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Sustainable Environmental responsibilities in the age of Artificial Intelligence

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Abstract

Artificial intelligence (AI) offers major social and economic benefits, but its rapid growth has environmental costs that are less often discussed. This paper reviews the main environmental impacts of AI—energy use and carbon emissions, water use and cooling, hardware production and e-waste, and the broader supply-chain impacts—and presents practical routes toward more sustainable AI. We summarize empirical findings on the scale of the problem, examine technical and policy solutions (including "Green AI," hardware efficiency, renewable energy, and circular economy practices), and discuss regulatory and governance approaches that can guide sustainable deployment. The paper ends with recommendations for researchers, industry, and policymakers to reduce AI's environmental footprint while retaining the technology's benefits.

Keywords: artificial intelligence, environmental impact, Green AI, data centers

1. Introduction

Artificial intelligence (AI) is transforming many areas—healthcare, education, business, and government. However, the growth of compute-intensive AI models and the infrastructure that supports them carries environmental costs. These include direct energy consumption and greenhouse gas emissions, water use for cooling, ecological harm from hardware extraction and manufacture, and rising volumes of electronic waste (e-waste). Addressing these costs is essential if society is to gain AI's benefits without undermining climate and sustainability goals.

The rapid advancement of Artificial Intelligence (AI) has transformed the global landscape of innovation, enabling smarter decision-making, automation, and data-driven governance. Yet, this technological evolution carries a growing environmental cost that often remains overlooked. The development, deployment, and maintenance of AI systems require significant computational power and energy consumption, contributing to greenhouse gas emissions and resource depletion. As nations, including India, strive for both digital transformation and ecological balance, the legal system must evolve to reconcile these competing priorities. Environmental law, therefore, plays a crucial role in ensuring that the growth of AI remains aligned with the principles of sustainable development — fostering innovation while safeguarding environmental integrity for future generations.

This paper brings together recent research and policy discussions to provide a clear, actionable overview of AI's environmental footprint and the practical ways to reduce it. It is written for researchers, graduate students, industry practitioners, and policymakers who need an accessible but rigorous summary.

2. Literature review: framing the problem

The environmental concerns around AI have two main sources. First, training and running modern machine learning models—especially large language models and deep neural networks—require large amounts of computation that translate into energy use and emissions.

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Second, the physical infrastructure (chips, servers, and data centers) relies on mineral extraction, manufacturing processes, and disposal practices that carry environmental and social costs.

The idea of designing AI with efficiency in mind—often called “Green AI”—was introduced to make the research community evaluate not only accuracy but also energy and resource costs of models (Schwartz et al., 2020). Subsequent reviews and empirical studies have quantified energy and emission patterns for models and data centers, and broader technical literature has proposed methods to lower costs via algorithmic improvements, more efficient hardware, and smarter deployment strategies (de Vries, 2023; Bolón-Canedo et al., 2024). Finally, growing policy work recognizes the need to regulate AI not only for safety and ethics but also for environmental sustainability (European Commission, 2024).

3. Environmental impacts of AI

3.1 Energy consumption and carbon emissions

AI systems consume electricity both during model training and during inference (the step where a trained model answers queries). Training large models can require weeks of continuous compute on many high-performance GPUs or accelerators; inference at global scale multiplies the energy use as millions of users access AI services.

Global data centers and transmission networks form the backbone of AI services. Recent international estimates place global data center electricity consumption in the range of hundreds of terawatt-hours per year—roughly 1–1.5% of global electricity use—though estimates vary with assumptions and what is included (e.g., cloud services, on-premises servers, and network transmission). One authoritative synthesis shows that data centers likely consumed on the order of 200–300 TWh in recent years, with the figure rising as demand for AI grows. These trends mean that AI-driven workloads are an increasingly important driver of data center energy demand. (IEA, 2023/2025).

Energy use maps to greenhouse gas emissions depending on the electricity mix: regions powered by coal or gas will generate more CO_2 per kWh than regions powered by renewables. Therefore, the environmental impact of the same AI workload varies by location and time of day.

3.2 Water use and cooling

Many large data centers rely on water for cooling, especially in regions where air cooling is inefficient. Cooling systems—chillers, cooling towers, and evaporative systems—consume water and, indirectly, energy. In water-stressed regions, data center cooling amplifies local resource pressures. Although research on AI-specific water footprints is less mature than for energy, case studies indicate that high-intensity AI facilities can be significant local water users.

3.3 Hardware production, mineral extraction, and supply chain impacts

AI’s demand for high-end GPUs, tensor processing units (TPUs), and other specialized chips intensifies pressures on mineral extraction (e.g., copper, cobalt, rare earths) and on manufacturing processes that require energy and generate emissions. The cradle-to-factory footprint—mining, refining, and chip fabrication—contributes a nontrivial share of the full life-cycle environmental cost of AI hardware. Responsible sourcing, better manufacturing efficiency, and longer hardware lifetimes are central to lowering this footprint.

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3.4 E-waste and disposal

Hardware used in AI systems becomes obsolete quickly: rapid model and architecture changes, and the drive for higher compute-per-dollar, mean frequent hardware upgrades. Improper disposal of obsolete devices creates e-waste streams that often end up in countries with weak waste processing infrastructure, leading to soil and water contamination and human health harms. Recent environmental reviews highlight that the production and disposal phases of AI hardware should receive much more attention in sustainability planning. (Oeko Institute, 2025).

3.5 Uneven distribution and justice concerns

The environmental burdens of AI are unevenly distributed. Heavy mineral extraction typically affects low- and middle-income regions, while data centers cluster near regions with cheap electricity or favorable regulations. This spatial separation can create environmental injustice, as the benefits tend to flow to wealthy users and companies while harms concentrate elsewhere.

4. Quantifying the footprint: examples and empirical findings

Several recent studies have attempted to measure AI's energy and carbon footprint. De Vries (2023) provides an overview of how AI workloads contribute to cloud energy use and notes that, for many providers, inference—serving models to users—accounted for a significant share of AI's energy use in recent years; this is particularly true as large models are embedded into consumer apps. The study shows that changes in deployment strategy and infrastructure can materially change emissions. (de Vries, 2023).

Other empirical work shows that training some very large language models can produce emissions equivalent to the annual emissions of several households. These findings do not necessarily imply that all AI development is unsustainable, but they underline the importance of measuring and reporting energy and carbon metrics alongside performance metrics.

5. Sustainable AI approaches

A range of technical, operational, and governance approaches are available to reduce the environmental impact of AI:

5.1 Green AI and efficiency-oriented research

Green AI calls for adding efficiency to the list of model evaluation metrics. Researchers should report compute usage, energy consumption, and cost estimates for training and inference, and prioritize algorithmic choices that reduce compute while preserving performance. Simple changes—like tuning hyperparameters more efficiently, using smaller models for specific tasks, or preferring sparse architectures—can deliver large energy savings.

5.2 Algorithmic and software optimizations

Algorithmic improvements include model distillation (training smaller models to mimic larger ones), pruning (removing redundant parameters), quantization (using lower-precision arithmetic), and more efficient training procedures (e.g., fewer epochs, better optimizers). Software tooling that profiles energy use and estimates carbon impact during model development helps developers make informed tradeoffs.

5.3 Hardware and infrastructure efficiency

Modern accelerators (GPUs, TPUs) are becoming more energy-efficient per operation. Co-design of algorithms and hardware—optimizing models to run on energy-efficient chips—can

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improve performance per watt. Data center design matters too: server utilization, waste heat recovery, and advanced cooling strategies (e.g., liquid cooling, reuse of heat in district heating) reduce the total environmental cost of compute.

5.4 Renewable energy procurement and flexible operation

Data centers and cloud providers can reduce carbon intensity by sourcing renewable electricity and by shifting non-urgent tasks to times when renewable power is abundant. Companies can also invest in on-site solar or wind, use power-purchase agreements (PPAs), or procure renewable energy certificates. However, the actual climate benefit depends on additionality—the degree to which renewable procurement leads to additional clean generation rather than merely reshuffling existing renewable credits.

5.5 Circular economy and hardware lifecycle management

Extending the lifetime of servers, refurbishing components, and implementing take-back programs reduce e-waste and lower life-cycle emissions. Design for recyclability, transparent supply chains, and certified recycling channels help ensure hardware is reused or recycled responsibly.

5.6 Benchmarking and transparency

Standardized reporting of compute, energy, and emissions—both during development and deployment—enables comparisons and accountability. Benchmarks should be infrastructure-aware: the same model can have different environmental impacts depending on the hardware and data center used.

6. Policy, governance, and market instruments

Technical fixes alone are insufficient. Governments and international organizations can create the right incentives and rules.

India's environmental governance system is guided by statutes such as the Environment (Protection) Act, 1986; the Air (Prevention and Control of Pollution) Act, 1981; and the Water (Prevention and Control of Pollution) Act, 1974. However, these laws were not designed with digital technologies like AI in mind. There is currently no explicit regulatory framework addressing the ecological footprint of AI systems or data infrastructures.

Internationally, policy efforts are emerging. The European Union's **AI Act (2024)**, for instance, includes sustainability as one of its guiding principles, requiring developers to consider energy efficiency and life-cycle impact assessments. Similarly, the **OECD Principles on AI (2019)** encourage responsible AI development consistent with environmental protection. India could adopt similar principles through the upcoming **Digital India Act**, embedding environmental sustainability into AI governance norms.

6.1 Existing international and regional approaches

Global bodies and regional regulators have started to address AI's societal impacts. The European Union's AI Act (finalized in 2024) is a landmark regulation that sets risk-based rules for AI systems and includes provisions that push providers toward transparency, documentation, and risk assessment—elements that can be extended to environmental reporting and sustainability obligations. (European Commission, 2024).

At the global level, UNESCO's Recommendation on the Ethics of Artificial Intelligence (2021) sets principles for responsible AI; while its focus is ethical and human-rights oriented, its frameworks encourage states to consider broader societal impacts, which can include environmental harms.

6.2 Regulatory options specifically for sustainability

Policymakers may consider several interventions:

- **Mandatory environmental disclosure** for high-impact AI providers: energy use, carbon emissions, water use, and e-waste handling during model training and commercial deployment.
- **Eco-design standards** for data centers and AI hardware that set minimum efficiency levels.
- **Incentives for circular practices**, such as tax credits for refurbishment, or extended producer responsibility (EPR) schemes that require manufacturers to manage end-of-life electronics.
- **Procurement rules** that prioritize low-carbon AI services in public sector contracts.
- **Grid planning and coordination** to ensure increased electricity demand from data centers does not lock regions into fossil-fuel-heavy generation.
- Require standardized environmental disclosure for large AI providers and data centers.
- Encourage circular economy practices through EPR and incentives for refurbishment and recycling.
- Integrate AI demand into national energy and grid planning to avoid lock-in to fossil generation.

Industry initiatives—such as renewable energy purchasing, voluntary carbon commitments, and sustainability certifications—can reduce impact, but they work best when combined with clear reporting standards and independent verification.

7. Discussion: trade-offs, measurement, and equity

7.1 Trade-offs

AI can also produce environmental benefits: optimizing supply chains for lower emissions, improving energy grid operations, and enabling better climate modeling. These positive uses mean that an outright ban or severe restriction on AI would be inappropriate. The goal is to maximize net benefit—retaining AI's positive contributions while minimizing its costs.

There are trade-offs between model performance and environmental cost. For some tasks, slightly smaller or more efficient models perform nearly as well as the largest models and offer large reductions in energy use. In other areas, higher model capacity enables breakthroughs (e.g., in medicine), and restricting compute could slow valuable advances. This is why nuanced, task-aware approaches are needed.

7.2 Measurement challenges

Estimating the exact environmental footprint of AI is difficult. Public disclosure by companies about compute usage, energy intensity, and hardware lifecycle is inconsistent. Even when companies report electricity use, differences in methodology (which parts of the supply chain are included, how grid carbon intensity is calculated) complicate comparisons. This uncertainty argues for standardized reporting frameworks.

7.3 Judicial, ethical and distributional dimensions

Environmental burdens from hardware production and e-waste often affect lower-income countries more than the wealthy users who benefit. Ethical AI frameworks must therefore integrate environmental justice: demanding responsibility not only for the carbon footprint but also for labor conditions, mining impacts, and safe recycling.

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Constitution of India discusses under various provisions with regard to environment protection under Article48-A, Article 51and 51A . The Indian courts have consistently interpreted Article 21 of the Constitution — the right to life — to include the right to a clean and healthy environment (*Subhash Kumar v. State of Bihar*, 1991, SC). Applying this reasoning, the judiciary could extend such principles to include technological impacts, holding industries accountable for the environmental costs of AI deployment.

Ethically, the principle of **intergenerational equity**—a cornerstone of sustainable development—demands that technological progress today does not compromise environmental integrity for future generations. Balancing the ethical imperative for innovation with ecological preservation thus becomes a constitutional and moral obligation.

To balance AI-driven innovation with environmental sustainability, India's legal framework could incorporate the following strategies:

- **Green Data Centers Regulation:** Introduce emission and energy-efficiency standards for AI data centers under the Environment (Protection) Act 1986 and E-Waste (Management) Rules, 2016 (and 2022 amendments.
- **Environmental Impact Assessment (EIA) for Tech Projects:** Amend EIA guidelines to include digital infrastructure projects with high energy or land-use implications.
- **Extended Producer Responsibility (EPR):** Apply EPR principles from electronic-waste rules to AI hardware manufacturers and cloud service providers. EPR , a policy framework that makes producers, importers, and brand owners (PIBOs) responsible for the collection, recycling, and disposal of their products after consumer use.

8. Recommendations

Based on the review above, we offer practical recommendations for three groups.

- Adopt Green AI practices: favor efficient architectures, reuse pretrained models where possible, and report model carbon estimates.
- Use model compression techniques (distillation, pruning, quantization) when feasible.

For industry and cloud providers-Publish transparent, third-party audited metrics on data center energy use and the carbon intensity of AI services.

- Invest in energy-efficient hardware and design data centers with circularity in mind.
- Shift non-time-critical workloads to periods of high renewable generation and explore on-site renewables and heat reuse.

9. Conclusion and future directions

AI technologies are reshaping society, but they also raise important environmental challenges. Energy consumption and carbon emissions, water use, hardware production impacts, and e-waste are central concerns. Fortunately, there are practical, evidence-based ways to reduce these impacts: algorithmic efficiency, better hardware and data-center design, renewable energy use, circular economy measures, and robust policy frameworks. Key steps forward include creating standardized measurement and reporting frameworks, making energy and environmental costs a routine part of model evaluation, and designing policy that aligns commercial incentives with sustainability. Future work should develop more accurate life-cycle assessments of AI systems, study regional and justice impacts in depth, and test policy pilots that combine disclosure, procurement rules, and incentives. By treating sustainability as a core design objective—alongside accuracy, fairness, and safety—the AI community can help ensure that AI's promise is realized without undermining planetary boundaries.

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