# Sustainable AI Infrastructure: A Scenario-Based Forecast of Water Footprint Under Uncertainty


Manuel Herrera

*School of Engineering, Newcastle University, UK*

manuel.herrera@ncl.ac.uk

Xiang Xie

*School of Engineering, Newcastle University, UK*

Andrea Menapace

*Free University of Bozen-Bolzano, Italy*

Ariele Zanfei

*AIaqua s.r.l., Italy*

Bruno M. Brentan

*Universidade Federal de Minas Gerais, Brazil*



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# Sustainable AI infrastructure: A scenario-based forecast of water footprint under uncertainty*

Manuel Herrera[a,*], Xiang Xie[a], Andrea Menapace[b], Ariele Zanfei[c], Bruno M. Brentan[d]

[a]*School of Engineering, Newcastle University, Newcastle upon Tyne, NE1 7RU, United Kingdom*
[b]*School of Engineering, Free University of Bozen-Bolzano, Bolzano, 39100, Italy*
[c]*AIaqua s.r.l., Via Volta 13/A, Bolzano, Italy*
[d]*Dipartimento di Ingegneria Civile e Architettura, Universidade Federal de Minas Gerais, Belo Horizonte, 31270-055, Brazil*

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**Abstract**

The rapid expansion of artificial intelligence (AI) and cloud computing is creating a significant but often overlooked impact on global water resources. This paper presents a global assessment of water consumption in AI-driven data centres, distinguishing between operational water use at the facility and at the electricity generation stage, and embodied water associated with hardware manufacturing and supply chain. To anticipate future demand, a scenario-based probabilistic forecasting framework inspired by Bayesian methods is developed, combining sparse empirical data with expert-informed assumptions and policy-relevant growth trajectories for the years 2030 and 2050. Results suggest that, without mitigation, global water use associated with data centres could increase more than seven times by mid-century, with

*Part of the data, visualisation, and code are available on GitHub and Glitch. 

*Corresponding author: manuel.herrera@ncl.ac.uk (Manuel Herrera)

cooling-related operational use accounting for the majority of demand. Several mitigation pathways are identified, including improvements in cooling efficiency, adoption of alternative technologies, and infrastructure planning that takes into account regional water availability. A sensitivity analysis highlights the strong influence of compute growth and efficiency trends on future outcomes. The findings offer a transparent and adaptable basis for aligning AI infrastructure development with long-term water sustainability goals.

*Keywords:* Artificial intelligence, Water footprint, Probabilistic forecasting, Data centres, Digital sustainability

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## 1. Introduction

Artificial intelligence (AI) and cloud computing are reshaping industries, economies, and daily life. By 2030, global AI adoption is projected to reach unprecedented levels. An estimated 70% of companies worldwide will be using AI technologies, becoming up to roughly $15 trillion in economic output and productivity gains. For instance, China alone anticipates a 26% GDP boost from AI by 2030, while it will be around 14% in North America (PwC, 2018). Discussions about the environmental impact of data centres have mostly focused on electricity use. Data centres currently account for 1–2% of global electricity consumption, and this share is expected to increase significantly as AI models become more complex and widespread (Cowls et al., 2023; Sachs, 2024). Their extension in number and use will lead to global electricity consumption potentially exceeding 3,000 TWh annually by 2030 (Masanet et al., 2020). Water use will consequently increase, both directly for cooling and indirectly through electricity generation, which can have a substantial water footprint depending on the energy mix (Oró et al., 2015). Fossil fuel-based power generation, such as coal and natural gas, typically consumes between 2–3 litres per KWh of electricity. Nuclear power (often cited for its low-carbon benefits) can also be water-intensive, especially when once-through cooling systems are used (Jin et al., 2019; Lin et al., 2024).

In response to growing energy demands, companies have invested in renewable energy, efficient processors, and improved energy management systems (Khosravi et al., 2024). Yet water use has received much less attention overall. Data centres rely heavily on water for cooling, particularly in systems such as evaporative towers and direct liquid cooling. Water usage effectiveness (WUE) measures the amount of on-site cooling water used per KWh of energy consumption, while power usage effectiveness (PUE) reflects the ratio of total energy use to IT energy. Operational water includes both on-site cooling water and off-site water used in electricity generation, whereas embodied water use (EWU) refers to the water required to manufacture hardware such as servers, GPUs, and networking components.

Recent studies show that large-scale AI data centres already use millions of litres of water per day (Hao, 2024; Dgtl Infra, 2024; Mytton, 2021). Many of these centres are located in regions with limited freshwater availability, including parts of Latin America, the southwestern United States, India, and Australia (Li et al., 2023). Siting decisions often prioritise proximity to data demand hubs or latency constraints, which may not always align with local environmental or water conditions. In addition, the physical separation between data centre operations, electricity generation, and hardware manufacturing contributes to a dispersed environmental footprint. Actually, off-site water use from power production and the embodied water associated with globally sourced hardware is often manufactured in water-stressed regions, which further complicate sustainability planning (Bolón-Canedo et al., 2024).

Despite the importance of water in the broader sustainability of AI systems, quantitative projections of future demand remain rare, especially those that distinguish between different components of water use or account for uncertainty. Most existing assessments focus on electricity or treat water consumption only in general terms. This gap makes it difficult to plan for sustainable expansion of AI infrastructure. This paper addresses that gap by introducing a scenario-based probabilistic approach to forecast the water footprint of AI data centres. The method separates water use into operational (on-site and off-site) and embodied components and incorporates uncertainty in future trajectories through probabilistic modelling. The analysis considers three distinct scenarios to reflect different technological and policy pathways: a business-as-usual scenario, in which AI compute demand continues to grow rapidly with limited efficiency gains; a moderate intervention scenario, which assumes sustained but slower growth coupled with incremental improvements in infrastructure efficiency; and a sustainable transformation scenario, where AI expansion is stabilised and aggressive measures are taken to reduce water and energy intensity. These scenarios aim to capture a realistic range of future outcomes based on current trends and policy ambitions.

Bayesian-inspired models are well suited to this task, as they enable the integration of sparse empirical data, expert judgment, and scenario-based assumptions (Van de Schoot et al., 2021; Bonomi et al., 2016; Leoni et al., 2021). The analysis focuses on global trends in AI infrastructure, with forecasts until 2050. This time horizon aligns with international sustainability goals, including the UN Sustainable Development Goals and global net-zero commitments for 2030 and 2050. The results offer a structured and transparent basis for more informed planning and policy decisions, particularly in regions already experiencing water stress.

The remainder of the paper is structured as follows. Section 2 introduces the main drivers of water consumption in AI data centres, outlining both the scale of the challenge and a framework for quantifying water use. Section 3 reviews and compares key cooling technologies in terms of their water footprint. Their impacts vary by regional water availability, as further discussed in Section 4. Section 5 presents a probabilistic scenario-based forecasting methodology for global water consumption until 2050, followed by a sensitivity analysis to assess the influence of key parameters. Sections 6 and 7 conclude the paper with a discussion of results, policy implications, and recommendations for a sustainable digital infrastructure, along with a summary of key findings and directions for future research.

## 2. Drivers of AI data centre water consumption

The ongoing expansion of AI and cloud computing has led to a surge in data centre infrastructure, raising serious concerns about water use. AI workloads, in particular, demand far more computational power than traditional applications, which in turn increases the need for intensive cooling and drives up water consumption (Cowls et al., 2023). Data centres have done substantial research on their energy use, but their water footprint has received far less attention. Some projections suggest that data centres could consume around 1.7 billion litres of water per day by 2030 (Bluefield Research, 2023), though this figure may underestimate actual demand given the accelerating deployment of large-scale AI models and the specialised hardware they require. The current section first introduces the scale and significance of the AI water footprint, and then outlines a methodology for quantifying water demand in data centre operations.

### *2.1. AI water footprint: Impact at scale*

The rapid expansion of AI infrastructure, including hyperscale facilities for cloud servers (e.g., operated by Google, Amazon AWS, and Microsoft) and AI data centres dedicated to specialised workloads such as training LLMs or running inference tasks, has intensified concerns over water sustainability. These centres host clusters of high-performance computing infrastructure, such as GPUs and TPUs, which generate substantial heat and require continuous cooling to operate within thermal safety limits. Overall, AI infrastructure relies on computing setups with high power density that concentrate significantly more processing power per unit of space. AI-focused centres frequently exceed 40 kW, with some reaching up to 80 kW for advanced deep learning workloads (Al Kez et al., 2022, 2025), which is significantly higher than standard enterprise centres, typically operating at power densities of 5 to 10 kW.

The elevated power needs of AI data centres amplify thermal loads, making them strongly dependent on cooling systems, many of which consume large volumes of water. This impact becomes clearer when considering real-world examples. Training GPT-3, a large-scale language model (LLM) developed by OpenAI, required around 1,287 MWh of electricity for a single training cycle, an intensive process typically repeated every one to two years to incorporate new data and enhance model performance (De Vries, 2023). Google's Gemini model, another high-end generative AI system, was estimated to use over 1 million litres of water for a single training cycle, depending on region-specific cooling configurations (Leon, 2024). Between these major retraining events, smaller fine-tuning operations are conducted more frequently, usually on a monthly or quarterly basis, albeit with significantly lower resource demands. When cooled using typical evaporative systems, this single training run could consume close to 700,000–1,000,000 litres of water—equivalent to the daily water use of 5,000–7,000 people (Hao, 2024; Bhaskar and Seth, 2024). Yet, the rapid evolution of AI makes GPT-3 appear almost prehistoric, given the emergence of more powerful and resource-intensive successors like GPT-4 (released in 2023) and potentially GPT-5 in the near future. A major GPT-scale training event could translate into a water footprint between approximately 1.9 and 4.9 million litres (given typical cooling efficiencies ranging from 1.5 to 3.8 litres per kWh). These newer generations demand exponentially higher computational resources, driving water consumption even further upward.

The previous examples demonstrate how the resource footprint of AI is already significant and growing. The computational requirements of AI models have been following an exponential trend often referred to as the "AI compute scaling law" (Diaz and Madaio, 2024). Since 2012, the amount of compute needed to train state-of-the-art models has doubled every 3–4 months

(Turchin, 2019), even before the widespread adoption of LLMs like ChatGPT. In production settings, inference (the deployment of trained models) also adds ongoing water demand due to the sustained computational loads it generates. Although individual inference requests consume far less water than initial training, their cumulative impact is substantial, especially as billions of daily interactions with AI services become the norm. Addressing this growing sustainability challenge will require targeted improvements in computational efficiency, cooling technologies, and water management practices. Figure 1 shows the trajectory of AI infrastructure suggests continued and accelerating growth.

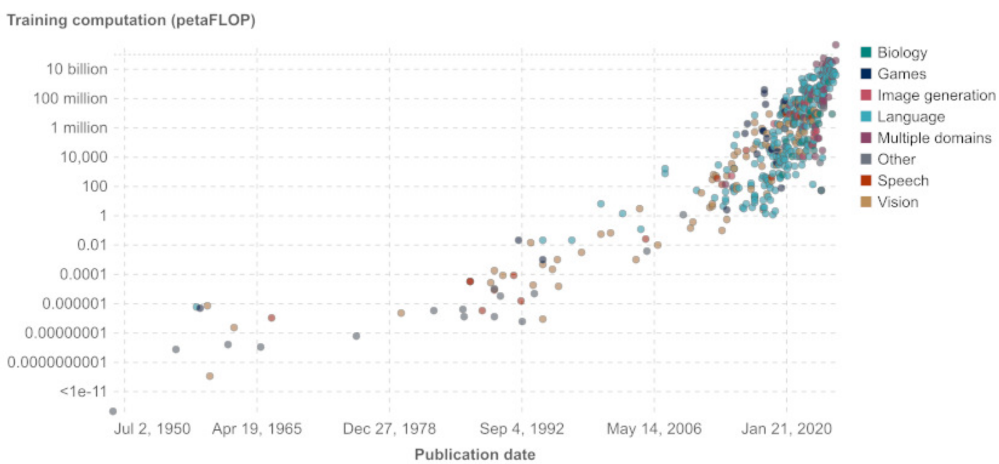


Figure 1: Computation is measured in total petaFLOP, which is $10^5$ floating-point operations. Estimates are expected to be accurate within a factor of 2, or a factor of 5 for recent undisclosed models like GPT-4. Source: OurWorldinData.org/artificial-intelligence

Given the exponential growth described by the "AI compute scaling law", forecasts indicate that computational requirements for frontier models could increase 10- to 100-fold by 2030 (Amodei and Hernandez, 2018; Hoffmann et al., 2022; Zhang et al., 2023). Without proactive measures, such dramatic increases will magnify the environmental impacts of AI, disproportionately affecting regions already experiencing water scarcity. Therefore, addressing the sustainability of AI-related water consumption will become increasingly critical as computational demands continue to escalate.

### *2.2. AI water footprint: Quantification*

Estimating the water footprint of AI-driven data centres requires breaking it down into its core components. This paper adopts a three-part structure, similarly to the framework introduced by Li et al. (2023) that distinguishes between: (1) on-site water use for cooling, (2) off-site water use tied to electricity generation, and (3) embodied water use from hardware manufacturing and supply chain. Equation (1) formalises this breakdown, offering a transparent framework to assess both direct and indirect water impacts from AI infrastructure.

$$W_{\text{tot}}(t) = W_o(t) + W_x(t) + W_e(t), \tag{1}$$

where the total water consumption, $W_{\text{tot}}(t)$, comes defined in terms of all possible data centre water use at time $t$:

- $W_o(t)$: on-site operational water used directly for cooling server hardware,
- $W_x(t)$: off-site water consumed in electricity generation required to power the data centre,
- $W_e(t)$: water embedded in the manufacturing of data centre hardware.

The on-site component is calculated using the water usage effectiveness (WUE), which measures, through Equation (2), cooling water used per unit of IT energy consumed,

$$W_o(t) = e(t) \cdot \rho_o(t), \tag{2}$$

where $e(t)$ is server energy consumption (kWh/day) at time $t$, and $\rho_o(t)$ is the WUE in litres per kWh. WUE varies with cooling technology, facility design, and ambient climate, and tends to be higher in AI-focused centres due to their denser compute configurations.

The off-site component captures the water associated with electricity production. This is estimated using power usage effectiveness (PUE) and the electricity water intensity factor (EWIF), as per Equation (3),

$$W_x(t) = e(t) \cdot \theta(t) \cdot \rho_x(t), \tag{3}$$

where $\theta(t)$ is the PUE, defined as the ratio of total energy input to energy used for computing, and $\rho_x(t)$ is the average water consumption per kWh for electricity generation. EWIF depends heavily on the regional energy mix. Fossil fuel-based electricity typically requires around 2–3 litres per kWh, nuclear generation can have similar or higher water demands depending on cooling technology, while solar and wind are almost water-free (Jin et al., 2019; Lin et al., 2024).

Finally, Equation (4) represents the embodied water. That is the water required to manufacture IT hardware and infrastructure. This is treated as a fixed quantity amortised over the equipment's lifespan,

$$W_e(t) = \frac{T \cdot W}{T_0}, \tag{4}$$

where $W$ is the total water used in production, $T_0$ is the expected lifespan (in years), and $T$ is the duration of analysis. Though smaller in daily volume, this component grows with rapid hardware turnover and increasing demand for high-performance AI processors.

Estimates suggest that producing a single AI accelerator GPU can require between 20,000 and 30,000 litres of water, with AI data centres deploying thousands of such units each year (Davenport et al., 2024). The embodied water footprint is becoming increasingly important as hardware demand grows, refresh cycles shorten, and model complexity increases.

## 3. Cooling systems and their role in operational water demand

The growing computational demands of AI have intensified thermal loads in data centres, placing increasing pressure on cooling systems and their associated water use. While advances in energy efficiency have helped stabilise electricity consumption despite rising service demand (International Energy Agency, 2020; Masanet et al., 2020), maintaining this balance has relied heavily on improvements in cooling infrastructure. This is particularly relevant for AI workloads, which depend on high-performance hardware such as graphics processing units (GPUs) and tensor processing units (TPUs), generating considerably more heat than conventional CPUs (Li et al., 2023).

Cooling demand is further exacerbated by the extended duration of AI training cycles, which can last weeks or even months. Traditional air-based systems are increasingly unable to keep up with these loads, prompting a shift toward more advanced solutions such as liquid and immersion cooling. Liquid cooling offers greater thermal efficiency but often relies on water-based coolants, contributing to total water use. Immersion cooling, which submerges servers in dielectric fluids, can substantially reduce on-site water consumption; however, its adoption remains limited due to technical and infrastructural constraints (Jones, 2018; Gao and Evans, 2021).

The following subsections examine the main cooling systems currently used in AI data centres (air-based, evaporative, and liquid-based approaches) focusing on their water consumption profiles.

### *3.1. Air-based cooling systems*

Air cooling is a widely used method that relies on ventilation systems to dissipate heat from servers. Cool air is circulated through server racks, absorbs heat, and is expelled either directly into the environment or through heat exchangers. Figure 2 illustrates a conventional air cooling setup.

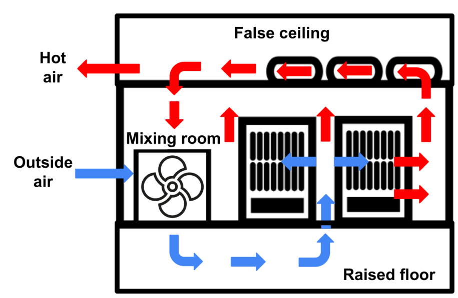


Figure 2: Schematic of a traditional air cooling system used in data centres.

Air cooling has the advantage of minimal direct water use, making it preferable in regions where water scarcity is a concern. However, this method typically requires higher energy input, particularly in warmer climates where mechanical cooling systems must supplement ventilation. Studies suggest that air cooling can increase total data centre energy demand by 10–30% compared to evaporative cooling, depending on ambient temperature and humidity levels (Li et al., 2023).

### *3.2. Evaporative cooling towers*

Evaporative cooling towers are commonly used in large-scale data centres, particularly in regions where water is relatively abundant, due to their high thermal efficiency (Kim et al., 2014; Chu and Huang, 2023). These systems function by circulating heated water through a cooling tower, where it is sprayed onto fill material to maximise surface area. As air passes through the tower, a portion of the water evaporates, carrying away heat. Figure 3 illustrates the evaporative cooling process.

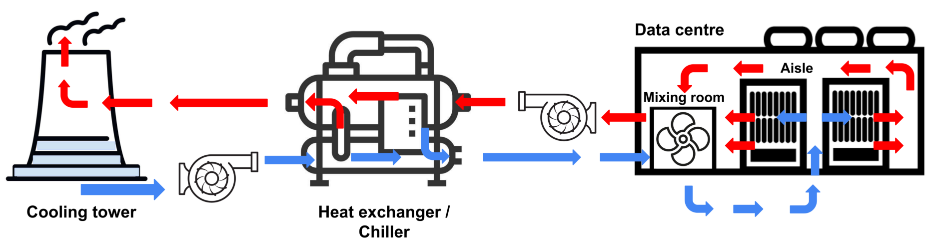


Figure 3: Schematic of a typical data centre evaporative cooling system.

While effective at heat dissipation, evaporative cooling is highly water-intensive. A significant volume of water is lost through evaporation, with additional losses due to blowdown—water discharged to remove accumulated minerals and contaminants (Wang et al., 2024). In hot and arid climates, these systems can consume millions of litres of water annually, raising sustainability concerns (Ristic et al., 2015).

### 3.3. Liquid and immersion cooling

Liquid cooling is gaining traction as a more sustainable alternative, offering high thermal efficiency while reducing water reliance. Two primary techniques are in use:

- *Direct liquid cooling*: A coolant is circulated through cold plates attached to key hardware components such as CPUs and GPUs, drawing heat away efficiently.
- *Immersion cooling*: Servers are fully submerged in dielectric fluid, which absorbs heat and is then cycled through a cooling loop for heat rejection.

Figure 4 shows a schematic of a direct liquid cooling system. In this configuration, liquid coolant is circulated through cold plates that are directly attached to high-heat components such as CPUs and GPUs. The coolant absorbs heat at the source and transports it to a heat exchanger, where the thermal energy is dissipated before the fluid is recirculated. This method provides highly efficient heat removal with minimal thermal resistance, allowing for greater cooling performance in high-density computing environments while significantly reducing reliance on water-intensive evaporative systems.

Liquid cooling significantly reduces water usage, especially in systems where closed-loop coolants replace evaporative methods. It also enables data centres to support higher power densities while reducing cooling energy consumption by up to 50% compared to air-based systems (Google, 2021). However, broader adoption remains limited due to infrastructure costs, integration complexity, and hardware compatibility requirements. Immersion

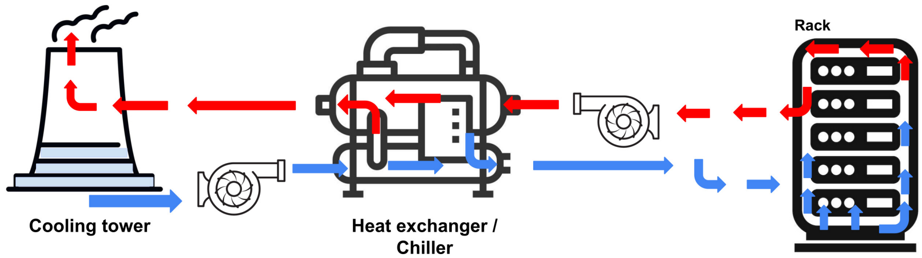


Figure 4: Schematic of a direct liquid cooling solution.

cooling, in particular, demands significant retrofitting and specialised equipment.

### *3.4. Adoption rate of cooling technologies*

Table 1 compares the three main cooling technologies discussed in this section based on qualitative water use, energy efficiency, and adoption level.

Table 1: Comparison of cooling technologies in AI data centres.

| Cooling Method | Water use | Energy efficiency | Adoption level |
|---|---|---|---|
| Air-Based | Low | Moderate–Low | High |
| Evaporative | High | High | High |
| Direct Liquid Cooling | Low | Very High | Emerging |
| Immersion Cooling | Very Low | Very High | Limited |

As AI workloads continue to scale, selecting appropriate cooling strategies, will be essential for ensuring the long-term sustainability of data centre operations, particularly those that minimise water demand.

Recent market reports show that air-based cooling systems remain dominant, with computer room air conditioners and air handlers accounting for a significant share and growing 64% in the US market between 2020 and 2023 (Research, 2024). However, the shift toward AI and high-density computing is driving increased adoption of advanced cooling methods. The global liquid cooling market is projected to grow from $5.65 billion in 2024 to over $48 billion by 2034 (GlobeNewswire, 2025). Immersion cooling, in particular, is gaining traction in North America, which held more than 35% of the global market share in 2023 (Global Market Insights Inc., 2023). These trends indicate a growing transition toward more water- and energy-efficient thermal management strategies.

## 4. Regional variations in data centre water usage

Water consumption in AI data centres is not uniform across the globe. Facility clusters tend to emerge in regions with strong digital infrastructure, tax incentives, and access to renewable energy. However, many of these locations coincide with areas already experiencing water stress, exacerbating competition between data centres, agriculture, and residential use. This geographic mismatch raises environmental and social concerns, particularly where water-intensive cooling technologies are deployed without adequate regulation or local consultation. Moreover, regional disparities in data availability and transparency can complicate assessments of water use and hinder long-term planning.

Figure 5 illustrates the global distribution of major data centres as of 2025, overlaid with national water stress levels. Data centre deployment remains heavily concentrated in regions such as North America, Europe, India, and parts of Oceania. These locations reflect established digital infrastructure hubs, though not always aligned with regional water sustainability. Data centres number by country were compiled from Data Center Map (2025), while World Resources Institute (2024) provides water stress classifications.

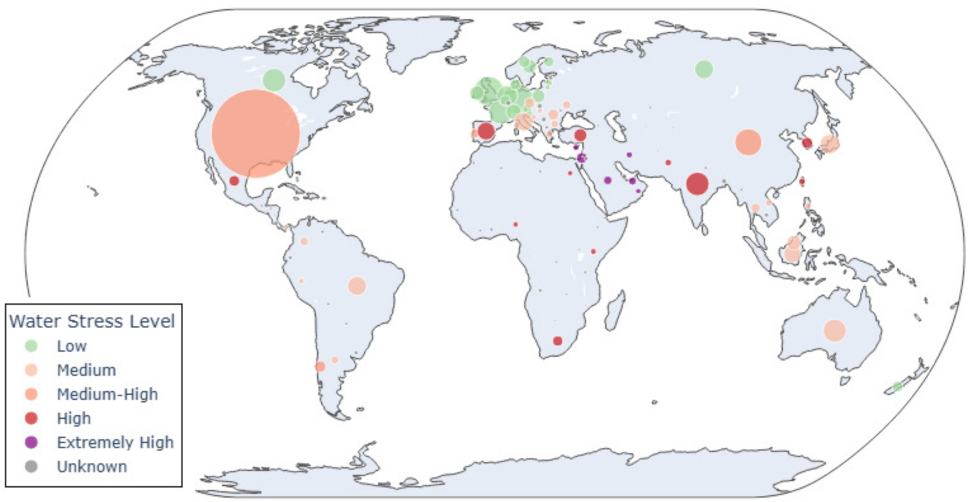


Figure 5: Global distribution of data centres and national water stress levels. The size of the bubble is proportional to the number of data centres, while the colour relates to water stress: from green (low) to purple (extremely high). Interactive HTML version and underlying data are available on GitHub and Glitch.

Figure 5 shows how the United States hosts by far the largest number of data centres, yet many of these are situated in regions classified as having medium-high water stress. India, a rising digital powerhouse, also shows substantial growth in data centre infrastructure despite facing high water stress across much of the country. In Europe, Spain stands out as a nation with high water stress yet a significant number of facilities, in contrast to nearby countries like Germany or the United Kingdom, where water stress is generally lower. A number of local but representative examples of the growing tension between AI-driven computational expansion and increasingly strained water resources is enumerated in the following bullet points:

- In the United Kingdom, Thames Water has raised concerns over the impact of data centre water consumption, warning that restrictions may be imposed during heatwaves (Zuo et al., 2015; BBC News, 2025).

- In the southwestern United States, major tech companies in Arizona and Virginia consume millions of litres of water daily, leading to mounting public scrutiny and regulatory discussions on sustainable cooling practices (Mytton, 2021). Some operators have begun exploring the use of recycled water and liquid cooling to reduce dependency on potable sources.

- In China, data centres water use is expected to exceed three billion cubic meters annually by 2030. Most facilities are concentrated in the country's northern provinces, many of which already experience chronic water scarcity. In response, national policy initiatives are encouraging a shift toward less water-intensive cooling solutions (e.g., direct liquid and air-based cooling) and greater adoption of renewable energy (He et al., 2019).

- Latin America has also seen a rapid rise in data centre construction, often in areas lacking the infrastructure to support industrial-scale water use. In countries like Chile and Brazil, this has sparked debate over the long-term viability of data centre evolution under worsening drought conditions (Farfan and Lohrmann, 2023).

These regional disparities emphasise the need for context-specific water management strategies that account for local hydrological conditions, infrastructure constraints, and regulatory frameworks. They also highlight the importance of anticipating regional vulnerability when projecting future demand.

The Köppen climate classification offers an additional perspective for evaluating regional suitability. It categorises global regions based on long-term temperature and precipitation patterns (Beck et al., 2018), providing an eco-climatic lens often linked to vegetation cover and water resource availability (Sohoulande, 2024). Arid climates, such as BWh (hot desert) and BSh (hot semi-arid), include regions like the southwestern United States, northern Mexico, Australia, and northern Africa. These areas are poorly suited for water-intensive cooling systems like evaporative towers, as their high temperatures, low humidity, and limited freshwater availability exacerbate evaporative losses and strain local water resources. Temperate climates, in contrast, including Cfb (temperate oceanic) and Cfa (humid subtropical), offer more favourable conditions for air-based or hybrid cooling systems thanks to lower ambient temperatures and higher humidity levels. Incorporating Köppen-based climate criteria into siting assessments can help align infrastructure development with regional water sustainability, particularly as climate variability and digital infrastructure demand increase globally.

Cooling systems are not the only factor influencing water use. Policy, operational practices, and infrastructure design also affect overall demand. The next section presents forecast scenarios for 2030 and 2050, using a probabilistic framework to examine potential outcomes under different trajectories of growth and efficiency.

## 5. Forecast scenarios for 2030 and 2050: A probabilistic scenario-based approach

Accurately estimating the future water footprint of AI-driven data centres is challenging due to the lack of high-resolution global data and the rapid pace of technological change. Traditional forecasting methods, which rely heavily on historical trends, are poorly suited to emerging infrastructures such as large-scale AI deployments, where future demand is shaped not by past behaviour, but by evolving models, hardware, and operational strategies.

This paper adopts a probabilistic scenario-based forecasting framework to address the above challenges. This semi-quantitative approach is particularly appropriate in data-scarce contexts, as it allows uncertainty to be handled transparently by combining sparse empirical observations with expert-informed assumptions. It models three key components of water use: on-site operational, off-site operational (linked to electricity generation), and embodied water (linked to hardware manufacturing and supply chain). Ultimately, the proposal generates probabilistic estimates rather than single-point predictions.

Scenario-based forecasting is used to explore a range of plausible futures in the absence of reliable trend data. The three scenarios used are business-as-usual, moderate intervention, and sustainable transformation. They represent different trajectories of compute evolution and efficiency improvements. The probabilistic approach enables a more robust and flexible assessment of long-term water demand under uncertainty, providing useful guidance for infrastructure planning and environmental governance.

### 5.1. Probabilistic scenario-based forecasting

The forecasting approach uses Monte Carlo simulation to propagate uncertainty in model parameters and compute global water demand under different future scenarios. Although it does not implement full Bayesian inference, it incorporates prior assumptions about input variables and generates probabilistic estimates of future outcomes. This setup allows us to explore a range of plausible trajectories given current knowledge, scenario-specific assumptions, and anticipated efficiency improvements.

The forecast years 2030 and 2050 are particularly interesting as they align with international environmental targets, including the UN Sustainable Development Goals and the European Union's Green Deal horizon. The prior distributions for model inputs are defined based on current conditions, including server electricity consumption in the base year 2025, denoted as $e(2025)$. This is modelled as a Normal distribution, as shown in Equation (5), using industry estimates for AI infrastructure (Masanet et al., 2020).

$$e(2025) \sim \mathcal{N}(\mu = 1.0 \times 10^9, \sigma = 0.1 \times 10^9) \quad \text{(kWh/day)}. \tag{5}$$

Parameters for water-related efficiency: WUE, PUE and EWIF, that is $\rho_1(t)$, $\theta(t)$, and $\rho_2(t)$, respectively; are treated as deterministic values that improve incrementally each year. Based on recent technical reports and industry trends (International Energy Agency, 2020; Google, 2021), annual efficiency improvements in the range of 0.5–1% are assumed. These rates reflect modest but realistic gains from gradual adoption of more efficient cooling technologies, infrastructure optimisation, and cleaner energy sources. The embodied water use (EWU) is similarly assumed to improve at a fixed annual rate, denoted EWU$^*$, as manufacturing processes and supply chains become more efficient.

Computational expansion rates are scenario-dependent, considering three representative cases:

- *Business-as-usual* (BAU): AI use continues to grow rapidly, with compute demand increasing by 10% per year.

- *Moderate intervention*: Growth slows due to policy and efficiency measures, with compute demand rising by 5% per year.

- *Sustainable transformation*: No further growth in compute demand; AI infrastructure stabilises at current levels.

These scenarios represent plausible upper, middle, and lower bounds of future AI adoption, based on historical data and expert forecasts (Amodei and Hernandez, 2018; Zhang et al., 2023; Hoffmann et al., 2022). This three-tier scenario structure is inspired by frameworks commonly used in climate policy modelling, especially those assessing greenhouse gas trajectories. The BAU case corresponds to a continuation of current trends without significant mitigation, analogous to baseline emissions scenarios. The moderate intervention scenario aligns with intermediate mitigation pathways, where policy and technological improvements yield gradual reductions in impact. The sustainable transformation case mirrors net-zero policy ambitions, involving aggressive shifts in infrastructure, energy efficiency, and environmental stewardship. Drawing this parallel underscores the importance of water governance in AI infrastructure, similar to that of carbon management in climate action. Comparable scenario structures have been widely adopted in climate modelling literature, such as the Shared Socioeconomic Pathways (SSPs) developed by the Intergovernmental Panel on Climate Change (IPCC) (Riahi et al., 2017).

Using the defined scenario-specific growth rates, baseline energy consumption, and incremental improvements in efficiency parameters (WUE, PUE, EWIF, and EWU), the process constructs likelihood functions based on plausible developments in computational demand, cooling performance, and hardware turnover.

Monte Carlo simulation is applied with 10,000 iterations to generate probabilistic estimates of future water demand across the defined scenarios. In each iteration, random samples are drawn from the prior distributions, and total water demand is computed using Equation (1). This process makes it possible to trace how uncertainty in the inputs, such as future energy use or efficiency gains, shapes the range of possible outcomes (Zhang, 2021). Monte Carlo methods are particularly well-suited to contexts where uncertainty is high and model variables interact in complex ways. Rather than producing a single forecast, the simulation yields a range of plausible outcomes, helping to assess how different assumptions influence projected water consumption. For each forecast year and scenario, this results in an empirical distribution of daily water demand values that captures the variability in the underlying inputs.

Let $\{w_t^{(1)}, w_t^{(2)}, \ldots, w_t^{(N)}\}$ be the set of $N = 10,000$ model outputs computed using Equation (1) for year $t$. The 90% credible interval is constructed as the central interval containing 90% of the distribution mass, as shown in Equation (6),

$$\mathrm{CI}_{90\%}(W_t) = [q_{0.05}, q_{0.95}]\,, \tag{6}$$

where $q_{0.05}$ and $q_{0.95}$ are the 5th and 95th percentiles of the sorted simulated values, respectively. These quantiles are computed non-parametrically, without assuming any specific distribution shape. The resulting 90% credible interval reflects the range within which the true value of $W_t$ lies with 90% probability, conditional on the data and prior-informed assumptions (Gelman et al., 2015).

Algorithm 1 summarises the full computational workflow used to generate the scenario-based forecasts. It outlines the sampling of prior distributions, the forward projection of efficiency parameters, and the iterative computation of total water demand across all scenarios and years, including the construction of simulated means and credible intervals. Note that in, Algorithm 1, superscript asterisks ($^*$) denote annual improvement rates for each efficiency parameter. The framework could be adapted to include spatial disaggregation using location-specific efficiency parameters, subject to data availability. We considered this extension out of the current scope and is discussed as future research in Section 7.

**Algorithm 1** Monte Carlo simulation algorithm for scenario-based forecasting of annual water consumption (2025–2050) in AI data centres

**Input:** Prior distribution for server energy use $e_{2025} \sim \mathcal{N}(\mu, \sigma)$
Initial values for WUE $\rho_1(2025)$, PUE $\theta(2025)$, EWIF $\rho_2(2025)$
Annual improvement rates: WUE$^*$, PUE$^*$, EWIF$^*$, EWU$^*$
Initial embodied water use $W_{\text{emb}}(2025)$ and equipment lifespan $T_0$
Scenario-specific compute growth rate $g$
**Output:** Simulated distribution of $W_{\text{T}}(t)$ for each year $t = 2025$ to 2050

**for** each scenario in {BAU, Moderate, Sustainable} **do**
  **for** each year $t$ from 2025 to 2050 **do**
    $y \leftarrow t - 2025$ ▷ Years since base year
    Sample $N$ values of $e^{(i)}(2025) \sim \mathcal{N}(\mu, \sigma)$
    Compute $e^{(i)}(t) = e^{(i)}(2025) \cdot (1 + g)^y$
    Update parameters:
      $\rho_1(t) = \rho_1(2025) \cdot (1 - \text{WUE}^*)^y$
      $\theta(t) = \theta(2025) \cdot (1 - \text{PUE}^*)^y$
      $\rho_2(t) = \rho_2(2025) \cdot (1 - \text{EWIF}^*)^y$
      $W_{\text{emb}}(t) = W_{\text{emb}}(2025) \cdot (1 - \text{EWU}^*)^y / T_0$
    **for** each $i = 1$ to $N$ **do**
      $W_{\text{on}}^{(i)}(t) = e^{(i)}(t) \cdot \rho_1(t)$
      $W_{\text{off}}^{(i)}(t) = e^{(i)}(t) \cdot \theta(t) \cdot \rho_2(t)$
      $W_{\text{T}}^{(i)}(t) = \left(W_{\text{on}}^{(i)}(t) + W_{\text{off}}^{(i)}(t)\right)/10^9 + W_{\text{emb}}(t)/10^9$
    **end for**
    Store simulated mean and credible interval of $W_{\text{T}}(t)$
  **end for**
**end for**

### *5.2. Probabilistic scenario projections from scenario-based simulations*

The scenario simulations provide a probabilistic view of global water consumption for AI data centres under the three defined scenarios. Table 2 summarises the results, reporting the mean estimates and 90% credible intervals for the years 2030 and 2050.

Table 2: Probabilistic scenario projections of global data centre water consumption (billion litres/day).

| Scenario | 2030 | 2050 |
|---|---|---|
| Business-as-usual (BAU) | 4.18 [3.67–4.68] | 28.11 [24.71–31.47] |
| Moderate intervention | 3.06 [2.68–3.44] | 8.36 [7.31–9.72] |
| Sustainable transformation | 1.86 [1.63–2.09] | 1.38 [1.15–1.61] |

These projections highlight the influence of both computational use and efficiency gains. Under the BAU scenario, global water demand is projected to increase nearly sevenfold between 2030 and 2050. In contrast, moderate intervention results in a more manageable trajectory, while the sustainable transformation scenario leads to a net reduction in water use by mid-century.

The results align with recent concerns raised in studies on the environmental impact of AI infrastructure. For example, Hao (2024) estimate that global water consumption by data centres could exceed 20 billion litres/day by 2050 under baseline assumptions—closely matching the trajectory of BAU scenario. However, the framework presented here adds a probabilistic interpretation that accounts explicitly for uncertainty and expert-informed variability. Figure 6 visualises the simulated means and 90% credible intervals for each scenario.

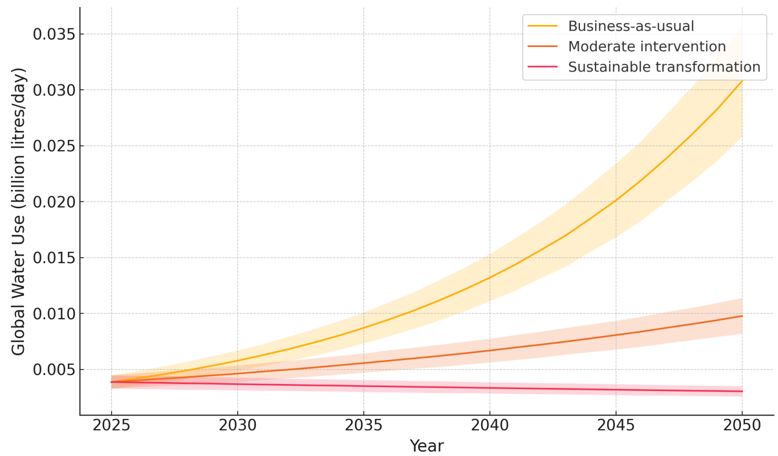


Figure 6: Simulated mean estimates and 90% credible intervals for data centre water consumption under each scenario.

These results reflect the importance of policy and design interventions. Under a BAU trajectory, exponential increasing trend in water use could intensify water stress in already vulnerable regions. Moderate growth coupled with efficiency improvements yields significant reductions, while the sustainable transformation scenario suggests that systemic changes, such as transitioning to non-water-based cooling and extending hardware lifespans, can decouple AI adoption from rising water consumption.

Achieving the sustainable scenario will require a combination of regulatory measures, technological innovation, and forward-looking infrastructure planning.

### *5.3. Sensitivity analysis*

A sensitivity analysis was conducted how changes in key efficiency parameters affect long-term water projections, a relative sensitivity analysis was conducted for the year 2050. The analysis evaluates the impact of ±20%

changes in input parameters (WUE, PUE, EWIF, and EWU) on total projected water demand under the BAU scenario.

Figure 7 presents the results as a tornado plot, showing the relative change in 2050 water use compared to the baseline. WUE has the highest influence on water demand, followed closely by EWIF and PUE, which together govern the operational water footprint. EWU shows a smaller, but still relevant, impact, consistent with its amortised contribution to daily water use.

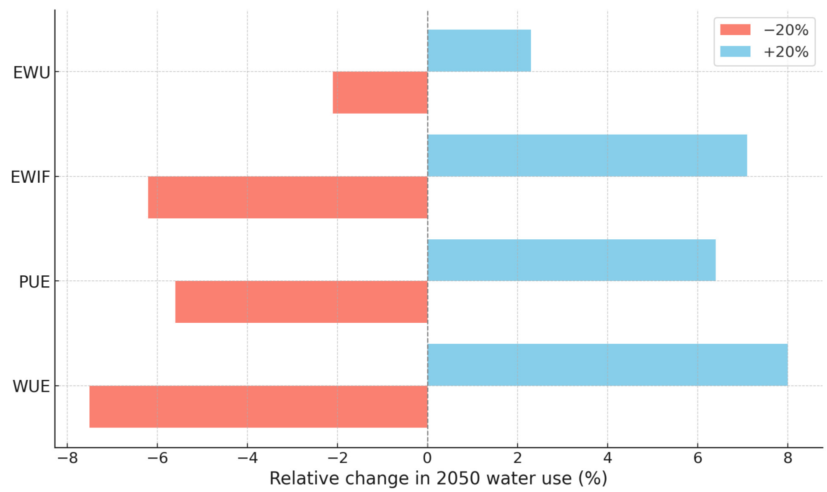


Figure 7: Sensitivity of 2050 water use forecasts to ±20% changes in key input parameters, relative to BAU baseline.

Table 3 shows how these relative differences translate into absolute changes in projected water consumption. Under the BAU baseline of 28.11 billion litres/day, a 20% improvement in WUE corresponds to a reduction of 4.69 billion litres/day, while a deterioration increases water use by a similar amount. Comparable absolute effects are observed for EWIF and PUE, with differences of 4.24 and 4.02 billion litres/day, respectively. EWU contributes a smaller difference of 1.29 billion litres/day, reflecting the lower sensitivity of the embodied component.

Table 3: Absolute differences (billion litres/day) in projected 2050 water demand under ±20% parameter shifts. BAU baseline = 28.11 billion litres/day

| Parameter | Relative diff. (%) | Abs. diff |
|---|---|---|
| WUE | 16.7% | 4.69 |
| PUE | 14.3% | 4.02 |
| EWIF | 15.1% | 4.24 |
| EWU | 4.6% | 1.29 |

This analysis highlights that improvements in cooling and power infrastructure have the greatest potential for reducing long-term water demand. Nonetheless, advances in hardware design and procurement practices also play a role and should not be overlooked in water sustainability strategies.

## 6. Discussion and recommendations

This section examines the implications of projected water demand from AI data centres. The analysis shows that cooling systems are the primary driver of water use, and that without targeted intervention, global consumption could rise sharply by mid-century. A scenario-based probabilistic framework was used to identify key leverage points for mitigation and to support planning under uncertainty. The discussion is organised around interpretation of the results, evaluation of the modelling approach, and policy and design recommendations for reducing the water footprint of AI infrastructure.

### *6.1. Interpreting the scenarios: Trade-offs and leverage points*

The analysis shows that global water consumption by AI data centres could rise dramatically by 2050, particularly under a BAU trajectory driven by increasing model complexity and compute demand. However, the results also show that this trend is not inevitable. If the industry adopts more efficient cooling systems and moderates infrastructure expansion, water demand could be substantially reduced, even under moderate compute growth.

The sensitivity analysis confirms that operational water use dominates total demand and is most responsive to improvements in water usage effectiveness (WUE) and power usage effectiveness (PUE). Embodied water use (EWU) contributes a smaller share but remains relevant, particularly as hardware refresh cycles shorten.

These findings suggest that water sustainability cannot be achieved through energy decarbonisation alone. A wider view is needed to integrate water, energy, and emissions into the design and operation of AI infrastructure.

### *6.2. Probabilistic scenario-based framework: Strengths and limitations*

The scenario-based approach used in this study is well-suited to situations where data is scarce or changing rapidly. It combines expert judgement with scenario-based assumptions to handle uncertainty in a transparent way. This makes it particularly useful for forecasting the environmental impacts of fast-moving technologies like AI.

A key strength of the probabilistic scenario-based approach is its ability to produce credible forecasts without relying on comprehensive historical datasets, a common limitation in the context of private digital infrastructure. Many companies do not publicly disclose detailed water usage statistics due to commercial sensitivities or cybersecurity concerns, making it difficult to build traditional models. This reinforces the value of probabilistic forecasting tools that are robust to data scarcity while still supporting policy making.

Nevertheless, the framework has limitations. Relationships between variables are treated as static, and the assumptions driving input distributions are necessarily simplified. In reality, technological disruption and regional feedback loops may introduce nonlinear effects that future models should seek to capture. Incorporating real-time monitoring data and adapting the model into a dynamic Bayesian framework are promising directions for improving accuracy.

*6.3. Interpretation of results and policy implications*

The scenarios presented here have clear implications for water governance in the AI age. Without targeted interventions, global water use could increase by nearly sevenfold by 2050, largely driven by computational trending use and the power density of AI workloads. While energy-related emissions have received considerable attention, water consumption remains a largely underappreciated consequence of AI scaling. The scenario design also reflects a conceptual parallel to climate mitigation pathways, suggesting that water-related impacts of AI infrastructure may benefit from policy tools, scenario planning, and regulatory foresight similar to those used in carbon emissions governance.

Water-related tensions surrounding data centre operations are emerging in many regions, particularly where infrastructure expansion overlaps with existing water stress. These conflicts are likely to intensify as extreme weather events become more frequent and climate variability increases. Several utilities and regulators have already signalled the possibility of restricting water access for data centres during periods of drought or peak demand (BBC News, 2025). Such developments reinforce the point that strategies centred solely on energy decarbonisation are insufficient. Water sustainability must be treated as a core pillar of responsible AI infrastructure planning.

At the same time, it is important to recognise that certain AI applications actively contribute to environmental sustainability. Models developed for smart grid management, building optimisation, climate forecasting, and ecosystem monitoring offer tangible benefits for energy and water efficiency. These workloads can support mitigation and adaptation goals across multiple sectors. Encouraging such environmentally focused AI, while managing the resource intensity of large-scale generative models, could help align digital innovation with broader climate and sustainability agendas.

Achieving reductions in water use will require adoption of water-efficient cooling technologies (e.g., liquid and immersion cooling), shifts to renewable and low-water energy sources, and regulations that account for EWU in hardware procurement and life cycle assessments. International standards for sustainability reporting and site location planning could also help prevent water stress clustering across borders. Current frameworks such as the EU's Green Deal and state-level regulations in the US (e.g., California's Water Conservation Act) offer promising models for implementation (Commission, 2020; California Department of Water Resources, 2023).

Technological developments, such as AI-based energy optimisation and modular data centre design, could further reduce both operational and embodied water demands. Based on the paper findings, it is recommended a multi-pronged strategy to support sustainable AI infrastructure:

- Accelerate deployment of low-water and closed-loop cooling technologies, including direct liquid and immersion systems (Microsoft, 2020; Google, 2021).
- Incorporate grey-water and non-potable sources for data centre cooling, especially in regions facing municipal water stress (Farfan and Lohrmann, 2023).
- Promote real-time cooling optimisation through AI-driven management systems.
- Require disclosure of water use metrics (e.g., WUE, EWIF, EWU) in sustainability reporting frameworks (United Nations, 2019).
- Integrate water availability into data centre siting decisions to avoid clustering in already-stressed regions.

## 7. Conclusions

This paper introduces a scenario-based framework for forecasting the global water footprint of AI-driven data centres. It offers a structured quantification of on-site, off-site, and embodied water use, and applies a probabilistic simulation approach to generate forecasts until 2050 under varying assumptions of technological growth and efficiency. The approach provides a flexible tool for strategic planning, particularly in data-sparse environments, and identifies which technical factors have the most leverage for reducing long-term demand (i.e., cooling efficiency, compute growth). This information can support infrastructure design, sustainability reporting, and policy development.

The findings suggest that, if current trends continue unchecked, global data centre water demand could increase more than sevenfold by mid-century. However, this trajectory is not inevitable. Improvements in cooling performance, the adoption of alternative water sources, and better alignment between siting decisions and regional climate conditions could substantially curb demand. While the current model operates at a global scale, incorporating geospatial variation represents a valuable extension. A regionally disaggregated version could express water demand as a summation over all regions, each with location-specific parameters for WUE, EWIF, and embodied water intensity. This would better capture the uneven distribution of infrastructure and environmental pressure, offering stronger guidance for climate-aligned siting decisions and water governance.

Future work should develop regionalised models that reflect country-level differences in climate, infrastructure, electricity mix, and regulatory conditions. Indexing water use by region or country would allow for integration of data centre density, cooling technology adoption, and local water stress. Dynamic Bayesian models could also be explored to incorporate real-time data as it becomes available. Finally, integrating water, energy, and emissions into a unified sustainability metric would provide a more comprehensive assessment of AI's environmental impact.

The growth of AI does not have to come at the expense of water resources. With the right technologies, policies, and foresight, digital expansion and environmental responsibility can advance together. Strategic improvements in cooling systems (WUE), electricity sourcing (EWIF), and hardware lifecycle management (EWU) could reduce 2050 water use by up to 95% relative to business-as-usual scenarios. Realising this potential will require coordinated action from industry, regulators, and researchers to:

- Accelerate the deployment of immersion and closed-loop cooling technologies;
- Develop standardised frameworks for water accounting across operational and embodied domains;
- Enforce climate-aware siting policies that reflect regional water constraints;
- Fund research, development, and demonstration (RD&D) of water-efficient AI hardware and systems.

Improved transparency from technology providers, especially around real-time water use, will also support more accurate forecasting and help guide long-term planning for sustainable infrastructure.

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