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MEASURING AI'S WATER FOOTPRINT: HIDDEN IMPACTS OF DIGITAL TECHNOLOGY

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Abstract:
This study investigates the hidden water consumption associated with artificial intelligence (AI) systems, focusing on the water used to generate electricity and cool data center servers. The research examines different AI models, their energy requirements, and their corresponding water footprints. Using available literature, technical reports, and numerical estimations, this study highlights the variability of water usage depending on model complexity, infrastructure efficiency, and geographical location. Recommendations for reducing AI's water footprint are also discussed.

Keywords: Artificial intelligence, water consumption, data centers, server cooling, energy usage, sustainability, GPT, AI models, user behavior.

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Introduction

Recent years have shown that artificial intelligence (AI) and large-scale models carry not only "intelligent" computational capability but also an often invisible environmental burden — particularly a hidden demand for water resources. The computational power required for AI systems is concentrated in data centers, where water is consumed both in the production of electricity and in the cooling of server infrastructure. As a result, digital technologies function as indirect but substantial water consumers. In 2022, global data center electricity consumption was estimated at approximately **240–340 TWh**, accounting for **1–1.3%** of total worldwide electricity demand — and the associated water requirements cannot be overlooked.

To measure water use efficiency in data centers, the industry employs metrics such as **Water Usage Effectiveness (WUE)**; however, the actual range of water consumption varies widely. Some infrastructures demonstrate **0.00–4.4 L/kWh** of water consumption, while water withdrawal can range from **0.31 to 533.7 L/kWh**. This means that geographical location, cooling technology, and system architecture significantly alter the water footprint. Such variability complicates the assessment of AI's water use: identical computational workloads may generate vastly different water impacts depending on where they are executed.

A defining characteristic of AI is its dependence on model size and computational complexity. Large language models and neural networks (e.g., GPT-scale systems) require substantial energy during both training and inference. This energy is often sourced from water-intensive power plants, or the data centers rely directly on evaporative cooling systems that consume significant amounts of water. Therefore, AI's water footprint is shaped not only by cooling systems inside data centers but also by the water intensity of the electricity grid and energy sources.

Recent analyses suggest that AI's water footprint has not been adequately addressed; however, emerging studies now examine this issue systematically. Contemporary reviews separate **direct** water consumption in AI-driven data center operations from **indirect** water use associated with electricity generation. Both are assessed through infrastructure efficiency and scenario-based geographic modeling. From this perspective, measuring AI's water footprint compels a reassessment of corporate water policies, water-related risks, and the legal–ethical dimensions of community engagement.

Practically, the issue is rapidly entering policy and public attention: data centers are frequently located in regions experiencing water scarcity, and some communities have already reported pressure on drinking water sources and groundwater supplies due to digital infrastructure. Consequently, major operators are adopting technologies aimed at reducing water use—such as air-based cooling, closed-loop water circulation, and water-free liquid cooling—and announcing “water-positive” sustainability commitments. Nevertheless, regulatory oversight and public accountability mechanisms are still needed on a larger scale.

This article aims to systematically analyze the “water footprint” of AI systems, identify the interdependence between energy and water use, and present quantitative assessments across model architecture, infrastructure efficiency, and geographical conditions. Based on the evidence outlined in the introduction, we seek to answer the following questions: What are the direct and indirect components of AI’s water consumption? Where are the most water-intensive hotspots located? How can technological, infrastructural, and policy interventions reduce this footprint? This analysis is intended to provide actionable insights for policymakers, data center operators, and AI model developers.

Purpose and relevance of the study

As more people use AI in daily life, concerns about the environmental impact of these systems, especially their hidden water use, are growing. With water scarcity becoming a global issue, it is essential to understand the water footprint of AI to make sustainable choices in technology, data center management, and public policies.

Materials and methods

We gathered data for this study from independent research articles, Google and Microsoft technical reports, and industry analyses. Key metrics included energy consumption per AI query (watt-hours) and estimated water use per unit of electricity (milliliters per watt-hour). We calculated water usage using the formula: Energy per prompt (watt-hours) × Water factor (milliliters per watt-hour) = Water per prompt (milliliters). Data were collected from studies and reports published between 2018 and 2024.

Results

This study evaluated the water consumption of artificial intelligence (AI) systems through three key indicators: **energy usage**, **water demand of data center cooling systems**, and **geographical water-intensity variations**. The findings demonstrate that AI infrastructure has a substantial and often hidden dependence on water resources.

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Energy consumption of AI models and their indirect impact on water use.
Energy consumption required to train large neural networks continues to increase annually; training a GPT-scale model requires thousands of GPU/TPU clusters. Electricity generation—especially in thermal power plants—is closely tied to water consumption per kWh. In some regions, this indicator can be extremely high. Estimates show that during the training of a large AI model, the **direct water consumed within the data center** and the **indirect water used for electricity production** both constitute a significant environmental burden. For example, in well-optimized data centers, **1–4 liters of water** may be consumed per 1 kWh of energy, while some cooling technologies may require significantly more.

Water consumption of data center cooling systems.
The results indicate that: **Evaporative cooling systems** require the highest amount of water — large data centers can consume volumes equivalent to the annual water use of a small nation; **Air cooling** significantly reduces water usage but may be less energy-efficient; **Water-free liquid immersion cooling** minimizes the water footprint but is not yet widely implemented.
Water Usage Effectiveness (WUE) varies significantly depending on cooling technology and location:

Cooling Technology	**Water Use (L/kWh)**	**Characteristics**
Evaporative cooling	1.8 – 4.4	Highly efficient, but requires the most water
Hybrid cooling	0.5 – 1.2	Balanced approach, used in modern facilities
Air cooling	0.00 – 0.10	Minimal water use, higher energy demand
Liquid immersion	≈0	Water-free, but complex to implement

Water footprint of the inference stage. Although AI training is resource-intensive, everyday inference at global scale generates a massive cumulative water demand. Each AI query (e.g., generating a few paragraphs of text) may be associated indirectly with water use ranging from **milliliters to several liters**, depending on model size, server location, and cooling technology. Billions of daily AI queries demonstrate the vast global scale of AI's water footprint.

Geographic variations. Data centers in arid regions (Arizona, Nevada, UAE, Central Asia) are highly vulnerable to water stress. Humid and cool regions (Finland, Ireland, Canada) require minimal water due to efficient use of outside air for cooling. AI infrastructure amplifies economic and ecological risks directly tied to regional water availability.

Discussion. The findings of this study reveal that measuring the water footprint of AI technologies is complex and influenced by multiple factors. Unlike fast fashion or heavy industry — which produce tangible physical waste — AI's resource consumption is often **invisible**, yet its impact is substantial.

The concept of a "hidden water footprint" and AI's emerging ecological challenge. Users of AI systems rarely perceive the associated water consumption. However: During model training, thousands of servers generate continuous heat, Cooling these servers directly consumes water, Electricity production also requires water.

Thus, AI imposes a two-layered burden on the water chain: **(1) cooling systems**, and **(2) water-intensive electricity generation**.

Combined, these factors can bring AI's water footprint to levels comparable with some metallurgical or chemical industries.

Rapid expansion of AI computing increases risks in water-scarce regions.

AI data centers tend to cluster in regions offering: tax incentives, cool climates, high-speed connectivity, inexpensive land.

However, as AI technologies grow, regions already facing water scarcity are experiencing additional pressure.

Discussion yields the following conclusions: The surge in global AI demand is creating **new policy challenges for water sustainability**; In countries with limited water resources, locating data centers poses **strategic environmental and economic risks**; Corporate "water-neutral" or "water-positive" commitments are important, but **insufficient** at the current rate of AI expansion.

Technological solutions: feasibility and limitations. The discussion identified several promising technologies: **Air cooling** — minimal water usage but higher electricity consumption; **Closed-loop liquid cooling** — minimal water loss due to recirculation; **Immersion cooling** — servers submerged in dielectric fluid, eliminating water usage entirely.

AI model optimization — model compression, distillation, and token-efficiency improvements reduce water use indirectly.

Green energy adoption — wind and hydro power significantly lower the water intensity of electricity generation.
Despite these opportunities, barriers remain: high implementation costs, need for advanced infrastructure, uneven global energy policies.

Political and ethical considerations. Reducing AI's water footprint is not solely a technical challenge — it is a **social responsibility**. Key implications include: Water consumption should be explicitly included in AI regulatory frameworks; Strict quotas or monitoring mechanisms are needed for data centers in water-stressed regions; As user-generated AI queries also contribute to global water and energy demand, **responsible AI usage** is becoming an important concept.

Conclusion and Recommendations

AI systems have a hidden but measurable water footprint, mainly linked to server cooling and electricity generation. To lessen their environmental impact, AI developers and data center operators should adopt more efficient cooling systems, such as immersion or closed-loop liquid cooling.
They should also optimize energy consumption, use low-water-power sources, position data centers in cooler, wetter climates to lessen reliance on evaporative cooling, and improve transparency in reporting AI energy and water use to encourage sustainable policies and public awareness.
Besides technological solutions, user behavior significantly influences reducing AI's environmental impact. Thoughtful use of AI systems, including avoiding unnecessary queries, can support infrastructural optimizations and reduce the overall environmental footprint. Encouraging users to plan prompts wisely and use AI for meaningful tasks can further aid in minimizing this footprint.

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