Key points from research

1. **The Anatomy of AI's Carbon Emissions**

AI's carbon footprint is primarily categorized into two main components: "embodied" emissions and "operational" emissions

(<https://www.carbon-direct.com/insights/understanding-the-carbon-footprint-of-ai-and-how-to-reduce-it>)

**Training**: The computational power required to train large-scale AI models, especially generative AI models with billions of parameters like OpenAI's GPT-3 and GPT-4, demands a staggering amount of electricity, directly leading to increased carbon dioxide emissions. For instance, training GPT-3 alone consumed an estimated 1,287 megawatt-hours (MWh) of electricity, generating about 552 tons of CO2. The training of just a few AI models can emit over 626,000 pounds of CO2, which is equivalent to nearly five times the lifetime emissions of an average American car.

**Inference**: Once an AI model is trained, energy demands persist during inference, which is the process of using a trained model to make predictions or generate outputs. A single ChatGPT search, for example, consumes 10 times as much data as a Google search 1 and is estimated to use about five times more electricity than a simple web search. 2 Experts anticipate that the electricity demands of generative AI inference will eventually dominate, as these models become ubiquitous and future versions grow larger and more complex.

1. **Beyond Carbon: Water Consumption and E-Waste**

**Water Demands for Cooling Data Centers:** a non-peer-reviewed study estimated that training GPT-3 in Microsoft's US data centers could have consumed up to 700,000 liters (184,920.45 gallons) of freshwater.

**Electronic Waste from AI Hardware Lifecycle:** The production and improper disposal of AI hardware generate electronic waste (e-waste), which contains harmful chemicals that can contaminate the environment.

1. **Data Centers: The Energy Nexus of AI**

Current and Projected Electricity Consumption

In 2023, US data centers accounted for over 4% of total US electricity consumption, with 56% derived from fossil fuels, generating more than 105 million tons of CO2e. This share is projected to rise to 6% by 2026. Globally, electricity demand from data centers is projected to more than double by 2030, reaching approximately 945 terawatt-hours (TWh), which is slightly more than the entire electricity consumption of Japan today. AI-optimized data centers alone are expected to quadruple their electricity demand by 2030.

**2. Impact of Power Mix and Location**

Only about 40% of a data center's electricity demand is used for actual computing; the remaining 60% is for non-computing uses, with approximately 40% for heating, ventilation, and air conditioning (HVAC) and 20% for power supply systems, fans, and IT equipment drivers.

**the short shelf-life of generative AI models, driven by the constant demand for new applications, means that the energy used to train prior versions often goes to waste, contributing to a compounding effect of resource depletion**

**Table 1: Estimated Carbon Footprint of Major AI Models (Training)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model Name | Approximate Parameters | Estimated CO2e (Unit) | Equivalence | Key Factor Influencing Emissions | Source |
| BERT | 200 million | 626,000 pounds | ~5x lifetime emissions of an average American car | Model size, training process |  |
| GPT-3 | 175 billion | 500 metric tons (1M+ pounds) | ~610 one-way direct flights from NYC to Paris | Model size, training process, energy source |  |
| BLOOM | 175 billion | 25 metric tons | ~5% of GPT-3's footprint | Energy source (trained on nuclear-powered supercomputer) |  |
| GPT-4 | 170 trillion | Equivalent to 61,000 transatlantic flights (single training) | Exponential increase in parameters | Model size, training process |  |

A screenshot of a computer

AI-generated content may be incorrect.

<https://libguides.ecu.edu/c.php?g=1395131&p=10318505>

**Measuring and Reporting AI's Environmental Impact**

1. Methodologies and Key Metrics

1. Life Cycle Assessment (LCA)

2. Data Center Efficiency Metrics

B. Tools and Platforms for Carbon Footprint Calculation

1. Open-Source Tools

a. **CodeCarbon**: A lightweight, open-source Python package that seamlessly integrates into codebases to estimate CO2 emissions from computing resources.

b. **Cloud Carbon Footprint**: An open-source tool designed to help businesses measure and manage the carbon emissions associated with their cloud usage across multiple providers like AWS, Google Cloud, and Microsoft Azure

2. Commercial Platforms

**C. The Challenge of Transparency and Regulatory Landscape**

A significant challenge in accurately assessing AI's environmental impact is the pervasive lack of transparency from large technology companies developing AI models.

**2. Emerging Regulations and Standards**

In response to growing concerns and the need for accountability, a regulatory landscape is emerging to mandate environmental reporting:

* **California's Climate Accountability Laws (SB 253 and SB 219)**: These laws mandate businesses with over $1 billion in annual revenues operating in California to report their Scope 1 (direct), Scope 2 (purchased energy), and Scope 3 (supply chain) greenhouse gas emissions.

**European Union’s Corporate Sustainability Reporting Directive (CSRD)**: This directive compels large companies and listed SMEs to regularly report their environmental and social impacts, including detailed ESG impacts within their value chains

**European Commission’s Energy Efficiency Directive (EED)**: This directive requires data centers operating in the EU that use more than 2,780 MWh of energy annually to report publicly on their energy performance

Good thing:

**1. Resource Efficiency**

AI algorithms can lead to substantial resource savings. For instance, simulations suggest that AI algorithms can save up to 27.6% of water and 57% of energy during tomato seasons compared to conventional practices. AI optimizes irrigation, fertilization, and crop rotations based on historical records, sensor data, and satellite imagery for improved harvests and resource utilization.

2. Supply Chain Optimization

AI algorithms like reinforcement learning have been used to optimize energy-intensive processes, achieving up to 15% reductions in energy consumption. Supervised machine learning models can predict capture efficiency with over 90% accuracy based on historical data and real-time sensor inputs. In the **transport phase**, AI aids in promoting efficient transmission pipelines and optimizing shipment schedules, potentially reducing transport costs by 15% and shipping delays by 20%. For **storage**, AI can assist in site selection and observation of stored CO2. AI-driven simulations also significantly accelerate material discovery for CCS, making it 500% faster compared to traditional trial-and-error methods.

**Conclusions and Recommendations**

The analysis indicates that Artificial Intelligence stands at a critical juncture, presenting both significant environmental challenges and unparalleled opportunities for sustainability. The escalating carbon footprint of AI, driven by energy-intensive training and inference, substantial water demands for cooling data centers, and the embodied emissions from hardware manufacturing, necessitates urgent and comprehensive action. The lack of transparency from major AI developers exacerbates this challenge, hindering accurate measurement and accountability. Furthermore, the potential for a "rebound effect," where efficiency gains are outpaced by exponential growth in AI adoption, underscores the need for systemic changes in how AI is developed and deployed.

However, the evidence also strongly suggests that AI can be a powerful catalyst for environmental stewardship. Its capabilities in climate modeling, smart grid optimization, environmental monitoring, sustainable agriculture, and carbon capture offer transformative potential to address some of the world's most pressing ecological crises. The path forward requires a dual approach: mitigating AI's negative impacts while strategically leveraging its strengths for broader environmental benefits.