The Dual Environmental Impact of AI: An Empirical Assessment of its Problem-Making and Problem-Solving nature

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ABSTRACT

Background: Artificial Intelligence (AI) affects the environment in complex ways. Large-scale AI systems consume substantial electricity and water, generate carbon emissions, and produce e-waste. The training and running of these systems is increasingly shaping the global ecological landscape. Conversely, AI applications can optimize energy use, forecast renewable production, and support climate change mitigation, creating a dual environmental impact. While AI may exacerbate environmental harm through its resources and its high demands, it also offers the potential tools for sustainability. Both sides have not been examined enough, leaving lots of questions about AI's net ecological impact.

Aims: This study empirically examines AI's dual environmental role, asking: *To what extent does AI act as a problem-maker versus a problem-solver for the environment?*

Method: We analyzed datasets on energy consumption, emissions, and resource use in AI model training and deployment, and reviewed case studies where AI improved environmental outcomes. A mixed-methods approach combined quantitative evaluation and qualitative insights.

Results: Findings show that training large-scale AI models significantly contributes to ecological costs, while AI applications in energy optimization, agriculture, and climate monitoring offer measurable benefits. The net impact varies with deployment scale, domain, and development practices.

Conclusions: AI's environmental role is dual: it can exacerbate ecological harm but also provide sustainable solutions. Promoting energy-efficient algorithms, green data centers, and responsible governance is essential to minimize negative impacts and amplify benefits.

KEYWORDS

Artificial Intelligence, Environment, Sustainability, Energy Efficiency, Software Engineering, Carbon Footprint, Green AI, ICT sector emissions, Corporate carbon footprint

1 INTRODUCTION

Artificial intelligence (AI) is increasingly becoming integrated into everyday life, but its environmental impact is also a growing concern. Training and maintaining large-scale AI models requires substantial electricity and water, which can lead to significant carbon emissions and e-waste [4]. Although simultaneously, AI has also shown potential as a means of addressing sustainability challenges, making it important to investigate its dual impact [3].

In the Software Engineering (SE) context, environmental considerations have not received the same systematic attention as conventional non-functional requirements such as performance or reliability. At present, there is no widely accepted framework in SE research or practice for consistently measuring and comparing these costs, even though recent work has shown the enormous amounts of water and electricity required for large-scale AI training [5]. They highlight that trade-offs related to transparency, benchmarking, and sustainability continue to be a major barrier to the improvement of AI and need more reliable methods to calculate the direct use of AI resources, as well as the indirect advantages of AI-enabled improvements [5]. Because of this gap, SE researchers are unable to reliably assess the net environmental trade-offs of AI, which limits their ability to design more environmentally sustainable systems and make informed decisions about AI adoption.

The lack of systemic attention to sustainability is a significant problem. Without reliable methods to evaluate AI's ecological impact, software engineering researchers cannot make fully informed decisions about integrating or scaling these systems. As a result, AI may be implemented without fully understanding its environmental trade-offs, leading to unintended ecological consequences. As the *Sustainable AI* paper emphasizes, "*we cannot optimize what cannot be measured*" and current AI research lacks investment in sustainability metrics, limiting the ability to evaluate environmental trade-offs [5].

The use of AI in SE contexts has yet to be thoroughly studied. We can dive into the use of AI in other settings and use this information to elaborate on an SE context. One study suggests that AI models can be used to increase efficiency and sustainability in allocation of data in industrial systems [3]. In these contexts, AI is a powerful tool that can reduce the carbon footprint, as energy consumption in these systems was shown to decrease after AI was integrated [3]. In contrast, we can look at the energy consumption of AI. Air-cooled AI systems utilize 10% more energy than water-cooled AI systems; while CO2 emissions may lower as we create more water-cooled systems, water use will increase [2]. Both the carbon and water footprint of AI systems will need to be taken into account. While these studies are important in providing a baseline of information on the environmental impact of AI, they tend to be one-sided. In our research, we will formulate a fundamental understanding on both negative and positive environmental impacts of AI to establish the net impact of AI use and make predictions in a SE context.

In this research, the ecological footprint of large-scale AI is shown from two perspectives. One that the efficiency gains AI can produce in resource-intensive industries like energy and water management [3]. Two the the substantial resource consumption that is needed for the training and to maintain advanced and up to date models. Showing the data in this way will highlight the goal is to assess the balance between costs and the benefits rather than adopting a one sided view that could either be critical of AI's carbon and water consumption or the view of being only optimistic about its sustainability efforts [2, 5].

RQ. *"What is the net environmental impact of large-scale AI, considering both the resource consumption of model training and the efficiency gains AI delivers in domains such as energy and water management?"*

2 METHOD

We will be using publicly accessible information and reports that document the advantages and disadvantages of artificial intelligence in order to respond to our research question. When researching about expenses, we will take advantage of using sources from International Energy Agency (IEA) and institutional reports from data centers and universities on their carbon emissions, water usage, along with electricity consumption from modern extensive AI model training. Looking at the advantages, we will look through case studies and performance reports that show how AI applications can, and do, enhance sustainability results in fields such as climate monitoring, water management and energy optimization.

2.1 Data Sources

Our main data sources will be publicly available datasets and reports from the **International Energy Agency (IEA)** [1] as well as leading educational institutions. These sources offer detailed information on energy use, water consumption, and carbon emissions linked to large-scale computing and AI systems. In addition, we will examine case studies and annual reports from both the energy sector and academic institutions to uncover real-world examples of how AI has been used to improve resource efficiency.

2.2 Data Collection Techniques

The data will then be gathered through a combination of database access, literature reviews, and automated scripts that, when they are practical, extract the structured data and data sets. Journal articles and proceedings from conferences in the fields of SE and sustainability will also be used to find case studies to compile more data.

2.3 Data Processing

We will process through the datasets by cleaning the missing values and normalizing the units (e.g, CO2 tons, kWh), and coding the qualitative data for overall consistency. Though qualitative coding allows us to collect every aspect of AI's application across all domains keeping it objective, and allowing us to have comparative metrics of the environmental impact. We can then evaluate AI's overall impact more deeply by integrating the two.

2.4 Data Analysis

We will be using a mixed method approach in our analysis. This will help to facilitate comparisons across the systems and contexts. We will then standardize the quantitative measurements such as tons of CO2 released, liters of water utilized, and the kilowatt-hours of power consumed. In order to measure the indirect or the more difficult to measure advantages of AI optimizations, we will qualitatively examine case studies. We will address both the quantifiable effects and the context specific data and insights we find through this process.

2.5 Contingency Plan

Our contingency plan is to conduct in person interviews to collect first hand data from local departments from **Colorado State University (CSU)** in the event that out primary data sets are unavailable or incomplete. The Department of Computer Science would provide us with information on resource usage for operating lab equipment and compute infrastructure while the College of Agriculture will then provide us with information on AI applications in water and electricity management.

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