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Article

One Quarter of Global Data Centers are Located in Water-Stressed Areas

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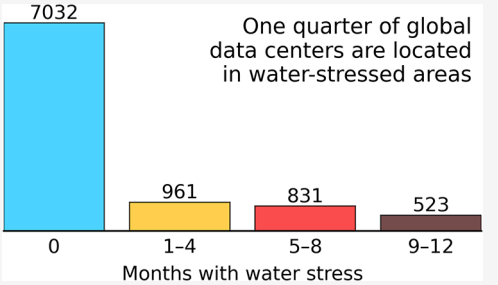
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ABSTRACT: The rapid growth of digital services is increasing the demand for high-performance computing within data centers, intensifying the demand for local natural resources, particularly energy and water. This study assesses the current and future exposure of all 9347 currently identified data centers worldwide to water gap conditions, areas where water demand exceeds available supply, resulting in unsustainable water consumption and an increase in water stress. We find that 25% of data centers would already have experienced at least 1 month of water gap annually under 2001−2010 hydrologic conditions. While such conditions rarely prevent continued operation, they intensify stress with other water-dependent sectors. 33% of currently identified data centers would be in regions experiencing water gaps under future hydrological conditions. Data centers overlap with water demands from municipal (41%), irrigation (28%), manufacturing (18%), and power generation (8%) sectors. The United States hosts 39% of data centers, with 21% located in water-scarce regions, where overlap with municipal and agricultural demands is pronounced. The extent to which water-stress exposure translates into operational impacts for data centers themselves or into measurable consequences for other water users remains an open question to address. Ensuring data center long-term viability will require siting and governance choices that account for local hydrological limits.



KEYWORDS: *water stress, data centers, critical infrastructure, water risks, water sustainability, artificial intelligence*

INTRODUCTION

Global data center capacity is expanding at an unprecedented rate, reflecting the exponential growth in demand for computational power and data storage.[1] Data centers currently consume about 415 TWh of electricity per year, around 1.5% of global demand.[1] With rapidly expanding compute needs, electricity use by data centers is projected to rise to 945−1065 TWh by 2030, roughly equal to Japan's total electricity consumption in 2025 or 3% of global electricity demand.[1] Direct water demand is rising in parallel: data centers currently consume 313−764 billion liters per year,[2] with projections suggesting that this could more than double to 1200 billion liters by 2030,[3] equivalent to the annual household and municipal water withdrawals of a country like The Netherlands. This rapid expansion illustrates how Artificial Intelligence (AI), though virtual in its services, is dependent on the use of natural resources, particularly energy and water.[4]

Data centers' water demands remain systematically overlooked compared with energy, whose demand and carbon footprint have received extensive research and policy attention,[5−8] leaving water-related risks largely peripheral in analyses of data centers.[9,10] Unlike energy, which can often be imported across large distances, water use is spatially constrained to local basins and subject to strong seasonal and interannual variability.[11,12] These constraints make water-related risks both highly localized and difficult to mitigate through technological or market-based solutions. In many regions, data-center water use must also comply with regulatory limits designed to protect ecosystems and compete with priority uses such as municipal and agricultural sectors.[13] As a result, even where water is physically available, facilities may face operational restrictions during periods of drought, reduced water quality, or increased demand from other sectors.

Water stress occurs when water availability falls short of meeting human and environmental demands, driven not only by

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limited quantities of freshwater but also by declines in water quality that make supplies unusable or more expensive to access and treat.[14,15] Growing demand from agriculture, households, industry, and energy systems, combined with climate-driven shifts in hydrology, has intensified pressure on rivers, lakes, and aquifers, often depleting water resources and compromising the environmental flows needed to sustain aquatic ecosystems.[16] In this context, the expanding water demands of data centers add another layer of competition, heightening water stress and increasing vulnerability for both human activities and natural systems.[13]

Because data centers operate continuously and require reliable cooling,[2] their water use during periods of low availability can accelerate resource depletion and intensify competition between economic activities and the preservation of essential ecosystem functions. Data centers are structurally inflexible in both water and energy demand: continuous operation limits their capacity to curtail consumption during droughts or other scarcity events. Much like perennial agriculture,[17] AI-driven infrastructure cannot be readily idled without substantial economic losses, leading operators to adopt buffering strategies, such as on-site storage, desalination, or wastewater reuse, when supplies become constrained.

Data centers rely on water both directly for cooling and indirectly through the water-intensive electricity systems that power them. As a result, they compete for limited water resources with agriculture, households, industry, and energy production, potentially intensifying local water stress and exacerbating the unsustainable water consumption. Direct water use primarily stems from cooling processes required to keep servers operating efficiently, with further water demands associated with space conditioning.[18] Beyond their direct water use, data centers impose substantial indirect water demands through the water embedded in electricity generation and in the lifecycle of each facility.[19] These indirect needs vary widely across regions, reflecting differences in generation technologies and power mixes.[19,20]

Stoichiometric relationships provide useful bounds on the water demand associated with data centers. Typical evaporative cooling systems require 1−3 m^3 of water per MWh of IT load, while an additional 1−10 m^3 of water per MWh is commonly embedded in electricity generation where thermal power plants dominate.[2] Expressed in capacity terms, a 1-GW data center cluster operating at high utilization can therefore be associated with 10−40 million m^3 of water demand per year, depending on cooling architecture, power mix, and local climate.[2]

Previous research has shown that water stress can limit the sustainability and resilience of both rainfed[21−24] and irrigated agriculture,[25−27] curtail power production,[28−32] create a competition for water resources between agriculture and fossil fuel extraction,[33−36] as well as disrupt carbon capture and storage,[37,38] hydrogen production,[39,40] and ammonia and fertilizer manufacturing.[41] Despite this extensive body of knowledge across resource-intensive sectors, comparable evaluations remain limited to data centers.

Existing studies on water stress and data centers remain largely local or country-level, mostly focused on the United States,[19,42−44] China,[45] or a few other regions,[46,47] and rarely examine the issue at a global scale. While data center expansion is growing in other regions, including emerging markets in Africa and Southeast Asia, literature seldom accounts for the water quantity and quality vulnerabilities in those regions. Recent analyses show that digital infrastructure is increasingly being established in the Global South, regions often facing rapid digitalization, investment growth, and historical patterns of resource extraction, raising concerns about unequal resource burdens.[48]

Despite the recent acceleration of the global expansion of data center capacity, there is no comprehensive global assessment of how the geographic distribution and rapid proliferation of data centers, particularly outside the United States and Europe, intersect with regional hydrological stresses. Additionally, as climate change intensifies, many regions that today host data centers may face increasing water supply variability, drought periods, and water stress conditions. Therefore, it is also far from certain whether many data center locations will have sufficient water resources to operate without straining local supplies.

This study provides a global assessment of existing data centers' exposure to water gaps based on a process-based hydrological model that explicitly accounts for water availability and existing water-using sectors, including irrigated agriculture, municipal, manufacturing, electricity, mining, and livestock. Our analysis is not specific to AI data centers but instead represents the broader global data center sector. Using a global data set of 9347 data center locations, we combine geospatial information on data centers' location with climate and hydrological model estimates to evaluate site-specific water gaps. For each data center location, we assess water gaps under different climate conditions. Water gaps measure the imbalance between how much renewable water a region has and how much it uses.[16] When monthly water consumption outpaces locally available resources, the deficit must be drawn from groundwater, rivers, lakes, and environmental flow reserves—a pattern that signals unsustainable water consumption.[16] These shortfalls of water can carry serious consequences for communities, agriculture, industry, energy systems, and ecosystems alike.[16] We identify the exposure of existing data center locations to current and future hydrological conditions, rather than projecting the future evolution of the data center sector. Furthermore, by linking data center locations to sectoral water consumption, we highlight which water-using sectors are colocated.

METHODS

The methodological contribution of this study lies in the integration of three components not previously combined at the global scale: a facility-resolved data set of 9347 data centers, a process-based hydrological model accounting for sectoral water demand and environmental flows, and a spatial overlay framework quantifying water stress exposure and colocation with other water users. This study does not aim to estimate facility-level water consumption of data centers, which depends on factors such as the IT load, water usage effectiveness, and cooling technology. Instead, we assess the exposure of data center locations to existing and future water stress by evaluating their spatial overlap with that of regional water gaps. Quantifying direct water demand globally would require detailed, standardized data sets on facility characteristics that, to our knowledge, are currently unavailable. Our analysis identifies locations where data centers coincide with existing water stress rather than quantifying the incremental contribution of data centers to water consumption.

Data Center Database

The analysis is based on a global database of 9347 operational data centers, representing one of the most comprehensive overviews currently available of worldwide data center infrastructure. The data set was derived from a proprietary compilation provided by Saoradh Enterprise Partners LLC. This data set likely underestimates the true global count, particularly for undisclosed, smaller, or newly constructed facilities amid the current period of rapid expansion.

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Assessment of Water Gaps

Water gaps are defined as the imbalance between available water resources and water consumption within a given region. For a given climate model, month, and spatial pixel, a water gap occurs when renewable water availability is lower than water consumption. Water gaps were quantified by solving a monthly water balance at a 30-arcminute spatial resolution (~50 km at the Equator), utilizing monthly surface and subsurface runoff data from climate model outputs. Monthly water availability and consumption are computed for the baseline and 3 °C warming scenarios. The baseline scenario refers to the 2001−2010 period and was selected as the hydrological baseline because the most comprehensive globally validated sectoral water consumption data set currently available corresponds to this period.[50]

We derived future water demand and supply under a warming target corresponding to a global mean temperature increase of +3 °C relative to preindustrial conditions. A +3 °C warming level is relevant to high-impact risk assessment and is within the range of concern under insufficient mitigation, although SSP5-8.5 should be interpreted as a high-emissions forcing pathway rather than a direct representation of current policies[54] The global mean warming in 2024 was estimated to be 1.55 ± 0.13 °C above the average temperature of the late 19th century, from 1850 to 1900, a period commonly used as a preindustrial baseline for global temperature targets.[55] We imposed a +3 °C warming target by using SSP5-8.5 projections and selecting the time periods when each climate model reaches the specified warming. Warming-level analysis reduces dependence on a fixed calendar-year SSP comparison, but the resulting climate fields still reflect the SSP5-8.5 forcing pathway and the selected global climate models. The five climate models—GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL—were selected for their structural diversity and ability to capture the spread of the broader CMIP6 ensemble, spanning a range of climate sensitivities: GFDL-ESM4, MPI-ESM1-2-HR, and MRI-ESM2-0 exhibit lower sensitivity, while IPSL-CM6A-LR and UKESM1-0-LL exhibit higher sensitivity.

Using logistic regression,[16] we estimated the probability of exceeding the +3 °C global warming threshold for each year and identified the year at which this probability reached 0.5 for each climate model. These years represent the midpoint of the probabilistic transition to +3 °C warming in our analysis and are therefore not expected to coincide exactly with the deterministic threshold years reported by ISIMIP3b. The resulting midpoint years were 2039, 2042, 2048, 2064, and 2068 for UKESM1-0-LL, IPSL-CM6A-LR, MRI-ESM2-0, MPI-ESM1-2-HR, and GFDL-ESM4, respectively. For each model, we then defined the +3 °C analysis period as the 10-year window centered on the corresponding 0.5-probability year (±5 years), naturally accounting for intermodel differences in climate sensitivity. These decades correspond to 2035-2044 for UKESM1-0-LL, 2038-2047 for IPSL-CM6A-LR, 2044-2053 for MRI-ESM2-0, 2060-2069 for MPI-ESM1-2-HR, and 2064-2073 for GFDL-ESM4.

Runoff Data

We used monthly runoff (surface and subsurface) under both baseline and 3 °C warming scenarios. Baseline estimates were drawn from PCR-GLOBWB 2.0, which provides simulated runoff based on standard global parametrization, evaluated against river discharge, GRACE total water storage, and AQUASTAT withdrawals.[49] For the 3 °C warming scenario, we used CMIP6 SSP5-8.5 data, with monthly runoff retrieved from five IPCC Sixth Assessment Report climate models (IPSL-CM6A-LR, UKESM1-0-LL, GFDL-ESM4, MPI-ESM1-2-HR, and MRI-ESM2.0)[52] processed through the global hydrological model H08.[53] The use of different hydrological models for historical and future periods introduces structural uncertainty due to differences in model formulations and parametrizations. However, we consider this approach preferable to replacing the historical baseline with H08, as PCR-GLOBWB has undergone a more extensive evaluation against multiple hydrological variables and incorporates a more detailed representation of key hydrological processes, including groundwater dynamics, whereas H08 has primarily been evaluated against river discharge and adopts a more simplified representation of several of these processes. To minimize inconsistencies among models, we applied projected changes in runoff from each future model−climate combination as perturbations to the historical baseline rather than directly comparing absolute values across models.

For each climate model, we computed the difference between projected and baseline (2001−2010) runoff. We then added these anomalies to the baseline 2001−2010 runoff. This "delta" or perturbation approach, adding the model-simulated climate change signal (future minus baseline 2001−2010) to the reference climate, is standard practice in climate impact assessments because historical simulations differ substantially across models.[27] These differences arise from limited observational constraints and divergent assumptions about key forcing, particularly aerosols and land-use change, as well as from model-specific representations of aerosols, clouds, and associated precipitation processes. By anchoring projected climate changes to a common reference climate, from which present-day water consumption is derived, we ensure greater consistency and confidence in our estimates of water gaps. Our results are reported as the ensemble average of five CMIP6 simulations for each warming level; we therefore focus on the central tendency of projections rather than the full spread between the driest and wettest models. We do not account for the impact of long-term climate events (e.g., El Niño-Southern Oscillation) due to the use of a 10-years combination of monthly climate model outputs.

Water Consumption Data

Sectoral baseline monthly water consumption—covering irrigation, livestock, electricity generation, domestic, mining, and manufacturing—was drawn from Huang et al.[50] This data set spans the 2001−2010 baseline period and aggregates outputs from four hydrological models (WaterGAP, H08, LPJmL, and PCR-GLOBWB). It is widely used in hydrological modeling, with consumption estimates validated against observational data and subjected to uncertainty analyses—including country-level water withdrawal figures cross-checked against the FAO AQUASTAT database—supporting its reliability for global-scale assessments.[50]

Future monthly irrigation consumption was derived from CMIP6 SSP5-P8.5 outputs across five global climate models (IPSL-CM6A-LR, UKESM1-0-LL, GFDL-ESM4, MPI-ESM1-2-HR, and MRI-ESM2.0) and the global hydrological model H08.[53] Following the same approach applied to future runoff, projected changes in irrigation consumption were expressed as the delta relative to historical values and added to the baseline. Consumption in all other sectors (livestock, electricity generation, domestic, mining, and manufacturing) was held constant across warming scenarios, limiting additional uncertainty and enabling a cleaner evaluation of climate-driven changes in water use.

Unlike thermal power plants, which may employ open-loop cooling with large withdrawal volumes, data centers predominantly rely on recirculating cooling systems, making consumptive water the more relevant metric for assessing their local water impact.[2] Facility-level water consumption of data centers cannot be assessed directly, because the underlying data set provides only geographic coordinates, excluding information on facility capacity, electricity consumption, water quality, or cooling demand. Therefore, we do not explicitly include the operational water consumption of data centers in the water balance. Rather, data centers are overlaid on spatially explicit water gaps derived from the existing sectoral water consumption. This approach allows us to assess the degree to which data centers are in water-stressed regions while avoiding assumptions about heterogeneous cooling technologies and facility-specific water intensities. Water demands associated with data center employees are negligible and are not considered in this study.[67]

Our analysis evaluates the exposure of data centers to regional water gaps on the basis of their geographic location and local renewable water availability. We do not explicitly distinguish between cooling technologies or water sources at the facility level because globally consistent data sets on data center cooling systems and water sourcing are currently unavailable. While many facilities rely on freshwater-dependent evaporative cooling, some data centers increasingly use alternative approaches, including recycled wastewater,[73] brackish water,[74] seawater cooling,[75,76] and dry or hybrid cooling technologies.

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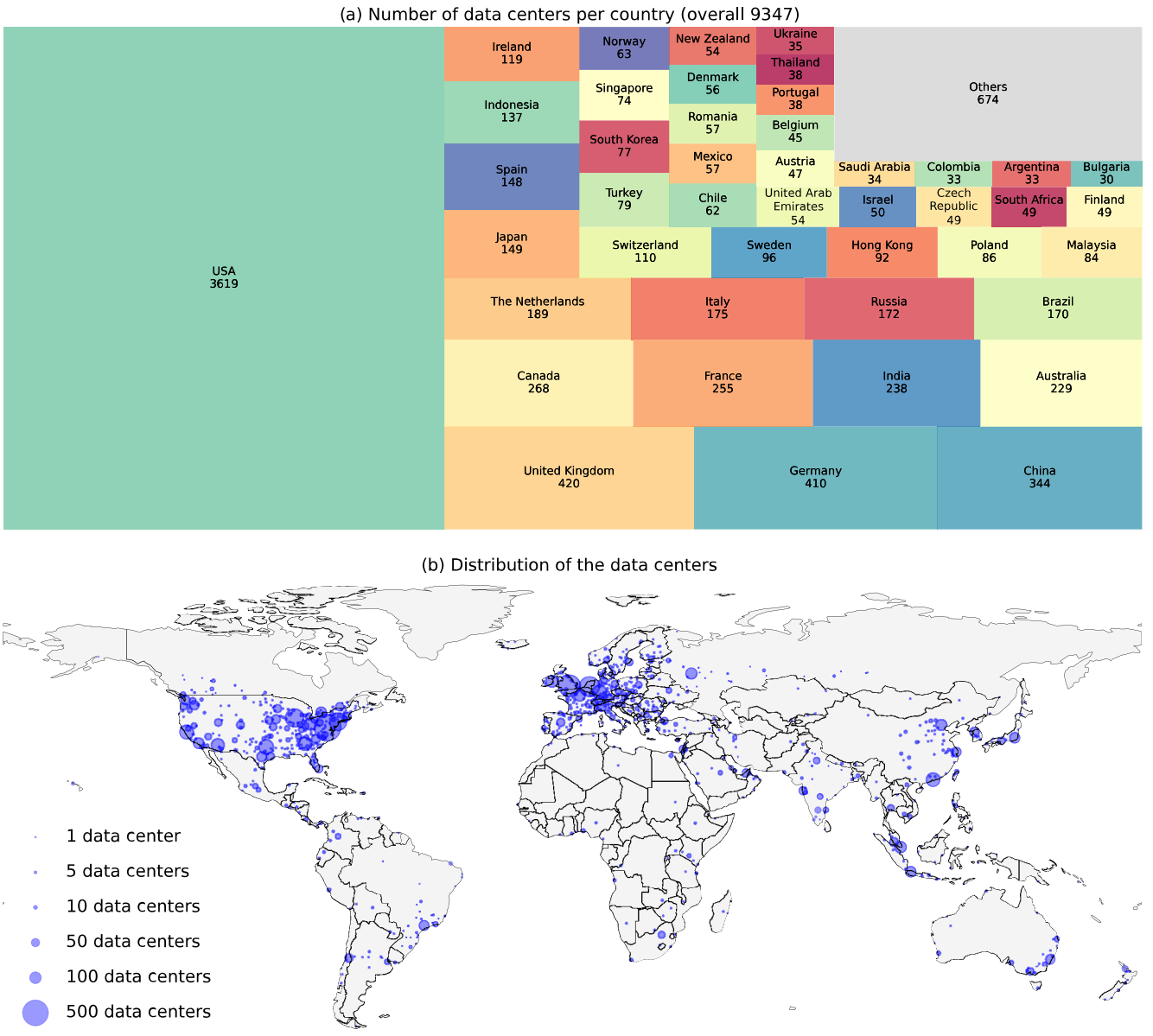


Figure 1. Global distribution of data centers. (a) Number of data centers per country (overall total: 9347), shown as a treemap where block size indicates the country's share. Countries with fewer than 30 data centers are grouped in "Others". (b) Geographic distribution of data centers worldwide. Bubble size reflects spatial clusters of geographically proximate data centers, identified through the density-based clustering algorithm (DBSCAN),[56] with size proportional to the number of data centers in each cluster.

These strategies can reduce the dependence on local freshwater resources and potentially mitigate exposure to water stress, although they may involve trade-offs related to energy consumption, infrastructure costs, and cooling performance under high-temperature conditions. Consequently, our results should be interpreted as potential exposure to local water stress rather than direct freshwater consumption by all of the facilities.

Assessment of Renewable Water Availability

Renewable blue water availability was calculated by subtracting environmental flow requirements from blue water flows generated within each grid cell. Monthly blue water flows were estimated from local runoff using an upstream−downstream flow accumulation routing module,[16] which accounts for both local runoff (surface and subsurface) and inflows from upstream grid cells via river networks. A portion of these flows must be reserved to sustain healthy aquatic ecosystems.[51] Environmental flow requirements were quantified using the variable monthly flow method,[51] which incorporates the seasonal variability of blue water flows when determining these ecological thresholds.

Assessment of Data Center Exposure to Water Gaps

To assess water gap exposure at each data center, we overlaid their locations onto the 0.5° × 0.5° gridded water gaps. For each grid cell containing one or more data centers, we tallied the number of months per year (0−12) characterized by water gaps under the baseline and each future scenario. This yields a distribution of facilities by months of water gaps per year and per scenario.

In addition, we considered the relative contribution of each sector (irrigation, livestock, electricity generation, municipal, mining, and manufacturing) to total water consumption within each cell that hosts at least one data center and classified each cell by its dominant sector (the one with the largest water consumption). Finally, we counted the number of data centers in cells dominated by each consumptive sector to provide a global and country-scale overview of the concurrent water consumption by data centers and other sectors.

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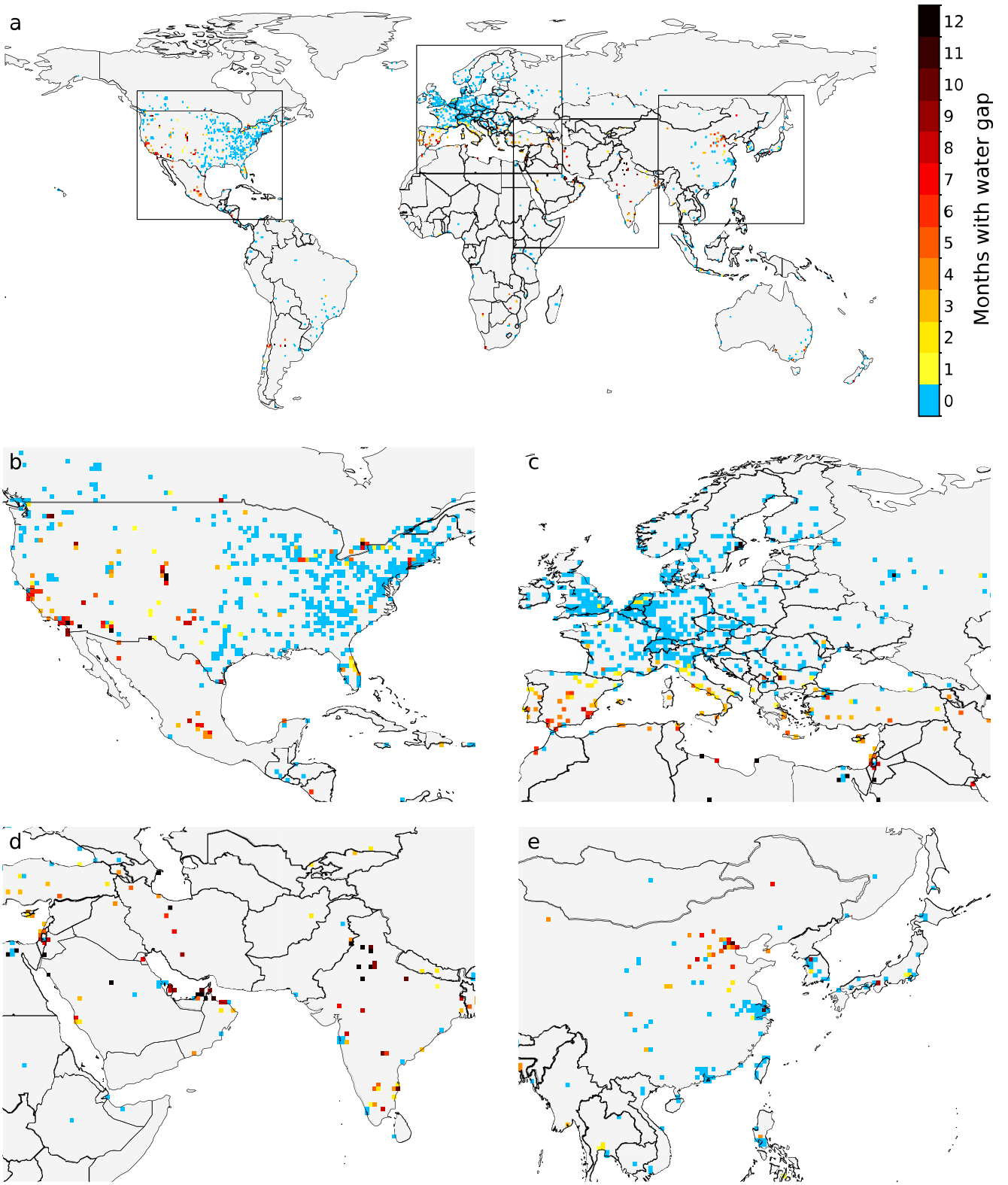


Figure 2. Monthly water gap exposure at data center locations in the baseline climate scenario. Each pixel (50 km resolution at the Equator) corresponds to a grid cell containing at least one data center, colored according to the number of months per year experiencing water gaps (0 = no water gap, 1 = one month per year of water gap, 12 = year-round water gap). Panel (a) shows the global distribution, while panels (b–e) provide regional zooms for North America, Europe, South Asia, and East Asia, respectively. Water gaps represent an upper-bound estimate because buffering strategies (e.g., interbasin transfers, desalination, managed aquifer recharge, reservoir operations, and water allocation mechanisms) are not explicitly represented.

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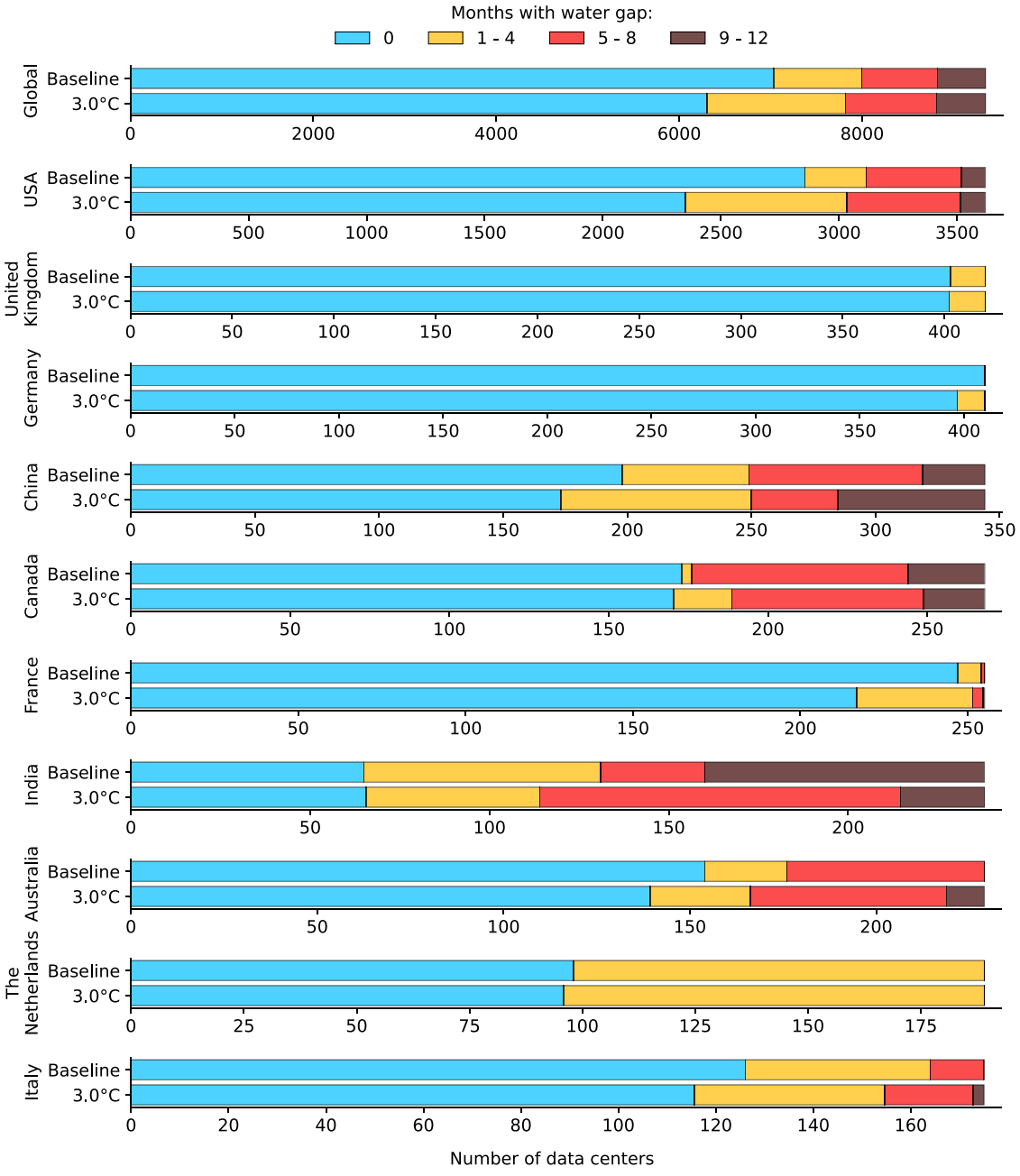


Figure 3. Number of data center locations affected by water gaps. Number of months with water gaps globally and for the ten countries with the most data centers. The two stacked bars correspond to the two scenarios considered: baseline (top bar) and 3.0 °C (bottom bar) warming relative to preindustrial conditions. Values for the future scenarios are obtained by averaging the output of 5 global climate models.

RESULTS

Geographic Distribution of Data Centers

We find that the global footprint of data centers is concentrated in a small number of countries (Figure 1a). The United States alone hosts 3619 facilities (39% of the global total), far exceeding the next largest hosts: the United Kingdom (420), Germany (410), China (344), and Canada (268). A second tier, including Italy, The Netherlands, Australia, India, and France, has each between 175 and 255 facilities, while most countries operate fewer than 150. All other nations host a total of 674 data centers.

North America hosts 43% of all data centers, followed by Europe at 30% and Asia at 18% (Figure 1). South America accounts for just 4%, Oceania 3%, and Africa only 2%. This pattern underscores the dominance of advanced economies in the Global North, where most of the world's computing capacity, and corresponding electricity and water use, takes place. Dense, resource-intensive clusters appear in the eastern and western United States, Western Europe (the UK, Germany, France, The Netherlands), and East Asia (Japan, South Korea, coastal China) (Figure 1b). Other hubs are visible in India, Brazil, and Australia, whereas much of Africa, the Middle East, and Central Asia remain sparsely represented (Figure 1b).

Baseline Water Gaps

Using a water balance model that accounts for water availability and demand,[16] we calculate monthly water gaps for each of the 9347 data center locations worldwide under baseline conditions representative of climatic and hydrologic conditions over the

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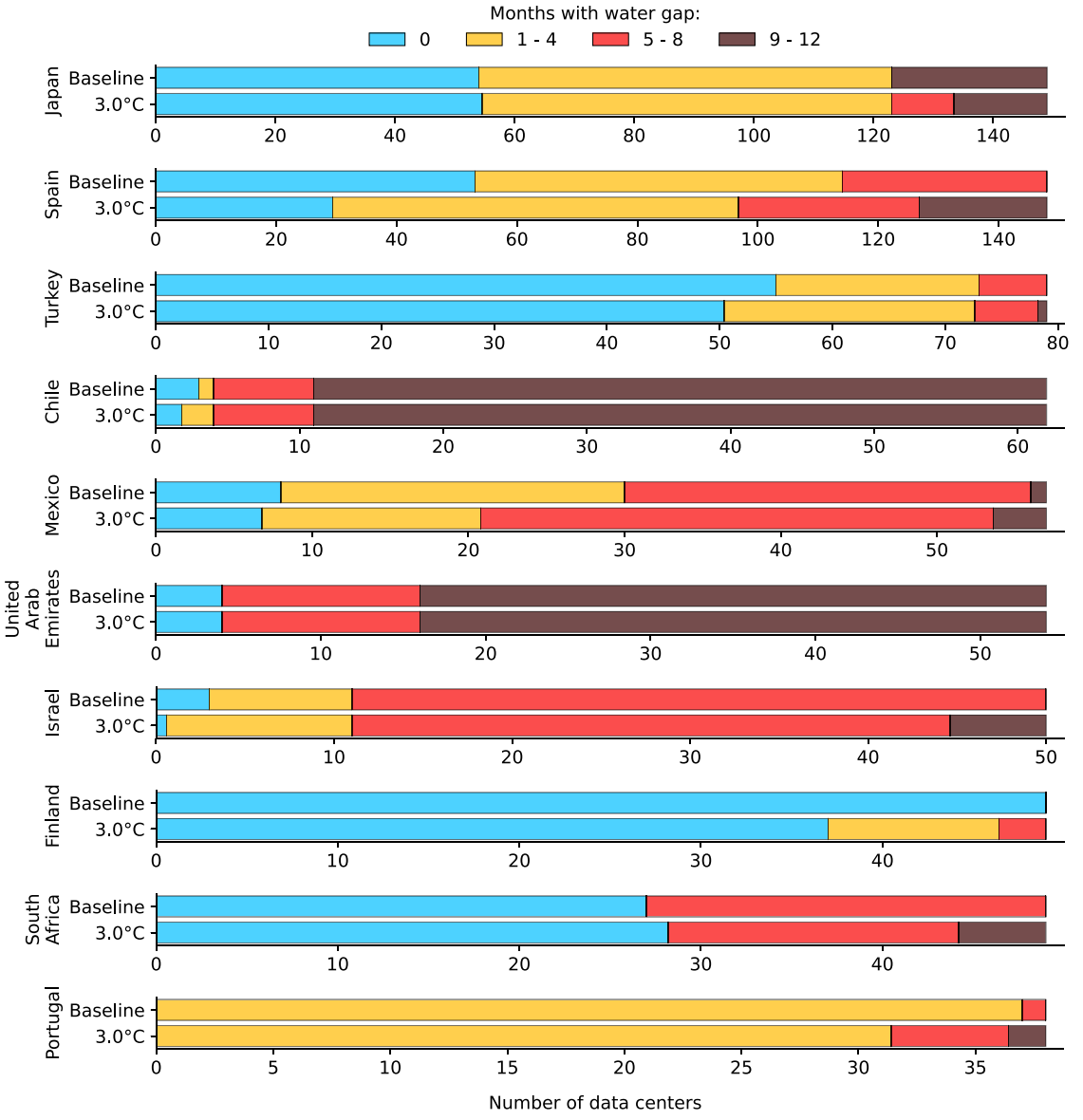


Figure 4. Similar to Figure 3, but showing the number of data center locations affected by water gaps for ten selected countries facing different water gap trends. The two stacked bars correspond to the two scenarios considered: baseline (top bar) and 3.0 °C (bottom bar) warmer climate.

period of 2001−2010. Figure 2a maps global exposure, highlighting hotspots in the western United States, Mexico, the Mediterranean, the Middle East, India, and northern China. In contrast, regions such as Northern Europe and parts of the eastern United States experience relatively low water gap conditions. Overall, 25% of global data centers (2315 facilities) face at least one month of water gaps per year: 7032 experience none, 961 face 1−4 months, 831 experience 5−8 months, and 523 are affected 9−12 months annually (Figure 3).

In the United States, 79% (2855) of data centers are not exposed to water gaps (Figure 3). Among the remaining facilities, 260 experience 1−4 months, 402 face 5−8 months, and 102 endure 9−12 months annually. Water gaps are minimal in the eastern United States, home to dense clusters of data centers, whereas parts of the West and South of the United States experience 4−8 months of gaps, with some locations affected most of the year (Figure 2b). In Canada, 35% (95) of data centers encounter at least one month of water gaps per year.

In Europe, northern and central regions, where most facilities are located, experience little to no stress, while Spain, Italy, and Greece face higher water stress, often exceeding six months annually (Figure 2c). Germany hosts 410 data centers with no exposure to water gaps, while the United Kingdom and France see small shares affected by 1−4 months of water gaps (4%, 17 facilities and 3%, 8 facilities, respectively) (Figure 3). In Italy, 28% (49) of data centers are exposed to water gaps, with 22% (38) facing 1−4 months and 6% (11) experiencing 5−8 months (Figure 4). Spain shows the highest exposure in the region, with 64% (95) of facilities affected: 41% (61) experience 1−4 months and 23% (34) 5−8 months of water stress annually (Figure 4).

South Asia and the Middle East stand out as the most water-stressed regions (Figure 2d). Many data centers in India and the Gulf states face prolonged water stress, often 8−12 months per year. In India, 73% (173) of facilities experience at least one month of water gaps: 28% (66) for 1−4 months, 12% (29) for 5−8 months, and 33% (78) for 9−12 months annually (Figure 3). In the United Arab Emirates, 93% (50) of data centers are

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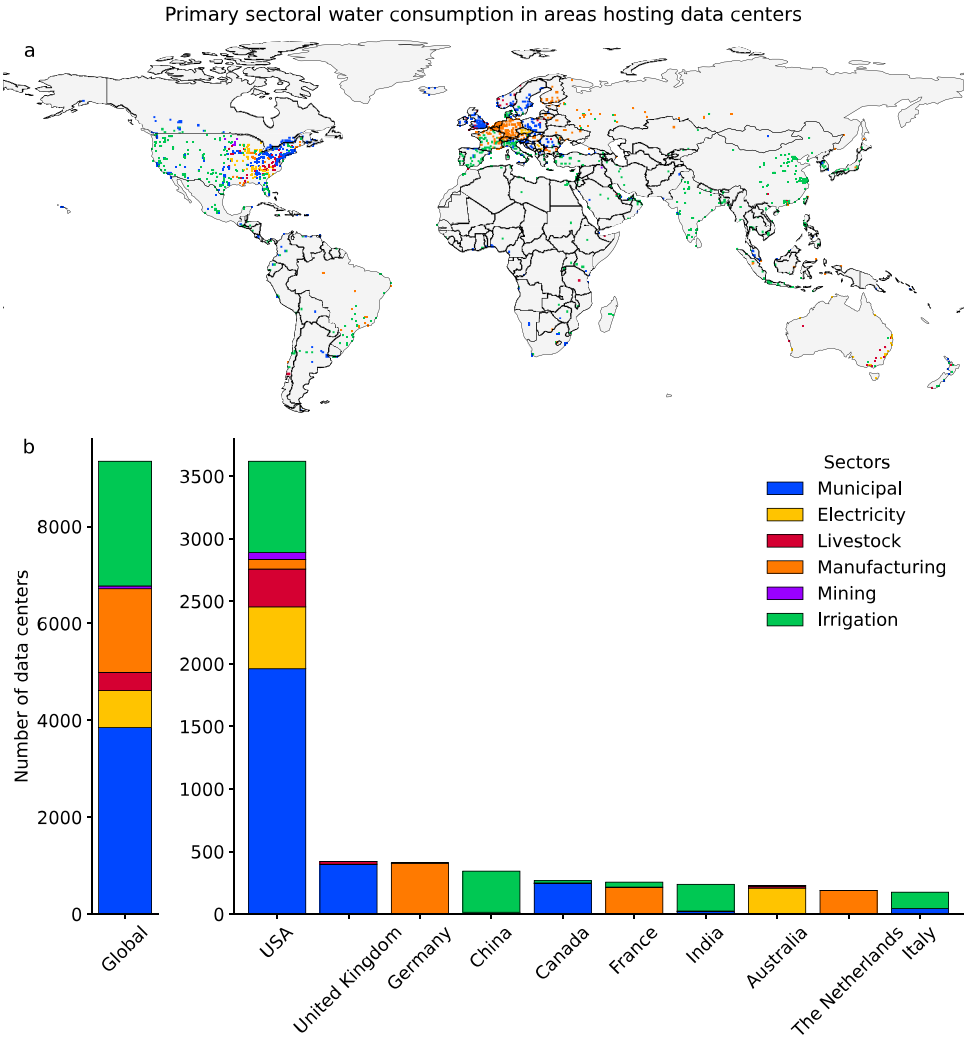


Figure 5. Sectoral water consumption in areas hosting data centers. (a) Global map showing the spatial distribution of data centers and, for each 0.5° grid cell containing a data center, the sector with the highest water consumption. (b) Number of data centers located in grid cells where a particular sector dominates total water demand, shown globally and for the ten countries with the largest number of facilities. Colors indicate the dominant sectoral demand in each grid cell: municipal, electric power generation, livestock, manufacturing, mining, and irrigation.

exposed to at least one month of water gaps (Figure 4). In East Asia, exposure varies across regions (Figure 2e). Coastal data centers in China typically face 3−7 months of seasonal stress, while northern inland locations experience more severe water gaps. Overall, nearly half of Chinese facilities (42%) are affected by at least one month per year. In Japan, most data centers experience water stress, with some (17%) impacted up to 9−12 months annually. In Australia, water gaps are less widespread but still impact a notable portion of facilities, primarily for 5−8 months per year (Figure 3). In South Africa, 45% (22) of data centers are affected by water gaps 5−8 months per year (Figure 4).

Future Water Gaps

Climate change is projected to alter water gap patterns at data center locations. Using climate model outputs, we assess how monthly water gaps will evolve under +3 °C warming (Figure 3). We find that 730 additional data centers are affected, for a total of 3,045 (33% of global facilities). In this scenario, 6302 sites experience no water gaps, 1517 face 1−4 months, 994 endure 5−8 months, and 534 are affected 9−12 months per year (Figure 3). These results indicate that a warmer climate will increase water gaps at global data center locations, highlighting the growing importance of integrating changing hydroclimatic conditions into infrastructure planning.

In the United States, under +3 °C warming, 505 additional facilities are affected, for a total of 1269 data centers (35% nationwide). Here, 2350 sites experience no water gaps, 682 face 1−4 months, 483 endure 5−8 months, and 104 encounter 9−12 months of water gaps each year (Figure 3). In Canada, under +3 °C warming, roughly three additional facilities are affected, for a total of 98 (37%).

Europe exhibits heterogeneous responses to warming. In the UK, the number of affected data centers remains nearly unchanged at 18 (4%) under both warming scenarios (Figure 3). In Germany, warming adds about 13 facilities facing at least one month of water gaps (3.2%) (Figure 3). France sees an increase from 8 currently affected centers to 38 (15%), with small rises in the 5−8 and 9−12 month categories (Figure 3). In Italy, exposure grows from 49 to 59 (34%) under +3 °C, mainly in the 5−8 and 9−12 month ranges (Figure 4). Spain experiences the largest impact: affected centers rise from 95 to 119 (80%) under +3 °C, with substantial growth in the 9−12 month category (Figure 4).

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Asia and the Pacific exhibit diverse responses to warming. In China, warming affects about 31 additional facilities, bringing the total number facing some water gaps to 177 (51%). In India, future warming show a relatively stable exposure pattern compared to the baseline, with the main change being a pronounced shift toward the 5−8 month category (from 29 facilities in the baseline to 101 under +3 °C), reflecting a shift away from both lower and higher exposure classes, particularly the most severe 9−12 month category (noting that results in this region are sensitive to how monsoon dynamics are represented in climate models, which remains a known source of uncertainty).[16] In Australia, +3 °C warming raises affected facilities from 75 to 90, and a pronounced increase in the 9−12 month category (10 facilities corresponding to 4%). In Japan, warming shifts affected facilities modestly: +3 °C warming results in a small rise in the 9−12 month range, with total exposure remaining largely unchanged.

Colocation with Other Water Users

Co-locating data centers with other major water-dependent sectors creates challenges for both existing water uses and data center needs. For each 0.5° grid cell containing at least one data center, we identify the sector with the highest water consumption in that grid cell. Using this approach, globally, 41% (3852) of data centers are situated in areas where municipal water demand is high, followed by irrigated agriculture (28%; 2573 data centers), manufacturing (18%; 1729), electric power generation (8%; 765), livestock production (4%; 372), and mining (<1%; 56) (Figure 5b). These overlaps indicate that data center siting rarely occurs in isolation; instead, facilities are embedded within complex hydrological and socio-economic systems where additional water demand can exacerbate existing water gaps and undermine the sustainability of water resource use.

The United States shows the most heterogeneous pattern of colocation between data centers and major water-using sectors. More than half of the United States facilities (54%, 1961) lie in areas where water demand is dominated by municipal water consumption (Figure 5). Irrigated agriculture overlaps with 20% (729) of data centers, while electric power generation is prominent in 14% (495) of the locations. Livestock production intersects with 8% (302) of facilities, manufacturing (77), and mining (55), both around 2%.

In the United Kingdom, 95% of facilities are colocated with municipal water consumption, with 5% associated with livestock areas. In Germany, data centers are located in manufacturing-intensive regions. France exhibits a mixed profile, with 84% overlapping manufacturing and 16% being associated with irrigated agriculture. The Netherlands is entirely manufacturing-related. In Canada, 93% of data centers co-occur with municipal water consumption and 7% with irrigated agriculture. Australia exhibits a distinctive pattern dominated by electric power generation (91%), with smaller shares linked to livestock (8%) and irrigation (1%).

In China, 96% of data centers are in regions with important irrigated agriculture, with 3% associated with manufacturing. In India, irrigation accounts for more than 89% of colocation. Japan presents a balanced structure: 53% of data centers overlap with irrigated agriculture and 47% with manufacturing, reflecting their distribution across both agricultural landscapes and industrial corridors.

These colocation patterns have important implications. They determine which sectors bear the trade-offs of data center expansion, where trade-offs over water resources are most likely to emerge, and which regions face the greatest operational risk as AI-driven demand accelerates.

DISCUSSION

Water stress has profound implications for water use, infrastructure planning, and environmental outcomes in addition to operational risk. Approximately 25% (2315) of data centers experience at least one month of water gaps annually under the baseline conditions. While such conditions rarely force permanent shutdowns, they could constrain operational flexibility and intensify water stress with other water-dependent sectors, including ecosystems, agriculture, households, and electricity generation.[72] While water scarcity is often framed as a potential constraint on data center expansion, in practice, data centers typically have the financial capacity and institutional priority to secure water supplies whenever water is available. As a result, the primary risk may not be to data center operations themselves but to other water users within the same basins.

We find that 41% (3852) of data centers are in areas where municipal water use is the dominant sectoral demand, implying stress between cooling and ancillary uses and household, commercial, and public service needs. These facilities often rely on the same potable or treated municipal supplies, creating stress with urban users during periods of peak demand and constrained availability while also raising concerns about water quality as increased withdrawals and the discharge of heated or treated effluents place additional pressure on already stressed municipal and downstream systems.

Interpreting these patterns also requires careful consideration of the institutional and data constraints. Although this study integrates geospatial information with hydrological modeling and sectoral water-use data sets, the underlying data remain incomplete and uneven across regions. Public information about data center capacity, cooling technologies, and operational water use remains limited.[9,57] Even in regions with relatively transparent reporting, the situation evolves quickly and actual water consumption can differ substantially from design specifications. Moreover, allocation rules, pricing mechanisms, and legal priorities often favor municipal, industrial, and strategic infrastructure uses, including data centers, over agriculture and ecosystems under scarcity. These factors imply that current global assessments likely underestimate both existing exposure and downstream impacts on less economically or politically powerful users.[58,59] Future work integrating facility-level data on cooling technologies, operational water use, and capacity would substantially strengthen this line of research, enabling a transition from exposure-based assessments to direct quantification of data center water demand on the global scale. Addressing such gaps will require greater collaboration among data providers, regulators, and infrastructure operators.

Technological and operational approaches offer promising avenues to reduce the freshwater footprint of data centers. Several emerging options, such as wastewater reuse, nonpotable cooling loops, and district-scale thermal systems, could help decouple data center cooling from potable water demand in urban regions.[60,61] In coastal and arid zones, renewable-powered desalination remains technologically feasible, although its broader environmental footprint requires careful evaluation.[62,63] Advances in data center cooling efficiency, including immersion cooling and dynamic thermal management, further reduce water use while improving energy performance.[64−66] Wastewater

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reuse—while beneficial at the facility or municipal scale—is not a basin-scale solution, as water that is reused locally would otherwise have continued downstream to support other users and ecosystems; its net benefit therefore depends critically on the hydrological context and the degree to which return flows are already relied upon by downstream rights holders. Importantly, the colocation of data centers with other major water users does not necessarily imply direct competition for water resources. In many regions, available water supplies may be sufficient to meet demands across sectors, and water utilities typically assess supply capacity, infrastructure constraints, and regulatory requirements before approving new large water users. We show the largest water-consuming sector colocated with each data center to provide a comprehensive representation of where data centers are located and the dominant water uses in their surrounding regions, rather than to imply existing conflicts. Potential competition is more likely in locations where data centers coincide with substantial water gaps. However, these estimated water gaps should be interpreted as an upper-bound estimate because the analysis does not explicitly represent buffering and adaptation strategies, including interbasin water transfers, desalination, managed aquifer recharge,[77] reservoir operations, and water rights or allocation mechanisms. Future assessments incorporating these local water management strategies and infrastructure constraints would provide a more refined estimate of potential competition between data centers and other water users.

Water appropriation by data centers is also embedded within broader water−energy−land trade-offs. Data centers can partially mitigate exposure to local water stress through alternative cooling strategies, such as dry cooling, or by shifting to less water-intensive power generation pathways. Systems that minimize freshwater use, such as dry cooling, typically require more electricity and are less energy-efficient than water-cooled systems, leading to an energy penalty that can increase indirect water demand upstream, particularly at thermoelectric power plants.[67] Conversely, wet cooling reduces on-site energy use but intensifies competition for municipal water in stressed regions.[67] Similarly, changes in energy sourcing, such as relying on single-cycle natural gas or renewable electricity, can reduce direct water withdrawals but often come at the cost of lower efficiency, higher emissions, or increased land requirements.[68,69] Hybrid cooling systems attempt to balance these extremes. Energy sourcing further complicates these trade-offs: while renewables reduce water footprints, they require substantially more land area per unit of energy, introducing land-use pressures where deployment is large-scale.[68,69] These adaptation strategies therefore shift, rather than eliminate, resource pressures across sectors.

Beyond technology, strategic siting and governance are central to addressing these challenges. Locating data centers in water-rich regions can reduce displacement pressures, while distributed networks of smaller facilities may limit localized competition in stressed basins.[70] More speculative approaches, such as orbital data centers,[71] underscore the growing recognition that terrestrial energy and water constraints are binding for continued expansion.

The findings of this study demonstrate that a substantial number of currently identified data centers are located in regions already experiencing or projected to experience water stress. The extent to which this exposure translates into operational impacts for data centers themselves or into measurable consequences for other water users remains an open question that will require future research integrating facility-level operational data, future infrastructure scenarios, and higher-resolution local assessments to address.

■ ASSOCIATED CONTENT

Data Availability Statement

Results of this study are available at: https://zenodo.org/records/22912911

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Author Contributions

L.R. conceived the study with inputs from M.S., B.S., M.M., J.B., and A.M.M. M.S. and L.R. performed the analysis. L.R. collected data. All authors designed the study and analyzed the results.

Notes

The authors declare no competing financial interest.

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