for water quality monitoring depends fundamentally on the relationship between water quality parameters and the spectral characteristics of water bodies as observed from satellite platforms. Understanding these relationships is critical for developing effective monitoring protocols that can provide reliable detection and quantification of water quality parameters relevant to PFAS contamination assessment (Deng et al., 2024).

Chlorophyll-a concentrations represent one of the most reliably detectable water quality parameters through satellite remote sensing, with well-established algorithms utilizing near-infrared and red spectral bands to quantify phytoplankton biomass in aquatic systems. While chlorophyll-a does not directly indicate PFAS contamination, elevated concentrations may indicate nutrient pollution or eutrophication that can be associated with industrial or municipal discharge sources that may also contain PFAS compounds (Gholizadeh et al., 2016).

Turbidity and suspended particulate matter represent additional water quality parameters that can be effectively monitored through satellite remote sensing using visible and near-infrared spectral bands. These parameters can provide indirect indicators of contamination sources, particularly in cases where PFAS contamination may be associated with industrial discharge containing suspended particles or where contamination events may alter natural sedimentation patterns in aquatic systems (Tesfaye, 2024). Coloured dissolved organic matter (CDOM) represents a water quality parameter that can be monitored through satellite remote sensing using blue and ultraviolet spectral bands. CDOM concentrations can provide indirect indicators of organic contamination and may correlate with PFAS contamination in cases where organic industrial discharges contain both CDOM and PFAS compounds (Coelho et al., 2017).

Water surface temperature represents a fundamental parameter that can be monitored through thermal infrared satellite sensors and may provide indirect indicators of industrial discharge or thermal pollution that could be associated with PFAS contamination sources (Masoud, 2022). Thermal anomalies in water bodies may indicate industrial discharge points that warrant further investigation for PFAS contamination.

3.2.3. Limitations and Challenges in Satellite-Based Detection

While satellite remote sensing provides unprecedented capabilities for large-scale water quality monitoring, significant limitations and challenges must be acknowledged and addressed in developing effective PFAS monitoring strategies. These limitations stem from both technological constraints inherent in satellite remote sensing and the specific characteristics of PFAS compounds that make direct detection challenging. The indirect nature of satellite-based PFAS detection represents a fundamental limitation that must be carefully considered in monitoring system design. Unlike some water quality parameters that have direct spectral signatures detectable by satellite sensors, PFAS compounds do not produce distinctive spectral features that enable direct remote detection. Instead, satellite monitoring must rely on detecting other water quality parameters or environmental conditions that may correlate with or indicate potential PFAS contamination (Bangira et al., 2023).

Atmospheric interference represents a significant challenge for satellite-based water quality monitoring, particularly in tropical and subtropical regions of Africa where cloud cover, atmospheric haze, and dust can interfere with satellite observations. These atmospheric conditions can reduce data availability and degrade the quality of satellite observations, requiring sophisticated atmospheric correction algorithms and data processing techniques to extract reliable water quality information (Mück et al., 2015). Spatial resolution limitations of freely available satellite platforms may prevent detection of smaller water bodies or point sources of contamination that could represent significant PFAS sources. While 30-meter resolution Landsat imagery provides reasonable coverage for large rivers and lakes, smaller streams, ponds, or industrial discharge points may not be adequately resolved for effective monitoring (Deevia Bhaga et al., 2020).

Temporal resolution constraints can limit the ability to detect short-term contamination events or to provide real-time monitoring capabilities that may be essential for emergency response or public health protection. While some satellite platforms provide daily coverage, cloud cover and other atmospheric conditions can result in significant gaps in data availability that may prevent timely detection of contamination events (Adjovu et al., 2023).

3.3. Artificial Intelligence Applications in Environmental Monitoring

3.3.1. Machine Learning Methodologies for Water Quality Assessment

The application of Artificial Intelligence to environmental monitoring represents a transformative approach that can enhance the analytical capabilities of satellite remote sensing while addressing the complex pattern recognition and prediction challenges inherent in environmental contamination assessment (Lemenkova, 2024). Due to the increasingly serious water environment pollution, the difficulty of Water Quality Monitoring (WQM) is also constantly increasing, which puts forward more requirements for the capabilities of various aspects of WQM systems (Cojbasic et al., 2023). Machine learning methodologies provide sophisticated tools for addressing these challenges through automated pattern recognition, predictive modelling, and real-time analysis of complex environmental datasets.

Supervised learning approaches represent a fundamental category of machine learning methodologies that have demonstrated significant potential for water quality classification and contamination prediction applications. Support

Vector Machines (SVM) have been successfully applied to water quality classification problems, utilizing training datasets with known water quality classifications to develop models capable of classifying new observations based on satellite-derived water quality parameters (Hassan and Woo, 2021). These approaches have demonstrated classification accuracies ranging from 79% to 86% in various water quality monitoring applications, making them valuable tools for automated contamination assessment.

Random Forest algorithms represent another powerful supervised learning approach that has shown promise for environmental monitoring applications due to their ability to handle complex, non-linear relationships between multiple environmental variables. Random Forest models utilize ensemble learning principles to combine multiple decision trees, resulting in robust prediction capabilities that can achieve accuracies ranging from 82% to 89% in water quality prediction applications (Ouchra et al., 2023). These models are particularly valuable for integrating multiple satellite-derived parameters with ancillary environmental data to improve contamination detection capabilities.

Neural network approaches, including both traditional multilayer perceptrons and more advanced deep learning architectures, have demonstrated exceptional performance in environmental monitoring applications. Artificial Neural Networks (ANNs) have been particularly successful in tasks like object recognition and speech recognition, where they have achieved human-level performance in some cases. Deep neural networks can achieve accuracy rates ranging from 91% to 96% in multi-parameter water quality analysis applications (Dave et al., 2024), making them particularly valuable for complex environmental monitoring challenges.

Convolutional Neural Networks (CNNs) represent a specialized category of deep learning architectures that have demonstrated promise for satellite image analysis and environmental monitoring applications. CNNs are specifically designed to analyse spatial data such as satellite imagery, utilizing convolutional layers to extract spatial features that are relevant for classification and detection tasks (Pardeshi et al., 2023). These approaches have achieved accuracy rates ranging from 87% to 94% in satellite image classification applications, making them valuable tools for automated analysis of satellite imagery for environmental monitoring purposes.

Table 3 Artificial Intelligence Applications in water quality assessment

AI Method	Accuracy (%)	Precision (%)	Recall (%)	Application
CNN	87-94	89-92	85-91	Satellite image classification
Random Forest	82-89	84-88	80-87	Contamination prediction
SVM	79-86	81-85	78-84	Water quality classification
Deep Neural Networks	91-96	92-95	89-94	Multi-parameter analysis

3.3.2. Unsupervised Learning Approaches for Pattern Recognition

Unsupervised learning methodologies provide essential capabilities for environmental monitoring applications where labelled training data may be limited or unavailable, which is often the case in African contexts where comprehensive environmental monitoring datasets may not exist (Janjua et al., 2024). These approaches can identify patterns and anomalies in environmental data without requiring extensive training datasets, making them particularly valuable for exploratory analysis and contamination hotspot identification.

K-means clustering algorithms represent a fundamental unsupervised learning approach that can be applied to identify contamination hotspots and spatial patterns in environmental data. These algorithms group observations with similar characteristics, enabling the identification of areas with similar water quality characteristics or contamination patterns. This capability is particularly valuable for identifying previously unknown contamination sources or for characterizing the spatial extent of contamination plumes (Fischer, 2014).

Principal Component Analysis (PCA) represents another valuable unsupervised learning approach that can reduce the dimensionality of complex environmental datasets while preserving the most important information content. PCA can be particularly valuable for integrating multiple satellite-derived water quality parameters into composite indicators that are more interpretable and easier to analyse than individual parameters. This dimensionality reduction capability is essential for managing the complexity of multi-spectral satellite data while extracting meaningful environmental information (Suyal and Sharma, 2024).

Anomaly detection algorithms represent a specialized category of unsupervised learning approaches that are particularly valuable for environmental monitoring applications. These algorithms can identify observations or spatial areas that deviate significantly from normal or expected conditions, potentially indicating contamination events or environmental disturbances. Anomaly detection approaches are particularly valuable for real-time monitoring applications where rapid identification of unusual conditions is essential for public health protection (Pham and Lee, 2016).

3.3.3. Deep Learning Applications and Performance Characteristics

Deep learning represents the most advanced category of Artificial Intelligence methodologies currently available for environmental monitoring applications, offering sophisticated pattern recognition and prediction capabilities that can address the most challenging aspects of environmental contamination assessment (Khan, 2024). This study introduces a novel method for assessing water quality, employing a cutting-edge sensor system integrated with Artificial Intelligence (AI), demonstrating the potential for advanced AI applications in water quality monitoring. Recurrent Neural Networks (RNNs) and their advanced variants, including Long Short-Term Memory (LSTM) networks, provide sophisticated capabilities for analysing temporal patterns in environmental data that are essential for understanding contamination dynamics and predicting future contamination conditions. These approaches are particularly valuable for analysing time series of satellite observations to identify trends, seasonal patterns, and contamination events that may not be apparent through individual observations (Ismail et al., 2024).

Generative Adversarial Networks (GANs) represent an emerging category of deep learning approaches that have demonstrated potential for enhancing satellite imagery and generating synthetic training data for environmental monitoring applications. These approaches can potentially address limitations in training data availability by generating synthetic satellite imagery that can be used to train and validate environmental monitoring models (Ramaraj and Sivakumar, 2023). Transfer learning represents a powerful approach for applying deep learning models developed for other applications to environmental monitoring challenges. This approach can leverage models that have been trained on large datasets from other domains and adapt them for specific environmental monitoring applications, potentially overcoming limitations in training data availability while achieving high performance in environmental analysis tasks (Li and Lee, 2021).

The performance characteristics of deep learning approaches in environmental monitoring applications demonstrate their significant potential for addressing complex environmental challenges. Accuracy rates exceeding 90% have been demonstrated in various environmental classification and prediction tasks, while the ability to process large volumes of satellite data in real-time makes these approaches practical for operational environmental monitoring applications (Saini et al., 2024).

3.4. Current Implementation Status and Case Studies

3.4.1. Pilot Projects and Demonstration Studies

Pioneering pilot programs across Africa have shown the practical potential of satellite-AI integration for water quality monitoring, revealing the opportunities and constraints of deploying these technologies in African contexts. These pilot projects are crucial proof-of-concept studies that inform implementation strategies and increase local competence and institutional experience with advanced monitoring systems.

The Ghana Water Quality Monitoring Initiative, one of the largest pilot programs, uses Landsat 8 imagery and machine learning algorithms to monitor water quality in the Volta River watershed. The Ghana Water Company Limited and international academic institutions collaborated on this study to prove satellite-based monitoring can detect contamination sources and track water quality changes. Supervised learning techniques, notably Random Forest classifiers, were used to evaluate satellite-derived water quality indicators and identify locations with high contamination risk with 89% accuracy (Asilevi et al., 2024).

The Ghana pilot project used satellite-derived metrics like turbidity, chlorophyll-a concentrations, and thermal anomalies to create composite water quality indicators. Though analytical capacity limits limited PFAS analysis, focused field sampling campaigns collected water samples for conventional water quality parameter analysis to validate ground-truth. The experiment proved that satellite monitoring can direct targeted field sampling and optimise analytical resources (Kurekin et al., 2019).

The South African coastal monitoring program is another major pilot project that uses Sentinel-2 satellite data and convolutional neural networks to monitor coastal water quality along 2,400 kilometres of coastline. The Council for

Scientific and Industrial Research (CSIR) and the Department of Environment, Forestry, and Fisheries worked together to locate industrial discharge points and follow coastal contamination plumes. The South African pilot study successfully correlated satellite-detected water quality anomalies with field-measured pollution levels, with correlation values reaching 0.73 (Bhaga et al., 2023). Deep learning, specifically convolutional neural networks, was used to automatically identify and classify water quality anomalies in satellite imagery, reducing manual analysis time for monitoring large coastal areas while maintaining high accuracy.

3.4.2. Operational Monitoring Systems

Most satellite-AI applications for water quality monitoring in Africa are pilot projects, however many operational monitoring systems provide continuous monitoring for specific water bodies or regions. These operational systems are the next step in technology maturation and provide actual experience with long-term monitoring difficulties. With support from international development organisations, Uganda, Kenya, and Tanzania monitor Lake Victoria's 68,800 square kilometre water quality daily using MODIS satellite data and machine learning algorithms. The system's scientific framework can be modified to detect PFAS contamination (Vanderkelen et al., 2018). Its main focus is eutrophication and algal bloom dynamics. The Lake Victoria system uses automated data processing pipelines to acquire MODIS data daily, apply atmospheric correction algorithms, extract water quality parameters using bio-optical algorithms, and generate monitoring products for water management agencies in all three countries. Since 2021, the system has worked consistently, gaining expertise with African satellite-based monitoring system maintenance (Boergens et al., 2024). The Nile River monitoring network uses satellite data to monitor water quality in different countries along the river. The Nile Basin Initiative and foreign development partners use Landsat and Sentinel-2 data to evaluate water quality and contamination sources along the river system. The system does not target PFAS contamination, but it shows that basin-wide monitoring systems can be modified for PFAS monitoring (Kansara and Lakshmi, 2022).

4. Discussion

4.1. Transformative Potential and Strategic Implications

The integration of satellite imagery with Artificial Intelligence for PFAS contamination monitoring in African aquatic systems represents more than a technological advancement; it constitutes a fundamental transformation in environmental monitoring capabilities that addresses critical gaps in current monitoring infrastructure while supporting broader environmental justice and sustainable development objectives. The evidence synthesized in this review demonstrates that this technological integration offers unprecedented opportunities to overcome traditional monitoring limitations while providing comprehensive, cost-effective surveillance capabilities that can support evidence-based environmental management and public health protection across the African continent (Vanderkelen et al., 2018).

The transformative potential of satellite-AI integration is perhaps most evident in its ability to provide comprehensive spatial and temporal coverage that would be impossible to achieve through traditional monitoring approaches. Continental-scale monitoring of African aquatic systems using traditional analytical methods would require thousands of monitoring stations and hundreds of analytical laboratories, representing infrastructure investments that would exceed the economic capacity of most African countries. In contrast, satellite-based monitoring systems can provide comprehensive coverage of entire river basins, lake systems, and coastal areas with relatively modest infrastructure investments while delivering monitoring results with daily to weekly temporal resolution (Gijsel et al., 2009).

The economic implications of this transformation are equally significant, with cost-benefit analyses demonstrating that satellite-based monitoring can reduce operational costs by 60-80% compared to traditional laboratory-based approaches while providing substantially enhanced spatial and temporal coverage. This economic advantage is particularly important in African contexts where limited financial resources must be allocated efficiently to address multiple competing environmental and public health priorities (Viana and Haftka, 2009). The ability to achieve comprehensive monitoring coverage with limited financial investment represents a critical enabler for environmental protection initiatives that might otherwise be financially infeasible. The strategic implications of enhanced monitoring capabilities extend beyond immediate environmental protection benefits to encompass broader development objectives related to water security, public health protection, and sustainable economic development. Reliable environmental monitoring capabilities provide the foundation for evidence-based policy development, support international investment and development initiatives that require environmental safeguards, and enable African countries to participate more effectively in global environmental protection efforts (Suyal and Sharma, 2024).

4.2. Environmental Justice and Equity Considerations

Satellite-AI monitoring of PFAS pollution in African aquatic systems has major environmental justice implications that connect with equity, human rights, and sustainable development. Environmental justice frameworks emphasise everyone's entitlement to clean water and healthy environments, regardless of location, income, or politics. Satellite technology can empower communities and encourage evidence-based environmental justice activism by democratising environmental monitoring (Froehlich, 2019). Geographic and socioeconomic biases in traditional environmental monitoring methods favour areas with more economic resources or political power, while underserved communities may receive inadequate monitoring despite higher exposure risks. Satellite-based monitoring systems can provide complete coverage regardless of local economic or political constraints, guaranteeing that all communities receive equal monitoring protection (Ali, 2022).

Communities can better participate in environmental decision-making and advocate for better environmental protection by democratising environmental data through satellite monitoring. Communities can document environmental conditions, identify contamination sources, and support environmental health policy initiatives with credible environmental monitoring data. In Africa, where communities may lack political authority or technical means for environmental campaigning, empowerment is crucial (Chimbunde, 2021). Community-based monitoring methods that combine satellite technology with local knowledge and engagement are promising for environmental justice. These methods can combine satellite monitoring's wide coverage with local knowledge of environmental conditions and community priorities to create technically advanced and community-responsive monitoring systems. Community monitoring can enhance local ability and create sustainable monitoring skills beyond project implementation (Turyahikayo and Nyerere, 2009). Given that PFAS contamination disproportionately affects vulnerable populations like children, pregnant women, and those with impaired immune systems, its environmental justice implications are severe. Satellite monitoring can alert vulnerable people to pollution incidents, improving environmental justice and public health (Yang and Broby, 2020).

4.3. Technical Limitations and Validation Challenges

Despite the significant potential of satellite-AI integration for PFAS contamination monitoring, numerous technical limitations and validation challenges must be acknowledged and addressed to ensure that monitoring systems provide reliable and accurate results that can support public health and environmental protection decisions. These limitations reflect both the inherent constraints of satellite remote sensing technologies, and the specific challenges associated with monitoring PFAS compounds, which do not have direct spectral signatures detectable by satellite sensors (Adelusi et al., 2025).

The indirect nature of satellite-based PFAS detection represents the most fundamental technical limitation that influences all aspects of monitoring system design and validation. Unlike water quality parameters such as chlorophyll-a or turbidity that have well-established spectral signatures, PFAS compounds do not produce distinctive optical properties that can be directly detected through satellite remote sensing. Instead, satellite monitoring must rely on detecting correlated water quality parameters or environmental conditions that may indicate potential PFAS contamination, introducing uncertainty and limiting the specificity of contamination detection (Adelusi et al., 2025). This indirect detection approach requires establishing empirical relationships between satellite-observable parameters and PFAS contamination levels through extensive field validation studies that may be challenging to implement in African contexts where analytical capacity for PFAS analysis is limited. The strength and reliability of these empirical relationships may vary across different environmental contexts, water body types, and contamination sources, requiring site-specific calibration and validation that may limit the generalizability of monitoring approaches across different regions (Houngnibo et al., 2023).

Spatial and temporal resolution constraints of satellite platforms create additional limitations that may prevent detection of smaller contamination sources or short-term contamination events that could represent significant public health risks. While 30-meter spatial resolution provided by freely available satellite platforms such as Landsat is adequate for monitoring large rivers and lakes, smaller streams, industrial discharge points, or localized contamination sources may not be adequately resolved for effective detection and monitoring (Thiemig et al., 2012). Atmospheric interference represents a persistent technical challenge that can significantly impact data availability and quality, particularly in tropical and subtropical regions of Africa where cloud cover, atmospheric haze, and dust storms are common. These atmospheric conditions can reduce the frequency of usable satellite observations and degrade the quality of water quality parameter retrievals, potentially limiting the ability to provide continuous monitoring coverage or timely detection of contamination events (Ineichen, 2010).

Validation challenges are compounded by the limited availability of ground-truth data for PFAS contamination in many African contexts, creating fundamental difficulties in establishing the accuracy and reliability of satellite-based monitoring approaches. Comprehensive validation requires extensive field sampling programs that can provide reference data across the range of environmental conditions and contamination levels that monitoring systems are intended to detect, but such validation programs require substantial analytical capacity and financial resources that may not be available in many African countries (Aborode et al., 2025).

4.4. Capacity Building and Technology Transfer Requirements

The successful implementation of satellite-AI monitoring systems for PFAS contamination assessment requires comprehensive capacity building and technology transfer initiatives that address multiple levels of technical, institutional, and policy requirements. These requirements reflect the multidisciplinary nature of satellite-based environmental monitoring and the need to develop sustainable local capabilities that can maintain and operate monitoring systems over extended periods without extensive external support (Shukla et al., 2019). Technical capacity building must address multiple specialized skill areas, including satellite data acquisition and processing techniques, Artificial Intelligence model development and implementation, environmental monitoring and assessment methodologies, and system maintenance and troubleshooting capabilities. Each of these skill areas requires specialized training and experience that may not be readily available through existing educational or training programs in many African countries, necessitating the development of specialized training programs that can provide both theoretical knowledge and practical experience with monitoring technologies (Byfield et al., 2007). Satellite data analysis requires expertise in remote sensing principles, image processing techniques, atmospheric correction methods, and bio-optical algorithms for water quality parameter retrieval. These skills are typically developed through specialized graduate-level education programs in remote sensing or geographic information systems, but such programs may not be widely available in African universities or may not include specific training in water quality monitoring applications. Targeted training programs that focus specifically on satellite-based water quality monitoring could address these capacity gaps while building local expertise in environmental remote sensing (Shukla et al., 2019).

Artificial Intelligence applications in environmental monitoring require expertise in machine learning algorithms, statistical analysis, software development, and model validation techniques. These skills are increasingly in demand across multiple sectors, but their application to environmental monitoring requires specialized knowledge of environmental processes and monitoring requirements that may not be addressed in general AI training programs. Integrated training programs that combine AI technical skills with environmental monitoring expertise could provide the multidisciplinary capabilities necessary for effective implementation of satellite-AI monitoring systems (Amadi-Echendu, 2015). Institutional capacity building represents an equally important requirement that addresses the organizational frameworks and policy structures necessary for the effective implementation and operation of monitoring systems. This includes establishing institutional roles and responsibilities for monitoring system operation, developing standard operating procedures and quality assurance protocols, creating data management and sharing policies, and integrating monitoring results into existing environmental management and public health protection systems (Shukla et al., 2019).

Technology transfer initiatives must address both the technical aspects of implementing monitoring systems and the broader institutional and policy frameworks that support sustainable technology adoption. Effective technology transfer requires long-term partnerships between technology developers and implementing organizations that provide ongoing technical support, training, and system maintenance capabilities. These partnerships must be designed to build local capacity and eventual self-sufficiency rather than creating long-term dependence on external technical support (Amadi-Echendu, 2015).

5. Conclusion

The rapidly evolving fields of satellite remote sensing and Artificial Intelligence present numerous opportunities for advancing the capabilities and effectiveness of PFAS contamination monitoring in African aquatic systems. Future research directions should focus on addressing current technical limitations while exploring innovative approaches that can enhance monitoring capabilities and expand the scope of satellite-based environmental monitoring applications.

Recommendations

Technical Implementation Recommendations

- The successful implementation of satellite-AI monitoring systems for PFAS contamination assessment in African aquatic systems requires a phased approach that builds technical capabilities progressively while addressing immediate monitoring needs and establishing sustainable operational frameworks. These technical recommendations are organized into immediate, medium-term, and long-term implementation phases that provide a roadmap for systematic technology deployment across the continent.
- Comprehensive capacity building initiatives are essential for ensuring the sustainable implementation and operation of satellite-AI monitoring systems across African countries. These initiatives must address multiple levels of technical expertise while building institutional capabilities that can support long-term technology adoption and innovation. The capacity building recommendations are organized to address immediate training needs, institutional development requirements, and long-term educational infrastructure development.
- Specialized training workshops should be conducted regularly to provide hands-on experience with satellite data analysis, AI model development, and monitoring system implementation. These workshops should be conducted at regional centers and should include both theoretical instruction and practical exercises using real satellite data and monitoring scenarios. Workshop curricula should be regularly updated to reflect advances in technology and monitoring methodologies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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