

# Making AI Less “Thirsty”: Uncovering and Addressing the Secret Water Footprint of AI Models

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## Abstract

The growing carbon footprint of artificial intelligence (AI) models, especially large ones such as GPT-3, has been undergoing public scrutiny. Unfortunately, however, the equally important and enormous water (withdrawal and consumption) footprint of AI models has remained under the radar. For example, training GPT-3 in Microsoft’s state-of-the-art U.S. data centers can directly evaporate **700,000 liters** of clean freshwater, but such information has been kept a secret. More critically, the global AI demand may be accountable for 4.2 – 6.6 billion cubic meters of water withdrawal in 2027, which is more than the total annual water withdrawal of 4 – 6 Denmark or half of the United Kingdom. This is very concerning, as freshwater scarcity has become one of the most pressing challenges shared by all of us in the wake of the rapidly growing population, depleting water resources, and aging water infrastructures. To respond to the global water challenges, AI models can, and also must, take social responsibility and lead by example by addressing their own water footprint. In this paper, we provide a principled methodology to estimate the water footprint of AI models, and also discuss the unique spatial-temporal diversities of AI models’ runtime water efficiency. Finally, we highlight the necessity of holistically addressing water footprint along with carbon footprint to enable truly sustainable AI.

## 1 Introduction

- “Water is a finite resource, and every drop matters.” — *Facebook (now Meta) Sustainability Report 2020* [1].
- “Fresh, clean water is one of the most precious resources on Earth ... Now we’re taking urgent action to support water security and healthy ecosystems.” — *Google’s Water Commitment 2023* [2].
- “Water is a human right and the common development denominator to shape a better future. But water is in deep trouble.” — *U.N. Secretary-General António Guterres at the U.N. Water Conference 2023* [3].
- “Historic droughts threaten our supply of water ... As the source of both life and livelihoods, water security is central to human and national security.” — *U.S. White House Action Plan on Global Water Security 2022* [4].

Artificial intelligence (AI) models have witnessed remarkable breakthroughs and success in numerous areas of critical importance to our society over the last decade, including in the ongoing combat against several global challenges such as climate change [5]. Increasingly many AI models are trained and deployed on power-hungry servers housed inside warehouse-scale data centers, which are often known as energy hogs [6]. Consequently, despite the numerous benefits and potential of AI, the environmental footprint of AI models, in particular carbon footprint, has been undergoing public scrutiny, driving the recent progress in AI carbon efficiency [7–11]. Unfortunately, however, the enormous water footprint of AI models — many millions of liters of freshwater *withdrawn* or *consumed* for electricity generation and for cooling the servers — has largely remained under the radar. If not properly addressed, the increasing water usage can become a potential major roadblock to the socially responsible and environmentally sustainable AI in the future.

Despite the water cycle through our planet’s natural ecosystem, clean freshwater resource available and suitable for use is extremely limited and unevenly distributed across the globe. In fact, freshwater scarcity is one of the most pressing challenges shared by all of us in the wake of the rapidly growing population and extended megadroughts [12, 13]. Severe water scarcity has already been affecting 4 billion people, or approximately two-thirds of the global population, for at least one month each year [13, 14]. Without integrated and inclusive approaches to addressing the global water challenge, nearly half of the world’s

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population will endure severe water stress by 2030 [4], and roughly one in every four children worldwide will be living in areas subject to extremely high water stress by 2040 [14].

Warehouse-scale data centers — physical “homes” where many AI models, especially large ones like GPT-3 and GPT-4 for language services, are physically trained and deployed — are known to be energy-intensive, collectively accounting for about 1-2% of the global electricity usage [6]. As such, it is well-known that data centers are responsible for a significant scope-2 carbon footprint associated with location-based electricity generation [7, 15–17]. Nonetheless, what is much less known is that data centers are also extremely “thirsty” — even excluding the embodied water usage due to supply chains (e.g., scope-3 water for chip manufacturing), data centers use an enormous amount of water for both on-site cooling and off-site electricity generation [18, 19], which, similar to the scope definitions for carbon emissions, are referred to as scope-1 and scope-2 water usage, respectively [20].

Even putting aside the water usage in leased third-party colocation facilities, Google’s self-owned data centers alone directly withdrew 25 billion liters and consumed nearly 20 billion liters of scope-1 water for on-site cooling in 2022, the majority of which was potable water [21].<sup>2</sup> Overall, Google’s data center water usage (both withdrawal and consumption) in 2022 increased by 20% compared to 2021 [21, 22], and Microsoft’s total water usage even saw a 34% increase for the same period [23]. Such significant increases are likely attributed in part to the growing demand for AI.

In addition, the combined on-site scope-1 and off-site scope-2 global water withdrawal of Google, Microsoft, and Meta reached an estimate of **2.2 billion cubic meters** in 2022, equivalent to the total annual water withdrawal (including municipal, industrial, and agricultural usage) of two Denmark [24].<sup>3</sup> This includes **1.5 billion cubic meters** of water withdrawal in the U.S., accounting for about **0.33%** of the total U.S. annual water withdrawal. Simultaneously, out of the total global water withdrawal, approximately 0.18 billion cubic meters (including 0.13 billion cubic meters in the U.S.) was “lost” due to evaporation and hence considered “consumption”, which was even more than the total annual water *withdrawal* of Liberia (a country of about 5 million people in West Africa) [24]. Note that [24] does not provide country-wide water consumption data. As a rule of thumb, the ratio of water consumption to water withdrawal varies from 5 to 15% in urban areas and from 10 to 50% in rural areas [26]. The growing tension over the enormous water usage between data centers and human needs may create new environmental risks and even social conflicts (e.g., the protest against Google’s planned data center construction in Uruguay amid its extended drought [27]).

AI represents one of the most prominent and fastest expanding workloads in data centers [7, 28, 29]. For example, a recent study suggests that the global AI demand might consume 85–134 TWh of electricity in 2027 [30]. If this estimate materializes, the combined scope-1 and scope-2 operational water withdrawal of global AI may reach **4.2 – 6.6 billion cubic meters** in 2027, which is more than the total annual water withdrawal of **4 – 6 Denmark** or **half of the United Kingdom** that is currently under the threat of droughts [31]. If the U.S. hosts half of the global AI workloads, the operation of AI may take up about 0.5 – 0.7% of its total annual water withdrawal. Additionally, the total scope-1 and scope-2 water consumption of global AI may exceed 0.38 – 0.60 billion cubic meters, i.e., roughly evaporating the annual water *withdrawal* of half of Denmark or 2.5 – 3.5 Liberia. Therefore, AI models can, and also must, take social responsibility and lead by example in the collective efforts to combat the global water scarcity challenge by cutting their own water footprint.

Despite its profound environmental and societal impact, however, the enormous water footprint of AI models has received disproportionately less attention from the AI community as well as the general public. For example, while the scope-2 carbon emissions are routinely included as part of AI model cards [32], even scope-1 water usage (either withdrawal or consumption) is missing, let alone scope-2 water usage. This may impede innovations to enable water sustainability and build truly sustainable AI. Importantly, water and carbon footprints are complementary to, not substitutable of, each other for understanding the environmental impacts [33]. Indeed, optimizing for carbon efficiency does not necessarily result in, and

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<sup>2</sup>The detailed difference between water *withdrawal* and water *consumption* is presented in Section 2.1.

<sup>3</sup>As data centers predominantly rely on the electric grid instead of being directly powered by renewables [23, 25], our scope-2 water withdrawal (and consumption if applicable) is for *location*-based electricity generation throughout the paper. The detailed calculation method is available in the appendix. Nonetheless, Google, Microsoft, and Meta often adopt alternative sustainability programs (e.g., renewable purchasing agreements) to offset their location-based electricity usage and thus have lower or zero *market*-based carbon and water footprints. The current ESG reports typically include both location-based and market-based carbon emissions.

may even worsen, water efficiency, which varies with the energy fuel mixes for electricity generation and outside weather conditions in its own unique way [34].

On the other hand, unlike many other workloads, the highly flexible nature of AI workloads opens up novel scheduling opportunities to minimize the water footprint of AI. (1) *Spatial* flexibility: Both AI model training and inference can be processed in almost any data center with little impact on latency due to recent advances in data center networking [35]. (2) *Temporal* flexibility: AI models can be trained intermittently by a certain deadline. (3) *Performance* flexibility: For the same inference service, a set of heterogeneous AI models with distinct computing resource consumption and accuracy performance are often available via model pruning and compression (e.g., GPT-3 has eight sizes, ranging from 125 million parameters to 175 billion parameters [36]).

Therefore, it is truly a critical time to uncover and address AI models’ secret water footprint amid the increasingly severe freshwater scarcity crisis, worsened extended droughts, and quickly aging public water infrastructure. The urgency can also be reflected in part by the recent commitment to “*Water Positive by 2030*” by increasingly many companies, including Google [22], Microsoft [37] and Meta [38].

In this paper, we make the first-of-its-kind efforts to uncover the secret water footprint of AI models. Specifically, we present a principled methodology to estimate the total water (both withdrawal and consumption) footprint, including both operational water and embodied water. By taking the GPT-3 model (with 175 billion parameters) for language services as a concrete example [36], we show that training GPT-3 in Microsoft’s state-of-the-art U.S. data centers can *consume* a total of 5.4 million liters of water, including **700,000 liters** of scope-1 on-site water consumption. Additionally, GPT-3 needs to “drink” (i.e., consume) a **500ml bottle of water** for roughly 10-50 responses, depending on when and where it is deployed. These numbers may increase for the newly-launched GPT-4 that reportedly has a substantially larger model size [39].

Next, we show that WUE (Water Usage Effectiveness, a measure of water efficiency) varies both spatially and temporally, implying that judiciously deciding “when” and “where” to train a large AI model can significantly cut the water footprint. We also point out the need for increasing transparency of AI models’ water footprint, including disclosing more information about operational data and keeping users informed of the runtime water efficiency. Finally, we highlight the necessity of holistically addressing water footprint along with carbon footprint to enable truly sustainable AI — *the water footprint of AI models can no longer stay under the radar*.

## 2 Background

### 2.1 Water Withdrawal vs. Water Consumption

There are two related but different types of water *usage* — water withdrawal (a.k.a. water abstraction) and water consumption, both of which are important for holistically understanding the impacts on water stress and availability [40,41].

- **Water withdrawal:** It refers to freshwater taken from the ground or surface water sources, either temporarily or permanently, and then used for agricultural, industrial or municipal uses (normally excluding water used for hydroelectricity generation) [42]. As water is a finite shared resource, water withdrawal indicates the level of competition as well as dependence on water resources among different sectors. In an emergency, a country may only have enough water withdrawal for 48 hours, and the change in water quality after withdrawal contributes to water stress levels for downstream usage [40].

- **Water consumption:** It is defined as “water withdrawal minus water discharge”, and means the amount of water “evaporated, transpired, incorporated into products or crops, or otherwise removed from the immediate water environment” [41]. Water consumption reflects the impact of water use on downstream water availability and is crucial for evaluating watershed-level water scarcity [40].

These two types of water usage also correspond to two different types of water footprints, i.e., water withdrawal footprint (WWF) [43] and water consumption footprint (WCF), respectively [6,19]. By default, water footprint refers to the water consumption footprint unless otherwise specified.

## 2.2 How Does AI Use Water?

Following the scope definition for carbon emissions [25], we describe AI’s water usage according to on-site water for server cooling (scope 1), off-site water for electricity generation (scope 2), and supply-chain water for server manufacturing (scope 3).

### 2.2.1 Scope-1 Water Usage

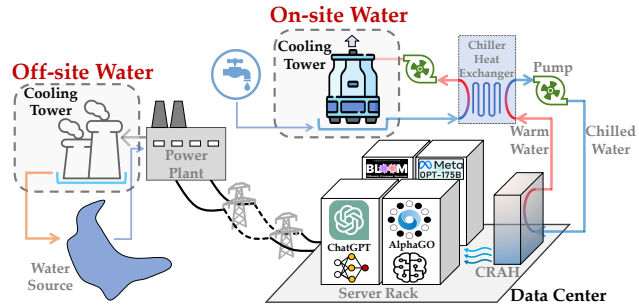
Computing servers, especially those equipped with multiple graphic processing units (GPUs) hosting AI workloads, are energy-intensive. Nearly all the server energy is converted into heat, which must then be removed from the data center server room to avoid overheating. There are two basic types of cooling systems — cooling towers and outside air cooling — which both use water and we describe as follows.

**Cooling towers.** Many data centers, including some of Google’s data centers [22], use cooling towers as the heat rejection mechanism. While the specific designs may differ, a common system contains two water loops as illustrated in Figure 1: one *closed* loop between the chiller and data center server room, and one *open* loop between the cooling tower and the chiller. The closed loop does not withdraw or consume water — the water circulating inside is pumped from the chiller into the data center to cool down the air handling unit’s supply air in order to maintain a proper server inlet temperature, and the warm water that absorbs heat from the hot air returns to the chiller. In other words, the closed-loop water simply transfers the heat from the hot air exiting the servers’ outlets to the chiller unit, which then must be cooled by further rejecting the heat into the outside environment. The chiller may be turned off and operate in a natural “bypass” mode for energy saving when the outside temperature is sufficiently low.

While air-cooled chillers are available, a more efficient design is to use an open loop that carries water to move the heat from the chiller to a cooling tower. Along the open loop, some water gets evaporated (i.e., “consumed”) in the cooling tower to dissipate heat into the environment, while the remaining water moves to the chiller unit to further absorb heat. Additionally, the remaining non-evaporated water in the open loop can only be cycled up to a few times (e.g., 3 – 10, depending on the water quality) and must be discharged to avoid high concentrations of salt and minerals. Thus, to keep the cooling tower working, new water must be constantly added to make up for the evaporated water and discharged water. Importantly, clean freshwater (potable water in many cases [21]) is needed to avoid pipe clogs and/or bacterial growth.

For cooling towers, water withdrawal refers to the amount of water added to the cooling tower (including both evaporated water and discharged water), while water consumption exclusively indicates the amount of evaporated water. Typically, given good water quality (that allows more water cycles before discharging), roughly 80% of water withdrawal is evaporated and considered “consumption” [21]. On average, depending on the weather conditions and operational settings, data centers can evaporate about 1 – 9 liters per kWh of server energy (about 1 L/kWh for Google’s annualized global number [21] and 9 L/kWh for a large commercial data center during the summer in Arizona [44]).

**Outside air cooling with water assistance.** When the climate condition is appropriate, data centers may use “free” outside air to directly cool down the servers without cooling towers. A large amount of outside air is blown through the servers and then exhausted to the outside. For outside air cooling, however, water evaporation is still needed when the outside air is too hot (e.g., higher than 81 or 89 degrees Fahrenheit); additionally, water is needed for humidity control when the outside air is too dry [38, 45, 46]. The added water is considered withdrawal, out of which about 70% is evaporated based on Meta’s report [25]. Typically, the average water efficiency of outside air cooling is better than that of cooling towers (e.g., water consumption of 0.2 L/kWh averaged over Meta’s global data centers) [25]. Nonetheless, when the outside air temperature is high, outside air cooling evaporates a significant amount of water, thus resulting in a low



*Figure 1: An example of data center’s operational water usage: on-site scope-1 water for server cooling (via cooling towers in the example), and off-site scope-2 water usage for electricity generation. The icons for AI models are only for illustration purposes.*

average but high peak water withdrawal. This may be especially problematic when the demand for water is also higher for other users on certain hot summer days [47]. Additionally, the application of outside air cooling may have significant challenges in hot regions and/or for many colocation facilities that are located in business districts.

Some data centers may also use a *hybrid* design that dynamically switches between cooling tower and outside air cooling [48]. Note also that AI servers often have high power densities due to specialized designs, including multiple GPUs and/or purpose-built hardware, to speed up AI model training and inference. As such, on-chip liquid cooling may be employed: closed-loop circulating liquid directly moves the heat from the servers to the data center facility (e.g., the facility’s cooling water loop). Then, the heat moved to the facility will be rejected by cooling towers or simply outside air [48].

## 2.2.2 Scope-2 Water Usage

Despite the increasing adoption of solar and wind energy, 73% of the utility-scale electricity generated in the U.S. came from thermoelectric power plants in 2021 [49]. Thus, electricity generation does not only emit carbon, but also uses a huge amount of water [20,41]. Just like scope-2 carbon emissions, data centers, including AI workloads, are also responsible for off-site scope-2 water usage due to electricity generation [6, 19, 44]. Different thermoelectric power plants (e.g., coal and natural gas) use different amounts of water for each kWh generation. The amount of water withdrawal also depend on the cooling techniques [49]. Typically, water withdrawal due to hydropower generation is excluded from the calculation of water withdrawal, but water consumption due to expedited water evaporation from hydropower generation is often included [6]. In many countries, thermoelectric power is among the top sectors (including agriculture) in terms of water withdrawal and water consumption [41]. For electricity generation, the U.S. national average water withdrawal and consumption are estimated at about 43.8 L/kWh [49] and 3.1 L/kWh [20], respectively. While Google and Microsoft did not disclose their scope-2 water usage, Meta’s self-reported average water consumption for its global data center fleet was 3.58 L/kWh (i.e., 41,172,356 cubic meters divided by 11,508,131 MWh) in 2022 [25].

## 2.2.3 Scope-3 Water Usage

AI chip and server manufacturing uses a huge amount of water [50,51]. For example, ultrapure water is needed for wafer fabrication, and clean water is also needed for keeping semiconductor plants cool. Overall, a large semiconductor plant may withdraw several million liters of water each day [52]. Importantly, the discharged water can contain toxic chemicals and/or hazardous wastes, which need additional processing before reused for other purposes. While water recycling at semiconductor plants can effectively reduce water withdrawal, the water recycling rate in many cases can still remain low, e.g., the average recycling rate for wafer plants and semiconductor plants in Singapore are 45% and 23%, respectively [51]. Unlike scope-1 and scope-2 water usage, the data for scope-3 water usage (including withdrawal and consumption) remains largely obscure.

# 3 Estimating Water Footprint of AI Models

While an AI model’s water footprint depends in part on its energy consumption, such dependency varies spatially and temporally. As a result, simply multiplying the AI model’s energy consumption by a constant and fixed WUE may not yield an accurate estimate of AI models’ water footprint. Next, by accounting for time-varying WUE, we present a methodology for a fine-grained estimate of an AI model’s water footprint. Here, we focus on water **consumption** footprint to describe our water footprint modeling methodology. To obtain the water *withdrawal* footprint, we simply replace the WUE with a new coefficient that represents water withdrawal efficiency.

## 3.1 Operational Water Footprint

We collectively refer to on-site scope-1 water and off-site scope-2 water as the operational water. To model the operational water footprint, we need to know the on-site WUE and off-site WUE.

- **On-site WUE.** We denote the on-site scope-1 WUE at time  $t$  by  $\rho_{s1,t}$ , which is defined as the ratio of the on-site water consumption to server energy consumption and varies over time depending on the outside temperature. Concretely,  $\rho_{s1,t}$  increases significantly for cooling towers when the outside wet bulb temperature increases [34,53], and increases for outside air cooling when the outside dry bulb temperature is

too hot or the humidity is too low [38,46]. For example, the monthly average on-site WUE for a commercial data center reaches as high as about 9 L/kWh in the summer and becomes about 4 L/kWh in the winter [44]. Thus,  $\rho_{s1,t}$  can be modeled as a function in terms of the outside weather condition based on empirical operational data (see [34] for an example of on-site WUE based on cooling towers).

- **Off-site WUE.** We denote the off-site scope-2 WUE at time  $t$  as  $\rho_{s2,t}$ , which is defined as the ratio of off-site water consumption for each kWh of electricity generation and measures the electricity water intensity factor (EWIF). In practice,  $\rho_{s2,t}$  depends on the energy fuel mixes (e.g., coal, nuclear, hydro) as well as cooling techniques used by power plants [20, 54, 55]. Since electricity produced by different energy fuels becomes non-differentiated once entering the grid, we consider the average method to calculate  $\rho_{s2,t}$ , which can be estimated as  $\rho_{s2,t} = \frac{\sum_k b_{k,t} \times EWIF_k}{\sum_k b_{k,t}}$  where  $b_{k,t}$  denotes the amount of electricity generated from fuel type  $k$  at time  $t$  for the grid serving the data center under consideration, and  $EWIF_k$  is the EWIF for fuel type  $k$  [56,57]. As a result, variations in energy fuel mixes of electricity generation (to meet various demand levels) result in temporal variations of the off-site WUE. Moreover, the off-site WUE also varies by location, because each fuel type has its own distinct WUE and the energy fuel mix is typically different between states as some states may use less water-efficient energy generation than others [18,20,34,55].

- **Operational water footprint.** The on-site scope-1 water consumption can be obtained by multiplying AI’s energy consumption with the on-site WUE, while the off-site scope-2 water consumption depends on the electricity usage as well as the local off-site WUE. Consider a time-slotted model  $t = 1, 2, \dots, T$ , where each time slot can be 10 minutes to an hour depending on how frequently we want to assess the operational water footprint, and  $T$  is the total length of interest (e.g., training stage, total inference stage, or a combination of both). At time  $t$ , suppose that an AI model uses energy  $e_t$  (which can be measured using power meters and/or servers’ built-in tools), the on-site WUE is  $\rho_{s1,t}$ , the off-site WUE is  $\rho_{s2,t}$ , and the data center hosting the AI model has a power usage effectiveness (PUE) of  $\theta_t$  that accounts for the non-IT energy such as cooling systems and power distribution losses. Then, the total water footprint  $W$  of the AI model can be written as

$$WaterOperational = \sum_{t=1}^T e_t \cdot [\rho_{s1,t} + \theta_t \cdot \rho_{s2,t}]. \quad (1)$$

If we are interested in the operational water withdrawal footprint, we simply replace  $\rho_{s1,t}$  and  $\rho_{s2,t}$  with new values that represent the on-site and off-site water withdrawal efficiencies, respectively.

### 3.2 Embodied Water Footprint

The embodied water footprint is primarily due to server manufacturing. Like accounting for embodied carbon footprint [16,58], the total water for manufacturing is amortized over the lifespan of a server. Specifically, suppose that it uses  $W$  amount of water for manufacturing the AI servers in total and the servers are expected to last an effective period of  $T_0$  time (i.e., the total lifespan multiplied by the average utilization rate). Then, for a total length  $T$  of interest (e.g., training stage, total inference stage, or a combination of both), the embodied water footprint for AI servers is obtained by adding up the amortized per-time manufacturing water over the total time  $T$ , i.e.,

$$WaterEmbodied = \frac{T \cdot W}{T_0}. \quad (2)$$

By adding up the operational and embodied water footprints, we obtain the total water footprint as

$$WaterTotal = \sum_{t=1}^T e_t \cdot [\rho_{s1,t} + \theta_t \cdot \rho_{s2,t}] + \frac{T \cdot W}{T_0}. \quad (3)$$

Our methodology for estimating AI models’ water footprint is general and applies to data centers with any cooling systems. We simply plug in the values  $\rho_{s1,t}$ ,  $\theta_t$  and  $\rho_{s2,t}$  to obtain a fine-grained estimate of the operational water footprint. Alternatively, to obtain a rough estimate, we can use the (annualized) average values for these parameters and the estimated AI server energy consumption (e.g., by multiplying the average GPU power consumption with the total training or inference time) [7].

**Table 1: Estimate of GPT-3’s average operational water consumption footprint.** “\*” denotes data centers under construction as of July 2023, and the PUE and WUE values for these data centers are based on Microsoft’s projection.

Location	PUE	WUE (L/kWh)	Electricity Water Intensity (L/kWh)	Water for Training (million L)			Water for Each Inference (mL)			# of Inferences for 500ml Water
				On-site Water	Off-site Water	Total Water	On-site Water	Off-site Water	Total Water	
U.S. Average	1.170	0.550	3.142	0.708	4.731	<b>5.439</b>	2.200	14.704	<b>16.904</b>	<b>29.6</b>
Wyoming	1.125	0.230	2.574	0.296	3.727	<b>4.023</b>	0.920	11.583	<b>12.503</b>	<b>40.0</b>
Iowa	1.160	0.190	3.104	0.245	4.634	<b>4.879</b>	0.760	14.403	<b>15.163</b>	<b>33.0</b>
Arizona	1.223	2.240	4.959	2.883	7.805	<b>10.688</b>	8.960	24.259	<b>33.219</b>	<b>15.1</b>
Washington	1.156	1.090	9.501	1.403	14.136	<b>15.539</b>	4.360	43.934	<b>48.294</b>	<b>10.4</b>
Virginia	1.144	0.170	2.385	0.219	3.511	<b>3.730</b>	0.680	10.913	<b>11.593</b>	<b>43.1</b>
Texas	1.307	1.820	1.287	2.342	2.165	<b>4.507</b>	7.280	6.729	<b>14.009</b>	<b>35.7</b>
Singapore	1.358	2.060	1.199	2.651	2.096	<b>4.747</b>	8.240	6.513	<b>14.753</b>	<b>33.9</b>
Ireland	1.197	0.030	1.476	0.039	2.274	<b>2.313</b>	0.120	7.069	<b>7.189</b>	<b>69.6</b>
Netherlands	1.158	0.080	3.445	0.103	5.134	<b>5.237</b>	0.320	15.956	<b>16.276</b>	<b>30.7</b>
Sweden	1.172	0.160	6.019	0.206	9.079	<b>9.284</b>	0.640	28.216	<b>28.856</b>	<b>17.3</b>
Mexico*	1.120	0.056	5.300	0.072	7.639	<b>7.711</b>	0.224	23.742	<b>23.966</b>	<b>20.9</b>
Georgia*	1.120	0.060	2.309	0.077	3.328	<b>3.406</b>	0.240	10.345	<b>10.585</b>	<b>47.2</b>
Taiwan*	1.200	1.000	2.177	1.287	3.362	<b>4.649</b>	4.000	10.448	<b>14.448</b>	<b>34.6</b>
Australia*	1.120	0.012	4.259	0.015	6.138	<b>6.154</b>	0.048	19.078	<b>19.126</b>	<b>26.1</b>
India*	1.430	0.000	3.445	0.000	6.340	<b>6.340</b>	0.000	19.704	<b>19.704</b>	<b>25.4</b>
Indonesia*	1.320	1.900	2.271	2.445	3.858	<b>6.304</b>	7.600	11.992	<b>19.592</b>	<b>25.5</b>
Denmark*	1.160	0.010	3.180	0.013	4.747	<b>4.760</b>	0.040	14.754	<b>14.794</b>	<b>33.8</b>
Finland*	1.120	0.010	4.542	0.013	6.548	<b>6.561</b>	0.040	20.350	<b>20.390</b>	<b>24.5</b>

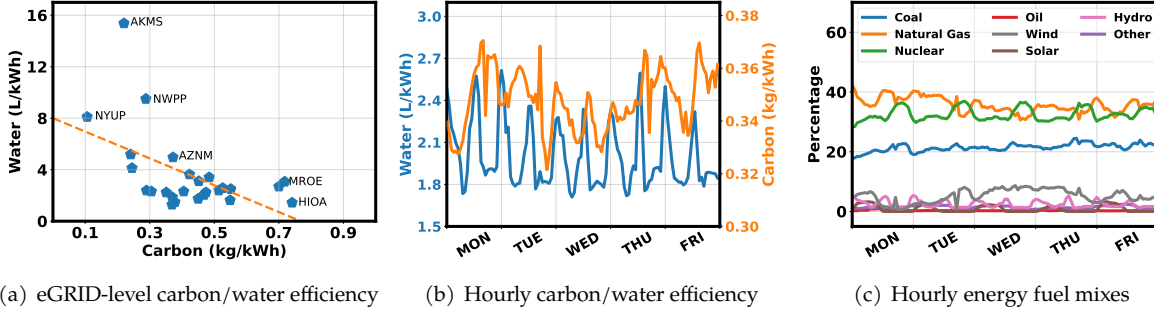
### 3.3 Case Study: Estimating GPT-3’s Operational Water Consumption Footprint

The core of ChatGPT, a popular online service, is a large language model built based on subsequent versions of GPT-3. Due to the limited public data available for GPT-4, we now present a case study to estimate GPT-3’s operational water *consumption* footprint. In particular, we consider the full GPT-3 model with 175 billion parameters, which is also the one considered for estimating its carbon footprint [7]. We exclude *embodied* water footprint due to the lack of public data for scope-3 water usage in GPT-3’s supply chain. We choose GPT-3 as Microsoft publishes its location-wise WUE and PUE [46], whereas such information is often limited for other companies. The results are shown in Table 1. Note that the newer GPT-4 model currently used by ChatGPT reportedly has a significantly larger model size [39] and hence likely consumes more training and inference energy than GPT-3 on average.

#### 3.3.1 Training

GPT-3 was trained and deployed by OpenAI in Microsoft’s data centers, with an estimated training energy of 1287 MWh [36, 59]. While Microsoft recently disclosed that OpenAI had used its Iowa data center for training some models such as GPT-4 [47], the specific data center location for training GPT-3 has yet to be public. Thus, we estimate the water consumption footprint for training GPT-3 by considering different data center locations, including non-U.S. data centers for references. In line with the practice of estimating the carbon footprint [7], we use the annualized average on-site power usage effectiveness (PUE) and water usage effectiveness (WUE) for each data center location. The PUE and WUE for each data center location are based on Microsoft’s most recent disclosure [46], while the average U.S. data center PUE and WUE are based on [60]. For data centers under construction, we use the PUE and WUE data projected by Microsoft.

To estimate the off-site scope-2 water consumption, we use the regional electricity water intensity provided by [20] wherever applicable to ensure maximum data consistency. Specifically, for each U.S. data center location, we use the eGRID-level average electricity water intensity [20]. For Microsoft’s Taiwan data center, we use the average electricity water intensity of 2.177L/kWh provided by [61]. For Microsoft’s Singapore data center, we calculate the electricity water intensity by considering a mixture of 96% natural gas and 4% renewables (with zero water operational water consumption) as Singapore’s energy sources for electricity generation [62] and using Malaysia’s water intensity for natural gas-based electricity generation provided by [20] as a substitute. For all the other non-U.S. data center locations, we use their country-level average electricity water intensities from [20].



**Figure 2:** (a) The U.S. eGRID-level scope-2 water consumption intensity factor vs. carbon emission rate [20, 63]. The dashed line represents a linear regression model, showing that the eGRID-level scope-2 carbon emission and water consumption efficiencies are not aligned. (b) A 5-day snapshot of scope-2 carbon emission rate and water consumption intensity for electricity generation serving Virginia, starting from April 4, 2022. The values are calculated based on the energy source mixes, carbon emission rate and water consumption intensity for each energy fuel type [20, 63, 64]. The scope-2 carbon and water efficiencies only have a Pearson correlation coefficient of 0.06, showing a weak correlation. (c) A 5-day snapshot of energy fuel mixes serving Virginia, starting from April 4, 2022 [64].

### 3.3.2 Inference

AI models are often deployed globally for inference to minimize the latency and/or comply with privacy regulations. We estimate the water consumption footprint for GPT-3 inference in different data centers. The PUE, WUE and electricity water intensity are the same as those used for estimating the training water footprint. The official estimate shows that GPT-3 consumes on the order of 0.4kWh electricity to generate 100 pages of content (e.g., 0.004kWh per page) [36]. Meanwhile, the average inference energy for BLOOM (a language model with a slightly larger size of 176 billion parameters than GPT-3) is about 0.00396kWh per request (914kWh for 230,768 requests), including both dynamic energy and amortized idle energy [16]. BLOOM was deployed on Google cloud, which has a similar energy efficiency as Microsoft’s Azure cloud. Thus, we consider 0.004kWh as the inference energy consumption per request.

**Remarks.** As Microsoft only reports its annualized PUE and on-site scope-1 WUE [60], the actual PUE and WUE at certain times of the year can be different from the annualized numbers. Moreover, if GPT-3 is deployed in third-party colocation data centers other than Microsoft’s own state-of-the-art data centers, the water footprint for inference may also be higher due to the often worse PUE and WUE in colocation data centers. Our electricity water intensity for the U.S. (i.e., 3.14L/kWh on average) is lower than 7.6L/kWh used by Lawrence Berkeley National Laboratory to estimate the offsite scope-2 water consumption [6]. Therefore, our estimated water footprint for GPT-3 can absorb some potential discrepancies in the estimated inference energy of 0.004kWh, while noting that GPT-4 currently used by ChatGPT may use different, and likely more, energy than GPT-3 on average due to the reportedly larger model size [39].

## 4 Our Findings and Recommendations

We provide our findings and recommendations to address the water footprint of AI models, making future AI more socially responsible and environmentally sustainable.

### 4.1 “When” and “Where” Matter

Judiciously deciding “when” and “where” to train a large AI model can significantly affect the water footprint. As shown in Figures 2(a) and 2(b), the water efficiency has *spatial-temporal* diversity — on-site water efficiency changes due to variations of outside weather conditions, and off-site water efficiency changes due to variations of the grid’s energy fuel mixes to meet time-varying demands (Figure 2(c)) [44, 65]. In fact, water efficiency varies at a much faster timescale than monthly or seasonably. Therefore, by exploiting *spatial-temporal* diversity of water efficiency, we can dynamically schedule AI model training and inference to cut the water footprint. For example, if we train a small AI model, we can schedule the training task at midnight and/or in a data center location with better water efficiency. Likewise, some water-conscious users may prefer to use the inference services of AI models during water-efficient hours and/or in water-efficient



data centers, which can contribute to the reduction of AI’s water footprint.

## 4.2 More Transparency is Needed

To exploit the spatial-temporal diversity of water efficiency, it is crucial to have better visibility of the runtime water efficiency and increase transparency by keeping the AI model developers as well as end-users informed. Nonetheless, such data is often lacking. For example, even scope-1 water usage (either withdrawal or consumption) is not included in today’s AI model cards (e.g., [32]), not to mention the scope-2 water usage. Additionally, there is very limited data available for embodied water usage by chip making, which adds challenges to a holistic lifecycle view of AI’s water footprint.

We recommend AI model developers and data center operators be more transparent. For example, what are the runtime (say, hourly) on-site scope-1 WUE and off-site scope-2 WUE? What about the water footprint of AI models trained and/or deployed in third-party colocation data centers? Such information will be of great value to the research community and the general public. As the first step, we recommend that the scope-1 and scope-2 water usage information be included in AI’s model cards.

## 4.3 “Follow the Sun” or “Unfollow the Sun”

To cut the carbon footprint, it is preferable to “follow the sun” when solar energy is more abundant. Nonetheless, to cut the water footprint, it may be more appealing to “unfollow the sun” to avoid high-temperature hours of a day when WUE is high. This conflict can be shown in Figure 2(a), where we see that the scope-2 water consumption intensity factor and carbon emission rate are not well aligned: minimizing one footprint might increase the other footprint. Thus, to judiciously achieve a balance between “follow the sun” for carbon efficiency and “unfollow the sun” for water efficiency, we need to reconcile the potential water-carbon conflicts by using new and holistic approaches. In other words, only focusing on AI models’ carbon footprint alone may be insufficient to enable truly sustainable AI.

## 5 Related Works

The growing resource and energy consumption of AI models have placed an increasing emphasis on sustainable AI [7–10, 36, 59, 66]. Specifically, a variety of approaches can be leveraged to make AI more sustainable, including novel GPU and accelerator designs [7, 67, 68], efficient AI model training and inference [69, 70], carbon-aware AI model scheduling [10, 15], green data center designs [71–74]. These studies have mostly focused on scope-2 carbon footprint, neglecting water footprint which is another environmental footprint [75–77]. Crucially, despite the correlation between water footprint and carbon footprint, the existing techniques that optimize for carbon efficiency do not necessarily equate to, and may even worsen, water efficiency [34].

Data centers have increasingly adopted climate-conscious cooling system designs (e.g., air-side economizers and purifying non-potable water) [21, 38]. These water-saving approaches can be viewed as *supply-side* solutions — saving water while supplying enough cooling to meet the given demand. But, the *demand-side* management — cooling demands are affected by “when” and “where” AI models are trained and used — is not addressed. Additionally, these approaches only focus on the on-site scope-1 water usage, whereas the off-site scope-2 water usage with time-varying off-site WUE due to variations in energy fuel mixes is not addressed.

Finally, it is worth mentioning that some data center operators have also begun to build water restoration projects to indirectly compensate for their water footprint [21, 25, 37]. While this is certainly encouraging, it is an *offsetting* method (like building renewables projects to offset location-based carbon emissions) and hence orthogonal to reducing water withdrawal or consumption in the first place.

## 6 Conclusion

In this paper, we recognize the enormous water usage as a critical concern for socially responsible and environmentally sustainable AI. Our key contribution is to make the first-of-its-kind efforts to uncover the secret water footprint of AI models. Specifically, we present a principled methodology to estimate AI’s water footprint. Then, using GPT-3 as an example, we show that a large AI model can consume a stunning amount of water in the order of millions of liters for training. We also discuss that the scope-1 and scope-2 water efficiencies vary spatially and temporally — judiciously deciding “when” and “where” to run a large AI

model can significantly cut the water footprint. In addition, we point out the need for increased transparency of AI models' water footprint, and highlight the necessity of holistically addressing water footprint along with carbon footprint to enable truly sustainable AI.

*AI models' water footprint can no longer stay under the radar — water footprint must be addressed as a priority as part of the collective efforts to combat global water challenges.*

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## Appendix

### A Operational Water for Google, Microsoft, and Meta in 2022

According to the sustainability reports [21, 23, 25], the electricity consumption by Google’s, Microsoft’s, and Meta’s data centers in 2022 was about 21.7 TWh, 18.1 TWh, and 11.1 TWh, respectively. In particular, their U.S. electricity consumption in 2022 was about 15.5 TWh, 10.9 TWh, and 8.6 TWh (excluding leased colocation facilities), respectively. Microsoft and Google did not report country-level data for their electricity consumption in North America, but they only have self-managed data centers in the U.S. as of 2023. Thus, we attribute their electricity consumption in North America to the U.S. The reported electricity consumption by Google and Microsoft may also include negligible usage by their offices and will be adjusted by rounding down our calculations.

The total combined electricity consumption of Google, Microsoft, and Meta was about 50 TWh in 2022. While Microsoft did not disclose country-/location-wise electricity consumption, these three companies all primarily operate in the U.S. Thus, we use the U.S. average electricity water withdrawal intensity factor 43.83 L/kWh [49], and electricity water consumption intensity factor 3.14 L/kWh [20] to calculate the scope-2 water withdrawal and water consumption, respectively. Note that the U.S. average electricity water withdrawal/consumption intensity factor is lower than the global average [20]. Also, our value of 3.14 L/kWh for the U.S. average water consumption factor is lower than 7.6 L/kWh used for estimating the U.S. data center water footprint [6] as well as lower than Meta’s global electricity water consumption intensity factor of 3.58 L/kWh (i.e., 41,172,356 cubic meters divided by 11,508,131 MWh) [25]. Therefore, 43.83 L/kWh and 3.14 L/kWh for electricity water withdrawal and consumption intensity factors are more on the conservative side, and our estimate for Meta’s global scope-2 water consumption is less than its self-reported value [25]. Google and Microsoft did not disclose their scope-2 water withdrawal or consumption. By multiplying 43.83 L/kWh and 3.14 L/kWh by 50 TWh, we obtain the total scope-2 water withdrawal of 2.19 billion cubic meters and water consumption of 0.157 billion cubic meters, respectively.

The on-site scope-1 water withdrawal for Google’s, Microsoft’s, and Meta’s data centers in 2022 were about 25 billion liters, 8.5 billion liters (assuming 80% of Microsoft’s total water withdrawal based on Meta’s and Google’s percentages), and 3.6 billion liters, respectively. Their scope-1 water consumption was about 19.7 billion liters, 6 billion liters (assuming the offices consumed 10% of their water withdrawal), and 2.5 billion liters, respectively. These result in a total scope-1 water withdrawal of about 37 billion liters and water consumption of 28 billion liters in 2022, respectively.

By adding up the scope-1 and scope-2 water usage together, we get a total water withdrawal of 2.2 billion cubic meters and total water consumption of 0.18 billion cubic meters, respectively, for Google, Microsoft, and Meta combined together in 2022. Similarly, their 2022 total water withdrawal and water consumption in the U.S. were about 1.5 billion cubic meters and 0.13 billion cubic meters, respectively.

According to the U.S. Central Intelligence Agency [24], the estimated annual water withdrawals of Denmark, Liberia and the U.S. in 2020 (the latest year available) were 0.98 billion cubic meters, 0.14 billion cubic meters, and 444 billion cubic meters, respectively.

### B Operational Water for Global AI in 2027

A recent study suggests that the global AI demand might consume 85 – 134 TWh of electricity in 2027 based on the GPU shipment [30]. Based on this study, we estimate the potential water usage of global AI in 2027.

To account for the cooling energy overheads, we assume a power usage effectiveness (PUE) of 1.1, which is a fairly low value even for state-of-the-art data center facilities [21]. We obtain an estimate of the total electricity consumption of 93.5 – 147.4 TWh.

For electricity water withdrawal and consumption intensity factors, we use the U.S. average electricity water withdrawal intensity factor 43.83 L/kWh [49], and electricity water consumption intensity factor 3.14 L/kWh [20], respectively. Note again that the U.S. average electricity water withdrawal/consumption intensity factor is lower than the global average [20] and that the value of 3.14 L/kWh for the U.S. average water consumption factor is also lower than Meta’s global electricity water consumption intensity factor of 3.58 L/kWh [25]. After multiplying 43.83 L/kWh and 3.14 L/kWh by 93.5 – 147.4 TWh, we obtain the total scope-2 water withdrawal of 4.10 – 6.46 billion cubic meters and water consumption of 0.29 – 0.46 billion

cubic meters, respectively.

For on-site scope-1 water withdrawal, we assume 1.2 L/kWh (roughly the same as Google’s global scope-1 water withdrawal efficiency [21]), which results in a total scope-1 water withdrawal of 0.11 – 0.16 billion cubic meters. Similarly, assuming 1 L/kWh based on Google’s global scope-1 water consumption efficiency, we obtain a total on-site scope-1 water consumption of 0.09 – 0.14 billion cubic meters.

By adding up scope-1 and scope-2 water usage together, the total water withdrawal and water consumption of global AI may reach 4.2 – 6.6 billion cubic meters and 0.38 – 0.60 billion cubic meters, respectively. According to the U.S. Central Intelligence Agency [24], the estimated U.S. annual water withdrawal in 2020 (the latest year available) was about 444 billion cubic meters. By using this number and assuming the U.S. hosts half of the global AI workloads, the operation of AI workloads in the U.S. may take up roughly 0.5 – 0.7% of its total annual water withdrawal in 2027.

The future water withdrawal and consumption efficiency may both improve in 2027 compared to the current values we use, especially for electricity generation. Also, the country-wide annual water withdrawal is estimated by the U.S. Central Intelligence Agency [24] for the year of 2020, and may vary in 2027. Therefore, like the prediction of global AI energy consumption in 2027 [30], the prediction of water withdrawal and consumption for global AI in 2027 should only be interpreted as a rough first-order estimate subject to future uncertainties.