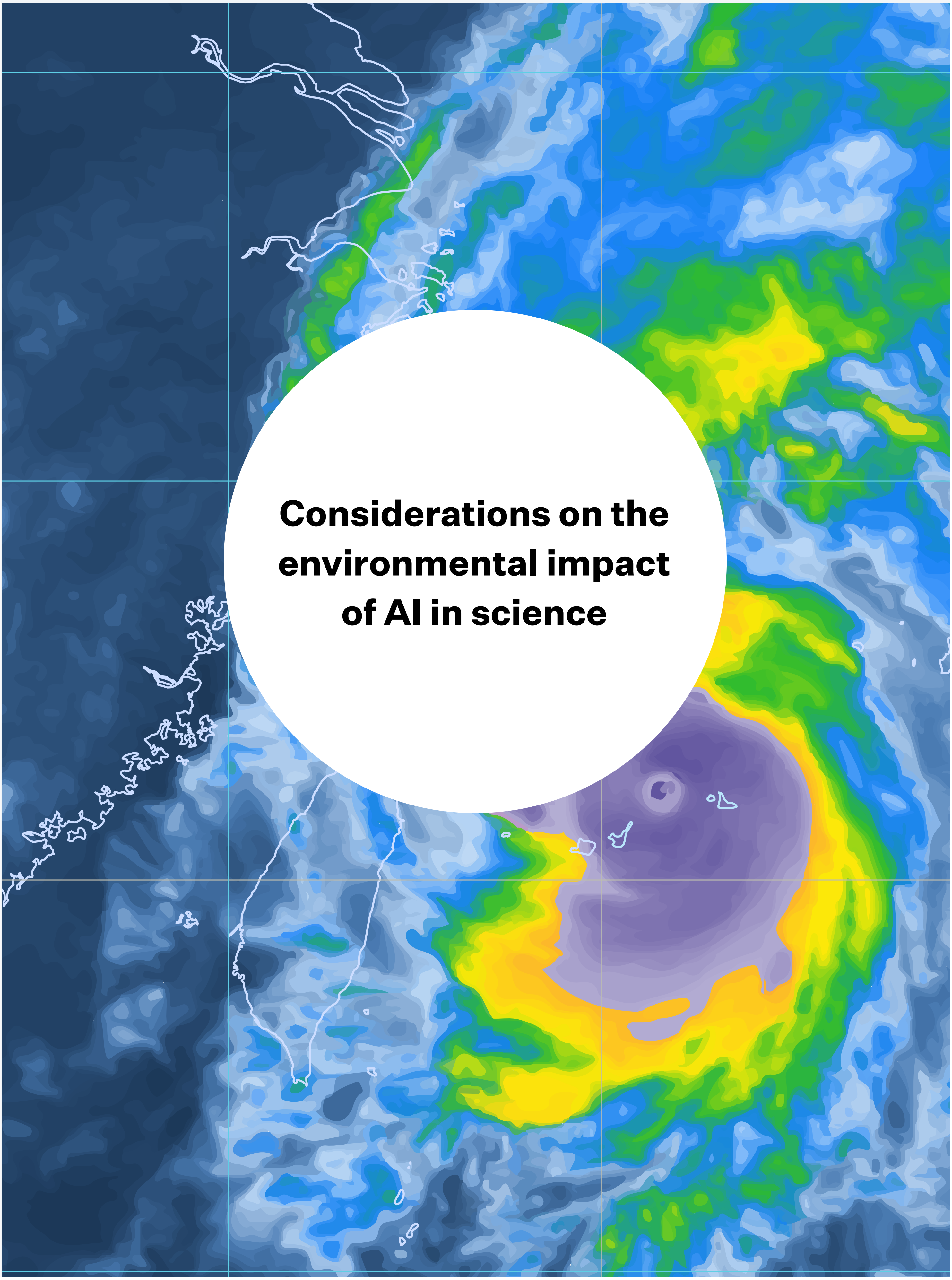

Considerations on the environmental impact of AI in science

CENTRE FOR SCIENCE FUTURES

International Science Council

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Contents

Key takeaways

- **There is limited awareness and evidence about the environmental costs of using artificial intelligence (AI) in scientific research.** This article offers frameworks and tools scientists and research institutions can consider to assess the environmental impacts of their research as part of a more sustainable, ethical and responsible use of AI in science.
- **Addressing the environmental impact of AI requires a multi-dimensional approach.** Scientists and researchers who are planning to incorporate AI into their workflows need to assess tools in light of their scientific value, social equity and environmental costs across the entire AI life cycle, with attention to rebound effects and long-term consequences.
- **Adopting more resource-efficient AI models has environmental and social benefits.** Smaller, local and frugal approaches to AI can improve accessibility, affordability, transparency and social inclusion around the use of AI, especially in diverse and resource-constrained research contexts.

About this paper

This paper examines the environmental implications of applying artificial intelligence (AI) in scientific research. It serves as a primer for scientists, research institutions and science policy-makers who seek to understand various approaches to addressing the environmental impact of AI in science. In addition, it offers guidance on how reducing environmental costs can contribute to the broader goals of sustainability and ethical AI use in research environments.

Although evidence on the specific environmental impacts of AI in scientific research is still emerging, the paper provides conceptual frameworks and practical tools to help assess the environmental implications of the full AI lifecycle within scientific projects. The first section introduces key frameworks for understanding environmental impacts in a holistic way. The second section outlines an approach for defining and measuring environmental costs across the AI lifecycle. The third section presents concrete strategies for reducing the direct environmental footprint of scientific projects that use or depend on resource-intensive AI applications.

This paper reflects on how environmental considerations intersect with the broader themes of AI sustainability and ethics, though an in-depth analysis of these frameworks falls outside its scope. Similarly, while the role of AI in advancing the Sustainable Development Goals is acknowledged, it is not explored in detail. Social and economic impacts of AI are discussed only in so far as they relate to environmental costs.

The paper is part of a series of three primers that explore various technical dimensions of AI and its impact on science. The other primers are “Types of AI in science” and “Data for AI in science”.

Introduction

Artificial intelligence (AI) is becoming a transformative tool across scientific fields (LeCun, 2025). A systematic review of over 70 million papers found that, since 2015, the influence and use of AI has spread to nearly every area of natural sciences, impacting biology, chemistry, geology and physics (Gao and Wang, 2024). Notable breakthroughs include highly accurate protein structure predictions with AlphaFold (Jumper et al., 2021); using machine learning to generate the first-ever photo of a supermassive black hole (Broderick et al., 2022); and improved forecasting models for extreme weather events (Bodnar et al., 2024). Advances in AI are impacting social science research as well, transforming methods in fields such as linguistics, political science and history (Penn Today, 2023).

Much of this progress has been driven by advances in machine learning and deep learning models that can more accurately identify patterns and make predictions from vast unstructured data (Choudhary et al., 2022). In the case of social science, generative AI, large language models and multimodal AI tools – all of which are powered by deep learning architectures – are also becoming powerful tools for data analysis, simulation and hypothesis generation (Grossman et al., 2023). The demand for large datasets, specialized hardware and high-performance computing resources required for complex AI systems has also raised questions for research institutions around the accessibility, affordability and environmental impact of incorporating AI across scientific domains (LeCun, 2025).

One of the key challenges is the environmental cost of AI applications (Luccioni et al., 2024b). A growing body of evidence has demonstrated that training complex AI models, such as deep learning or generative AI applications, involves substantial resource use and greenhouse gas emissions (Organisation for Economic Co-operation and Development, 2022). One study suggests that training one large language model can generate approximately 300,000 kg of carbon dioxide emissions, equivalent to 125 round-trip flights between New York and Beijing (Dhar, 2020).

The computational demands of training AI are doubling approximately every 100 days, with projections suggesting that by 2028, AI could consume more electricity than Iceland did in 2021 (World Economic Forum 2024). Reproducibility also remains a challenge, as many deep learning models are opaque and difficult to replicate. This creates situations in which, due to the lack of reporting and transparency, there are many unknowns surrounding the true environmental cost of AI tools used for scientific research, which can also lead to unnecessary energy use when models cannot be reused or require repeated experiments to reproduce results (Lannelongue et al., 2023).

The costs of AI extend beyond the training phase. Although often perceived as an intangible digital system, AI depends on extensive physical infrastructure that consumes energy and natural resources (Organization for Economic Co-operation and Development, 2022). The production of specialized hardware, such as graphics processing units, which are essential for training and running AI models, requires the extraction and processing of rare earth minerals and metals. This process contributes to environmental degradation through increased greenhouse gas emissions, added strain on overburdened water systems, and serious human costs, with workers involved in these supply chains facing unsafe conditions, exposure to toxic chemicals and violations of their human rights (Nayar, 2021).

Similarly, the energy demand of data centres, which power AI systems by storing and processing vast volumes of data, is doubling approximately every four years (Thangam et al., 2024). These facilities consume substantial amounts of energy, whether sourced from fossil fuels or renewable sources, and require large quantities of water for cooling and maintaining optimal hardware performance. This places further pressure on local energy grids and water supplies, particularly in regions facing resource constraints (Mytton, 2021). As AI use continues to grow, the increasing demand for data centre infrastructure is likely to place an even greater burden on countries in the Global South, where challenging climate conditions, water scarcity, limited connectivity and frequent power outages are ongoing concerns (United Nations Conference on Trade and Development, 2024).

These developments raise questions about the environmental sustainability of using AI for scientific research (Samuel and Lucassen, 2022). Awareness of AI's environmental costs varies widely among researchers, particularly in academic settings where computational resources may seem 'free' and their environmental impact largely 'invisible' (Lannelongue et al., 2021b). Emerging efforts are beginning to quantify the carbon footprint of data-driven methods across disciplines such as astrophysics, protein science, health research and computing (Lannelongue and Inouye, 2023; Jahnke et al., 2020; Lannelongue et al., 2023). For instance, a study found that training large deep learning models such as AlphaFold and ESMFold can have a carbon footprint of over 100 tonnes (Lannelongue and Inouye, 2023), the equivalent of powering over 20 homes in the United States for a year, demonstrating that even scientific breakthroughs as impactful as protein prediction can come at steep environmental costs.

These early findings provide evidence on how 'science can, and frequently does, impact the environment' (Lannelongue et al., 2023), raising questions about 'who should be responsible for these impacts and how these responsibilities should be distributed' (Samuel and Lucassen, 2022). As AI and other data-intensive technologies become more embedded in scientific workflows, researchers and funding bodies are increasingly integrating sustainability and environmental considerations into research ethics frameworks, exploring ways to support more environmentally responsible scientific practices (Murray et al., 2023).

Section 1: Foundational concepts and frameworks

Addressing the environmental impact of AI requires a multi-dimensional approach that integrates the principles of sustainable AI, green AI and responsible AI. This involves not only reducing the direct environmental costs of AI technologies, such as energy consumption and carbon emissions, but also developing holistic frameworks that assess their long-term sustainability. These efforts must be aligned with broader commitments to responsible and ethical AI, ensuring that the use of AI in knowledge production and society contributes positively and equitably to human and environmental wellbeing.

This section examines key concepts and frameworks to consider when addressing the environmental impact of AI in scientific research.

1.1 Green AI

Green AI is a field dedicated to understanding and reducing the ecological footprint of computing and data-driven technologies. It promotes energy efficiency and sustainable computing practices throughout the entire AI development lifecycle (Verdecchia et al., 2023). It aims to lower carbon emissions and environmental costs while supporting AI adoption that is also socially inclusive (Schwartz et al., 2020). A central concern of Green AI is the increasing energy use in high-performance "state-of-the-art" research, also referred to as **Red AI**.

Red AI emphasizes performance and accuracy, often relying on energy-intensive models that require vast datasets, substantial computational resources and repeated training (Bolón-Canedo et al., 2024). These practices, largely driven by Big Tech companies, have fuelled the development of increasingly complex and resource-demanding multi-purpose AI systems. In a competitive research landscape, the pressure to achieve superior results has further intensified the environmental and financial costs of AI development (Luccioni et al., 2024a).

In contrast, Green AI encourages more **energy-efficient alternatives** that preserve model performance while reducing resource use (Schwartz et al., 2020). This includes adopting technical solutions to make algorithm design, hardware and data management more energy-efficient. Green AI also supports the development of narrower and smaller models designed for specific tasks, which, in addition to reducing environmental costs, can be more appropriate and effective for many research tasks, domains and contexts. These practices are discussed in more detail in Section 3.

The emphasis on smaller, task-specific and purpose-driven AI solutions reflects the principle of **energy sufficiency**, which involves intentionally reducing energy consumption through energy-conscious design. This leads to more **affordable** and **accessible** architectures such as Frugal AI, which supports the use of AI in settings with limited computing power and infrastructure, which work well in environments with scarce resources (Yamada, 2024).

Related methods, such as Edge AI and distributed computing, prioritize local data processing and offer promising pathways for developing AI technologies that are environmentally sustainable, privacy-conscious and cost-effective.

1.2 Sustainable AI

The growing environmental costs of AI are often tied to concerns about sustainability. The field of **sustainable AI** considers sustainability from two perspectives (Van Wynsberghe, 2021).

AI for Sustainability refers to the application of AI systems to address Sustainable Development Goals, including environmental sustainability, and its applications in relevant fields such as climate science, environmental monitoring or nature protection. The second, ***Sustainability of AI,*** refers to the 'sustainable development' of AI systems, emphasizing practices that reduce their environmental, economic and social costs.

Both approaches are grounded in the United Nations Brundtland Commission's definition of sustainability, which emphasizes 'meeting the needs of the present without compromising the ability of future generations to meet their own needs' (The World Commission on Environment and Development, 1987). It recognizes the inherent tension of pursuing the innovation and efficiency afforded by AI systems, while addressing their environmental, economic and social impacts.

Applying a sustainability lens requires researchers to holistically address dimensions in AI development beyond performance and accuracy (Van Wynsberghe, 2021). A review of 100 highly cited machine learning papers found that only 15 percent addressed societal needs, and just 1 percent discussed negative impacts. Most papers emphasized values such as performance, efficiency and scalability as opposed to addressing impacts for underserved communities or the reduction of environmental harm (Birhane et al., 2022).

The rapidly growing ecological footprint of AI technologies has also resulted in coordinated action towards understanding and addressing the sustainability of AI (Raman et al., 2024). These include, but are not limited to:

- **Coalition for sustainable AI:** An initiative by the French government, the UN Environment Programme and the International Telecommunication Union, aimed at promoting the responsible development and use of AI for sustainable development, with an emphasis on the development of AI that is respectful of planetary boundaries.
- **Coalition for Digital Environmental Sustainability (CODES)[1]:** A global hub for policy-makers, academics, technology companies, and NGOs to lead and contribute to digital sustainability initiatives, including mitigating the negative environmental and social impacts of digitalization.
- **SustAIn: Sustainability index for AI:** A framework and practical checklists developed to support organizations in advancing the environmental, social and economic dimensions of 'sustainable AI', understood as the development and deployment of AI systems that respect planetary boundaries, do not reinforce problematic economic dynamics, and do not endanger social cohesion.

1 The International Science Council is a member of CODES.

Together, these efforts reflect a growing recognition that addressing the environmental impact of AI requires a holistic and interdisciplinary approach.

1.3 Ethical and responsible AI

Reducing the environmental impact of AI development also requires attention to its ethical dimensions. The growing adoption of **ethical AI and responsible AI frameworks** within scientific institutions (Bano et al., 2025) reflects a recognition that principles such as fairness, accountability and transparency are key to building trust in AI systems (ISO, n.d.). This shift is also evident across diverse contexts, including countries such as Australia, Uruguay, China and Malaysia, where the responsible use of AI in science is at the centre of national AI strategies (Castle et al., 2024).

However, to date, many of these frameworks fail to frame sustainability as a component of ethical and responsible AI practice (Luccioni et al., 2025). A 2019 global review found that only 14 of 84 AI guidelines mentioned sustainability (Jobin et al., 2019), including the European Guidelines for Trustworthy AI and the UNESCO Recommendation on the Ethics of AI, considering both environmental sustainability and societal wellbeing. In response to growing evidence, AI researchers are calling for a third wave of AI ethics that directly addresses the environmental crisis and places sustainable development at its centre (Luccioni et al., 2025).

Recent initiatives have begun to address this gap. The Working Group on Responsible AI of the Global Partnership on Artificial Intelligence has developed a 'Responsible AI Strategy for the Environment' to help Member countries assess the environmental footprint of AI models and applications. Research funding bodies, such as the Wellcome Trust, are integrating environmental considerations into funding requirements. New research ethics frameworks, such as **environmental responsibility**, are also emerging to guide researchers in adopting more ecologically conscious approaches when conceiving, planning, conducting and concluding research (Murray et al., 2023).

Applying an ethical lens to sustainability can also help researchers understand the implications of environmental harm for vulnerable populations. Researchers from Hugging Face and the Distributed AI Research Institute have highlighted how the uneven global distribution of AI's ecological impacts can exacerbate existing **socio-economic disparities** and **social-ecological justice concerns** (Luccioni et al., 2025). Examples include how the construction of data centres contributes to water scarcity in drought-prone regions and to the proliferation of electronic waste in nearby communities (Barratt et al., 2025). Addressing environmental equity contributes to the development of AI systems that are not only energy-efficient but also fair, just and equitable (Li et al., 2023).

Section 2: Environmental impact of AI across the lifecycle

Assessing the sustainability of AI requires a holistic, interdisciplinary approach that accounts for environmental, economic and social costs throughout the AI lifecycle – from hardware manufacturing and model training to deployment and decommissioning (Luccioni et al., 2024b). Although there are still no standardized methods for evaluating sustainability across all stages, significant progress has been made in measuring environmental impacts.

2.1 Environmental impacts of AI

Researchers distinguish between two types of environmental impacts (Organization for Economic Co-operation and Development, 2022):

1. **Direct impacts** are first-order impacts from the AI lifecycle and describe 'computing-related' consumption of resources: energy, water and mineral resources, as well as emissions and e-waste generated from operating AI systems. Evidence indicates that these are predominantly harmful to the environment and ecosystems.
2. **Indirect impacts** are effects driven by the *immediate application of AI* across sectors. They are difficult to predict and can be either beneficial or harmful. For example, AI may improve energy efficiency in smart grids but can also drive unsustainable consumption patterns through automation.

There are two types of indirect impacts: **second-order impacts** and **higher-order** or 'system-level impacts'. Both are indirect effects that emerge over time as AI reshapes production and consumption patterns, with the latter potentially driving structural changes in the economy and society. Indirect impacts could ultimately outweigh the efficiencies obtained by strategies focused on mitigating first-order impacts.

Rebound effects are an additional category that refers to situations in which efficiency gains lead to greater resource use that can offset initial environmental benefits. For example, more efficient data centres, while consuming less energy per operation, might be used to handle more data and power more services, ultimately increasing total energy consumption. Anticipating and measuring rebound effects can illustrate how initial efficiency gains can be outweighed by negative consequences, challenging the notion that energy efficiency alone will deliver climate benefits.

While there are increasing methodologies and metrics to measure direct environmental impacts of AI, limited consensus remains on how to measure indirect second-order and higher-order effects (OECD, 2022). Given the growing use of AI in science and its potential large-scale effect on planetary health, there is a need for a research agenda that addresses the indirect effects of AI systems on knowledge production.

2.2 A lifecycle approach to assessing environmental impact

This section examines key approaches to understanding and measuring **direct environmental impacts** across the AI lifecycle.

AI researchers and institutions, such as the Organization for Economic Co-operation and Development, the United Nations Environment Programme, the UN Commission for Trade and Development (UNCTAD, 2024), and the International Telecommunications Union, among others, propose using a lifecycle or end-to-end approach to assess environmental impacts (OECD, 2022; United Nations Environment Programme, 2024; International Telecommunication Union, 2024). The most established methodology is **Life Cycle Assessment,** which evaluates the environmental burdens associated with a product or service, from the extraction of raw materials to waste removal (Klöpffer, 1997).

A life cycle approach can help illustrate the wider scope of direct environmental costs involved in designing and deploying a model, clarify where emissions originate and concentrate, and highlight where targeted interventions and "sustainable AI practices" can reduce environmental costs. The AI lifecycle is typically described in two layers, or "stacks": software and hardware.

SOFTWARE LAYER

The first is the **operational** or **software layer** (UNEP, 2024), also called the model development cycle (Wu et al., 2022). This includes all decisions regarding the data and AI model architecture that influence energy and resource use. It covers relevant **data work** (data collection and preparation), **algorithmic design** (model architecture), **model training** and **model deployment** (including inference) (Clemm et al., 2024).

The environmental costs of this layer are called **operational costs** and are correlated to the **size of datasets and the model architecture,** which directly affect compute time and carbon footprint (Chen et al., 2022). Training and inference are usually the most significant contributors to life cycle energy consumption. For example, research found through an AI inference impact assessment that generative architectures are more energy-intensive than task-specific models as a result of inference (Luccioni et al., 2024a). Due to the commercial deployment of large multi-purpose generative AI models, like OpenAI's GPT-4, inference now represents an increasing majority of AI's energy demands, with an estimated 80–90 percent of computing power in AI training and deployment used for inference (O'Donnell and Crownhart, 2025).

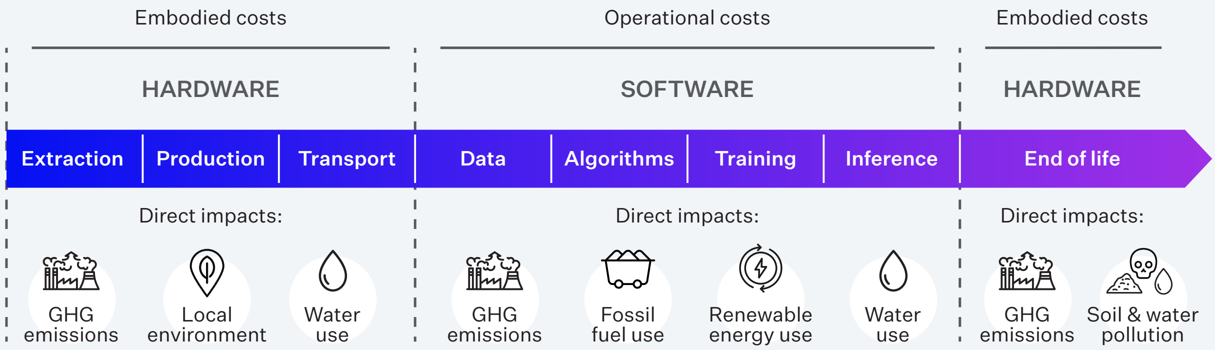
When it comes to energy usage of models, software design is one of the main drivers – and predictors – of the environmental impacts of AI systems. As such, it represents a critical area where researchers can take meaningful, proactive steps to reduce energy use when designing or adopting AI systems (Clemm et al., 2024).

HARDWARE LAYER

The second layer is the **hardware** layer. It refers to the processes involved in manufacturing and running ICT equipment and hardware, which are required to train and deploy an AI system.

This includes the **extraction** of raw materials, the **production** and **transportation** of equipment such as graphics processing units and tensor processing units used in model training and inference, the construction and operation of data centres that house AI infrastructure, and the management of electronic waste at the end of the equipment's life cycle (UNEP, 2024). These impacts are known as **embodied costs or embodied emissions**, associated with the production, transport and disposal of physical hardware.

Software and hardware stacks are deeply interconnected. In a life cycle approach, AI's environmental footprint considers both **operational costs** (from running AI systems) and **embodied costs** (from the infrastructure built to support them) (OECD, 2022). Centring sustainability and ethical considerations in design involves considering strategies to reduce environmental and social costs stemming from both stacks.



Full AI life cycle illustrating costs associated with software and hardware stacks. Based on Luccioni et al., 2022; OECD, 2022; UNCTAD, 2024 and Schneider et al., 2025.

2.3 Estimating direct environmental costs across the AI lifecycle

This section describes current practices to assess **direct environmental costs** at different life cycle stages.

ESTIMATING OPERATIONAL COSTS

Operational costs of model training and inference stages are estimated by using resource consumption (energy and water) and greenhouse gas emissions as key indicators (OECD, 2022). For example, a widely adopted metric is **carbon dioxide equivalents (CO_2eq)**, which aggregates greenhouse gases based on their global warming potential. International standards are under development to ensure consistent reporting across the diverse computing and ecological environments in which AI is deployed (International Telecommunication Union, 2024).

To support transparency around emissions, researchers have also developed tools and frameworks to estimate the carbon impact of AI models. Many of these can be used to estimate the footprint of data-driven or computation-heavy scientific research projects.

Tools to estimate carbon footprint:

- The Machine Learning Emissions Calculator estimates carbon emissions based on hardware specifications, usage time, cloud provider and geographic region.
- Experiment impact tracker tracks real-time energy consumption, carbon emissions and compute utilization.
- CarbonTracker and CodeCarbon monitor carbon output while training deep learning models.
- Green Algorithms Calculator estimates algorithmic emissions based on resource requirements and data centre location.

ESTIMATING EMBODIED COSTS

Embodied costs refer to impacts on greenhouse gas emissions and the local environment from extracting and processing raw materials, manufacturing and transporting relevant hardware, and emissions and pollution at the decommissioning stage.

Embodied costs are much harder to quantify and disaggregate from other digital infrastructure applications. Available measurements assess the total lifecycle emissions of ICT equipment and hardware, which are not necessarily attributable solely to AI workloads (OECD, 2022). Standardized metrics are necessary to assess and compare the specific emissions of hardware associated with the deployment of AI models.

Researchers are developing new methodologies to overcome this challenge. For example, a study by Hugging Face, which estimated the carbon footprint of language model BLOOM, developed a methodology to estimate emissions produced by the manufacturing equipment used to train the model (Luccioni et al., 2022). Similarly, researchers at Google evaluated AI hardware's environmental impact, developing a new metric: compute carbon intensity to evaluate AI hardware sustainability (Schneider et al., 2025). Nonprofit initiatives, such as CarbonTracker – a carbon calculator to track and monitor hardware power consumption – can also support researchers in estimating their embodied costs (Anthony et al., 2020).

2.4 Transparency and reporting

Reducing the environmental impact of AI requires transparency in reporting. This includes disclosing the full computational cost of training and deploying models, such as energy and water use, total runtime, the number of training iterations and the hardware used. These practices can also support reproducibility and contribute towards setting benchmarks for reducing the environmental impact of future AI research (Bolón-Canedo et al., 2024).

Open science practices, such as publishing **model cards and data sheets**, can also facilitate transparency around direct environmental costs. Publicly released models like BLOOM, Stable Diffusion or IkubaLM have begun to include environmental reporting, including information around model architecture, training time, hardware environment and estimated carbon footprint (Luccioni et al., 2024a). However, environmental reporting remains rare, with most industry actors not disclosing basic sustainability metrics.

While emissions reporting is a valuable first step, it must be followed by concrete efforts to develop software and hardware solutions that reduce energy demand and emissions in practise.

Section 3: Strategies for reducing direct environmental costs of AI applications in scientific research

This section outlines strategies for reducing the direct environmental impact of AI applications. While technical solutions to improve energy efficiency are not sufficient on their own to ensure the long-term sustainability of AI, the approaches presented here fall within the control of researchers and can help lower the environmental footprint of both the software and hardware used in scientific research (Luccioni et al., 2025).

3.1 Reducing environmental costs in the software life cycle

More than 30 green AI techniques have been identified to reduce training data through data-efficient learning and lower computational demands by optimizing algorithms and using smaller models (Clemm et al., 2024). These approaches are particularly relevant for scientific researchers, as studies have shown that software-level efficiencies, such as reducing the frequency of training runs, using smaller datasets or using less complex models, can achieve energy efficiency gains more rapidly than updating hardware and infrastructure (OECD, 2022).

DATA MANAGEMENT

Efficient data management starts with evaluating the quality and relevance of existing data and identifying opportunities to reduce the amount of labelled data required for training. A focus on '**data sobriety**' and **lean data practices** encourages collecting, storing and processing only essential data, helping to limit unnecessary computational and environmental costs (Shani et al., 2023). Key strategies include (Wu et al., 2021):

- **Data pruning** and **data deduplication** help eliminate redundant entries, reducing storage requirements and processing demands. These techniques rely on distinguishing valuable data from nonessential information and assessing appropriate data retention periods (Samuel and Lucassen, 2022).
- **Estimating data perishability**, the rate at which data loses predictive value. For instance, natural language datasets may lose half their utility within seven years (Valavi et al., 2022). By estimating the 'half-life' of different data types, developers can implement sampling strategies that retain only high-value data over time, reducing long-term storage needs.
- **Circular data practices** support the **reuse and repurposing of existing datasets.** Data collected for one purpose can often be applied to another, lowering the environmental and labour costs associated with creating and annotating new data.
- A shift towards a '**small data**' approach involves working with smaller, high-quality datasets, reducing processing and storage needs. Smaller datasets also make it easier to detect bias and errors or conduct research in contexts where large-scale data is unavailable or incomplete (Orrù, 2023).

- **From big data to high-quality data:** Adding more data does not always lead to better model performance. Rather than relying solely on large datasets, it is more effective to strike a balance between having sufficient data and ensuring that it is high quality and representative. Regularly evaluating data pipelines and applying best practices, including data cleaning and human oversight, can help maintain data quality and reduce the need for large volumes of data (Goswami, 2025).

Data-efficient AI can also support social equity by **reducing the human labour** required for data annotation. Large datasets like ImageNet have taken years to compile and label, often requiring extensive manual effort (Chen et al. 2022). Originally developed for image classification, ImageNet has since been repurposed for tasks such as image generation. By adopting data repurposing practices, developers can reduce both the environmental impact and the social burden of large-scale data collection.

ALGORITHMIC OPTIMIZATION

Algorithmic optimization aims to improve the efficiency of AI models by reducing their size and computational demands, without significantly compromising accuracy or performance (Lannelongue et al., 2021a). This can involve designing memory-efficient architectures (Wu et al., 2021), reducing the frequency of training runs (Lannelongue et al., 2021a) or encouraging model sharing to avoid redundant training (Chen et al., 2022).

A key approach to optimizing algorithms is **model compression**, which reduces model size to lower memory usage, energy consumption and inference time. This is especially effective for scaling down large language models into small language models that retain the original model's capabilities with less training time and data.

Common model compression techniques include (Wang et al., 2024):

- **Quantization** reduces parameter precision to lower computational and memory requirements without affecting accuracy.
- **Pruning** removes less critical parameters to simplify the model.
- **Knowledge distillation** transfers knowledge from *a large teacher model to a smaller student model*.

Lightweight and compact model architectures can also be an effective strategy to deploy more energy-efficient AI in **resource-constrained environments** and develop real-world applications for which limited training data is available (See Case Study #1)(Bolón-Canedo et al., 2024). More research is needed to understand the trade-offs involved in smaller models, particularly about the potential indirect and rebound effects (Morrison et al., 2025).

CASE STUDY 1: InkubaLM: A small language model for low-resource African languages (Tonja et al., 2024)

InkubaLM is a 0.4 billion parameter multilingual language model developed by Lelapa AI, a socially grounded, Africa-centric AI research lab. It is the first open-source and small-scale model built specifically for five African languages: isiZulu, Yoruba, Hausa, Swahili and isiXhosa, as well as for English and French. The model achieves performance comparable to models with larger parameter counts and larger datasets by demonstrating consistency across different languages and outperforming larger models in sentiment analysis.

Mainstream AI tools currently overlook the vast majority of over 2,000 African languages, training models in dominant languages such as English, Chinese or Spanish. InkubaLM addresses this by supporting languages with limited, fragmented or non-standardized data. Language is essential for making AI tools useful for locally led development interventions in ways that are culturally relevant and accessible to user communities.

The project also challenges the assumption that language model development must be resource-intensive. InkubaLM was developed with limited computational resources and attention to high-quality data. Lelapa publicly documented the steps to optimize model efficiency and reported its environmental impact, documented using a machine learning impact calculator.

3.2 Reducing environmental costs in the hardware life cycle

As computing demands for AI continue to outpace improvements in hardware performance, hardware optimization has become increasingly important (OECD, 2022). While some aspects of the hardware lifecycle, such as the working conditions involved in rare earth mining or the environmental impact of data centres, may lie beyond the control of individual researchers. However, researchers and science institutions can still play a meaningful role in improving the traceability of the embodied costs of AI and contribute to setting standards for more sustainable hardware design, deployment and end-of-life practices (Wu et al., 2021).

Hardware efficiency strategies, such as using more **efficient computing hardware**, processing data in **resource-efficient data centres**, and applying **circular economy principles**, can reduce environmental costs (Wu et al., 2021).

ENERGY-EFFICIENT HARDWARE AND COMPUTING

Selecting energy-efficient hardware, such as specialized processors for deep learning, can handle parallel processing more effectively, shorten training time and lower energy consumption. However, the limited lifespan of such hardware raises concerns about obsolescence, making it important to consider durability and reusability alongside performance. Green computing principles support this by promoting the responsible disposal of electronic components (Schwartz et al., 2020).

Approaches like **Edge AI** and **distributed computing** can offer additional opportunities for sustainable hardware use, particularly in resource-constrained or remote settings (Bolón-Canedo et al., 2024). Edge computing shifts data processing and storage closer to the data source, reducing transmission time, cutting costs and decreasing reliance on centralized, energy-intensive data centres. Distributed computing spreads the computational load across multiple devices, allowing resource sharing and reducing the need for expensive new equipment (See Case Study #2) (Tomé-Moure et al., 2024).

CASE STUDY 2: TinyML enables data analysis and research in low-cost devices (Heydari and Mahmoud, 2025; Zennaro et al., 2022; Ooko et al., 2021).

TinyML is a highly energy-efficient approach that enables small machine learning models to run on low-cost and low-power hardware, making it well-suited for resource-constrained environments. TinyML allows local data processing on microcontrollers and edge devices, reducing dependence on cloud connectivity, saving energy and lowering connectivity requirements.

An example is the **Offline Cholera Detector Kit** developed by the African Centre of Excellence in Internet of Things in Rwanda. It uses TinyML for real-time, on-site detection of cholera in rural water sources, providing a low-cost alternative to traditional lab testing. The model was selected for its effectiveness with small datasets and ability to recognize nonlinear patterns, and was compressed to run on readily available hardware such as mobile phones.

TinyML has been used in wildlife conservation, precision agriculture and self-diagnostic tools for detecting respiratory diseases (Ooko et al., 2021). Its affordability and accessibility make it valuable for scientific research in areas with limited connectivity or computing resources. However, its deployment requires careful consideration, given potential trade-offs in model accuracy and the constraints of using less powerful hardware.

3.3 Energy-efficient data centres

Data centres are a central component of the AI lifecycle, concentrating much of the energy and water consumption associated with data processing and algorithmic design, as discussed in the previous section. While scientists and research institutes often depend on institutional or university-provided computing infrastructure, by understanding its environmental footprint, they can advocate for greener alternatives within their institutions, research collaborations or procurement decisions.

The World Bank's framework for **Green Data Centres** outlines five key areas for reducing embodied emissions: building design, hardware efficiency, renewable energy use, cooling systems and e-waste management. The sustainability of a data centre is also shaped by its location, which affects access to renewable energy and water resources. Regions reliant on fossil fuels produce higher carbon emissions and those facing water scarcity may be less suitable for cooling-intensive operations (Clemm et al., 2024). Similarly, training a model on a coal-powered grid can emit up to 30 times more carbon dioxide than running the same task on a grid powered by renewables (Wu et al., 2021). As data centres expand into resource-stressed regions, **environmental equity** is a core factor in sustainability assessments (Graham, 2024).

Researchers can also adopt strategies to reduce the impact of their operations. **Workload scheduling**, for example, can align energy-intensive tasks with periods of lower grid emissions or higher renewable availability. When **geographic load shifting** is possible, selecting data centre regions powered by cleaner energy can significantly reduce emissions. Running AI workloads in energy-efficient data centres, especially those in cooler climates or designed for optimal thermal performance, can further reduce energy use (see Case Study #3).

CASE STUDY 3: Green AI infrastructures across regions

As demand for data centres increases, governments, industry actors and research communities are developing and setting up alternative solutions that use clean energy while navigating the social and ethical impacts of AI.

In **Brazil**, the government is positioning the country as a global and regional data centre hub, leveraging its local power grid, where nearly 90 percent of electricity comes from renewable sources like hydropower. Despite the bet on clean energy, concerns remain in local communities about broader environmental impacts that may result from the construction, including deforestation, threats to biodiversity and pressure on water resources (Lima et al., 2023).

In **Kenya**, a public-private partnership was developed, backed by Microsoft and UAE-based G42, which invested $1 billion in building a data centre campus powered entirely by renewable geothermal energy. The project includes water-efficient cooling systems and includes plans to set up an East Africa AI Innovation lab focused on developing AI models in local languages (Microsoft Source, 2024).

In the **United States,** the community group Earth Friendly Computation in California is piloting 'data terrariums': solar-powered, low-cost mini data centres housed in compact, off-grid enclosures. These units can run AI workloads using solar panels, batteries and low-power graphics processing units, offering a decentralized and ethical alternative to conventional cloud infrastructure, and are particularly suited for remote communities (Earth Friendly Computation, 2024).

3.4 Decommissioning and end-of-life management

Finally, **lifecycle assessments** and **inventory systems** can also support researchers and research institutions to track hardware use and identify opportunities for reuse before purchasing new equipment (Lannelongue et al., 2023). Sustainable practices include designing and selecting hardware that enables disassembly, ensuring proper recycling and disposal, and applying environmental criteria to procure new hardware. **Circular economy approaches**, such as extending hardware lifespan, refurbishing systems, and using modular designs for easy repair and replacement, are also gaining traction (Samuel and Lucassen, 2022).

Conclusion

Reducing the environmental impact of AI remains a significant challenge. While technical solutions alone are not sufficient, broader adoption of resource-efficient practices can help mitigate the immediate and direct environmental costs of using AI. Practical steps such as using computationally efficient algorithms, selecting low-energy hardware or relying on high-quality data over big data, offer concrete ways for scientists and research institutions to move towards more sustainable AI design and deployment.

However, decisions about using AI in scientific research must go beyond a narrow focus on energy efficiency to consider its broader impacts, such as rebound effects, longer-term consequences of environmental harm, and the disproportionate burdens placed on vulnerable communities. Promoting a responsible approach to the use of AI in science calls for holistic evaluations grounded in sustainability and ethics, that enable researchers to determine when – and what kind of – AI is truly fit for purpose, and to assess its potential not only to advance scientific progress, but also to support social wellbeing and planetary health throughout its entire life cycle.

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Appendix 1: Glossary

1. **AI:** In this paper, we use the OECD definition for 'AI' meaning an machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations or decisions that can influence physical or virtual environments. Different AI systems in their levels of autonomy and adaptiveness after deployment.

   Source: OECD. N.d. *Artificial Intelligence*. https://www.oecd.org/en/topics/artificial-intelligence.html (Accessed 11 July 2025).

2. **Direct environmental costs:** Direct or first-order effects result from digital devices and ICT infrastructure throughout their life cycle, spanning raw material extraction and processing, manufacturing, transportation for distribution, use and the end-of-life phase. It refers to the consumption of resources (energy, water and mineral resources), the production of greenhouse gas emissions and e-waste generated from operating AI systems.

   Sources: UNCTAD. 2024. *Digital Economy Report 2024: Shaping an Environmentally Sustainable and Inclusive Digital Future*. https://unctad.org/system/files/official-document/der2024_en.pdf (Accessed July 13, 2025).

3. **Indirect environmental costs**: Indirect (or second- and higher-order) effects describe other environmental impacts from the use of digital technologies and services in different sectors of the economy, going beyond the direct footprint of the ICT sector. These can be both environmentally beneficial and harmful.

   Sources: UNCTAD. 2024. *Digital Economy Report 2024: Shaping an Environmentally Sustainable and Inclusive Digital Future*. https://unctad.org/system/files/official-document/der2024_en.pdf (Accessed July 13, 2025).

4. **Sustainable AI:** Sustainable AI is a movement to foster change in the entire lifecycle of AI products (i.e. idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice. It refers to the development of AI that is compatible with sustaining environmental resources for current and future generations; economic models for societies; and societal values that are fundamental to a given society.

   Source: Van Wynsberghe, A. 2021. Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics*, 1(3), pp. 213–218. https://doi.org/10.1007/s43681-021-00043-6.

5. **Green AI:** Green AI seeks to mitigate its environmental impacts by optimizing algorithms, improving hardware efficiency and adopting sustainable data management practices. Green AI is characterized by a low carbon footprint, better quality data, small models and low computational complexity. To ensure people's trust, it also offers clear and logical decision-making processes, adding social sustainability as an advantage.

   Source: Bolón-Canedo, V. et al. 2024. A review of green artificial intelligence: Towards a more sustainable future. *Neurocomputing*, 599, p. 128096. https://doi.org/10.1016/j.neucom.2024.128096.

6. **Responsible AI:** Responsible AI is the practice of developing and using AI systems in a way that benefits society while minimizing the risk of negative consequences. It is about creating AI technologies that not only advance our capabilities, but also address ethical concerns, particularly with regard to bias, transparency and privacy.

   Source: ISO. 2025. *Building a responsible AI: How to manage the AI ethics debate*. 14 July 2025. https://www.iso.org/artificial-intelligence/responsible-ai-ethics.

7. **Lifecycle assessment:** Life cycle assessments evaluate the environmental impacts of a product or a service throughout its entire life span.

   Source: Klöpffer, W. 1997. Life cycle assessment: From the beginning to the current state. *Environmental Science and Pollution Research*, 4(4), pp. 223–228. https://doi.org/10.1007/BF02986351.

8. **Greenhouse gas emissions:** Greenhouse gases are gases that trap heat from the sun in our planet's atmosphere, keeping it warm. The main greenhouse gases released by human activities are carbon dioxide, methane, nitrous oxide and fluorinated gases used for cooling and refrigeration. Carbon dioxide is the primary greenhouse gas resulting from human activities, particularly from burning fossil fuels, deforestation and changing the way land is used.

   Source: United Nations Development Programme. N.d. *The Climate Dictionary*. https://www.undp.org/publications/climate-dictionary (Accessed 15 July 2025).

9. **Carbon footprint:** A carbon footprint is a measure of the greenhouse gas emissions released into the atmosphere by a particular person, organization, product or activity. A bigger carbon footprint means more emissions of carbon dioxide and methane, and therefore a bigger contribution to the climate crisis.

   Source: UNDP. N.d. *The Climate Dictionary*. https://www.undp.org/publications/climate-dictionary (Accessed 15 July 2025).

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