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PERSPECTIVE

Artificial Intelligence: A Great Solution or A Severe Problem for A Thirsty World?

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1. INTRODUCTION

In the whole world AI is considered as a crucial tool for transforming water management. In Europe AI is one of the five enabling areas to pave the way for a water resilient Europe [1]. In China AI-powered platforms enable real-time water quality monitoring and contaminant prediction [2,3]. A wastewater treatment plant in Ordos City uses AI combined with solar power to achieve 95% reuse, operating with zero wastewater discharge [4]. With high non-revenue water (NRW) rates, India is employing AI to identify leaks and reduce water loss, aligning with the AMRUT 2.0 and Jal Jeevan missions [5,6]. In central Asia UNESCO is implementing AI-powered early warning systems for glacial lake outburst floods, improving risk management [7,8].

In this context, it is not surprising that demand for AI is rising faster than the addition of capacity. Meanwhile, major hyperscalers such as Alphabet, Amazon, Meta, Microsoft and Oracle are investing increasing amounts of capital in data centres. However, political and public concern regarding the environmental footprint of AI infrastructure is also growing, particularly in regions already exposed to water and energy stress. AI's environmental impacts are related also to building ever-larger models. "The training of frontier models demands immense energy. For example, GPT-4 likely consumed 50 to 70 GWh of electricity over 100 days, roughly 40–55 times more than GPT-3 (1.287 GWh over a 34-day period) and the corresponding water footprint was about 600 million liters, enough to meet the minimum annual domestic water needs of 81,000 people in Sub-Saharan Africa, or to fill 237 Olympic-sized pools" [9].

Data-centre servers release considerable thermal energy during computational operations, making cooling systems essential for maintaining stable performance. In many facilities, cooling infrastructure may represent nearly 40% of total energy demand [10]. A common approach involves evaporative cooling technologies, in which water removes heat before partially dissipating into the atmosphere through evaporation. Since saline water may damage electronic components, operators frequently depend on freshwater obtained from municipal networks, potentially increasing competition with public water supplies. Although some companies are introducing reclaimed wastewater and closed-loop cooling technologies, these solutions are not yet widely implemented. Important trade-offs also exist between water and energy consumption: water-based cooling can lower electricity requirements, whereas dry-cooling systems reduce water use but generally require more power and may operate less efficiently during periods of extreme heat [11].

The emerging relationship between water, energy and artificial intelligence reveals a major sustainability paradox: while AI technologies can support more efficient water management, the rapid

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expansion of digital infrastructure may simultaneously increase stress on freshwater resources.

How much water do data centres use?

Water consumption associated with data centres originates from both electricity production and on-site cooling operations. Consequently, assessing the environmental footprint of AI infrastructure requires consideration of direct as well as indirect water demand.

Indirect consumption is strongly influenced by the source of electricity used to power digital infrastructure and by the operational efficiency of the facility itself. One commonly adopted indicator is the Power Usage Effectiveness (PUE), which evaluates how much total facility energy is required relative to the energy consumed directly by information and communication technology (ICT) equipment:

$$\mathrm{PUE} = \frac{\text{Data center total energy consumption}}{\text{ICT Equipment Energy Consumption}} \tag{1}$$

Projected electricity demand from data centres is expected to increase rapidly over the coming decade, driven largely by the expansion of AI applications and cloud-computing services [12]. Thermal power generation technologies – including coal, natural gas and nuclear energy – depend heavily on water throughout multiple operational stages. Water is used for steam production, cooling, contaminant removal and treatment processes. Depending on plant configuration, part of this water may evaporate, part may be discharged as effluent, while another fraction can be recirculated within the system.

Hydropower, although generally regarded as a low-carbon electricity source, may also contribute to substantial water losses through reservoir evaporation, particularly in arid climates. By contrast, wind and solar photovoltaic systems usually require comparatively low operational water inputs during electricity generation. Nevertheless, despite the ongoing expansion of renewable energy, fossil-fuel-based generation is still expected to support a considerable share of additional electricity demand linked to data-centre growth in the near future [12].

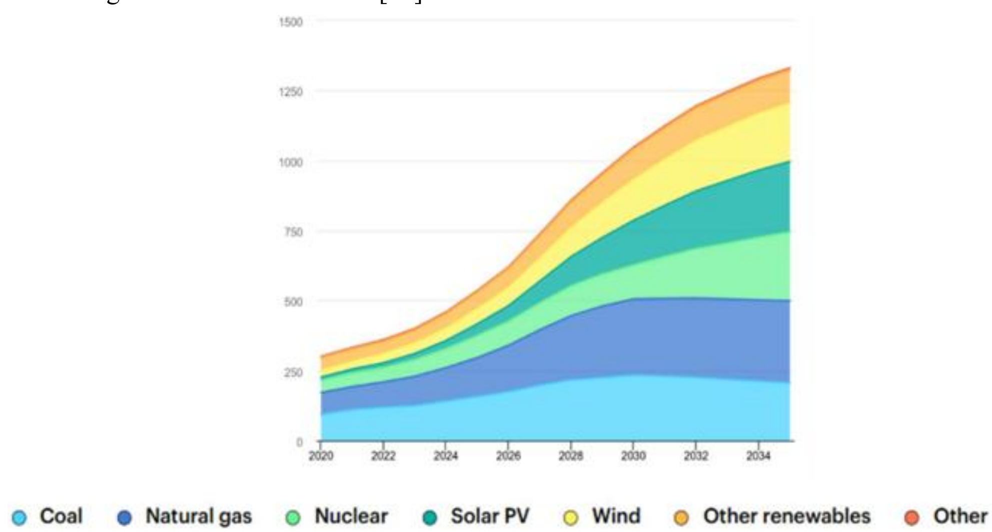


Figure 1. Energy supply for AI [12]

In addition to indirect water demand from electricity generation, data centres also consume water directly through cooling systems [13]. Several cooling approaches are currently employed across the sector. Conventional systems often rely on chillers that cool circulating water to temperatures typically ranging between 7 and 10 °C before transferring heat away from ICT equipment. Other facilities utilise evaporative cooling towers, where airflow passing across wet surfaces promotes heat dissipation through evaporation. Adiabatic cooling systems instead spray water into incoming airflow streams or onto heat-exchange surfaces to reduce air temperature before it enters the facility. In both evaporative and adiabatic configurations, part of the water is inevitably lost to the atmosphere.

Facilities operating in colder climates may partially reduce water demand by using free-air cooling systems that exploit naturally low outdoor temperatures. Such approaches can also decrease infrastructure and energy costs, although their effectiveness is more limited in regions characterised by high ambient temperatures.

To quantify direct operational water consumption, the sector commonly uses the Water Usage Effectiveness (WUE) metric:

$$\mathrm{WUE} = \frac{\text{Annual site water usage}}{\text{ICT Equipment Energy}} \tag{2}$$

WUE is generally expressed in litres per kilowatt-hour (L/kWh). However, this indicator only reflects water consumed directly at the facility and therefore does not capture the additional water footprint associated with electricity generation. For this reason, the broader indicator WUEsource was introduced to account for both operational and energy-related water demand:

$$\mathrm{WUEsource} = \frac{\text{Annual Source Energy water usage} + \text{Annual site water usage}}{\text{ICT Equipment Energy}} \tag{3}$$

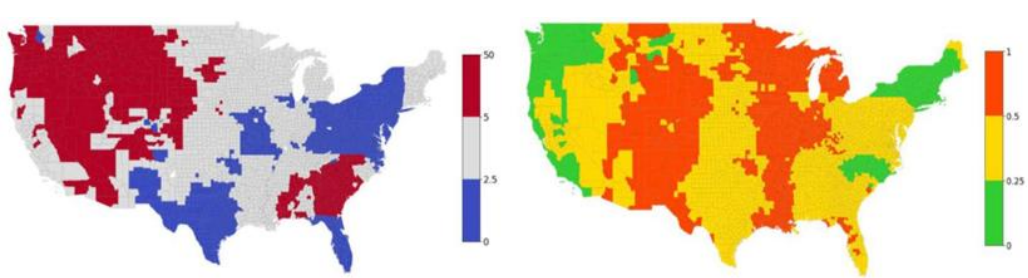
The geographical concentration of AI infrastructure also plays a critical role in determining environmental impacts. The United States currently hosts approximately 40% of global data-centre capacity. Although water use from data centres remains relatively modest at the national scale, local effects may become significant in regions already experiencing hydrological stress. In southwestern states such as Arizona and California, concerns regarding groundwater depletion and competition for municipal water supplies have intensified as new facilities continue to expand [14, 15].

Recent studies indicate that nearly two-thirds of U.S. data centres constructed since 2022 are located in areas classified as highly water stressed [16, 17]. In many cases, these facilities rely on the same municipal water systems that supply households and commercial activities. According to estimates from Lawrence Berkeley National Laboratory, direct water consumption by U.S. data centres reached approximately 17.5 billion gallons in 2023, and future projections suggest that this figure could increase substantially before the end of the decade [18].

Additional modelling studies estimate that annual water demand associated specifically with AI servers in the United States could rise to between roughly 731 and 1,125 billion litres by 2030 under moderate growth scenarios [19]. Importantly, most of this footprint may derive indirectly from electricity production rather than from cooling systems located within the data centres themselves.

The environmental burden associated with AI infrastructure is therefore highly uneven geographically. Facilities located in colder and water-abundant regions may operate with comparatively limited water stress, whereas installations situated in arid areas may intensify pressure on already constrained freshwater resources.

A）



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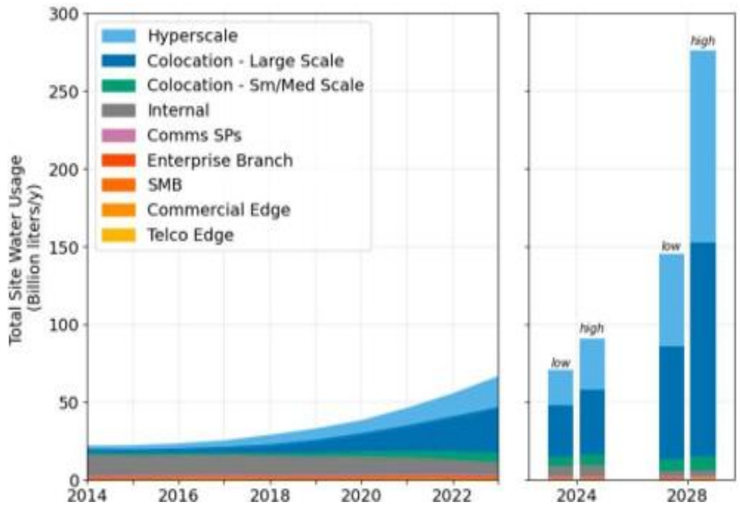

Figure 2. A) Indirect and B) direct water consumption [17]

2. IS AI REALLY A GREAT SOLUTION FOR WATER SAVINGS?

Artificial intelligence is increasingly being presented as a valuable tool for improving water efficiency across multiple sectors. In agriculture, AI-based systems can combine information from soil sensors, meteorological forecasts and crop requirements to optimise irrigation practices and minimise unnecessary water consumption. In urban water networks, machine-learning algorithms are capable of identifying abnormal pressure variations and flow irregularities, enabling earlier leak detection and reducing water losses in distribution systems. AI applications can also support demand forecasting by anticipating consumption peaks and improving resource allocation during drought conditions or periods of water scarcity.

Despite these potential benefits, the rapid expansion of AI infrastructure is simultaneously generating new environmental concerns. Large-scale AI data centres are projected to require enormous quantities of electricity, which may lead to increasing carbon emissions and significant freshwater consumption if energy systems remain strongly dependent on thermal power generation [20]. “The associated water footprint of projected 2030 electricity consumption of data centers is 9.3 trillion liters, or enough to meet the minimum annual domestic water needs of all 1.3 billion residents of Sub-Saharan Africa for a full year” [9].

The central challenge therefore lies in balancing the water-saving capabilities of AI applications with the growing environmental footprint associated with the infrastructure needed to support them.

Recent research conducted by a Stanford University team [20] suggests that waste heat generated by data centres could become an important resource rather than simply a by-product of computation. Advances in high-efficiency chip-cooling technologies may increase the temperature of recoverable waste heat, thereby expanding opportunities for thermal-energy reuse at large scale.

Within this perspective, waste-heat recovery could represent a key strategy for promoting a more circular digital economy. Several applications have been identified as compatible with the temperature ranges commonly produced by data-centre operations (approximately 30–70 °C). These include direct heat utilisation for buildings, industrial processes or district-heating networks; electricity generation through thermal conversion systems; cooling production via absorption chillers; thermal water purification and desalination technologies; atmospheric water harvesting systems based on sorption–desorption cycles; and direct air capture (DAC) technologies for carbon dioxide removal.

This approach highlights the possibility of integrating AI infrastructure into broader sustainability strategies rather than considering data centres exclusively as environmental burdens. Recovered waste heat could contribute to water purification, district heating and carbon-management systems, supporting the transition toward a more water-efficient and resource-conscious economy. Such strategies are also consistent with the objectives of the European Commission's Water Resilience Strategy [1], which promotes water conservation measures and more sustainable management practices across industrial and digital sectors. However, such proposed waste-heat recovery solutions should take into account three issues. The first is the need of high-grade waste heat with liquid cooling. Air cooling, which vents waste heat to the atmosphere at 25-35°C should be substituted with liquid cooling, able to produce high-grade hot water over 45°C. It is expected that in 2026 already, liquid cooling should prevail on air cooling in AI hyperscale builds. The second issue is related to the identification of the right location in the new perspective that waste heat is not a byproduct to be discarded, but a value-adding product that should be routed to existing demand. The third issue to be considered, i.e. sufficient heat demand over time, is strictly related to the second, i.e., the right regional location. colder countries should have a slight advantage. Moreover, in this context, non-urban areas heat sinks such as swimming pools, aquafarming are suitable solutions.

Remarkably, given the high complexity of the problem, SpaceX company argues that placing AI data centers in orbit, powered by solar energy and cooling by radiating heat into space could be the best way to overcome the environmental constraints in terms of water and energy footprint facing current AI data centers [21].

3. CONCLUSION

Although the digital economy is often perceived as immaterial, the infrastructure supporting artificial intelligence relies on highly material resources, including land, electricity and freshwater. AI technologies already contribute to improved water management through applications such as precision agriculture, leak detection and predictive demand analysis. At the same time, however, the rapid expansion of data centres is increasing pressure on energy systems and freshwater resources, particularly in regions affected by water scarcity.

The main challenge is therefore not whether artificial intelligence should continue to develop, but whether this expansion can occur within sustainable environmental and hydrological limits. Addressing this issue will require greater transparency regarding water consumption, wider adoption of reclaimed wastewater, increased reliance on renewable electricity generation and stronger deployment of waste-heat recovery technologies capable of supporting both water-treatment and district-heating systems.

In the coming decades, the interaction between water resources, energy systems and AI infrastructure may become one of the defining sustainability challenges of the digital era. Ensuring that artificial intelligence contributes positively to long-term environmental resilience will require coordinated action from policymakers, researchers and technology companies alike.

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