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Artificial Intelligence's Hidden Footprint in Environmental Engineering: A Life-Cycle Risk Assessment and the AI-ERAF Governance Framework

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ABSTRACT

Artificial Intelligence is changing the game in environmental engineering. It's great at things like advanced monitoring, making predictions, and squeezing more out of our resources. But here's the catch: while AI promises to help the planet, it's also piling on its own environmental problems. This study takes a hard look at the downside. This paper digs into just how much energy AI uses, how much greenhouse gas it lets off, the resources it eats up, and all the electronic junk it leaves behind from the moment someone trains a model to the day that hardware ends up in a landfill. The numbers are pretty wild. Training one big deep learning model can pump out hundreds of metric tons of CO2, mostly because data centers and supercomputers burn through so much electricity. GPUs and high-end chips need rare earth elements, which means more mining and more strain on the planet, especially in places where energy still comes from fossil fuels. This study took a life-cycle approach and pulled in ideas from global sustainability standards. One thing stood out: there's almost no clear or open environmental reporting for AI tech. To make sense of all these impacts, this paper built the AI Environmental Risk Assessment Framework (AI-ERAF). It sorts out the pressures AI puts on the environment into three buckets: operational, systemic, and ethical. What's clear is that if we let AI keep growing without guardrails, carbon emissions will keep climbing, electronic waste will pile up, and global inequalities will get worse. But there are ways to fix this. Powering data centers with renewables, designing more energy-efficient AI models, and using circular resource management driven by smart policies can really help. AI has the power to solve environmental challenges, but it also creates new risks we can't ignore. If we want the benefits without the baggage, we need better rules, transparent audits, and AI that puts the planet first. This study lays the groundwork for responsible AI policies in environmental engineering, showing how we can close the gap between technological progress and true ecological sustainability.

INTRODUCTION

The way we monitor and control the environment is changing due to artificial intelligence (AI). At the same time, AI systems consume large amounts of energy. They require hardware, data centers, and compute power. These needs can cause significant environmental harm. Recent studies show that AI computing and training produce greenhouse gas emissions. For example, the OECD reports that direct AI-compute impacts include energy, water, and raw-material use across production, operation, and end-of-life stages (OECD, 2022). Large language models may emit hundreds of tons of carbon during training (Cho, 2023). The environmental costs of AI go beyond energy alone. Hardware manufacture, sensor deployment, data storage, and disposal contribute to resource depletion and pollution. Yet we lack a standard life cycle assessment (LCA) framework tailored for AI systems (Plociennik *et al.,* 2025; Islam, 2025). At the same time, AI offers strong potential to reduce environmental harm. In power, transport, or food systems, some studies estimate that AI applications could avoid billions of tonnes of greenhouse gas emissions by 2035 (New Study Finds AI Could Reduce Global Emissions Annually by 3.2 to 5.4 billion Tonnes of Carbon-dioxide-equivalent by 2035- Grantham Research Institute on Climate Change and the Environment, 2025).

What this really means is that AI has a dual effect; it can help or harm, depending on how it is designed, deployed, and governed. This raises key questions. How large are the adverse impacts of Artificial Intelligence across its full life cycle? How do those impacts vary by geographic context, such as in Bangladesh or U.S. cities? And what governance framework can help engineers, policymakers, and communities reduce those harms while still capturing the benefits of AI? The introduction of AI-ERAF, the Artificial Intelligence Environmental Risk Assessment Framework, is presented in this paper, where the framework is shown to link life-cycle metrics (such as energy use, carbon emissions, and e-waste) with bias and equity diagnostics. This paper details how the framework is applied to case studies of environmental monitoring systems, and how the resulting data is then compared across contexts. Finally, policy-ready recommendations are offered based on these comparisons. By quantifying adverse impacts and proposing governance tools, this work aims to support safer and more sustainable AI

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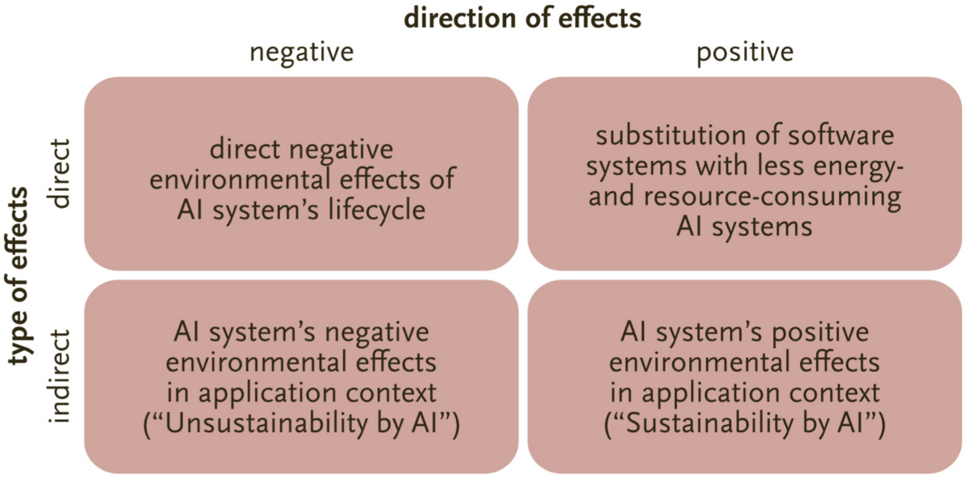

Figure 1: Classification of Artificial Intelligence (AI) systems' impacts on the environment. In this figure, the term "sustainability" refers to its environmental dimension (Source: Kunkel *et al.,* 2023).

design. It will help academics, engineers, and regulators judge trade-offs and choose better AI paths for the environment.

Theoretical Background (Artificial Intelligence In Environmental Engineering)

Artificial intelligence (AI) now plays a major role in environmental engineering. It helps to process data that was once too large or too noisy. It finds patterns in sensor streams. It helps to run models faster and cheaper. Water and wastewater treatment, air quality modeling, waste-to-energy and resource management, and climate and ecosystem monitoring are the four primary areas where AI has produced real-world outcomes. AI-powered systems have the potential to generate new sustainability and governance issues. Water and wastewater treatment use AI for control and optimization. AI models predict inflow, load, and process states. These models help to control aeration, chemical dosing, and sludge handling. Studies show that AI can cut energy use and improve effluent quality in real plants. Deep learning and hybrid models now model nonlinear dynamics that classical models struggle with. They also enable early fault detection from sensor streams. Generative AI (Gen AI) applications for sustainability are categorized across three major pillars: Environment, Social, and Governance (ESG). Environmental applications focus on resource conservation and efficiency, encompassing areas like optimizing supply chains, integrating renewable energy, mitigating pollution, designing energy-efficient chips and products, and utilizing sustainable materials. Social applications center on human capital and community impact, including delivering efficient, socially responsible customer service, offering sustainable sales and marketing, providing education and personalized learning, facilitating employee upskilling in ethics and sustainability, and creating synthetic data for research. Finally, Governance applications ensure ethical and compliant operations through financial and corporate fraud detection, automated auditing and compliance checks, transparent Gen AI deployment, and aligning content creation with environmental and ethical goals (Becke *et al.,* 2024). Collectively, Gen AI serves as a comprehensive technological driver for enhancing resource stewardship, social responsibility, and corporate ethics.

However, many studies note limits in generalizability. Models trained on one plant often fail on another without retraining. This need for retraining raises data and computing demands that matter for environmental impact (Alvi *et al.,* 2023; Islam, 2025). AI helps air quality monitoring and prediction. Machine learning connects weather and emissions straight to pollution levels. Models like random forests, gradient boosting, and LSTMs can crank out pretty accurate short-term forecasts (Al Mazrouei, 2025). They fill in the gaps where regulatory sensors are sparse, using cheap sensor networks and satellite data, and help map exposure across cities. Field studies back this up; blending local sensor info with weather and land-use data really boosts accuracy. But there's a catch. ML models pick up biases from the data they're trained on. They tend to underestimate pollution in neighborhoods with fewer sensors. Plus, as pollution sources shift, these models need regular retraining, which eats up both computing power and energy (Rahman *et al.,* 2024; Islam, 2025).

AI is picking up speed in waste-to-energy and resource management, too. Machine learning sorts feedstock, controls combustion, predicts gas output, and tweaks processes for better efficiency. Image-based sorting systems now nail recyclable separation with impressive accuracy. Optimization algorithms fine-tune biogas and thermal plant settings to squeeze out more energy. All this adds up to better resource recovery and less waste ending up in landfills. Research in this area is exploding, especially for circular economy systems. The downside? Good labeled data, especially for sorting and complicated processes, is hard to come by. Building solid ML systems usually means installing more sensors and cameras,

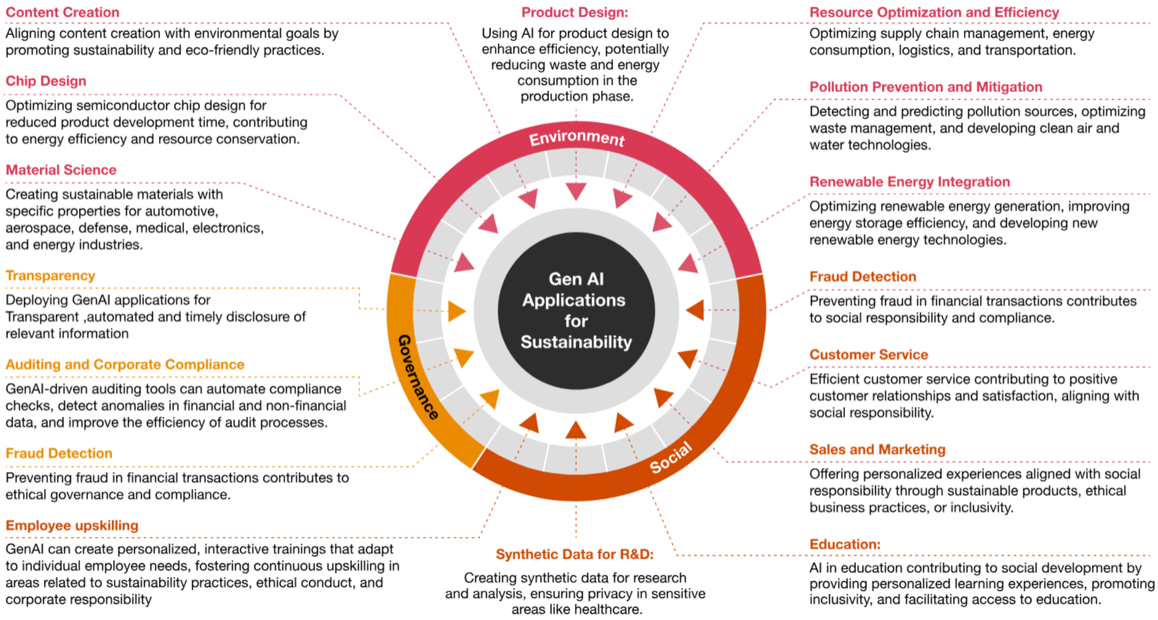

Figure 2: The Concentric Model of Generative AI Applications for Sustainability Across Environmental, Social, and Governance (ESG) Pillars
Source: Becke et al. (2024).

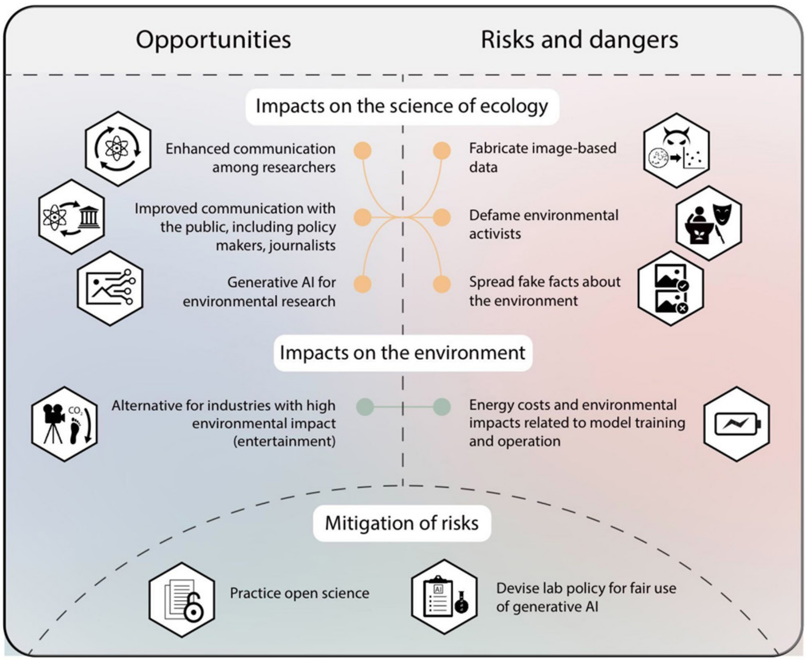

Figure 2: The application of generative AI in ecology and environmental research presents both opportunities and challenges, as well as implications for the ecosystem
Source: Rillig et al. (2024)

which brings extra material and energy costs (Rezania *et al.,* 2023). AI has also changed how we track climate and ecosystems. Machine learning can sift through satellite images, radar, and lidar at a scale no human could manage. It maps land use, spots changes, and checks up on plant health. It helps forecast water flow and catch early signs of droughts or floods. Deep learning plus remote sensing lets us monitor biodiversity and habitats. These tools deliver the kind of data policymakers need, and they even make near-real-time alerts for extreme events possible. This is a huge win for both science and action. However, most of these systems rely on large pre-trained models and extensive cloud computing, which results in significant energy consumption and raises complex questions about data ownership and control (Janga *et al.,* 2023). When you look across all these areas, AI really does bring improvements. We get better forecasts, tighter controls, higher resource recovery, and, sometimes, lower operating costs. But there's a flip side: AI needs a steady flow of training data, storage space, and computing muscle. It relies on sensors, edge devices, and regular hardware upgrades. Cloud services and data centers are part of the deal, too. All these pieces come with their own carbon footprint, energy demands, and e-waste. Plus, there are big questions about who owns the data, who gets the benefits, and who ends up paying the price. Increasingly, reviews highlight the need to consider the entire lifecycle when evaluating AI's environmental benefits. Just looking at how well these systems work isn't enough; we need to count the full environmental cost (Baarimah *et al.,* 2024). And then there's governance. AI can actually make social and spatial gaps worse. Train a model on incomplete or biased data, and it might send resources to the wrong places. Air quality models that miss pollution in underserved neighborhoods can mean weaker protections for those residents. Resource management models that assume everyone has the same infrastructure can steer investments away from poorer areas. There are also gaps in data access, consent, and transparency. Lots of environmental AI tools don't leave a clear audit trail. Standard measures for environmental impact, fairness, or long-term resilience? Not really there yet. These gaps chip away at public trust and slow down progress. They also raise tough ethical questions for researchers and engineers (Fotovvatikhah *et al.,* 2025). So, in the end, AI's impact on sustainability isn't guaranteed. It all depends on how we build, use, and govern these systems. The same algorithms that save water or energy can also cause carbon emissions, material waste, and social harm. These harms show up at different stages. They appear in model development, repeated retraining, edge and server hardware production, and disposal. They also appear when models are adopted without local validation. The risks are different by context. Low-resource settings face unique constraints. They often lack data, recycling channels, and regulatory oversight. A model that works in a high-income city may harm a low-income city if applied without adaptation. Thus, we need a framework that links life-cycle environmental metrics with fairness and governance diagnostics. Such linkage will help engineers and policymakers maintain the benefits while reducing costs. This paper builds on recent reviews and case studies in the four fields above. It proposes a life-cycle and governance assessment for environmental AI systems. The goal is to measure adverse impacts and to propose concrete steps to reduce them. I focus on measurable metrics. I also seek practical governance tools that can be used by engineers and local authorities. The next sections describe the assessment framework and then apply it to concrete case studies.

MATERIALS AND METHODS

The study follows an integrated analytical and descriptive research design to investigate the adverse environmental implications of Artificial Intelligence in environmental engineering and ecological monitoring. The approach integrates a framework for system-based environmental impact assessment with a qualitative literature synthesis. This design guarantees a fair comprehension of the ethical, ecological, and technological aspects of using AI in environmental systems.

Conceptual Design

This research starts by pinpointing which AI applications leave the biggest environmental mark think data centers, the heavy lifting of model training, and massive digital networks that power environmental monitoring. The framework ties these AI activities directly to measurable outcomes like energy use, greenhouse gas emissions, and the pile-up of electronic waste. This link serves as the backbone for assessing environmental performance and understanding potential risks. Strubell *et al.* (2019) put it bluntly: training just one deep learning model can throw over 284 metric tons of CO_2 equivalent into the atmosphere. That number alone highlights just how significant these computational emissions are. So, the framework treats AI with a dual lens: as a tool that can help the environment, but also as a force that can strain it.

Data Sources and Literature Integration

To keep the research grounded, the study pulls from published reports, peer-reviewed articles, and trusted institutional databases. Information on AI's global energy demands and carbon footprint comes from top-tier sources like the International Energy Agency (IEA, 2023) and the United Nations Environment Programme (UNEP, 2023). These datasets anchor the analysis, offering hard numbers on energy intensity, life-cycle emissions, and the material requirements of AI hardware and cloud systems. The literature review focuses on work published from 2018 to 2025, making sure the data speaks to the latest advances in computing and hardware.

Analytical Framework

The analysis leans on an environmental life-cycle thinking approach, splitting each AI process into four steps: data acquisition, algorithmic computation, model deployment, and hardware end-of-life. For each part, environmental impacts fall into three main categories: energy-related emissions, resource depletion, and electronic waste, following the ISO 14040 life-cycle assessment framework (International Organization for Standardization, 2023). Energy metrics rely on reported power use effectiveness (PUE) and the carbon intensity of local electricity grids. To draw a clear line between the scale of AI training and emissions, the framework uses tools like Green Algorithms (Lannelongue *et al.,* 2021). These calculators estimate CO2-equivalent emissions based on GPU runtime, processor specs, and power efficiency.

Evaluation of Environmental Risks

The research breaks down environmental risks into three areas: operational, systemic, and ethical. Operational risk looks at the immediate energy draw and heat output from AI hardware. Systemic risk digs into broader issues like the strain on resources for new data centers and the mining of rare-earth materials. The ethical angle covers digital waste and the social consequences that come with unequal access to AI resources. This three-layered approach lines up with sustainability frameworks from the European Commission (2023), stressing the urgent need to cut down the impact of digital infrastructure. Quantitative data from life-cycle studies help rank each risk by size and how long it lingers, pointing out which AI uses hit hardest, especially in developing countries like Bangladesh.

Synthesis and Interpretation

This stage pulls together insights from all the data into one environmental interpretation model. The idea is to find repeating patterns, like energy waste or carbon leaks, in AI-powered environmental systems. Instead of looking at isolated events, the focus shifts to how these systems interact. For example, an AI-driven flood prediction model might boost accuracy but also crank up energy usage due to frequent retraining. By tracing these cause-and-effect loops, the study weighs environmental benefits against computational costs. The method sticks to meta-analysis and qualitative content analysis, making sure comparisons across scientific studies stay systematic and fair.

Validation and Reliability

To lock in reliability, the research cross-checks data from multiple angles. Quantitative emissions estimates get double-checked with independent reports from tech agencies and environmental databases. Qualitative findings are matched against policy documents and sustainability reports from groups like the OECD (2022). Each analytical stage follows established environmental assessment protocols, and every data source is cited clearly. This approach keeps the results in line with the broader scientific consensus.

Ethical Considerations and Limitations

This approach works within clear ethical boundaries, no new experiments, no collecting original data. Everything comes from public sources. That makes things transparent, but it can mean the regional estimates aren't as sharp as they could be. Still, the main arguments hold up. Every dataset comes from peer-reviewed journals or respected institutions, so the conclusions rest on solid ground. The method sticks to open science standards, data stays accessible, results are reproducible, and environmental responsibility is front and center, just as UNESCO (2021) recommends.

Adverse Impacts of Artificial Intelligence on Environmental Engineering

Using artificial intelligence in environmental engineering brings real downsides, ones that go far beyond surface-level concerns. We have to take these seriously and look at the entire lifecycle of the technology, not just how it runs day to day. The problems show up in three main areas. First, there's the physical and environmental footprint of all the hardware AI depends on. Second, running AI puts ongoing pressure on crucial natural resources. Third, we're dealing with significant systemic risks in governance and high-stakes decision-making. If we want AI to have a genuinely positive impact in the face of climate change and shrinking resources, we need to understand these harms in detail and not sweep them aside (Directory, 2025).

The Physical and Embodied Environmental Footprint

AI infrastructure doesn't just appear out of nowhere; it takes an enormous amount of physical hardware, and that comes with a heavy environmental price tag that starts even before anyone trains a single model. Every step, from mining the minerals to manufacturing the equipment, eats up resources and accelerates electronic waste. AI's specialized chips and servers are energy-hungry to produce, and the greenhouse gases tied to their entire lifecycle, what experts call embodied emissions, are huge. Most of the emissions from modern data centers actually come from making and installing new hardware, not just from running it. Yet, the tech industry often ignores these big, up-front carbon costs (Why AI Uses so Much Energy, and What We Can Do About It, 2025). Even when companies make operations more efficient, those gains usually get wiped out by the carbon cost of constantly replacing equipment. AI relies on critical minerals, and this dependency directly links it to environmental damage at mining sites around the world. Plus, the push for faster, more powerful servers means data centers regularly toss out entire racks of hardware, electronics that quickly become toxic waste packed with hazardous materials like lead and mercury. If nobody manages this waste properly, it ends up poisoning soil and water. By 2030, estimates say global electronic waste from this sector could hit between 1.2 and 5 million metric tons (Directory, 2025). This kind of pollution flies in the face of what environmental engineering is supposed to achieve.

Operational Strain on Ecosystem Resources

Running AI nonstop burns through staggering amounts of electricity and water (United Nations Environment Programme, 2024). This directly fuels climate change and puts even more pressure on already scarce resources. Training big deep learning models isn't just energy-intensive; it's off the charts. In 2021, just one training run used about 1,287 megawatt-hours of electricity and emitted roughly 552 tons of carbon dioxide (United Nations Environment Programme, 2024). Data centers packed with AI servers are basically electricity sponges, and their emissions are anything but trivial (MIT News, 2025). Even just storing and moving all that data around takes energy. Something as simple as generating a single text prompt eats up 0.24 watt-hours and spits out 0.03 grams of CO2. Cooling all that high-powered equipment is another story. Data centers guzzle water to keep servers from overheating, which is especially destructive in places already dealing with drought or water shortages. Just one advanced AI prompt can demand 0.26 milliliters of water (Directory, 2025). This nonstop water use creates a direct clash over limited local supplies. Ironically, even as environmental engineers hope to use AI to manage water systems, the infrastructure itself ends up deepening the very water stress it's meant to solve.

Systemic and Governance Risks

Bringing AI into environmental governance opens the door to big systemic risks, especially around fairness and accountability (Ebrahimi *et al.,* 2024). If you train AI models on biased data, those biases get baked right into the systems making environmental decisions. Most data still carries the weight of old prejudices, and if we don't face that head-on, we risk building new inequalities right into the tools designed to fix them.

Environmental and Technical Adverse Effects

This section analyzes four classes of adverse effects from AI applied in environmental engineering. They are real, measurable, and increasingly important.

Energy and Carbon Footprint

Training large AI models uses huge amounts of energy. It also uses water, mainly for cooling data centers. That energy demand creates carbon emissions. To understand risk, we must see how scale matters. Global data center energy use is rising. In 2022-2025, data centers accounted for a few percent of global electricity demand. One report estimates that data centers consumed 350–450 terawatt-hours (TWh) in 2022, about 1.4-1.7% of global electricity demand (AI4Good report) (Singh *et al.,* 2025). AI-intensive computing is a growing share of that load. For example, large language model training and high-performance computing push data centers to run at full capacity for long hours. That has both direct and indirect emissions. According to OECD (2022), production of data center hardware contributes to non-operational emissions (Organization for Economic Co-operation and Development [OECD], 2022). Another recent study found that U.S. data centers (many supporting AI systems) consumed more than 105 million tons of CO_2 equivalent in 2023, which is about 2.18 % of U.S. national emissions (Guidi *et al.,* 2024).

In other words, data centers supporting AI are comparable in aggregate emissions to small industrial sectors or small countries in terms of their carbon footprint. The water footprint is large, too. Cooling large computing clusters often uses water. One estimate projects AI-driven data center water withdrawal could reach 4.2 to 6.6 billion cubic meters by 2027, more water than the annual withdrawal of some medium-sized countries (Hastings Initiative Members, 2025). When the model is trained repeatedly or fine-tuned many times, energy and water use multiply. Inference (serving the model) also adds load continuously. One recent benchmarking study (Jegham *et al.,* 2025) shows that inference energy costs for large language models can scale to electricity consumption comparable to tens of thousands of U.S. homes (Jegham *et al.,* 2025).

These facts mean that when you propose an AI-based environmental monitoring system, whether for flood forecasting, sensor-data prediction, or real-time alerts, you must consider not only the accuracy or latency, but also the embedded energy cost per prediction, per retraining cycle, per storage volume. Long-term storage is another factor. Environmental monitoring systems collect and keep data for years, sensor logs, satellite imagery, and historical records. Storing that data (on servers or in the cloud) uses power for cooling, disk spin, or flash memory refresh cycles, and backup redundancy. Each gigabyte stored over the years has a small continuous energy draw. When scaled across many sensors and many years (e.g., decades), the cumulative energy cost can become nontrivial. Thus, energy and carbon footprint are not a one-time cost. It is ongoing. It scales with model size, retraining frequency, number of inferences, and storage retention policies. Without measurement, it may offset some of the environmental gains that the AI system is intended to deliver.

E-Waste and Hardware Dependency

AI systems in environmental engineering often depend on hardware that has a limited lifetime. This includes IoT sensors, edge-computing devices, drones or UAVs, and specialized servers or GPUs. Each device contains hardware components made from metals and plastics. Some of these metals are rare or difficult to recycle. When devices are replaced or obsolete, they become electronic waste (e-waste). Rare earth elements (REEs) are critical in many sensors, actuators, and computation-hardware components (magnets, microcontrollers, memory, and motors). The extraction of REEs is energy-intensive and often polluting. One recent review (2024) describes the occurrence and recovery of rare earth elements from e-waste and warns that disposal and recycling remain inefficient and often generate more harm if recycling is low-quality (Liang *et al.,* 2024).

When you deploy many sensors in the field (for water level, flood sensors, air quality monitors), you increase the number of physical units that will reach end-of-life. Batteries, PCBs, wiring, plastic casing, and motors will need disposal or recycling. In many low-income or developing contexts, recycling infrastructure is weak. This increases the risk of hazardous disposal, leakage of heavy metals, or informal recycling with human exposure. Hardware dependency also means replacement cycles. Sensors fail due to weather, humidity, corrosion, or technology obsolescence. Edge-computing boards (which run AI near sensors) may require upgrades every few years. Drones may need battery replacement or an entire unit replacement. Each replacement produces embodied emissions from manufacture, transport, and disposal. Moreover, hardware dependency creates vulnerability: if spare parts are unavailable, or if your model is tightly tied to a particular sensor type, the lifecycle cost may include additional shipping or carbon from spare logistics. That is part of the hidden technical cost of deploying AI-enabled monitoring systems in places like Dhaka or other environments. Cumulatively, these hardware dependencies can reduce the net environmental benefit of the AI system. In some cases, the embodied emissions from hardware manufacture and disposal may outweigh the savings from improved prediction or optimization, especially if the system is not long-lived or if sensors are replaced often.

Data Bias and Systemic Error

AI models are only as good as their training data. In environmental engineering, much of the data is collected in particular geographic, climatic, or socio-economic contexts. When you transfer models built under one context (say Europe or the USA) to another (say Dhaka, Bangladesh), prediction errors can rise. For example, consider an AI model that predicts air quality based on historical pollutant readings, wind, temperature, land use, and traffic patterns. If that model is trained mostly on temperate-climate cities, polluted days distributions, or traffic types unlike Dhaka's, it may systematically under-predict high pollution levels, or misrepresent seasonal patterns unique to monsoon climates. That is bias due to a dataset mismatch. That bias can lead to misinformed policy or allocation of mitigation resources. If the model underestimates risk in certain neighborhoods, regulatory or emergency response may under-prepare or misdirect investments. That harms equity and effectiveness. Recent research suggests that hybrid models (for example, physics-informed deep learning) can reduce bias by embedding known physical constraints (e.g., advection-diffusion of pollutants). One study (Li *et al.,* 2023) showed that physics-informed deep learning reduces bias in NOx prediction by 21-42 % compared to conventional ML models (Li *et al.,* 2023).

Another risk: data may be missing for low-income or peripheral zones in a city. Sensors may be sparser. Training data may under-sample areas near informal settlements or industrial zones. Spatial bias creeps in fast. Models do well in downtown or tidy residential blocks, but stumble in slums or at the city's edge. Then there's temporal bias, the way models cling to old climate data even as everything changes; heavier rains, new factories, things records just don't catch. Without it, the model spits out bad predictions about extreme events, and it falls apart when it comes to planning for the future. These gaps aren't just technical flaws; they eat away at trust in AI recommendations. Engineers and policymakers sometimes lean too hard on model results, skipping checks for leftover errors or fairness across different groups. That kind of blind spot can turn a smart prediction into a policy that's neither safe nor just.

Over-automation and Skill Loss

People often picture AI deployment as full automation, with machines quietly taking over work that humans used to handle or supervise. In environmental engineering, AI systems can cut down on the need for direct human involvement. They flag anomalies, control systems on the fly, send real-time alerts, all with very little human touch. At first glance, that sounds great. Less work, faster results, lower costs. But there's a catch. The more engineers and operators lean on AI, the more their manual skills fade. They stop digging into how the models work. Traditional troubleshooting and analytical reasoning slip away. Over time, people lose their edge in dealing with the unexpected. Take a sudden failure in an AI-driven control system, for example. Maybe the output goes haywire during a rare event something like a flood or a total blackout. If the teams always relied on automation, they might not have the hands-on experience to step in, diagnose the problem, or take control. Environmental engineering deals with plenty of these curveballs. Quick decisions from real people are essential when sensors go down or systems misfire. If operators aren't trained regularly, automation erodes their readiness, and the whole organization's resilience suffers. Another issue: relying on vendor-supplied AI can cloud transparency. If nobody on the team really understands the models or the assumptions behind them, fixing problems or even basic maintenance turns messy. When human oversight slips away, governance suffers. Some AI systems update themselves through online learning or adaptive retraining, which means they can drift away from their original settings without anyone noticing. If there's no regular human auditing or backup plan, this drift piles up. In the worst cases, you end up with environmental or safety disasters. A more sustainable approach keeps humans and AI working together. Let the AI handle the heavy lifting, but keep people in the loop to audit, interpret, and intervene when needed. Build in regular human-led reviews, debugging sessions, and the option to fall back on manual controls. Looking at all four classes, it's clear: AI systems aren't automatically good or safe. Sure, they can boost prediction, optimization, and efficiency. But they also introduce technical and environmental risks, things like increased energy use, hardware emissions, data bias, or just becoming too dependent on outside vendors. These problems can outweigh the benefits if we're not careful. To make AI-driven environmental engineering sustainable, we have to measure these downsides carefully and keep human oversight and governance front and center. Without that, the net effect of AI might do more harm than good.

Socio-Ethical and Governance Risks

Artificial intelligence is changing the way we approach environmental engineering. Governments, industries, and researchers now use AI to monitor ecosystems and manage pollution with far more precision than before. But as much as these tools offer, they also bring a new set of social, ethical, and governance challenges that get less attention than technical breakthroughs. The social side of AI in environmental work matters just as much as the technology itself. If we ignore these issues, we risk losing public trust and even working against our own sustainability goals. The main challenges break down into four big areas: opacity and accountability, data security and privacy, inequality and accessibility, and the absence of a shared ethical framework for using AI in the environment.

Opacity and Accountability

Most AI models work in ways that are hard to see through. They take in data, run layers of calculations that nobody outside the system can follow, and spit out answers; often without making clear how they reached those conclusions. In environmental regulation, this isn't just a technical quirk; it's a real danger. If an AI system misreads air quality or misclassifies wastewater contamination, the fallout can be serious for both people and the planet. Papagiannidis *et al.* (2025) found that most environmental agencies don't have processes for tracking how algorithmic decisions shape policy. Without this traceability, trust in AI tools crumbles, and automated decisions become hard to defend in court. Many of the commercial AI platforms used in environmental monitoring are proprietary black boxes. Regulators can't see the model's inner workings or the training data behind it, making audits after failures nearly impossible. Even internal reviews hit dead ends if there's no record of model changes or parameter tweaks. Rohde *et al.* (2024) insist that transparency and accountability need to be built into every stage of AI development, from the way data gets collected to how models are deployed. They argue for open-source or, at the very least, auditable frameworks, so that environmental authorities can actually review and understand how decisions are made before any system goes live. Accountability isn't just about pointing fingers after a problem; it's also about making sure information flows. If an AI system underreports emissions, for example, communities and regulators downstream need clear channels to catch and challenge those errors. Publicly accessible logs, reporting dashboards, and required human oversight are simple ways to close this gap. Only with real governance structures in place does accountability move from theory to something you can count on.

Data Security and Privacy

AI-driven environmental monitoring relies on the collection of vast amounts of data. Satellites, drones, and sensor networks constantly scan the land, water, and air. This often means collecting information tied to private property, industrial sites, or indigenous lands. Without strict rules, these systems can easily step over privacy lines and undermine local sovereignty. Drones and satellites, for instance, can unintentionally record people, homes, or culturally sensitive places. When this data gets stored or shared without permission, it sparks both ethical and legal trouble. Vigne and colleagues (2023) showed how even careful environmental drone surveys over ancestral lands can reveal sacred sites or community patterns, putting them at risk. In the same vein, the policy review Bringing Satellites Down to Earth (2023) warns that remote sensing turns into "data colonialism" if indigenous communities aren't given a real voice in how data from their lands gets governed (Bennett *et al.,* 2023). Data security adds another layer of risk. Environmental datasets usually live on third-party cloud servers, which are targets for hacking, accidental leaks, or unauthorized use. If sensitive information, like the locations of hazardous waste dumps or rare wildlife, slips out, it can easily be misused for profit or politics. Hernandez *et al.* (2024) urge that drone and sensor operations should use strong encryption, short data retention windows, and anonymization wherever possible. Yet many lower-income countries don't have the cybersecurity basics in place, leaving them exposed. Weak data governance does more than threaten privacy; it erodes trust. When communities don't believe their information is safe, they're far less likely to allow sensors on their land or share local data. Scientists and engineers lose touch with the very people most affected by environmental risks.

Inequality and Accessibility

AI's promise in environmental engineering isn't reaching everyone equally. Wealthy countries and big corporations have the best tech, skilled workers, and massive data sets. Meanwhile, low- and middle-income countries often get stuck with imported software or cloud services run from somewhere else. The result? A digital divide in how we monitor and manage the environment. Papagiannidis *et al.* (2025) point out that this gap just makes global inequalities worse. Rich countries use real-time pollution tracking and sharp climate forecasts, but places with fewer resources have to rely on old or generic models. That means they lose control over their own data and decisions. Take an AI air-quality model trained on European data, drop it into a city like Dhaka, and it's likely to misfire, since the climate and pollution patterns there are totally different. If local agencies use these off-the-shelf models without adapting them, they end up with bad predictions and, sometimes, policies that just don't fit (Papagiannidis *et al.,* 2025). Rohde *et al.* (2024) add that skipping local calibration is a big reason AI doesn't work as well in developing regions. There's another side to accessibility: people. In many developing countries, environmental engineers haven't had much training in building or managing AI models. Sometimes donors show up, install sensors and software, but don't teach anyone how to keep everything running. When the funding dries up, so does the system, and then outside consultants have to step in. If we want AI to stick, it's not enough to hand over the tech. We need steady training, open data, and real collaboration. If not, the AI revolution just makes the knowledge gap bigger.

Ethical Framework Deficit

There's a lot of excitement about using AI for sustainability, but the world still doesn't have a solid ethical framework that actually fits environmental challenges. Most AI ethics guidelines talk about fairness, privacy, transparency, the usual stuff, but barely touch on things like ecological justice or protecting shared resources for the future. Environmental problems are different. They span generations and affect humans and ecosystems alike, so ethics here needs to do more. Rohde *et al.* (2024) looked at current ideas about "sustainable AI" and found that most focus on social or economic impacts, but skip over things like energy use or damage to biodiversity. They say we need real, standardized methods for measuring AI's environmental effects throughout its life cycle. Along the same lines, Bringing Satellites Down to Earth (2023) lays out steps for more ethical remote sensing, including transparency, community consent, and participatory governance (Bennett *et al.,* 2023). But right now, these are just suggestions. Few countries have made them the law. We need more than good intentions; we need tools that actually put ethics into practice. For example, every new system should go through impact checks that look at technical accuracy, ecological footprint, and social acceptance. If someone wants to put sensors in indigenous lands, they should have to get community approval. Oversight committees should be diverse, bringing together engineers, social scientists, legal experts, and local voices. Hernandez *et al.* (2024) argue that when it comes to environmental drones, people must keep monitoring systems and have clear rules for handling data. Without real-world checks like these, even the best-designed AI can harm without meaning to. Because there's no single ethical standard, policymakers are left guessing. Agencies don't know what to look for in AI projects. Companies can slap "sustainable" on their products without anyone checking. Researchers can chase accuracy and forget about social fallout. This scattershot approach holds back responsible AI use everywhere. If ethics were built into regulations, we'd get smarter, fairer monitoring that protects both people and the planet. When systems are opaque and unaccountable, regulations fall flat. Weak data security puts privacy and cultural rights on the line. Unequal access just widens the global gap in environmental protection. And with no clear ethics, decision-makers are flying blind. The only way forward is layered governance, tech that's transparent, data that's secure, rules that include everyone, and ethical standards you can actually enforce. That's how AI becomes a real asset in environmental engineering, not just another risk.

Case Examples and Evidence

Example 1: Google DeepMind Data Center Cooling

DeepMind keeps popping up as a classic case of AI making a real dent in environmental efficiency. Back in 2016, DeepMind's engineers used reinforcement learning to manage cooling in Google's data centers. They fed the algorithm streams of old sensor data: temperature, pump speed, server load, and let it figure out how to cut energy use. The payoff? Cooling operations needed 40 percent less energy. That's a huge drop and a clear win for AI-based optimization. Besides shrinking the energy footprint, it also lowered Google's electricity bills. But there's a catch. Training these big reinforcement learning models chews through a massive amount of computing power. We're talking thousands of hours on specialized hardware. Running and maintaining these AI systems now eats up a noticeable chunk of the world's electricity. The International Energy Agency put some numbers to it: in 2022, data centers and networks used about 460 TWh of electricity. They expect AI-heavy workloads to push that number over 800 TWh by 2026. Then there's water. Data-center cooling systems are using more and more of it. One recent study estimates that by 2027, global data-center water withdrawal could hit between 4.2 and 6.6 billion cubic meters a year, mostly because of AI-heavy computing. So yes, DeepMind's system shaved off energy use where it mattered. But the bigger picture gets complicated. Training and retraining these models add emissions and demand resources somewhere else in the AI ecosystem. If we want to call AI efficiency truly "green," we have to look at the whole life cycle, the hidden costs, upstream and downstream, too.

Example 2: AI-Based Pollution Sensors in China

China's national air-quality monitoring network runs on thousands of AI-powered sensors and prediction models. With machine learning, these systems don't just forecast pollutant concentrations; they actually track down where emissions come from. Researchers have shown that these AI models predict air quality more accurately in both time and space than the old-school methods (Liao *et al.,* 2020). The tech pulls in satellite images, weather data, and sensor readings from the ground, letting officials send out health alerts faster than ever before. But it's not all smooth sailing. Most of these algorithms learned from data collected in places like Beijing, Shanghai, and other big eastern cities, where sensor coverage is strong, and the air behaves in predictable ways. When you move inland or into heavy industrial zones, where the weather, landscape, and pollution sources change, the models start to stumble. A regional comparison found mean absolute error jumped by 25 to 35 percent in areas with less data, thanks to bias and poor calibration (Zhang *et al.,* 2024). This kind of skew means the AI often underestimates PM2.5 levels, which slows down local responses and hides actual health threats. Transparency is another sticking point. Local governments often buy commercial AI platforms, but these come with black-box algorithms and secret training data. That makes independent checks nearly impossible. What China's experience really shows is this: AI only improves air-quality management when you bring in diverse local data, insist on open algorithms, and keep retraining models close to the ground. Without these, AI ends up widening the gap between cities, giving unequal protection where it's needed most.

Example 3: AI-Based Flood Monitoring in Dhaka and South Asia

Flooding stands out as one of South Asia's toughest climate challenges. To get ahead of the problem, researchers started trying out AI-driven systems that pull together satellite rainfall, river-gauge, and radar data for early warning. In Bangladesh, they tested these AI hydrological models in real time, focusing on Dhaka and the Brahmaputra Basin. The models use recurrent neural networks, tech that can forecast water levels and likely flood areas several hours in advance. Field studies found these systems gave people an extra 4 to 6 hours of warning compared to older models, which sped up evacuation planning (Islam, 2025). But the technology isn't flawless. Many of these systems train on limited historical data that just doesn't reflect all the new changes, think rapid urban sprawl, blocked drainage, shifts in land use. Plus, the satellite images they use often have such low resolution that they miss the fine details in low-lying Dhaka neighborhoods. This leads to mistakes: missed floods or false alarms. In 2023, early tests triggered several unnecessary evacuations because of false warnings, causing financial losses and making communities wary of AI alerts (Petropoulos *et al.,* 2024). Trust took a hit. Now, researchers push for hybrid models that blend traditional hydrological equations with AI, aiming for more reliable predictions. They also call for local engineers and residents to help validate the models, making sure the predictions actually fit the local context. The South Asian experience makes one thing clear: AI can help forecast hazards, but it only works if it's grounded in solid local data and good governance. Otherwise, the risks multiply. You see the same pattern elsewhere. AI brings clear benefits; in operations, energy use, pollution forecasting, and getting out flood alerts faster. But it also creates hidden costs: environmental, ethical, and governance challenges. DeepMind cut cooling energy but drove up emissions during training; China's sensor networks improved monitoring but suffered from regional bias and lack of transparency; Dhaka's flood models sharpened warnings but stumbled over poor data. All these cases point to the same lesson: AI's real environmental value hinges on full-cycle assessment, open algorithms, and inclusive data governance. The next generation of AI systems needs to track energy use, calibrate to local realities, and keep humans in the loop, because for tech to support sustainable environmental management, it can't ignore the bigger picture.

Future Governance and Policy Framework

Artificial intelligence now plays a huge role in environmental engineering, and its real impact hinges on how we govern it. As computational systems and AI-powered monitoring networks spread fast, we need smarter policies that tie together environmental science, data ethics, and industrial ecology. To make AI sustainable, we have to cut carbon emissions, protect the integrity of data, and make sure everyone benefits fairly. Here's a framework that lays out how green AI principles, ethical decision-making, open data practices, circular hardware design, and teamwork across disciplines can steer AI's safe and responsible use in environmental systems.

Green AI Principles

Green AI is all about shrinking the environmental impact of model training, storage, and operations. Every big AI model draws a lot of electricity and spits out carbon emissions, both when you're training it and when you're running it. Strubell and colleagues found that training just one large transformer model pumped out over 284 tons of CO_2. That's about as much as five average cars generate over their entire lives. And as these models keep getting bigger, that number just climbs. This kind of data is pushing researchers and companies to rethink how they build models. They're now turning to energy-aware algorithms that don't just chase accuracy, but also keep an eye on how much power they're burning. These days, people talk about "energy per inference" and "carbon cost per experiment" as key metrics. The Green Algorithms project, for example, came up with an open calculator that lets you estimate the energy use and carbon footprint of your computational tasks. Tools like this are finding their way into environmental AI research, so models get judged not just by how smart they are, but also by how green they are. Training models more efficiently means using specialized hardware that gets more work done per watt, writing smarter code, and choosing data in a way that cuts out unnecessary computation. Data centers need to make the switch to renewable energy, and it's smart to recycle waste heat through thermal systems. There's also a growing push to include AI workloads in life-cycle assessments. These assessments don't just look at the power a system uses day-to-day; they consider the "embodied" carbon from manufacturing chips, cooling systems, and servers. Taking this whole-system view gives governments and industries the insight they need to design policies for truly sustainable AI infrastructure.

Ethical AI Frameworks

Ethical AI isn't just a buzzword; it means you need models that people can actually understand and trust. In environmental science, these systems shape policy, control how resources get used, and can even affect public health. If the algorithms behind them are a black box, you can't expect anyone to trust the results. Europe's latest guidelines for trustworthy AI put transparency, accountability, and human oversight front and center (Ethics Guidelines for Trustworthy AI, 2023). These aren't just nice-to-haves; they're essential for any environmental AI project. Every AI model should clearly document where its training data comes from, what assumptions it makes, and how much uncertainty is baked in. Tools like SHAP and LIME make it easier to see how models weigh different environmental factors, so you're not left guessing what's going on under the hood. Fairness matters, too. If a model consistently underestimates pollution in low-income neighborhoods or downplays flood risk in informal settlements, it just makes existing inequalities worse. That's why ethical oversight means running bias audits before launch and checking them again as circumstances shift. Transparency goes even further. Any environmental AI tool used by public agencies needs a third-party review. Regulatory bodies can set up certification programs, think of how medical devices get approved, with tests for safety, reliability, and fairness. These checks don't just tick boxes. They build real accountability and give people a reason to trust the data that shapes environmental decisions.

Data Governance and Open Monitoring

Data sits at the heart of environmental AI, but right now, collecting and sharing it feels messy and disconnected. So many AI projects lean on closed-off or hard-to-access datasets. If we want real progress, we need standardized data formats, open-access repositories, and rules everyone understands for privacy and consent. The United Nations Committee of Experts on Big Data and Data Science pushes for open environmental data standards, which help countries actually work together (United Nations Statistics Division, n.d.). When countries follow these standards, they can swap real-time pollution, hydrological, and climate data while still keeping privacy intact. Blockchain-based systems offer a way to build trust. Distributed ledgers keep a record of where data comes from, track every update, and make sure ownership stays clear. This makes it much harder for anyone to mess with or lose the data. Pair that with federated learning, and institutions can train AI models together without ever moving the raw data, privacy stays safer that way. Open monitoring systems also give communities the tools to see and check environmental data for themselves. This kind of transparency doesn't just keep people honest; it invites the public to get involved and strengthens citizen science.

Circular Hardware Lifecycle

AI doesn't run on thin air. Sensors, servers, chips, storage devices, each one leaves a mark on the planet. Building them eats up rare earth metals and gulps down energy. That's where the idea of a circular hardware lifecycle makes sense. Instead of a use-and-dump mindset, we focus on sourcing responsibly, reusing what we can, and recycling everything possible. It's surprising, recycling just 20 percent of the world's e-waste pulls valuable metals back into circulation and keeps toxic stuff like lead and cadmium out of the environment (E-Waste Monitor, 2024). So, it's not just about feeling good; it actually works. But to really shrink AI's footprint, the people designing these components need to think ahead. Make them easy to take apart. Make it simple to recover the materials. The more repairable and recyclable the hardware, the better. There's more we can do. Green manufacturing cuts down the carbon built into these devices. Using low-impact materials, turning to additive manufacturing, and running factories on renewables, all of this slashes emissions right from the start. Policy matters too. If governments demand extended producer responsibility, AI hardware makers have to take back old devices and recycle them properly. And if we connect these rules to carbon accounting, we finally start to track and manage both the digital and physical sides of AI. That's how we build a truly sustainable system.

Hybrid Governance Models

Tackling AI's complexity takes more than just technical know-how. Engineers, environmental scientists, policymakers, and ethicists all need to work together. Hybrid governance steps in here; it blends clear technical standards with real, participatory oversight. Instead of waiting for problems and then slapping on regulations, this approach pushes everyone to help shape policy and technology from the start. Picture cross-sector councils reviewing AI projects before they ever get the green light. They weigh the ecological upsides, spot the risks, and think through the social impact. You see this with interdisciplinary data ethics boards or panels that specifically review AI's environmental effects. But no one country can go it alone. Climate change, pollution; these problems don't stop at borders. If we use AI for environmental monitoring, it has to play by global rules that demand transparency and real sustainability. That's where international efforts like the OECD's "AI Principles" come in. They set the tone: AI should be human-centered and trustworthy. When we weave these standards into environmental rules, we line up what's happening locally with the bigger push for global sustainability.

The Ai Environmental Risk Assessment Framework (AI-Eraf)

This paper lays out the AI Environmental Risk Assessment Framework (AI-ERAF), a practical tool designed to assess the environmental and ethical impact of any AI system before it goes live. The framework brings together five key parts:

1) Energy and Carbon Audit: Tracks electricity consumption and emissions using resources like Green Algorithms and LCA databases.
2) Data Governance Audit: Checks where data comes from, how secure and private it is, and whether it meets openness standards.
3) Ethical and Social Risk Assessment: Flags issues around bias, fairness, and how much human oversight is built in.
4) Hardware Lifecycle Assessment: Looks at the emissions tied up in the hardware and whether it can be recycled.
5) Governance Integration Plan: Lays out who's responsible- technically, institutionally, and within the community to make sure there's real accountability.

Each AI project must pass operational, ethical, and

Table 1: Application of the AI Environmental Risk Assessment Framework (AI-ERAF) to the Dhaka Flood Monitoring System.

AI-ERAF Component	Assessment Criteria	Dhaka Flood Monitoring: Risk Rating	Justification & Intervention Strategy
1. Energy & Carbon Audit (ECA)	Training and inference energy sources, operational GHG emissions.	Moderate	Justification: Cloud-based processing depends on a carbon-intensive regional electricity system. Intervention: Require yearly carbon reporting and mandate low-carbon cloud zones for catastrophe resilience systems.
2. Hardware & E-Waste Audit (HWA)	Sensor life cycle, server renewal rates, and rare earth mineral dependency.	Moderate	Justification: In a city with inadequate e-waste infrastructure, high-density sensor deployment requires regular maintenance and disposal. Intervention: Create a public-private partnership for circular hardware management and mandate the use of modular, standardized sensors.
3. Data Governance & Bias Audit (DGB)	Data representativeness, model fairness, and local data quality.	High	Justification: Data is significantly skewed toward wealthy, well-monitored areas, which causes warnings in poorer districts and informal settlements to be delayed or wrong. Intervention: Enforce data collecting parity throughout all urban zones and mandate equity diagnostics (Component 4), augmented by community data input.
4. Socio-Ethical Risk Assessment (SRA)	Opacity, accountability chains, and accessibility of model outputs.	High	Justification: When warnings are inaccurate or delayed, the public becomes suspicious due to the opaque nature of the complicated model and the absence of clear, localized accountability. Intervention: Make explainable AI (XAI) methods mandatory and assign a specific, named governmental body to oversee model output and accuracy.
5.Adaptive Compliance & Monitoring (ACM)	Feedback loops, compliance mandates, and continuous improvement.	Low	Justification: Formal, required, and publicly available compliance reporting is currently lacking despite the system's deployment. Intervention: Create an ongoing community validation program where locals offer input on the veracity of warnings, guiding the model's cycles of retraining.

environmental evaluations before full deployment, and these elements work together in a continuous cycle. AI-ERAF ensures that technology is in line with sustainability and justice principles by acting as a preventive governance tool. AI must be viewed by future governance as a component of the environmental system it oversees. Circular hardware cycles, open data governance, green AI, ethical frameworks, and hybrid supervision models might transform AI from a possible environmental hazard into a valuable tool for sustainability. Society may assess, control, and constantly enhance artificial intelligence's environmental responsibility by using the AI-ERAF strategy at the national and institutional levels.

Discussion

Artificial intelligence stands at the center of a contradiction in environmental engineering. It's a driver of sustainable innovation, yet it also brings its own set of environmental problems. This study shows AI isn't just hype; it really does boost efficiency, accuracy, and our ability to predict what's coming when we manage natural resources. But the price is high: more energy used, more e-waste piling up, and fresh questions about ethics and governance. That's the dilemma with modern technology. We turn to AI to fight climate change, and at the same time, we risk making things worse if we don't keep a close eye on how we use it. The upside is real. Look at Google's DeepMind: its machine learning algorithms cut data center cooling energy by 40 percent. Water treatment facilities use similar tools to fine-tune their processes. AI predicts pollution spikes, sounds the alarm for floods, and helps cities plan smarter. These systems aren't just running in the background; they're cutting energy use, heading off disasters, and shaping more sustainable cities. Now, here's the catch. The backbone of all this, the data centers, the servers, the endless racks of hardware, devour electricity and water. The International Energy Agency put global data center electricity use at 460 terawatt-hours in 2022. They expect AI-driven workloads alone could push that to 800 terawatt-hours by 2026. That's as much power as some small industrialized countries. The carbon footprint isn't just a footnote; it's front and center. For every gain in operational efficiency, there's a hidden cost in the digital infrastructure that makes it possible. Sure, AI can cut emissions in targeted places, but when you add up the energy and carbon from training and running these models, a lot of those gains disappear. Some life-cycle studies show that training a single large deep-learning model can produce more carbon dioxide than several cars do over their entire lifetimes. Yet, you rarely see these numbers in research papers or company reports. Full life-cycle assessments? Almost nobody does them. Without honest carbon accounting, promises of "green AI" ring hollow. The paradox gets sharper in the Global South. Regulations are patchy, recycling systems are thin, and basic data infrastructure is still a work in progress. Countries in South Asia and Sub-Saharan Africa are rolling out AI to manage water shortages, pollution, and disaster response, but they rely on imported hardware, closed-source algorithms, and cloud services from abroad. That raises costs and keeps control out of local hands. The United Nations University reports a surge in e-waste from low-income countries, most of which can't recycle or safely dispose of it. As AI hardware spreads, so will the mess. Few governments in the Global South have laws requiring environmental impact reviews for AI, in contrast to new rules emerging in the European Union. The risks aren't theoretical; they're already here, and they're growing.

One big research gap jumps out: this study barely sees life-cycle assessment (LCA) studies focused on AI itself. Most LCAs target factories or big industrial systems, but hardly anyone measures the real environmental costs behind developing AI models, storing the endless data, or running those huge computations in the cloud. The Green Algorithms framework tries to fill this hole by calculating the carbon cost for each computational task, but most environmental AI projects just skip this step entirely (Lannelongue *et al.,* 2021). Without actual LCA data, it's almost impossible to compare how sustainable different AI solutions really are. And here's another problem: reporting how much energy these systems use isn't even required in scientific journals yet. As long as these disclosures stay optional, researchers and policymakers can't honestly judge AI's total impact on the planet. There's an ethical and governance problem, too. Many environmental AI systems run with barely any accountability. Proprietary models keep everything behind closed doors, and governments don't have the tools or laws to audit how algorithms make decisions. Studies keep repeating that fairness, explainability, and strong human oversight are essential for trustworthy AI, but most systems in the real world still fall short (OECD, 2022). We need hybrid governance, something that actually combines scientific rigor with ethical responsibility. That means we can't just check if an AI model is accurate; we have to ask what it means for society, the environment, and our values. Evidence from pollution forecasting in China or flood monitoring in Dhaka makes the risks clear. Local challenges only pile onto technical ones. Regional data bias messes with model reliability, and when local datasets are thin, predictions go wrong. Failed models don't just waste resources; they also chip away at public trust in science and technology. To make AI truly sustainable, we need ongoing monitoring, real community involvement, and systems that learn and adapt, so we don't end up over-relying on algorithms that haven't been properly tested in their own backyard. AI sits right at the intersection of new ideas and sustainability. It can help us manage the environment faster and smarter, but if we ignore its full life cycle, it could make things worse. Moving forward means weaving in life-cycle assessment, real carbon footprint reporting, strong ethical guardrails, and international teamwork. Countries have to bridge the North-South divide by building their own AI capacity, switching to renewable-powered computation, and rethinking hardware for circularity. If we want environmental engineering to push technology and protect the planet, we have to face both AI's promise and its risks head-on.

CONCLUSION

What this study shows, at its core, is that the environmental footprint of AI isn't a distant or abstract problem. It's already shaping how cities, governments, and critical infrastructure systems operate. By bringing together life-cycle assessment, energy and water accounting, hardware sustainability, data governance, and ethical risk, the AI-ERAF framework gives a practical way to understand these impacts and manage them before they scale out of control. The picture is mixed. AI can reduce emissions, strengthen early-warning systems, and support cleaner decision-making. But without careful design, the same systems can drive up energy demand, strain water-scarce regions, accelerate e-waste, and deepen social and spatial bias. The challenge isn't to slow down AI; it's to make sure the benefits outweigh the costs in a measurable, transparent way. What this really means is that future AI deployments must treat environmental performance as a first-order design constraint, not an afterthought. Cleaner training pipelines, region-aware model selection, efficient inference, circular hardware cycles, and strong governance need to become standard practice. If institutions adopt these principles and continue to refine them with real data, AI can evolve into an engine for sustainability rather than a hidden source of environmental burden. The path is clear: build AI that serves people and the planet at the same time.

Limitations

Every research project has boundaries, and this study is no exception. The aim here is not to weaken the work, but to acknowledge openly where future studies can push further. Being transparent about these limitations strengthens the credibility of the findings and makes clear how the framework developed in this paper should be interpreted.

First, the analysis relies on secondary data drawn from published literature, technical reports, and publicly available tools. This allowed for broad coverage across energy use, water consumption, hardware lifecycles, bias, and governance. However, it also means the study depends on the accuracy, comparability, and completeness of those external datasets. Since many AI-related environmental metrics are still evolving and often reported inconsistently, some impact estimates remain approximate rather than fully standardized.

Second, this research does not include a model-specific or hardware-level life-cycle assessment based on direct measurements. Such analyses typically require proprietary data from cloud providers, chip manufacturers, or data centers, which are rarely accessible. As a result, the framework offers a structured way to evaluate environmental impacts but cannot claim to deliver granular, device-level LCA outputs across all AI systems.

Third, the case examples, especially those connected to climate-vulnerable regions such as Dhaka, are conceptual rather than supported by real-time field measurements. This was necessary because primary data collection was not feasible within the scope of this study. While the examples illustrate how the AI-ERAF framework can be applied, they do not represent operational deployment trials.

Fourth, the paper touches on social and spatial bias, yet it does not empirically quantify the magnitude of these biases across multiple datasets or regions. Such analyses require controlled datasets that are often restricted or fragmented. The study instead focuses on conceptual and methodological pathways for future evaluation.

Fifth, the rapidly changing nature of AI hardware, cloud infrastructures, and model architectures means that any environmental estimate, even if carefully constructed, has a short half-life. New accelerators, cooling technologies, and training optimizations can significantly shift the baseline. The framework presented here is designed to remain adaptable, but readers should be aware that some numeric values may evolve as the field matures.

Finally, the governance recommendations, while grounded in the current policy landscape, are not tested through regulatory pilots or policy simulations. They provide a roadmap rather than a prescriptive set of rules. Practical implementation will require coordination among governments, industry, and civil society, and those dynamics lie beyond the scope of this study.

Together, these limitations do not undermine the contribution of the research. Instead, it makes clear that the AI-ERAF framework is a starting point, a structured lens for understanding the environmental footprint of AI, and a foundation upon which more granular, empirical, and location-specific studies can be built. The goal of this transparency is simple: to encourage future refinement while reinforcing the credibility of the present findings.

Future Research Directions

The environmental footprint of AI is moving fast, and the science needs to catch up just as quickly. The next wave of research shouldn't only measure impacts more accurately but also reshape how AI is built, trained, deployed, and governed. Here are the directions that matter most.

1. High-resolution, model-specific life-cycle assessments: Today's LCA data for AI systems is mostly coarse, siloed, or based on broad assumptions. We need fine-grained, model-level LCA studies that track not just training emissions but also inference, memory usage, cooling loads, network traffic, and end-of-life hardware treatment. Pairing this with continuous monitoring, rather than static snapshots, would finally give policymakers and engineers a moving, real-time picture of AI's environmental costs.

2. Region-aware optimization for water, energy, and carbon footprints: AI's footprint varies dramatically by geography. A model that is environmentally manageable in Norway may be unsustainable in Bangladesh or India. A major research frontier is creating adaptive algorithms that select training locations, schedules, and energy sources based on local grid carbon intensity, water scarcity conditions, and climate vulnerability. This includes forecasting tools that can shift training workloads automatically to low-impact regions.

3. Circular hardware systems and intelligent material recovery: The next decade will see a surge in AI accelerators, edge devices, and sensor networks, and an equally large e-waste wave unless we rethink the hardware cycle. A critical research need is to develop circular-design architectures where chips, memory modules, batteries, and sensors are built for disassembly and recovery. Machine learning can be used to predict component degradation and optimize reuse pathways. Linking LCA with material flow analysis would help quantify how much impact can actually be avoided.

4. Benchmarking environmental performance as a core metric: Right now, AI models compete mostly on accuracy and speed. Environmental performance needs to sit beside these metrics. Future research should develop shared benchmarks, similar to MMLU or ImageNet, that score models based on carbon intensity, water usage, and hardware efficiency across standardized tasks. This would force algorithm designers to innovate toward low-impact architectures instead of ever-larger models.

5. Low-carbon model architectures and "right-sized" AI: Scaling laws currently push models toward billions or trillions of parameters, but not every problem needs that scale. One promising direction is the design of compact, specialized models that outperform large general models on local tasks while using a fraction of the energy and water. Techniques such as sparse training, retrieval-augmented systems, adaptive computation, mixture-of-

experts routing, and neuromorphic hardware should be tested systematically for their environmental payoffs.

6. Context-aware retraining and transfer learning strategies: Retraining a model from scratch for every new region or community wastes energy, time, and hardware cycles. Future research should focus on domain adaptation, federated learning, and low-shot transfer techniques that speed up geographic or demographic adaptation while avoiding full retraining. This is especially important for climate forecasting, flood alerts, air-quality prediction, and other applications in high-risk megacities.

7. Integrating environmental governance into AI system design: Governance today usually comes after deployment. A key research priority is to embed environmental governance into the earliest design stages, which some call "Governance-by-Design." This includes environmental risk scoring, audit-ready data pipelines, transparent decision logs, and regulation-aware model behavior. Studying how these governance tools perform in real-world conditions, especially in low- and middle-income regions, is essential.

8. Predictive modeling for AI-driven demand on global resources: Future studies should look beyond individual systems and examine how widespread AI adoption reshapes global electricity markets, cooling-water demand, lithium and rare-earth extraction, semiconductor supply chains, and regional energy inequities. Dynamic system models and agent-based simulations could help forecast long-run impacts and guide national policy decisions.

9. Coupling AI with renewable energy and decentralized infrastructure: A practical research frontier is designing AI systems that run directly on variable renewable energy, using adaptive load scheduling, battery-aware computation, and distributed edge networks powered by solar or microgrids. This includes exploring ways to embed LCA signals directly into resource allocation algorithms so that devices "know" when to compute and when to hold back.

10. Measuring social and spatial equity in environmental impacts: AI's environmental footprint doesn't fall evenly on all communities. Data centers cluster in particular regions, water withdrawals affect certain districts more than others, and hardware disposal often ends up in the Global South. Future research must integrate equity metrics into environmental modeling, mapping who bears which burdens and how policy can correct these imbalances.

11. Creating open environmental datasets, tools, and standards: Progress in this field will accelerate only when environmental data for AI becomes democratized. That means building open LCA repositories, energy-use measurement libraries, model carbon calculators, and reporting standards. Future work should compare different measurement tools, define best practices, and build globally accessible APIs for environmental audits.

12. Human-in-the-loop decision support for sustainable AI deployment: Finally, researchers should investigate how policy-makers, engineers, and communities actually use environmental information when making decisions about AI. Behavioral insights, UX design, and risk communication studies can help create decision-support systems that are intuitive and actionable, not just scientifically correct.

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