ISSUES NOTE
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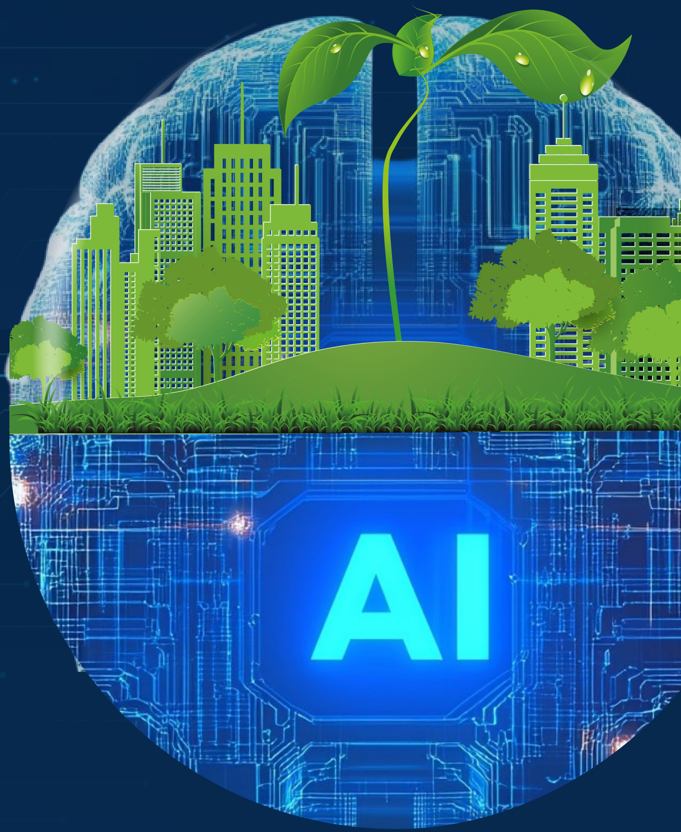
Artificial intelligence (AI) end-to-end:

The environmental impact of the full AI life cycle needs to be comprehensively assessed



The United Nations Environment Programme (UNEP) is the leading global environmental authority that sets the global environmental agenda, promotes the environmental dimension of sustainable development within the United Nations system, and serves as an authoritative advocate for the global environment with a mandate to keep under review the world environmental situation.

Against this mandate, UNEP has been requested by UN Member States to consider the environmental dimensions of digital technologies, assessing their opportunities to enable environmental sustainability and the impact they can have on the environment.

This note outlines key areas identified by UNEP regarding the environmental impact of Artificial intelligence (AI) across its life cycle. The note aims to inform Member States, civil society, the private sector and the public, while encouraging the research community to develop and use scientific methods to allow the objective measurement of AI's environmental footprint.

[i] This Issues Note provides a review of the latest literature on specific topics that are of relevance to UNEP's mandate as outlined in "The future we want: outcome of the Conference on Sustainable Development, Rio de Janeiro, Brazil, 20–22 June 2012; paragraph 88". It also presents a set of agreed approaches and recommendations regarding UNEP's communication of the subject matter.

[ii] The Ministerial Declaration adopted at the sixth session of the United Nations Environment Assembly (UNEA-6) emphasized the importance of leveraging emerging technologies and closely monitoring their development to ensure they contribute to sustainability. The declaration also stressed the need to ensure that digitalization is inclusive, equitable and sustainable.

1. There is no universally accepted definition of AI. For the purposes of this Issues Note, a key technical element from the United Nations Educational, Scientific and Cultural Organization (UNESCO) Recommendation on the Ethics of Artificial Intelligence [1, p.10] has been adopted to help unpack the environmental aspects of AI: "AI systems are information-processing technologies that integrate models and algorithms that produce a capacity to learn and to perform cognitive tasks leading to outcomes such as prediction and decision-making in material and virtual environments. AI systems are designed to operate with varying degrees of autonomy by means of knowledge modelling and representation and by exploiting data and calculating correlations".

2. AI offers transformative opportunities for the environment. It can play a crucial role in areas such as climate action, nature protection and pollution prevention. However, AI's rapid pace of innovation, exponential growth and demand for resources have raised significant concerns about its potential negative impact on the environment. As AI has evolved, its demand for larger datasets and increased computational power has grown [2], with associated pressures on natural resources.

3. The life cycle of AI can be seen through two lenses: software and hardware. The software life cycle involves data collection and preparation, model development, training, validation, deployment, inference, maintenance and retirement. The hardware life cycle involves the production of computer chips, including graphical processing units (GPUs) essential to the training and inference, and the construction and operation of data centres. It starts with raw material extraction, through manufacturing, shipping and data centre construction, and ends with operation, maintenance and disposal of e-waste. When assessing the environmental footprint of AI, it is important to examine both life cycles.

4. Until recently, the environmental impact of the AI software life cycle was thought to be mainly in the training phase due to the high data and computational load. However, with generative AI[iii] and large language models (LLMs)[iv], the inference stage now requires equal or more resources. Numerous institutions and research groups are working to develop AI frameworks that minimize the use of training data and optimize model operation during the inference stage to reduce compute and storage needs and address sustainability goals [3,4].

5. The AI hardware life cycle is much more complex and difficult to assess, as it requires a thorough analysis of every stage of the process. From mining and extraction practices to transportation methods, to water and energy consumption, all the way to waste and e-waste generation, with each stage having a different environmental footprint [5]. While the software and hardware life cycles are inextricably linked (model optimization in the software lifecycle can reduce water consumption due to the decreased need for computing power), it is important to measure and seek to mitigate the effects of both life cycles on all aspects of the environment.

6. The environmental impact of AI across its software and hardware life cycle can be categorized into three levels: direct, indirect and higher-order effects. Direct impacts include the consumption of energy, water and mineral resources, and the production of emissions and e-waste. Indirect effects result from the increased environmental damage driven by advances in AI, such as the potential increased use of personal vehicles due to advances in autonomous vehicles [6]. Additionally, the widespread use of AI can exacerbate existing inequalities, particularly affecting women, minorities and individuals from low-income backgrounds. This is primarily driven by biases and poor quality in the training data, such as the scarcity of data from underrepresented groups resulting in decisions favouring other groups [7,8].

7. AI usage results in behavioral and structural changes to the economy and society that have systemic impacts on patterns of consumption and production, lifestyles, social trust, misinformation and governance [9,10]. As a more profound and long-term form of indirect effects, these higher-order effects can also be environmentally positive or negative. For instance, while generative AI models are very helpful in summarizing complex scientific information on the environment for non-academic readers [11], they can also enable the automation and rapid dissemination of intentional misinformation campaigns [12].

[iii] There is no universal definition of generative AI and large language models. As per the Organisation for Economic Co-operation and Development (OECD) [27, p.8], "Generative AI systems create content based on training data and in response to user prompts."

[iv] According to Gartner: "A large language model is a specialized type of artificial intelligence (AI) that has been trained on vast amounts of text to understand existing content and generate original content." Retrieved from https://www.gartner.com/en/information-technology/glossary/large-language-models-llm

8. Although studies have estimated the environmental impact of different stages of the AI life cycle, comprehensive research in this area remains scarce. This has resulted in the proliferation of media statistics, many of which lack credible backing. Accurately estimating AI's environmental impact is hindered by significant measurement challenges, particularly due to insufficient data on indirect and higher-order effects. Given the complexity of impacts assessment, attention should be focussed on direct impacts in the first instance. Special attention to the measurement of the use of minerals, energy and green house gas emissions, water consumption and pollution, and e-waste is required. For each of these aspects, the confidence level in AI footprint estimates is vastly different and lacks methodological maturity and granular data [13,14].

9. Minerals and metals are vital for digital technologies, such as data centres and graphical processing units chips. The increased popularity of AI tools is driving a massive growth in demand for these chips; from 2001 to 2022, the number of chips sold has quadrupled, with no changes in demand in sight [15]. The key minerals and metals needed for digitalization are nearly the same as those required for transitioning to a low-carbon economy [15]. While there is no specific data on the demand for minerals of the AI sector, multiple studies suggest minerals and rare earth elements (REE) mining has significant environmental impacts, such as water and air contamination, biodiversity degradation and greenhouse gas emissions [16,17]. For instance, 52 per cent of copper mines are located in high water stress areas [18]. The recycling rates for minerals remain rather low, varying between 46 per cent for copper and 1 per cent for REE [19, 20].

10. AI's energy consumption and greenhouse gas emissions are significant, with more sophisticated models, such as large language models (LLMs), driving a significant increase in energy use. One study suggests that a single LLM query requires 2.9 watt-hours of electricity, compared with 0.3 watt-hours for a regular internet search [18]. Another study suggests that training a single LLM generates approximately 300,000 kg of carbon dioxide emissions, "which is five times the lifetime emissions of an average car or equivalent to 125 round-trip flights between New York and Beijing" [21, p.423], noting the limitations of these estimates where data has not been systematically collected on AI's energy use, and the transparency is low. The number of data centres worldwide has surged from 500,000 in 2012 to over 8 million, with energy consumption doubling every four years, with AI contributing to this growth [22].

11. Despite the lack of scientific evidence concerning water consumption of AI, it is estimated that the global demand for water resulting from AI may reach 4.2–6.6 billion cubic metres in 2027 [23]. This would exceed half of the annual water use in the United Kingdom in 2023 [24]. Semiconductor production requires large amounts of pure water, while data centres use water indirectly or electricity generation and directly for cooling. The growing demand for data centres in warmer water scarce regions adds to water management challenges, leading to increased tension over water use between data centres and human need [23,25].

12. As AI scales, it will generate higher volumes of electronic waste. Electronic waste has become one of the fastest-growing waste streams in the world. It is unclear what scale of the volume is generated by data centres or AI chips [15]. Overall, only 22 per cent of e-waste is recycled and disposed of in an environmentally sound manner [26].

13. Several normative international and national instruments address environmental impacts of AI and other digital technologies but there are no standardized methods for measuring or reporting on the environmental impact of AI. National legislation, such as the Federal Artificial Intelligence Environmental Impacts Act of 2024 in the United States of America, addresses the need to assess and mitigate AI's environmental impacts. The European Union AI Act sets standards for reducing energy and resource consumption during AI training and deployment. The UNESCO Recommendations on the Ethics of Artificial Intelligence provides a global ethical framework for AI development and deployment, including environmental considerations. However, to date, there remains no standardized way of measuring, reporting, or mitigating the environmental impact of AI.

14. The potential environmental impacts of AI could be significant. On this basis, and with the purpose to keep the environment under review, UNEP recommends:

- Member States to establish standardized methods and metrics for measuring AI's environmental impacts. The immediate priority should focus on the most concerning direct effects, and those for which data is more accessible, namely consumption of energy, water and mineral resources, and the production of emissions and e-waste.

- Member States, with UNEP support, to develop mechanisms and frameworks for mandatory reporting and disclosure of AI's direct environmental impacts by companies offering AI products and services.
- UNEP, together with Member States and the private sector, to agree on ways to make the above metrics transparent and accessible, to empower end users to understand their environmental impact and make informed decisions, promoting behavioural changes toward more sustainable AI use (similar to individual carbon footprint calculations and off-sets in aviation).
- The private sector, together with the research community, to prioritize research on optimizing AI algorithms for energy efficiency by reducing computational complexity and data usage, thereby minimizing the energy required for AI models.
- Member States to encourage the adoption of green data centres, renewable energy sources and carbon-offset practices to reduce the direct environmental impact of AI.
- The UN and its Member States to integrate sustainability goals into their digitalization and AI strategies and to ensure that policies go beyond transparency mechanisms and include strategies like co-regulation, sustainability by design, and consumption caps.
- The research community and civil society organizations to explore further the indirect and higher order impacts, including possible negative impacts from overconsumption.

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