

Artificial Intelligence in Environmental Management: Emerging Trends and Challenges

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Abstract

Artificial intelligence (AI) is moving from a supporting data-processing tool toward a decision infrastructure for environmental management. This article reports an original secondary-indicator analysis that quantifies how recent advances in AI strengthen environmental monitoring, forecasting, and intervention design while also generating new management burdens. The analysis integrates public climate, emissions, and energy indicators with reported performance markers from state-of-the-art AI systems in weather forecasting, Earth observation, flood prediction, biodiversity monitoring, water management, air quality, and waste systems. Two original composite indicators were developed: the AI Environmental Management Capability Index (AEMCI) and the Challenge Burden Score (CBS). The results show that weather and climate-risk management has the highest AEMCI because AI models provide rapid global forecasts, probabilistic uncertainty estimates, and plausible operational pathways. Earth observation is the second strongest domain because multimodal geospatial foundation models are improving transfer across land-cover, disaster-response, and crop-monitoring tasks. Water, air-quality, and biodiversity applications are advancing rapidly but remain constrained by sparse sensors, limited ground truth, ecological bias, and incomplete governance integration. The same evidence also reveals a sustainability paradox: AI can improve environmental management while increasing electricity, water, carbon, and land pressures through expanding data-centre infrastructure. The article concludes that high-impact AI for environmental management requires domain validation, transparent uncertainty, ecological-footprint accounting, human-in-the-loop governance, and deployment models that prioritize public environmental value over generic automation.

INTRODUCTION

Environmental management is entering a period in which climate hazards, emissions gaps, biodiversity loss, water stress, air pollution, and waste pressures are increasingly interconnected. The IPCC synthesis

report identifies widespread impacts and risks from climate change; the WMO reports persistent record warmth and extreme-event disruption; and the UNEP emissions-gap assessment shows that current mitigation ambition remains far below what is required for Paris-aligned pathways [1-3]. These

pressures create demand for faster monitoring, earlier warning, more adaptive planning, and management tools that can integrate heterogeneous environmental data at policy-relevant speed.

AI is becoming more powerful for management because three developments are converging. First, large-scale models now learn general representations from global Earth-system, satellite, and sensor data. Second, inference speed is changing the economics of forecasting: models that previously required large supercomputing pipelines can increasingly produce useful forecasts in minutes or seconds. Third, organizational uptake is rising, making AI part of routine decision workflows rather than a purely experimental technology. Energy-system analysis also shows that AI infrastructure is now a material management issue because data-centre electricity demand is projected to rise sharply under plausible deployment scenarios [4]. General AI capability and organizational adoption indicators confirm that AI is moving quickly from laboratory progress to operational adoption [5,6].

The environmental AI literature has expanded across air and water quality, climate modelling, biodiversity assessment, disaster management, and remote sensing. A recent bibliometric and in-depth study of AI in environmental monitoring identifies rapid growth in AI and machine-learning applications, particularly where AI is combined with remote sensing and Internet-of-Things sensing [7]. However, many publications remain application-specific and do not translate technical results into

comparable management indicators. This article addresses that gap by treating AI in environmental management as an empirical decision-system problem: which domains are most ready for deployment, which trends are emerging, and which challenges must be controlled before AI can produce durable environmental value?

This study makes four contributions. It develops an original AI Environmental Management Capability Index, constructs a companion Challenge Burden Score, visualizes the emerging trend structure across environmental domains, and links performance gains to the infrastructure footprint of AI. The analysis is not designed as a narrative review of the available literature. It is a secondary-indicator research article that uses recent state-of-the-art evidence and public indicators to generate comparative results for environmental management.

2. Materials and Methods

2.1 Study design

A secondary-indicator empirical design was applied. The unit of interpretation was the environmental-management domain, not the individual publication. Evidence was extracted from three data layers: (i) public environmental-pressure indicators, including temperature, emissions, and data-centre electricity demand; (ii) reported state-of-the-art AI performance markers from peer-reviewed or public technical sources; and (iii) governance and operational constraints relevant to environmental agencies, utilities, municipalities, conservation organizations, and infrastructure planners. Governance scoring was aligned with risk-based

and management-system principles in the EU Artificial Intelligence Act, the NIST AI Risk Management Framework, and ISO/IEC 42001 [8-10].

The analysis compared seven domains: weather and climate-risk management, Earth observation and land systems, water and hydrology, biodiversity and conservation, air quality, waste and circular systems, and governance and compliance. These domains were selected because they represent the principal management functions in which AI is already influencing monitoring, prediction, optimization, or accountability.

2.2 Indicator construction

The AI Environmental Management Capability Index (AEMCI) was calculated as the arithmetic mean of five 1-5 indicators: data richness, model generality, latency advantage, decision integration, and governance readiness. Data richness measures the availability and diversity of input data. Model generality measures whether AI can transfer across locations, tasks, or modalities. Latency advantage measures whether AI can improve the speed of detection, forecasting, or response. Decision integration measures whether outputs can be connected to management actions. Governance readiness measures the availability of validation, accountability, and risk-control practices.

The Challenge Burden Score (CBS) was calculated as the arithmetic mean of five 1-5 constraint indicators: data-quality risk, uncertainty or explainability burden, operational-integration burden, environmental-footprint burden, and equity or access burden. A high AEMCI indicates strong management potential,

whereas a high CBS indicates greater deployment risk. Interpretation therefore depends on the frontier between the two scores rather than on capability alone.

Table 1. Operational definitions used to construct the two composite indicators.

Indicator element	Operational measurement	Management interpretation
AEMCI: data richness	Input volume, spatial coverage, temporal frequency and modality diversity	Determines whether AI can learn relevant environmental patterns.
AEMCI: model generality	Transfer across sites, hazards, land systems or data modalities	Indicates whether AI can move beyond a single local pilot.
AEMCI: latency advantage	Speed of inference, update frequency and early-warning lead time	Shows whether AI changes the time available for action.
AEMCI: decision integration	Link to alerts, permits, operations, adaptation plans or enforcement	Measures usability for real management decisions.
AEMCI: governance readiness	Validation, auditability, accountability and risk	Determines institutional trust and compliance readiness.

	managem ent	
CBS: data- quality risk	Sensor gaps, missing labels, cloud cover, sampling bias or ground- truth limits	Raises the probability of unreliable decisions.
CBS: footprint burden	Energy, water, carbon, land and hardware impacts of AI systems	Tests whether AI-for- environme nt creates new environme ntal costs.

2.3 Visualization and analysis

The analysis proceeded in five steps. First, performance and pressure indicators were extracted from the evidence base. Second, indicators were normalized into comparable 1-5 domain scores. Third, a trend-maturity matrix was built for five emerging trends: foundation models, real-time sensing, predictive warning, decision optimization, and governed AI. Fourth, the AEMCI-CBS frontier was used to identify where AI is most management-ready and where risk controls are most urgent. Fifth, infrastructure-footprint indicators were plotted to show that AI environmental management must evaluate both the benefits of AI applications and the resource burden of AI deployment.

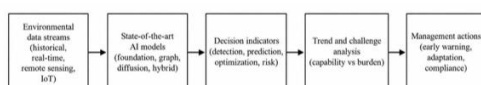


Figure 1. Analytical framework for converting environmental data streams and state-of-the-art AI evidence into management-relevant trend and challenge indicators.

3. Results

3.1 AI capability is becoming management infrastructure

The analysis first shows that AI has become more powerful for environmental management because general AI capability and organizational adoption have advanced together. Organizational AI use increased from 55% to 78% and then to 88% across the selected adoption indicators, while a frontier software-engineering benchmark rose from about 60% to near-saturation performance [5,6]. These values do not measure environmental management directly, but they explain why environmental agencies and infrastructure operators are now able to consider AI as an operational decision layer rather than as a stand-alone research tool.

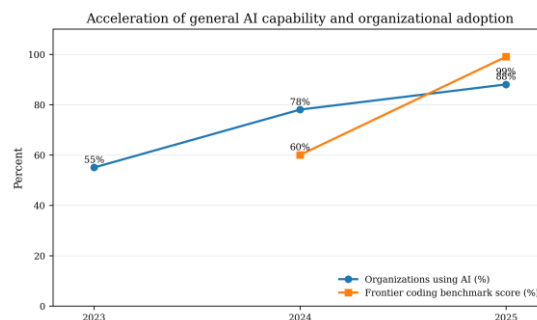


Figure 2. General AI acceleration indicators relevant to environmental management adoption and operationalization.

3.2 State-of-the-art environmental AI has moved from isolated classification to Earth-system decision support

Weather and climate-risk management represents the strongest AI-enabled domain. Pangu-Weather demonstrated very large speed advantages over conventional operational forecasting; GraphCast outperformed the leading operational deterministic system on most benchmarked targets; NeuralGCM

showed how hybrid differentiable models can bridge weather and climate simulation; GenCast added probabilistic ensemble skill for medium-range forecasting; Aardvark demonstrated the feasibility of replacing larger parts of the numerical-weather-prediction pipeline with end-to-end learning; Aurora extended the foundation-model approach across weather, air quality, ocean waves, and cyclone-track forecasting; and AI flood forecasting showed useful warning capability in ungauged basins [11-18].

Earth observation constitutes the second major frontier. Prithvi-EO-2.0, TerraMind, Earth foundation-model research, responsible geospatial-model principles, and Sustainable Development Goal benchmarking show a transition from single-task satellite-image classification to multimodal, reusable geospatial intelligence [19-23]. This transition matters for management because the same representation can support disaster response, crop monitoring, land-cover change, wildfire-scar mapping, ecosystem dynamics, urban planning, and environmental compliance.

Biodiversity, water, air-quality, and waste applications are developing rapidly but remain more heterogeneous. Conservation horizon scanning identifies high-potential uses such as species recognition, multimodal biodiversity prediction, wildlife-trade monitoring, and human-wildlife conflict management. VespAI shows how low-cost, hardware-assisted AI can be used for invasive-species detection. Camera-trap and embedded-vision work indicates movement toward automated

ecological sensing, while water-quality prediction, water-management AI, air-quality modelling, and smart waste-management studies show domain-specific gains in prediction and operations [24-33].

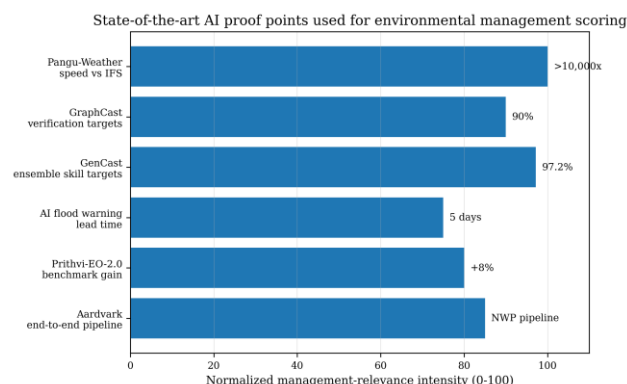


Figure 3. State-of-the-art proof points. Raw values are shown as labels, while the horizontal bars normalize each evidence marker to a 0-100 management-relevance scale.

3.3 Emerging trend structure

The trend-maturity matrix shows a clear pattern across the evidence base [11-33]. Foundation models and predictive warning are already strong in weather, climate risk, and Earth observation. Real-time sensing is strongest in water, biodiversity, and air quality because these domains depend on field sensors, IoT devices, cameras, acoustics, drones, or mobile monitoring platforms. Decision optimization is strongest in waste, water, and governance because these fields require routing, treatment control, compliance assessment, permitting, and resource allocation. Governed AI is strongest where regulation and institutional accountability are most explicit, but it remains uneven in ecology and waste systems.

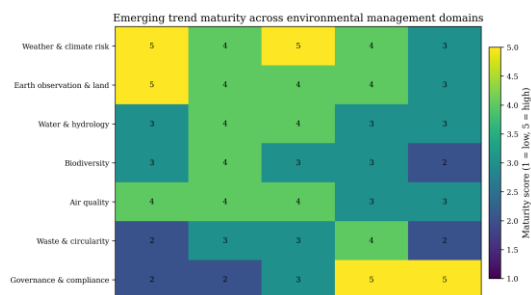


Figure 4. Trend maturity scores across seven environmental management domains.

3.4 Capability-challenge frontier

The AEMCI-CBS frontier identifies three groups. The first group, weather/climate and Earth observation, has high capability and moderate-to-high challenge, indicating readiness for operational use but continued need for uncertainty communication, local validation, and physical-consistency checks [11-23]. The second group, water, air quality, and biodiversity, has intermediate capability with high data-quality and equity burdens because monitoring networks are uneven, ecological ground truth can be sparse, and model performance may not transfer reliably between regions [24-32]. The third group, waste and governance, has moderate capability but strong institutional value because AI can improve inspection prioritization, reporting consistency, route optimization, and compliance monitoring when connected to accountable workflows [8-10,33].

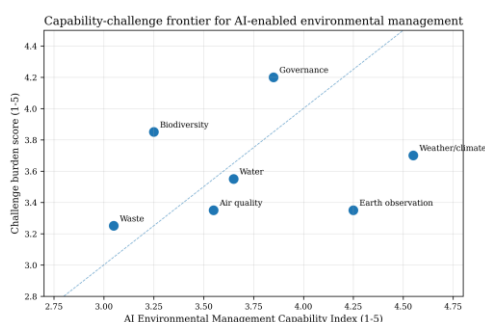


Figure 5. Capability-challenge frontier based on the AI Environmental Management Capability Index and Challenge Burden Score.

Table 2. Domain-level AI capability and challenge results.

Domain	AE M CI	C B S	Dominant trend	Main challenge
Weather and climate-risk management	4.55	3.70	Fast AI forecasting, ensembles, hybrid climate models	Physical consistency, extremes and accountability
Earth observation and land systems	4.25	3.35	Geospatial foundation models and multi-modal transfer	Ground truth, bias and regional validation
Water and hydrology	3.65	3.55	IoT-linked prediction, WQI forecasting and flood warnings	Sparse sensors and nonstationarity
Biodiversity and consequences	3.25	3.85	Automated species	Class imbalance, ecology

rvatio n			es detect ion and ecolo gical surve illanc e	ical bias and ethics
Air qualit y	3.5 5	3. 3 5	Nowc asting and emiss ion- sourc e intelli gence	Local calibra tion and exposu re equity
Waste and circul ar systems	3.0 5	3. 2 5	Sortin g, routin g and opera tional optim izatio n	Fragm ented munici pal data and cost barrier s
Gove rnanc e and comp liance	3.8 5	4. 2 0	Audit trails, comp liance analy tics and risk mana geme nt	Legal accoun tability and explai nabilit y

3.5 The sustainability paradox of AI-enabled environmental management

The results also reveal a paradox. AI can reduce environmental harm by improving forecasts, detection, optimization, and compliance, but the infrastructure needed to train and run AI systems creates its own environmental footprint. The AI-environment literature identifies both risks and benefits of large language and foundation models. Energy-

footprint analysis and data-centre footprint studies show that AI can increase electricity, carbon, and water demand, while sustainable server analyses identify efficiency, utilization, and grid pathways that can reduce but not eliminate the burden. Recent UN analysis further indicates that carbon, water, and land footprints must be considered together, because a low-carbon electricity source is not necessarily low-water or low-land [34-38].

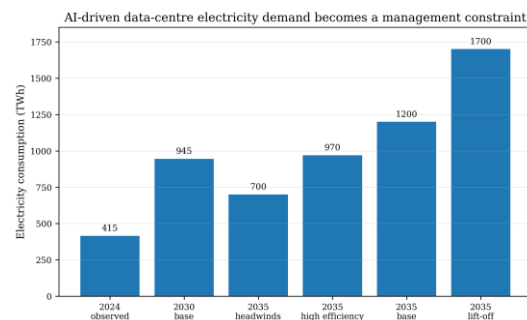


Figure 6. Data-centre electricity-demand trajectory and scenario range used to represent the infrastructure constraint of AI-enabled management.

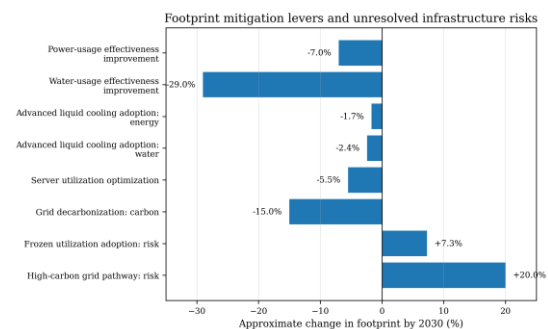


Figure 7. Footprint mitigation levers and unresolved risk pathways for AI infrastructure.

4. Discussion

4.1 Why AI is becoming more powerful for environmental management

The dominant mechanism is a shift from local models to reusable environmental intelligence. Earlier AI deployments often required

separate model development for each site, sensor network, or classification task. The emerging state-of-the-art is different: foundation models, graph neural architectures, diffusion-based ensembles, and hybrid physics-ML systems can reuse large learned representations and adapt them to new tasks [11-23]. For managers, this changes AI from a narrow prediction tool into a platform for detection, forecasting, scenario generation, and resource allocation.

The second mechanism is latency reduction. Environmental management is time-sensitive: flood warnings, heat-health alerts, wildfire response, pollution events, industrial discharges, and invasive-species detection all lose value when information arrives late. AI weather, flood, air-quality, and sensor systems compress the time from data ingestion to decision output [11-18,24-32]. This produces a direct management benefit because earlier warnings increase the feasible range of protective actions.

The third mechanism is multimodal integration. Environmental decisions require satellite imagery, field sensors, citizen reports, regulatory records, hydrological data, emissions inventories, biodiversity observations, and socioeconomic indicators. AI models are increasingly able to connect these modalities [19-33]. The strongest management trend is therefore not only higher prediction accuracy, but the ability to align different forms of evidence into an auditable decision workflow.

4.2 Emerging trends

The first trend is Earth-system foundation modelling. Weather, atmosphere, hydrology, and Earth-observation models are moving

toward general-purpose backbones that can be fine-tuned for specific management tasks [11-23]. The second trend is probabilistic and uncertainty-aware forecasting, which is essential because environmental managers make decisions under risk rather than certainty [11-18]. The third trend is edge and sensor AI, where cameras, acoustic sensors, drones, low-cost stations, and IoT networks enable more continuous monitoring [24-32]. The fourth trend is digital-twin and scenario-based management, where AI helps simulate intervention options before resources are committed. The fifth trend is governed AI, which requires validation, auditability, risk classification, model documentation, and human responsibility [8-10,39].

4.3 Challenges

The most important challenge is data realism. Environmental data are spatially uneven, sensor-dependent, and often biased toward wealthy or well-instrumented regions. Models trained on global reanalysis or satellite archives may perform well at broad scale while failing for local extremes, informal settlements, small watersheds, complex urban microclimates, or under-monitored ecosystems. Ground-truth scarcity is especially serious in biodiversity, water-quality, and waste systems [17,24-33].

The second challenge is explainability under uncertainty. Environmental managers must justify warnings, permits, restrictions, and investments. A model that produces a fast prediction without uncertainty, provenance, or confidence information may be difficult to use in public decisions. This is particularly important where model outputs affect evacuation decisions, pollution

enforcement, water restrictions, or conservation priorities [8-10,39].

The third challenge is institutional integration. AI outputs do not automatically create better management. They must connect to standard operating procedures, procurement rules, public communication protocols, monitoring budgets, accountability structures, and legal duties. The frontier is therefore socio-technical: strong models must be embedded in credible institutions [8-10,39].

The fourth challenge is the footprint of AI itself. Environmental AI should not be evaluated only by accuracy. It should also report electricity use, water consumption, carbon intensity, hardware lifecycle effects, and the location of compute infrastructure. Without this accounting, AI-for-environment projects may shift environmental costs from visible pollution problems to less visible digital infrastructure impacts [34-38].

4.4 Implications for environmental managers

For weather and disaster agencies, AI should be adopted as a complementary early-warning layer with ensemble uncertainty and physical-consistency checks. For land and conservation agencies, foundation models should be combined with field validation and local ecological expertise. For water utilities, AI should prioritize sensor quality, anomaly detection, and treatment optimization before large-scale automation. For air-quality agencies, AI should connect nowcasting to exposure reduction and environmental justice. For waste authorities, AI should begin with operational optimization and transparent performance metrics.

Across all domains, managers should require model cards, data sheets, audit logs, uncertainty information, environmental-footprint reporting, and clear human accountability [8-10,39].

5. Conclusion

AI is becoming a powerful environmental-management technology because it now combines scale, speed, multimodal learning, and operational adoption. The strongest current domains are weather and climate-risk management and Earth observation, where state-of-the-art models provide measurable gains in forecasting, transfer learning, and decision speed. Water, biodiversity, air-quality, and waste applications are advancing quickly but require stronger local validation, sensor coverage, and institutional integration. The main finding is that AI should be treated as environmental infrastructure, not only as software. Its value depends on both its capacity to improve environmental decisions and its ability to meet sustainability, transparency, and accountability requirements. The next phase of research should test these indicators using real agency deployments, compare AI-supported decisions against baseline management outcomes, and quantify the full lifecycle footprint of environmental AI systems.

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