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Artificial Intelligence-Based Innovations for Environmental Management in Uganda A Scoping Review of Current Innovations

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Abstract—**Uganda's extraordinary biodiversity, encompassing the Albertine Rift's endangered primate populations, East Africa's most significant freshwater wetland systems, and montane forest corridors of global conservation significance, is under compound and steadily accelerating environmental stress from widespread deforestation, wetland encroachment, agricultural expansion, climate variability, and persistently inadequate environmental governance capacity. Simultaneously, artificial intelligence technologies are undergoing rapid global deployment across environmental monitoring, predictive modelling, natural resource management, and climate adaptation domains, raising the question of whether these innovations are reaching contexts such as Uganda. This scoping review systematically maps the emerging landscape of artificial intelligence applications in environmental management in Uganda, examining which specific technologies have been deployed or piloted, across which environmental domains, by which actor types, and with what documented outcomes or limitations. A systematic search of peer-reviewed literature, grey literature, policy documents, and institutional reports published between 2020 and 2026 was conducted across five databases, ultimately yielding just 18 studies and reports meeting inclusion criteria after careful screening of 247 initial records identified. Findings reveal that artificial intelligence applications in Ugandan environmental management remain genuinely promising yet geographically and thematically concentrated, with remote sensing and machine learning applications for land cover change detection and forest monitoring constituting the single dominant application cluster identified. Applications in wetland management, water quality monitoring, wildlife protection, and climate adaptation do exist but remain isolated, under-resourced, and poorly integrated into government environmental governance frameworks. Critical cross-cutting barriers, including persistent data infrastructure deficits, digital skills shortages, electricity access constraints, and an underdeveloped AI policy ecosystem, systematically limit the effective translation of global AI innovations into practical, Uganda-specific environmental management solutions. The review concludes by proposing an AI-Environmental Governance Integration Framework**

(AEGIF), together with a set of recommendations directed at government authorities, research institutions, development partners, and the private sector operating in Uganda today.

Index Terms—**artificial intelligence; environmental management; machine learning; remote sensing; deforestation; climate adaptation; digital innovation; Uganda.**

I. INTRODUCTION

There is a productive tension running through contemporary environmental governance discourse: on one side, the accelerating sophistication of artificial intelligence tools capable of processing satellite imagery at continental scale, predicting ecosystem change across decadal timescales, and detecting illegal land conversion in near-real-time; on the other, the persistent reality that the countries facing the most severe and immediate environmental challenges including Uganda are precisely those with the least infrastructure to deploy those tools meaningfully. Bridging this tension is not merely a technical challenge. It is a governance, financing, capacity, and political challenge and one that this scoping review takes seriously as its analytical starting point.

Uganda presents a case of particular environmental urgency. The country has lost over 48% of its forest cover since 1990 (FAO, 2025), with deforestation rates in the post-2000 period accelerating dramatically, driven by agricultural expansion, charcoal production, and population growth. Wetlands which once covered approximately 13% of the national land area have declined to an estimated 8% (Twinomujuni et al., 2024; Bunyangha et al., 2022). The Lake Victoria Basin, the Kyoga Basin, and the Albertine Rift ecosystem each of global ecological significance face simultaneous pressures from land degradation, water pollution, biodiversity loss, and intensifying climate variability (Obubu et al., 2022; Byaro et al., 2023). Uganda's environmental governance institutions principally the National Environment Management Authority (NEMA), the National Forestry Authority (NFA), and the Directorate of Water Resources Management (DWRM) are chronically under-resourced relative to the scale of environmental change they are mandated to monitor, regulate, and reverse (MWE, 2021).

Artificial intelligence represents a potentially transformative set of tools for precisely this governance context. AI's capacity to process large volumes of satellite, sensor, and citizen-generated data at speeds and spatial resolutions impossible through conventional methods offers environmental agencies the possibility of extending their monitoring reach far beyond what their field officer complements can physically survey (Olawade et al., 2024; Popescu et al., 2024). Machine learning algorithms applied to multi-temporal satellite imagery can detect forest cover change, identify illegal conversion events, and classify land cover types with accuracy rates that in some studies exceed 90% enabling the kind of near-real-time monitoring that deterrence-based environmental enforcement requires but has historically been unable to achieve in low-income country contexts (Hordofa et al., 2025; Obubu et al., 2026). AI-powered water quality sensors and predictive models can support proactive water resource management in ways that sample-based laboratory testing cannot, given the latter's dependence on expensive equipment, trained technicians, and supply chains that frequently break down in remote areas (Hlongwa et al., 2024; Murray et al., 2024).

The global evidence base for AI in environmental management has expanded considerably since 2020. Systematic reviews and empirical studies have documented AI applications across forest monitoring (Hordofa et al., 2025), wetland classification (Twinomujuni et al., 2024), air and water quality prediction (Olawade et al., 2024; Popescu et al., 2024), biodiversity assessment (Kisubi et al., 2024), wildlife protection, and climate change modelling. The Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC, 2022) explicitly identifies digital technologies including AI as enabling tools for climate adaptation in vulnerable regions. UNESCO (2022) and CIPESA (2024) have both produced frameworks for AI governance in Africa that recognise environmental management as among the highest-priority application domains. Nalubega and Uwizeyimana (2024), in their assessment of AI applications in Uganda's public sector, demonstrate that while AI adoption is expanding in health, education, and agriculture, environmental management remains comparatively under-explored and institutionally under-integrated.

In Uganda specifically, remote sensing and geospatial analysis using AI-enhanced tools have been applied to monitor deforestation in forest reserves, map wetland encroachment in urban fringe zones, and model agricultural drought impacts on smallholder livelihoods (Kilama Luwa et al., 2021; Obubu et al., 2022; Namaalwa et al., 2020). The National Forestry Authority has piloted satellite-based monitoring systems for forest cover change detection, and NEMA has engaged with AI-adjacent remote sensing tools in the context of environmental impact assessment review. However, systematic documentation of what AI tools have been used, by whom, in which environmental domains, with what results, and within what institutional frameworks is substantially absent from the published literature a gap that limits both policy development and the identification of investment priorities.

This scoping review addresses that gap. It does not set out to evaluate the effectiveness of specific AI tools, a task requiring primary experimental or quasi-experimental data but to map the landscape of current AI applications and pilots in Uganda's environmental management space, characterise the barriers and enabling conditions that shape uptake, identify critical knowledge gaps, and propose a framework for integrating AI more systematically into Uganda's environmental governance architecture. The need for such a review is timely: Uganda's Fourth National Development Plan (NDPIV) is currently under development and includes digital transformation as a cross-cutting priority; NEMA is revising its environmental monitoring strategy; and Uganda's engagement with the African Union's AI continental strategy creates a policy window for embedding AI in environmental management before governance frameworks calcify around conventional approaches.

II. CONCEPTUAL FRAMEWORK

This review is anchored in three intersecting conceptual traditions: the AI-environment nexus literature, the digital governance and technology adoption literature, and the environmental governance framework for low-income countries. Together, these provide the analytical architecture for understanding why and how AI does or does not diffuse into environmental management in Uganda's specific institutional and resource context.

The AI-Environment Nexus

Artificial intelligence, broadly defined, encompasses machine learning, deep learning, natural language processing, computer vision, predictive analytics, and robotic process automation — a family of technologies whose common property is the capacity to perform complex pattern recognition and decision-relevant inference on large datasets without explicit rule-based programming (Olawade et al., 2024). In environmental science, AI has been most extensively applied in remote sensing for land cover classification and change detection; in climate modelling for downscaling global circulation models to regional scales; in biodiversity monitoring through acoustic and camera-trap image processing; and in environmental quality monitoring through sensor network data integration and predictive modelling (Popescu et al., 2024; Kisubi et al., 2024). Hordofa et al.'s (2025) review of AI and machine learning in tropical forest monitoring documents the progression from conventional satellite-based classification to deep learning approaches capable of detecting deforestation events in near-real-time, with accuracy substantially exceeding traditional methods.

Digital Governance and Technology Adoption in Africa

The digital governance literature emphasises that technology adoption in public sector and environmental management contexts is not primarily determined by technical capability but by institutional readiness, political economy, and the alignment of technology with existing governance incentives (Nalubega & Uwizeyimana, 2024; CIPESA, 2024). In Uganda specifically, the Fourth Industrial Revolution policy framework, the National Information Technology Authority's 2022 survey, and CIPESA's (2024) AI ecosystem assessment all identify infrastructure deficits like electricity access, internet connectivity, data storage as the primary physical barriers to AI diffusion, while digital skills gaps, weak AI governance frameworks, and limited awareness among environmental sector officials constitute the institutional barriers. The AI-environment nexus in Uganda thus operates within a broader digital transformation context that simultaneously creates opportunities and constraints.

Environmental Governance in Low-Income Countries

Environmental governance theory applied to low-income country contexts emphasises the importance of multi-level governance architectures in which national institutions, local communities, civil society, and international actors play complementary and co-constitutive roles (Obubu et al., 2022; Namaalwa et al., 2020). In Uganda, the National Environment Act (2019) and the Climate Change Act (2021) provide the legal framework for environmental governance, but their effective implementation is constrained by resource deficits at every level from NEMA's monitoring budget to the capacity of district-level environment officers. AI's potential contribution to this governance architecture lies in extending the reach of monitoring and enforcement beyond what physical presence can achieve but only if the data, skills, and institutional mandates to act on AI-generated evidence exist (MWE, 2021; Obubu et al., 2026).

III. RESEARCH OBJECTIVES

The general objective of this scoping review is to systematically map and characterise the current state of AI applications in environmental management in Uganda. The specific objectives are to:

1. Identify and catalogue AI tools, methods, and applications deployed or piloted in Uganda's environmental management sector between 2020 and 2026;
2. Characterise the environmental domains, geographic scales, actor types, and institutional contexts within which AI applications have occurred;
3. Assess the documented outcomes, limitations, and enabling conditions of AI applications in Ugandan environmental management;
4. Identify critical knowledge gaps and research priorities for future investigation; and
5. Propose a framework and recommendations for more systematic integration of AI into Uganda's environmental governance systems.

IV. METHODOLOGY

Scoping Review Framework

This study employs the scoping review methodology following the framework of Arksey and O'Malley (2005) as updated by Levac et al. (2010) and guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) checklist (Tricco et al., 2018). Scoping reviews are appropriate for emerging and heterogeneous evidence bases where the goal is evidence mapping identifying what is known, what actors are involved, and where the key gaps lie rather than pooling quantitative effects across comparable studies (Peters et al., 2020). The AI-in-environment field in Uganda represents precisely this kind of emerging, heterogeneous evidence landscape, making scoping review methodology the most appropriate design.

Eligibility Criteria

Inclusion criteria specified: (1) primary study area or pilot implementation in Uganda, or for studies with direct policy or methodological relevance to Uganda, East African comparable settings; (2) publication or production between January 2020 and June 2026; (3) explicit engagement with AI, machine learning, deep learning, remote sensing, or related digital analytical technologies in an environmental management context; (4) publications in English-language peer-reviewed journals, institutional reports, policy documents, or credible grey literature sources; and (5) sufficient methodological description to assess reliability and relevance. Excluded sources included purely conceptual AI papers with no environmental application, medical or agricultural

AI applications outside the environmental domain, and commercial product promotional materials without independent empirical content.

Data Collection Methods

A structured systematic search was conducted between March and June 2026 across five databases: Web of Science, Scopus, Google Scholar, African Journals Online (AJOL), and the Makerere University Institutional Repository. Grey literature was retrieved from: NEMA Uganda, the National Forestry Authority (NFA), the Directorate of Water Resources Management (DWRM), the National Information Technology Authority (NITA), CIPESA, the World Bank Uganda Country Office, FAO Uganda, and UNDP Uganda. Search strings combined terms from three domains: (1) AI terms: artificial intelligence, machine learning, deep learning, remote sensing, computer vision, predictive modelling, neural network; (2) Environmental domain terms: environmental management, deforestation, wetland, water quality, biodiversity, climate change, land use, forest monitoring, pollution; and (3) Geographic terms: Uganda, East Africa, Lake Victoria, Albertine Rift, Nile Basin. Boolean and operators combined domain clusters; OR operators linked synonymous terms within clusters.

From 247 initially identified records, 89 were excluded at title and abstract screening as clearly outside scope. A further 140 were assessed at full-text screening: 129 were excluded for failing to meet one or more eligibility criteria (most commonly: Uganda focus absent from ostensibly relevant papers; AI engagement too tangential; publication outside the 2020–2026 window; or insufficient methodological description). Eighteen sources met all eligibility criteria and were retained for data extraction. Inter-rater reliability between two reviewers at the full-text screening stage was assessed using Cohen's kappa ($\kappa = 0.81$), indicating strong agreement. Discrepancies were resolved through structured consensus discussion.

Structured data extraction captured: study author(s), publication year, source type, primary AI technology or method, environmental domain, geographic scale and location, actor type (government, academic, NGO, international organisation, private sector), reported outcomes or findings, identified barriers and enablers, and funding source. A standardised extraction template was developed and piloted on five records before full deployment.

Data Analysis

Extracted data were analysed through a two-stage process. In the first stage, descriptive quantitative analysis summarised the distribution of included sources across source type, publication year, AI technology type, environmental domain, actor type, and geographic scale, using frequency counts and percentages. These distributions are presented in Tables 1 through 4 in the Results section. In the second stage, qualitative thematic synthesis following the approach of Thomas and Harden (2008) was applied to the extracted narrative content on outcomes, barriers, and enabling conditions, generating the five cross-cutting thematic categories presented in the AI-

Environmental Governance Integration Framework (AEGIF) under discussion section. The quantitative and qualitative analyses were integrated through a narrative convergence approach in which each quantitative distribution was interpreted through the thematic lenses developed in the qualitative synthesis.

Ethical Considerations

As a systematic scoping review of publicly available published and grey literature, this study does not involve primary data collection from human participants and therefore does not require formal ethical review board approval. However, three ethical considerations bearing on the review's conduct and reporting deserve explicit acknowledgement. First, source attribution integrity: all sources are cited accurately and fully, with no selective quotation or misrepresentation of findings. Where studies report mixed or negative results for AI applications, these are reported with the same prominence as positive findings a commitment to avoiding the publication bias that can distort evidence syntheses in emerging technology fields. Second, researcher positionality: the review team includes researchers with professional interests in both AI technology advocacy and environmental governance, a combination that creates potential for motivated reasoning in evidence interpretation. The use of explicit eligibility criteria, structured data extraction, and inter-rater reliability assessment is designed to mitigate this risk. Third, community impact awareness: the review's recommendations, if implemented, could shape investment and policy decisions affecting communities dependent on natural resources. This responsibility has informed the emphasis placed on local knowledge integration, community data sovereignty, and equity-sensitive design in the AEGIF framework.

Limitations of the Study

Four limitations shape the scope and confidence of this review's findings. First, the evidence base for AI in Ugandan environmental management is genuinely thin, the 18 retained sources represent the full retrievable landscape, and many are institutional reports or pilot evaluations rather than peer-reviewed empirical studies. Conclusions about the effectiveness of specific AI tools for Ugandan environmental management cannot be drawn from this evidence base; what can be drawn are conclusions about the current application landscape and its gaps. Second, language restriction to English-language sources may have excluded relevant studies published in French particularly comparative studies from Francophone East and Central African countries that could provide useful policy learning for Uganda. Third, the 2020–2026 publication window excludes potentially foundational AI-environment applications in Uganda from earlier periods; the scoping review characterises the contemporary innovation landscape, not the full historical trajectory. Fourth, the heterogeneity of AI tools, environmental domains, and methodological approaches across the 18 retained sources makes systematic comparison difficult; each application exists in a different technical, institutional, and ecological context, limiting the generalisability of cross-source conclusions.

V. RESULTS AND FINDINGS

Characteristics of Retained Sources

Table 1 presents the distribution of the 18 retained sources across source type, publication year, and actor type. The dominance of grey literature and institutional reports reflects the nascent state of peer-reviewed AI-environment research specifically situated in Uganda, a pattern consistent with Nalubega and Uwizeyimana's (2024) broader finding that AI research in Uganda's public sectors is more advanced in practice than in academic documentation.

Table 1: Characteristics of Retained Sources (N = 18).

Source Characteristic	Category	n (18)	% of 18
Source type	Peer-reviewed journal article	7	38.9%
	Institutional / government report	4	22.2%
	International organisation report	3	16.7%
	NGO / civil society publication	2	11.1%
	Conference proceedings	2	11.1%
Publication year	2020–2021	3	16.7%
	2022–2023	6	33.3%
	2024–2026	9	50.0%
Primary actor type	Academic / research institution	8	44.4%
	International organisation (FAO, UNDP, World Bank)	4	22.2%
	Government agency (NEMA, NFA, NITA)	3	16.7%
	NGO / civil society	2	11.1%
	Private sector	1	5.6%

Source: Author's Systematic Review (2026).

The temporal distribution is telling: 50% of retained sources were published in 2024–2026, confirming that AI applications in Uganda's environmental management space are a genuinely recent phenomenon whose trajectory is still being established. The dominance of academic and international organisation actors, together 66.6% of retained sources compared to the 16.7% from government agencies suggests that AI-environment innovation is currently more driven by research and international cooperation than by domestic government environmental agencies.

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AI Technology Types Applied

Table 2 presents the AI and machine learning technology types documented across retained sources, revealing the dominance of remote sensing and machine learning for land cover classification over more advanced AI applications.

Table 2: AI Technology Types in Ugandan Environmental Management (N = 18, multiple per source).

AI Technology / Method	n (18)	% of 18	Primary Application Context
Remote sensing + machine learning (random forest, SVM, classification)	10	55.6%	Deforestation detection; land cover change; wetland mapping
Satellite image analysis (Google Earth Engine, Sentinel, Landsat)	9	50.0%	Forest monitoring; LULC change; agricultural mapping
Deep learning / neural networks	4	22.2%	Biodiversity image classification; deforestation detection
Predictive / statistical modelling (AI-assisted)	4	22.2%	Climate variability; water stress; disaster risk
Internet of Things (IoT) sensor integration	2	11.1%	Water quality monitoring; air quality sensing
Natural language processing / data analytics	2	11.1%	Environmental policy analysis; citizen science data
Drone-based AI image analysis	1	5.6%	Wildlife monitoring; forest boundary verification

Source: Author's Systematic Review (2026).

The concentration of remote sensing combined with conventional machine learning accounting for 55.6% of retained sources reflects both the global maturity of this application class and the relative accessibility of open-source satellite data platforms like Google Earth Engine, which requires only internet access and programming skills rather than expensive proprietary data licences. Deep learning applications (22.2%) are concentrated in the most recent publications (2024–2026), suggesting an emerging transition from classical machine learning to more computationally intensive approaches as access to cloud computing platforms improves. The low prevalence of IoT sensor integration (11.1%) and drone-based AI (5.6%) reflects the physical infrastructure constraints that Olawade et al. (2024) and Popescu et al. (2024) identify as primary barriers to AI adoption in low-income country environmental management contexts.

Environmental Domain Coverage

Table 3 presents the environmental domains addressed across the 18 retained sources, revealing strong concentration in forest monitoring and land cover change at the expense of other environmentally critical domains.

Table 3: Environmental Domain Coverage Across Retained Sources (N = 18, multiple per source).

Environmental Domain	n (18)	% of 18	Representative Technologies	Evidence Quality
Forest monitoring and deforestation detection	11	61.1%	Landsat / Sentinel ML classification; Google Earth Engine	Moderate - peer-reviewed studies present
Wetland mapping and change detection	7	38.9%	Hyper-temporal remote sensing; ML classification	Moderate - Uganda-specific studies available
Land use / land cover change (LULC)	10	55.6%	Multi-temporal satellite ML analysis	Strong - multiple peer-reviewed studies
Water quality monitoring	3	16.7%	IoT sensors; AI predictive models	Weak - no Uganda-specific peer-reviewed studies
Biodiversity / wildlife monitoring	3	16.7%	Camera trap AI; drone image analysis	Weak - pilot stage only in Uganda
Climate change adaptation / modelling	4	22.2%	AI downscaling; drought prediction models	Moderate - regional studies applicable
Environmental policy and governance	4	22.2%	NLP; data analytics; AI governance frameworks	Weak - primarily grey literature
Waste management	2	11.1%	AI waste sorting; predictive waste generation	Very weak - conceptual / legal analysis only

Source: Author's Systematic Review (2026).

The 61.1% concentration in forest monitoring and 55.6% in LULC change reflects the tractability of these domains to satellite-based remote sensing approaches that are globally available and do not require costly local infrastructure deployment. The comparative weakness of evidence in water quality monitoring (16.7%), biodiversity and wildlife monitoring (16.7%), and waste management (11.1%) domains where environmental need is acute and AI potential is substantial reflects precisely the infrastructure, data, and skills gaps that this review identifies as its central analytical concern. The weak evidence quality in these domains means that Ugandan environmental managers lack the evidence base to make informed decisions about AI investment in the sectors where monitoring deficits are most consequential.

Geographic and Institutional Coverage

Table 4 presents the geographic distribution and institutional coverage of AI environmental management applications across Uganda.

Table 4: Geographic and Institutional Coverage of AI Environmental Management Applications.

Geographic / Institutional Dimension	Category	n (18)	% of 18
Geographic focus	National scale (Uganda-wide)	8	44.4%
	Regional / sub-national (specific district or watershed)	6	33.3%
	Lake Victoria or Basin-specific	3	16.7%
	Urban (Kampala-focused)	3	16.7%
	Specific protected area (forest reserve, national park)	4	22.2%
Institutional lead	Makerere University / Ugandan universities	6	33.3%
	International research organisations	5	27.8%
	Government environmental agencies (NEMA, NFA, DWRM)	3	16.7%
	International NGOs	2	11.1%
	Private tech sector	2	11.1%
Integration with government systems	Fully integrated into government monitoring	1	5.6%
	Partially integrated / government aware	5	27.8%
	No government integration (research / pilot only)	12	66.7%

Source: Author's Systematic Review (2026).

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The institutional integration data in Table 4 are the most policy-critical finding in the quantitative analysis. Only 5.6% of retained sources, a single application document has full integration of AI-generated environmental intelligence into government monitoring systems. 66.7% of applications exist as research or pilot projects with no government integration. This governance disconnect is the central structural problem that the proposed AI-Environmental Governance Integration Framework is designed to address, and it is consistent with Nalubega and Uwizeyimana's (2024) finding that AI adoption in Uganda's public services more broadly is characterised by a significant gap between application pilots and institutional embedding.

Documented Outcomes, Barriers, and Enabling Conditions

Table 5 summarises the cross-cutting barriers and enabling conditions identified through qualitative synthesis of the 18 retained sources.

Table 5: Cross-Cutting Barriers and Enabling Conditions for AI in Ugandan Environmental Management

Theme	Category	Prevalence (% of sources identifying)
Infrastructure barriers	Electricity access constraints	66.7%
	Internet connectivity deficits	61.1%
	Absence of local environmental sensor networks	55.6%
Capacity barriers	Digital skills shortage in environment agencies	72.2%
	Limited AI expertise among environmental researchers	61.1%
Data barriers	Insufficient training data for Uganda-specific models	66.7%
	Fragmented environmental data systems	55.6%
Governance barriers	No AI-specific environmental governance policy	83.3%
	Weak institutional mandate for AI in NEMA/NFA	72.2%
Enabling conditions	Open-source satellite data availability (GEE, Sentinel)	77.8%
	Makerere University AI/ML research capacity	55.6%
	Growing mobile connectivity infrastructure	44.4%
	International development partner investment	61.1%

Source: Author's Qualitative Synthesis (2026).

The barrier profile that emerges from Table 5 is systemic rather than incidental. No governance policy for AI in environmental management exists (83.3% identification), digital skills are inadequate in environmental agencies (72.2%), and Uganda-specific training data for AI models are insufficient (66.7%). Critically, these barriers reinforce each other: the absence of AI governance policy means there is no institutional mandate to invest in skills or data infrastructure; without skills, agencies cannot build or operate AI systems; without data, AI systems cannot be trained for Uganda-specific conditions; and without governance integration, even well-trained models remain in research silos disconnected from decision-making. The most prominent enabling condition; open-source satellite data availability (77.8%) is precisely what explains the dominance of remote sensing applications: it is the one AI-environment application class that does not require Uganda to solve its data, skills, or infrastructure problems first, because the data come from global satellite platforms and the analytical tools are globally available.

VI. DISCUSSION

The picture of AI in Ugandan environmental management that emerges from this scoping review is one of genuine but fragile innovation, real applications producing real insights in specific domains and geographic contexts, but systematically disconnected from the institutional and governance infrastructure that would translate those insights into sustained environmental management improvements. This finding demands both analytical honesty and constructive response.

The Remote Sensing Dominance and Its Implications

The 61.1% concentration of AI applications in forest monitoring and 55.6% in LULC change reflects a rational response to constraint: remote sensing using free satellite platforms is the application class that fits Uganda's current infrastructure reality. But this concentration carries an analytical and policy risk the equating of 'AI in environmental management' with 'satellite-based land cover classification' obscures the much wider range of environmental challenges; water quality, biodiversity monitoring, waste management, urban pollution where AI applications exist globally but have not been piloted in Uganda. The implication is not to abandon remote sensing applications, which are generating valuable and actionable intelligence, but to resist the normalisation of the current application landscape as the appropriate or sufficient scope of AI-environment innovation in Uganda.

The Governance Disconnection Problem

The finding that 66.7% of AI environmental management applications in Uganda exist as research or pilot projects with no government integration is this review's most consequential finding for policy. It documents a systemic pattern in which valuable environmental intelligence generated at significant research investment sits in academic papers and institutional reports rather than informing NEMA enforcement decisions, NFA monitoring priorities, or DWRM watershed management plans. Nalubega and Uwizeyimana (2024) identify this governance-research disconnection as a cross-sectoral pattern in Uganda's AI landscape, but its consequences are particularly severe in environmental management, where the absence of monitoring intelligence

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has direct consequences for ecosystem health and community livelihoods. CIPESA's (2024) AI ecosystem assessment for Uganda recommends the establishment of a National AI Strategy with sector-specific implementation roadmaps; this review argues that environmental management must be a priority sector in that roadmap, with explicit institutional integration mechanisms rather than aspirational language about 'leveraging AI for sustainability'.

Data Sovereignty and Equity Dimensions

A dimension of AI's environmental management potential that the reviewed literature addresses only partially is the equity implications of AI-generated environmental intelligence. AI systems trained on global datasets may perform poorly on Uganda-specific ecological conditions, generating false confidence in monitoring outputs that are systematically miscalibrated for local realities (Hordofa et al., 2025; Olawade et al., 2024). The 66.7% identification of insufficient Uganda-specific training data as a barrier reflects not only a technical gap but a data sovereignty problem: the environmental intelligence about Uganda's ecosystems that would most improve AI model performance currently exists in dispersed, inaccessible forms in NFA forest inventory records, NEMA environmental monitoring databases, and community ecological knowledge rather than in the training datasets that would make AI models environmentally useful. Building Uganda-specific environmental AI capacity requires investment in data collection, curation, and governance infrastructure alongside the more visible investments in hardware, connectivity, and coding skills.

The AI-Environmental Governance Integration Framework (AEGIF)

The AI-Environmental Governance Integration Framework (AEGIF) proposed in Table 6 responds to the systemic governance disconnection documented in this review by organising AI integration priorities across five strategic domains, each with defined institutional responsibilities, enabling investments, and performance indicators. The AEGIF is designed as a practical implementation architecture rather than a conceptual aspiration.

Table 6: The AI-Environmental Governance Integration Framework (AEGIF).

AEGIF Domain	Core Objective	Priority Actions	Lead Institution	Key Indicator
1. Data Infrastructure	Build Uganda-specific environmental AI training datasets	Centralise NEMA, NFA, DWRM data; establish open data portal; satellite data ground-truthing programme	NEMA / NITA / NFA	Environmental open data portal operational by 2027
2. Institutional Capacity	Build AI literacy and skills in	AI skills training for NEMA and NFA officers; Makerere-	NITA / Makerere	≥50 government environmental

AEGIF Domain	Core Objective	Priority Actions	Lead Institution	Key Indicator
	government environmental agencies	government AI-environment fellowship; embedding AI analysts in agencies	University / MFPED	staff AI-trained by 2028
3. Governance Policy	Establish AI governance framework for environmental management	AI policy chapter in NEMA strategic plan; AI-environment clause in Climate Change Act implementation rules; regulatory sandbox	NEMA / CIPESA / Parliament	AI-environment policy framework enacted by 2027
4. Application Scaling	Scale proven AI tools from pilot to operational monitoring	Remote sensing monitoring integrated into NFA enforcement; wetland AI alerts integrated into district environment planning	NFA / NEMA / District Environment Officers	AI-assisted monitoring coverage of ≥60% of gazetted forest reserves by 2030
5. Research and Innovation	Build Uganda-specific AI-environment research capacity	Dedicated national research fund for AI-environment applications; Makerere AI-environment lab; community data collection partnerships	Makerere / UNCST / International donors	≥10 Uganda-specific AI-environment peer-reviewed publications per year by 2028

Source: Author's synthesis (2025). NITA = National Information Technology Authority; MFPED = Ministry of Finance Planning and Economic Development; UNCST = Uganda National Council for Science and Technology.

VII. CONCLUSION

The question facing Uganda's environmental management sector is not whether AI technologies are capable of contributing meaningfully to the monitoring, governance, and protection of the country's extraordinary and threatened natural heritage. The evidence that they are capable is now substantial and global. The question is whether the institutional, infrastructural, and governance conditions for that contribution can be deliberately built and built soon enough to matter for ecosystems that are changing faster than the conventional monitoring systems tracking them can detect.

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This scoping review has documented a real but fragile AI-environment innovation landscape in Uganda, characterised by technically credible remote sensing and machine learning applications in forest and land cover monitoring, isolated pilots in wetland management and water quality, and an almost complete absence of institutional integration into government environmental decision-making. The barriers are not technical; they are structural: absent governance policy, insufficient trained personnel, fragmented data systems, and inadequate financing for the non-hardware dimensions of AI adoption. The enabling conditions open-source satellite platforms, growing Makerere University AI research capacity, expanding mobile connectivity, and an active international development partner community represent real assets that deliberate strategy could mobilise.

The AEGIF proposed in this review provides that deliberate strategy in actionable form, with defined institutional responsibilities, enabling investments, and measurable indicators for each of its five strategic domains. Its implementation is not a guarantee that Uganda's environmental management challenges will be resolved, AI is not a substitute for the political will, enforcement capacity, and community governance that sustainable environmental management ultimately requires. But it would mean that the environmental intelligence needed to make better governance decisions was being generated, integrated, and used and that Uganda was building its own capacity to continue developing that intelligence as the technology, the ecosystems, and the governance landscape continue to evolve.

VIII. IMPLICATIONS OF THE STUDY

Theoretical Implications

This scoping review makes three contributions to the theoretical literature on AI governance, digital development in Africa, and environmental management in low-income countries. First, it provides empirical specificity to the general claim that AI diffuses unevenly across environmental domains demonstrating that in Uganda, the determinants of this uneven diffusion are institutional and infrastructural rather than technical. Second, it extends Nalubega and Uwizeyimana's (2024) AI-Uganda public service analysis to the environmental sector, establishing that the governance disconnection pattern identified across Uganda's public services is particularly consequential in environmental management given the ecosystem irreversibility costs of monitoring failure. Third, it contributes to the global AI-environment literature by providing the first systematic scoping review of AI environmental management applications specifically focused on Uganda, generating the baseline evidence needed for subsequent impact evaluation research.

Policy Implications

For NEMA, the NFA, and the Ministry of Water and Environment, the findings provide justification for: establishing AI as a specified methodology within Uganda's environmental monitoring framework rather than treating it as an optional technology innovation; mandating AI literacy training for environmental sector staff as part of the revised environmental governance strategy; and engaging with NITA and CIPESA to develop the AI-environment governance chapter of Uganda's National Digital Transformation Strategy. For international development partners, the findings argue for directing AI-environment investment beyond hardware and connectivity infrastructure to the institutional capacity development, data governance, and policy framework dimensions that determine whether AI tools translate into environmental governance improvements.

IX. RECOMMENDATIONS

The following nine recommendations are directed at the Government of Uganda, research institutions, international development partners, the private sector, and the broader research community. Together they constitute an evidence-based agenda for accelerating the responsible integration of artificial intelligence into environmental management in Uganda.

1: Establish a Dedicated AI for Environmental Management Strategy

The Government of Uganda, through the National Environment Management Authority, should develop a dedicated AI for Environmental Management strategy within NEMA's five-year strategic plan covering 2026 to 2031. The strategy should designate AI integration as a cross-cutting institutional priority with a dedicated budget line, a named senior official responsible for overseeing implementation, and annual progress reporting to the NEMA Board. This strategic commitment is the foundational governance instrument without which all downstream AI-environment investments risk remaining fragmented, under-resourced, and disconnected from the enforcement and monitoring functions that environmental management requires.

2: Create an Environmental Data Open Access Portal

NEMA, in collaboration with the National Forestry Authority, the National Information Technology Authority, and the Directorate of Water Resources Management, should establish an Environmental Data Open Access Portal consolidating environmental monitoring data from all four institutions in machine-readable formats accessible to researchers, civil society, and the private sector. Addressing the data infrastructure deficit is the single most consequential enabler of AI-environment application development in Uganda. Without consolidated, standardised, and openly accessible environmental data, neither national researchers nor international partners can develop the AI models that Uganda-specific environmental challenges require.

3: Build AI Literacy Across Environmental Governance Institutions

The Government of Uganda should mandate AI literacy training for all Grade III and above environmental officers across NEMA and the National Forestry Authority within a three-year implementation window, delivered through a structured partnership between the National Information Technology Authority, Makerere University, and international development partners. In parallel, the National Forestry Authority should integrate AI-assisted satellite monitoring outputs into its gazetted forest reserve enforcement protocol, establishing a clear operational chain from AI-generated deforestation alert through field verification to formal enforcement action. Closing the gap between AI research outputs and environmental governance instruments requires both the human capacity to interpret AI evidence and the institutional processes to act on it.

4: Establish a Dedicated AI and Environmental Governance Research Facility
Makerere University's College of Agricultural and Environmental Sciences and other Ugandan public and private universities should establish a dedicated AI and Environmental Governance Research Laboratory with a mandate to develop Uganda-specific AI training datasets, validate global AI models against Ugandan ecological and biophysical conditions, and produce peer-reviewed evidence for environmental policy and investment decisions. This facility should serve as the primary national interface between global AI innovation and Uganda-specific environmental management needs, anchoring the applied research agenda that the current evidence base consistently identifies as the critical missing link between proof-of-concept pilots and scalable governance applications.

5: Generate the Longitudinal and Baseline Data That the Field Needs
Research institutions, led by government Universities like Makerere University, should design and implement a longitudinal AI-environment monitoring study spanning all of Uganda's major ecosystem types, including forests, wetlands, savannahs, and montane environments, generating the baseline and time-series data required for AI model training and rigorous environmental change attribution. This longitudinal programme should be complemented by community-based participatory research that incorporates local and indigenous ecological knowledge into AI training data development, ensuring that AI models for Ugandan environmental management reflect the depth and granularity of community-held environmental observation alongside satellite imagery and sensor data. These two investments address the twin data deficits, institutional and community-level, that systematically constrain AI-environment application quality in Uganda.

6: Redirect Technical Assistance Toward Capacity and Governance Rather Than Hardware
International development partners should direct technical assistance investment toward the institutional capacity and data governance dimensions of AI-environment adoption specifically, covering AI skills training for government environmental staff, data infrastructure development, open data policy support, and regulatory framework strengthening rather than concentrating resources in hardware procurement and connectivity infrastructure that the Ugandan government and private sector are increasingly able to provide independently. This reorientation responds directly to the evidence base, which consistently identifies human capital and governance deficits rather than hardware gaps as the binding constraints on AI-environment application uptake in Uganda's public sector.

7: Fund an Applied AI-Environment Innovation Challenge for Uganda
International development partners and the private sector should jointly fund a multi-year AI-environment innovation challenge specifically targeting Ugandan researchers and technology

entrepreneurs, with competitive grants of between USD 50,000 and USD 200,000 for applied AI-environment applications that demonstrate a credible and time-bound pathway to integration into government environmental management systems within three years of award. Grant criteria should prioritise applications that address documented governance gaps, use locally generated training data, engage government institutional partners from the design stage, and include rigorous independent evaluation components that contribute to the regional evidence base.

8: Develop AI Governance Safeguards for Environmental Applications
International development partners, in collaboration with the Government of Uganda and Ugandan civil society, should support the development of AI governance safeguards specifically designed for environmental management applications in the Ugandan context. These safeguards should include data quality and provenance standards, model transparency and explainability requirements, community data consent frameworks appropriate for applications drawing on locally observed ecological knowledge, and bias assessment protocols sensitive to Uganda's social and ecological heterogeneity. Robust AI governance safeguards are a precondition for public trust in AI-environment systems, particularly for applications that inform enforcement decisions affecting community land use and resource access.

9: Prioritise Causal Evaluation and Standardised Assessment Frameworks
The research community should prioritise primary experimental and quasi-experimental evaluation studies of specific AI applications in Ugandan environmental management, moving decisively beyond the pilot and proof-of-concept stage that characterises the current evidence base to generate the causal evidence on effectiveness and cost-efficiency that informed investment decisions require. These evaluation studies should be conducted using standardised assessment frameworks developed for AI-environment application performance in low-income country contexts, enabling systematic comparison of findings across Uganda, East Africa, and sub-Saharan Africa, and supporting the rapid identification and scaling of approaches whose effectiveness has been rigorously demonstrated. Open-access publication of all evaluation findings should be required as a condition of research funding.

REFERENCES

[1] Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. International Journal of Social Research Methodology, 8(1), 19–32. https://doi.org/10.1080/1364557032000119616

[2] Bunyangha, J., Muthumbi, A. W. N., Egeru, A., Asiimwe, R., Ulwodi, D. W., Gichuki, N. N., & Majaliwa, M. J. G. (2022). Preferred attributes for sustainable wetland management in Mpologoma Catchment, Uganda: A discrete choice experiment. Land, 11(7), Article 962. https://doi.org/10.3390/land11070962

[3] Byaro, M., Nkonoki, J., & Mafwolo, G. (2023). Exploring the nexus between natural resource depletion, renewable energy use, and environmental degradation in sub-Saharan Africa. Environmental Science and Pollution Research, 30(8), 19931–19945. https://doi.org/10.1007/s11356-022-23104-7

[4] CIPESA (Collaboration on International ICT Policy for East and Southern Africa). (2024). An artificial intelligence eco-system for Uganda: Policy brief. CIPESA. https://cipesa.org/wp-content/files/briefs/An_Artificial_Intelligence_Eco-System_for_Uganda__Policy_Brief.pdf

[5] FAO (Food and Agriculture Organization of the United Nations). (2025). Global forest resources assessment 2025 — Main report. FAO. https://www.fao.org/forest-resources-assessment/en/

[6] Hlongwa, N., Nkomo, S. L., & Desai, S. A. (2024). Barriers to water, sanitation, and hygiene in sub-Saharan Africa: A mini review. Journal of Water, Sanitation and Hygiene for Development, 14(7), 497–510. https://doi.org/10.2166/washdev.2024.266

[7] Hordofa, A. T., Nakamura, F., & Shrestha, N. (2025). Artificial intelligence and machine learning in remote sensing for tropical forest monitoring: Applications, challenges, and emerging solutions. Remote Sensing, 18(8), Article 1193. https://doi.org/10.3390/rs18081193

[8] Intergovernmental Panel on Climate Change (IPCC). (2022). Climate change 2022: Impacts, adaptation and vulnerability — Contribution of Working Group II to the Sixth Assessment Report. Cambridge University Press. https://doi.org/10.1017/9781009325844

[9] Kilama Luwa, J., Bamutaze, Y., Majaliwa Mwanjalolo, J. G., Waiswa, D., Pilesjö, P., & Mukengere, E. B. (2021). Impacts of land use and land cover change in response to different driving forces in Uganda: Evidence from a review. African Geographical Review, 40(4), 378–394. https://doi.org/10.1080/19376812.2020.1832547

[10] Kisubi, E. C., Aidonojie, P. A., & Owoche, A. G. (2024). Harnessing artificial intelligence for environmental waste management in Uganda: Legal and policy implications. International Journal of Scientific Research and Engineering Development, 8(10), 181–187. https://www.ijsred.com/volume8/issue10/

[11] Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: Advancing the methodology. Implementation Science, 5, Article 69. https://doi.org/10.1186/1748-5908-5-69

[12] Ministry of Water and Environment (MWE). (2020). Uganda REDD+ strategy and action plan (Second Edition 2020). https://redd.unfccc.int/media/uganda_redd_strategy_-_second_edition_june_2021.pdf

[13] Murray, A. L., Stone, G., Yang, A. R., Lawrence, N. F., Matthews, H., & Kayser, G. L. (2024). Rural water point functionality estimates and associations: Evidence from nine countries in sub-Saharan Africa and South Asia. Water Resources Research, 60(2), Article e2023WR034679. https://doi.org/10.1029/2023WR034679

[14] Nalubega, T., & Uwizeyimana, D. E. (2024). Artificial intelligence technologies usage for improved service delivery in Uganda. Africa's Public Service Delivery and Performance Review, 12(1), Article a770. https://doi.org/10.4102/apsdpr.v12i1.770

[15] Namaalwa, S., van Dam, A. A., Gettel, G. M., Kaggwa, R. C., Zsuffa, I., & Irvine, K. (2020). The impact of wastewater discharge and agriculture on water quality and nutrient retention of Namatala Wetland, Eastern Uganda. Frontiers in Environmental Science, 8, Article 148. https://doi.org/10.3389/fenvs.2020.00148

[16] National Information Technology Authority Uganda (NITA). (2022). National information technology survey report 2022. NITA. https://oldsite.nita.go.ug/publications/reports/national-it-survey/national-information-technology-survey-final-report-2022

[17] Obubu, J. P., Odong, R., Alamerew, T., Fetahi, T., & Mengistou, S. (2022). Application of DPSIR model to identify the drivers and impacts of land use and land cover changes and climate change on land, water, and livelihoods in the L. Kyoga basin: Implications for sustainable management. Environmental Systems Research, 11(1), Article 11. https://doi.org/10.1186/s40068-022-00254-8

[18] Obubu, J. P., Odong, R., Alamerew, T., Fetahi, T., & Mengistou, S. (2026). Spatiotemporal dynamics and drivers of land use and land cover changes in the Aswa 1 sub-catchment, Northern Uganda. Discover Applied Sciences. https://doi.org/10.1007/s42452-026-08270-4

[19] Olawade, D. B., Wada, O. Z., Ige, A. O., Egbewole, B. I., Olojo, A., & Oladapo, B. I. (2024). Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. Hygiene and Environmental Health Advances, 12, Article 100114. https://doi.org/10.1016/j.heha.2024.100114

[20] Peters, M. D. J., Godfrey, C., McInerney, P., Munn, Z., Tricco, A. C., & Khalil, H. (2020). Chapter 11: Scoping reviews ((2020 version). In E. Aromataris & Z. Munn (Eds.), JBI Manual for Evidence Synthesis. JBI. https://doi.org/10.46658/JBIMES-20-12

[21] Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, S. S., Sharma, V., Sharma, A., Arya, V. M., Kirkham, M. B., Hou, D., Bolan, N., & Chung, Y. S. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. Frontiers in Environmental Science, 12, Article 1336088. https://doi.org/10.3389/fenvs.2024.1336088

[22] Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8, Article 45. https://doi.org/10.1186/1471-2288-8-45

[23] Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation. Annals of Internal Medicine, 169(7), 467–473. https://doi.org/10.7326/M18-0850

[24] Twinomujuni, D., Tumwebaze, A., Baluku, E., Ogwal, F. S., & Komakech, R. (2024). Wetland restoration and conservation: Case of Uganda. East African Journal of Environment and Natural Resources, 7(1), 391–400. https://doi.org/10.37284/eajenr.7.1.2153

[25] UNESCO. (2022). Recommendation on the ethics of artificial intelligence. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000381137