

Energy and environmental impacts of rapid data-center expansion in the United Arab Emirates

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Abstract: Rapid growth in artificial intelligence (AI) is driving major data-center expansion globally, increasing demand on electric power and water-supply systems. Yet the energy and environmental implications of this growth remain comparatively understudied in hot, water-scarce regions such as the United Arab Emirates (UAE), where announced developments coincide with high cooling requirements, desalination-dependent water supplies, and a natural-gas-dominated electricity system. This study quantifies the electricity, water, and greenhouse gas (GHG) implications of UAE data-center expansion using a bottom-up capacity inventory, modeled operating loads, and a thermodynamic cooling model coupled to national electricity and water supplies. Scenario-aware Monte Carlo simulation propagates uncertainty across 2030–2040 operating scenarios with varying capacity expansion and clean-electricity generation levels. Median annual site electricity demand varies 6.62–37.8 TWh, reaching 11.5% of national generation. Attributed GHG emissions total 3.01–17.6 Mt CO₂e annually under baseline grid conditions but fall 12–32% under alternative grids with increased clean generation. Expansion also reduces national clean-generation shares, requiring substantial additional solar photovoltaic capacity to meet UAE decarbonization objectives under some grid scenarios. When clean generation does not expand further to supply the added demand, increased natural-gas generation raises system-wide GHG emissions by 2.27–19.9 Mt CO₂e (up to 22%) relative to a no-expansion reference. Water requirements remain high despite modeled power usage effectiveness near 1.22 for AI facilities. Median annual water demand is 10.6–63.1 Mm³, with desalinated cooling make-up comprising over 99% of demand. Dry-cooling configurations can reduce water demand by 98.2% but increase electricity demand by 11–13%, with the net electricity penalty roughly 20 times the desalination electricity avoided. These findings call for expediting clean-electricity deployment and planning water supplies alongside data-center expansion, given that low facility electricity overheads and lower attributed emissions from matching existing clean generation can coexist with substantial system-wide emissions and water requirements.

Keywords: data centers; artificial intelligence; electricity demand; greenhouse gas emissions; decarbonization; energy-water nexus; desalination; United Arab Emirates

1. Introduction

Despite a more than sixfold increase in global computing instances between 2010 and 2018, data-center electricity use only grew by 6% during that period.¹ This was largely due to the improvements in data-center energy efficiency that moderated electricity-demand growth. However, the rapid growth in artificial intelligence (AI) services and the associated expansion of server deployment and power requirements have outpaced these gains.^{2,3} This growth is now placing increasing demands on national electric power systems.⁴⁻⁷ Global data-center electricity consumption was estimated at 485 TWh in 2025 and is projected to reach approximately 950 TWh by 2030 (3% of global electricity demand).⁸ In the United States (US), data centers accounted for 4.7% of electricity consumption in 2024 and are projected to reach 9.5–15.3% by 2030.³

Where clean electricity generation does not sufficiently expand alongside demand, data-center growth can also increase fossil generation and power-sector greenhouse gas (GHG) emissions. A recent US assessment projected that combined data-center and cryptocurrency demand could increase power-sector CO₂ emissions by up to 28% in 2030 relative to a future without this demand growth, depending on natural gas prices and renewable incentives.⁹ Water requirements also arise from both on-site cooling at the facilities and from the electricity generation supplying data centers.^{10,11} Other emerging environmental impacts include increased regional air pollution associated with electricity generation and localized warming from heat released by facilities, which affect surrounding and far-away communities.^{12,13} Siting, cooling improvements, and grid decarbonization offer mitigation opportunities, but their effectiveness depends on the regional context and infrastructure serving the added load.^{9,14-16}

Yet the environmental implications in regions experiencing rapid AI data-center expansion, such as the United Arab Emirates (UAE), remain comparatively understudied. The announced 5 GW UAE-US AI campus illustrates the potential scale of growth.¹⁷ Recent Gulf-focused studies have examined AI workloads, data-center deployment, and sustainability scenarios,¹⁸⁻²¹ but have not jointly quantified how major announced capacity could affect national electricity and water demand, GHG emissions, and interactions with expanding clean-electricity generation. These interactions are particularly consequential in the UAE, where high temperatures and coastal humidity raise cooling requirements, while desalination supplies much of the country's potable water.^{22,23} The UAE's transitioning electric grid remains dominated by natural gas with growing contributions from clean sources including nuclear and solar generation.²⁴ More recently, UAE utilities have announced further solar expansion for 2030 and 2035²⁵⁻²⁸ with a national target of 35% clean electricity generation by 2031^{29,30}. The effects of data-center growth on the UAE's decarbonization goals therefore depend on whether additional clean-electricity generation can keep pace with growing demand.

The implications of this buildout extend beyond the UAE. The pace and scale of expansion can strain supply systems and remain environmentally consequential even if facilities achieve low cooling-electricity overheads.³ UAE project announcements, like those in other markets, also emphasize clean energy as part of the intended electricity supply^{17,31-34}; however, matching data-center demand to existing clean generation differs from expanding clean electricity supply to accommodate this growth. Therefore, this study examines three related issues concerning national resource planning and decarbonization for accommodating data-center growth: (i) total electricity and water requirements and GHG emissions associated with announced data-center capacity; (ii) changes in national clean-generation shares and system-wide GHG emissions, including additional clean generation required to safeguard different decarbonization-related objectives; and (iii) how cooling configurations and operating conditions affect and trade off electricity and water requirements.

The UAE provides an informative case for examining these issues because they intersect with distinctive cooling and water-supply conditions. High temperatures and humidity constrain opportunities

for economizer cooling, while desalinated cooling make-up requires additional electricity for water production.^{11,35,36} At the same time, seawater-cooled electricity generation can limit indirect freshwater consumption, which accounts for a large share of data-center water footprints in some US assessments.^{10,14,37–39} Consequently, grid decarbonization, water-saving cooling, and changes in operating conditions can affect different parts of the data-center footprint and introduce trade-offs in a system where energy and water requirements are high.

To address these issues, the electricity, water, and GHG implications of announced UAE data-center expansion are quantified using a bottom-up capacity inventory, archetype-specific operating loads, and a physics-based cooling model coupled to national electricity and water supplies. Uncertainty is propagated across alternative expansion and clean-electricity supply scenarios using scenario-aware Monte Carlo simulation (SA-MCs).^{40,41} The modeled expansion results in megatonne-scale annual GHG emissions attributed to data-center electricity use and tens of millions of cubic meters of cooling make-up water demand, despite relatively low facility electricity overheads. Matching existing clean-electricity generation reduces emissions attributed to data centers without changing system-wide GHG emissions, while several gigawatts of additional solar capacity are found to be required to reach the 35% national clean-generation benchmark under some modeled grid scenarios. Furthermore, substantial water savings from dry cooling configurations are accompanied by an electricity penalty that far exceeds the desalination electricity avoided. Together, these findings demonstrate that facility efficiency, clean-electricity matching, and national clean-generation shares alone cannot fully describe the environmental consequences of data-center expansion.⁴² By quantifying these differences under the UAE's electricity- and water-supply conditions and exploring how different mitigation measures shift burdens across those systems, this study provides insights relevant to Gulf countries and beyond planning similar expansion.

2. Methods

2.1 Overview

The modeling framework consists of four modules that quantify annual electricity demand, water demand, and GHG emissions from currently operating and announced UAE data-center capacity (**Figure 1**). Module 1 combines estimated 2025 installed IT capacity^{43–49} with three cumulative expansion scenarios (Confirmed, Central, and High Expansion), and assigns capacity to five archetypes: wholesale hyperscale, retail colocation, enterprise and telecom, AI training, and AI inference.² Module 2 quantifies annual IT electricity using fill rates and operational capacity factors (OCFs). Module 3 estimates power usage effectiveness (PUE) and site water usage effectiveness (WUE) using thermodynamic cooling models^{11,14} and UAE weather conditions, yielding site electricity and direct cooling-water demand. Module 4 combines these outputs with national non-data-center electricity demand under three clean-generation grid scenarios (Existing Grid, Planned Grid, and Ambitious Grid) to calculate GHG emissions attributed to data-center operation, system-wide emissions change from data-center expansion, indirect freshwater use, clean-electricity matching outcomes, and national clean-generation shares. Electricity for desalinating cooling make-up water is included in the national electricity balance and emissions.

Given uncertainty in project completion dates, results represent annual electricity, water, and emissions requirements assuming the capacity in each expansion scenario is built and operating at sampled fill rates and OCFs during 2030–2040, rather than forecasts for specific years. Within each grid scenario, it is assumed that clean-electricity generation does not increase in response to data-center expansion, but annual solar generation varies with sampled yields in the Planned and Ambitious Grids. Non-data-center background demand is obtained from sampled national demand projections for the analysis period.^{26–28,50} The three expansion and three grid scenarios are evaluated as nine capacity–grid combinations using SA-MCs, with 100,000 realizations per combination.⁴⁰ Within each scenario

combination, uncertain inputs are sampled and annual electricity, water, and emission balances are calculated for each Monte Carlo realization. Results are reported as medians and 5th–95th percentile intervals. Parameters and sources are provided in the Supplementary Information (SI) and Supplementary Data Sheets S1–S5.

2.2 Module 1: installed IT capacity and expansion scenarios

The inventory covers facilities operating and announced in the UAE, with reported capacity treated as installed IT capacity (MW_{IT}) unless stated otherwise. The 2025 installed IT base is informed by operator disclosures and published market estimates.^{43–49} Three cumulative expansion scenarios are considered: Confirmed Expansion includes projects under construction or with stated delivery dates, Central Expansion adds disclosed or inferred initial phases of announced projects, and High Expansion assumes the full announced buildout. Each scenario also includes a corresponding scale of Stargate UAE and broader UAE-US AI Campus (0.2, 1, and 5 GW, respectively).^{51–53} Conventional announced projects are assigned to archetypes using sampled shares based on operator descriptions. AI-dedicated capacity is divided among training, inference, and non-accelerated IT using assumed workload-share distributions, with the latter assigned to the wholesale archetype. Inventory details and sources are provided in SI Sections S1–S2 and Supplementary Data Sheets S1–S2.

2.3 Module 2: IT utilization, load, and energy

Annual IT electricity is estimated from installed capacity because UAE facility-level equipment inventories and configurations are unavailable. Two factors convert capacity to average IT load: the fill rate (i.e., the fraction of commissioned capacity populated with operating equipment) and OCF (i.e., the annual average power drawn by that equipment relative to its rated power). Their product defines the IT load factor. Fill rates are sampled separately for the 2025 base, announced additions, and AI-campus stages using assumed distributions informed by occupancy, pre-commitment, and customer-utilization data.^{43,54,55} Archetype-specific OCF values are derived from published server power–utilization relationships^{2,3,14,56} as shown in **Eqn. (1)**:

$$(1) \quad OCF_a = p_{idle,a} + (p_{op,a} - p_{idle,a})u_a$$

where a denotes the IT archetype, $p_{idle,a}$ and $p_{op,a}$ are the idle and operational power fractions of rated power, and u_a is the average computational utilization. The server-derived OCFs are used as proxies for the full IT load, including storage and network equipment. Annual IT electricity for each archetype is calculated using **Eqn. (2)**:

$$(2) \quad E_{IT,a} = C_{IT,a} f_a OCF_a \times 8760$$

where $C_{IT,a}$ is installed IT capacity (MW_{IT}), f_a is the capacity-weighted fill rate across the base, additions, and AI-campus components, and $E_{IT,a}$ is annual IT electricity (MWh_{IT}). Parameter distributions, derivations, and sources are provided in SI Section S2 and Supplementary Data Sheet S2.

2.4 Module 3: thermodynamic cooling model

Annual PUE and site WUE are estimated for eight cooling configurations using physics-based thermodynamic models adapted from Lei and Masanet¹¹ (conventional data-center configurations) and Xiao et al.¹⁴ (AI data-center configurations) under UAE conditions. PUE is the ratio of annual site

electricity to IT electricity, while site WUE represents cooling make-up water supplied per unit of IT electricity ($\text{L kWh}_{\text{IT}}^{-1}$), including humidification, evaporation, drift, and blowdown. Indirect freshwater used in electricity generation is calculated separately in Module 4.¹⁰

Equipment and operating parameters are sampled and evaluated using a typical meteorological year for Abu Dhabi International Airport⁵⁷, with weather conditions weighted by their annual frequency to produce paired annual PUE and WUE distributions for each configuration. Cooling-configuration shares are sampled by archetype around assumed central mixes informed by facility-type distinctions.² In each Monte Carlo realization, a paired PUE–WUE value is sampled for each configuration and combined using the same cooling shares, preserving their dependence on cooling design. Site electricity and direct cooling-water demand are then calculated for each archetype using **Eqn. (3)**:

$$(3) \quad E_{\text{site},a} = \text{PUE}_a E_{\text{IT},a} \quad ; \quad W_{\text{direct},a} = \text{WUE}_a E_{\text{IT},a}$$

where PUE_a and WUE_a are the cooling-share-weighted values for each archetype. Site electricity (MWh) and direct cooling-water demand (m^3) are summed across archetypes within each realization. Cooling configurations, parameter distributions, and assumed cooling shares are detailed in SI Section S3 and Supplementary Data Sheet S3.

2.5 Module 4: grid and clean-electricity supply

National grid factors are derived from 2025 utility reports for Abu Dhabi, Dubai, and the Northern Emirates.^{37,38} Three grid scenarios (Existing Grid, Planned Grid, and Ambitious Grid) represent increasing clean-electricity generation (nuclear, solar photovoltaic (PV), concentrating solar power (CSP), and wind), with annual clean-electricity generation of 59.4, 93.4 [89.2–97.5], and 141.2 [132.1–150.3] TWh, respectively. The Existing Grid retains current clean-electricity generation values under future electricity demand, while the Planned and Ambitious Grids represent stochastic utility-informed expansion plans for 2030 and 2035, respectively.^{26–28,50}

National non-data-center electricity demand (E_{nonDC}) is estimated by subtracting an assumed embedded data-center allocation^{47,58} from sampled national background-demand^{27,28,59,60}, given that national demand projections include unspecified levels of data-center electricity demand. In each realization, site electricity and electricity required for cooling-water supply are added to E_{nonDC} , with the modeled clean-electricity generation assumed to be used in full and natural gas supplying any residual demand. The annual balance assumes no transmission or distribution losses and does not resolve hourly dispatch or additional generation investment in response to data-center expansion.

Emission and freshwater intensities are calculated from the resulting generation mix. The assumed operational emission factors^{27,28,37,38} from utility reports use an all-to-power convention, assigning fuel emissions from electricity and desalination cogeneration entirely to electricity. Life-cycle contributions from fuel supply and generation technologies^{61–64} are added to operational emission factors, while freshwater factors reflect assumed UAE power-plant cooling conditions^{37–39}. Embodied emissions from data-center construction and IT equipment manufacturing are excluded.

Direct cooling water is assumed supplied by the municipal desalination network. Water-supply electricity is calculated using the electrical intensity of each grid scenario's desalination mix⁶⁵ and included in total electricity demand and GHG emissions. Total data-center electricity, modeled water demand, and GHG emissions attributed using the resulting national-average grid emission factors follow **Eqn. (4)**:

$$(4) \quad E_{\text{total}} = E_{\text{site}} + \epsilon_d W_{\text{direct}} \quad ; \quad W_{\text{total}} = W_{\text{direct}} + \omega E_{\text{site}} \quad ; \quad M_{\text{total}} = I_{\text{national}} E_{\text{total}}$$

where ϵ_d is the desalination electrical intensity (MWh m⁻³), ω is grid freshwater intensity (m³ MWh⁻¹), I_{national} is the national-average emission intensity (t CO₂e MWh⁻¹), and M_{total} is GHG emissions attributed to total data-center electricity (tCO₂e). Total water demand combines cooling make-up supplied and indirect freshwater consumption from site-electricity generation, excluding seawater withdrawals.

Clean-electricity agreements are represented by an annual matching fraction (f_{match}) of 0, 30, 80, or 100% of site electricity to existing eligible clean-electricity generation (E_{clean}), without assuming additional generation. Existing claims by other consumers are not modeled. Matching applies to site electricity only, while the remaining eligible clean generation and residual electricity mix are recalculated after the modeled claims are excluded. f_{match} is used to calculate the share of available clean-electricity generation claimed ($\frac{f_{\text{match}}E_{\text{site}}}{E_{\text{clean}}}$) and the remaining clean-electricity generation per unit of non-data-center and desalination electricity demand ($\frac{E_{\text{clean}} - f_{\text{match}}E_{\text{site}}}{E_{\text{nonDC}} + \epsilon_d W_{\text{direct}}}$). The residual-mix emission factor is quantified following the GHG Protocol's residual-mix approach⁶⁶ using **Eqn. (5)**:

$$(5) \quad I_{\text{res}} = \frac{(E_{\text{nonDC}} + E_{\text{site}} + \epsilon_d W_{\text{direct}})I_{\text{national}} - f_{\text{match}}E_{\text{site}}I_{\text{clean}}}{E_{\text{nonDC}} + (1 - f_{\text{match}})E_{\text{site}} + \epsilon_d W_{\text{direct}}}$$

where I_{clean} is the national generation-weighted life-cycle emission factor of the clean-electricity sources. The residual-mix emission factor (I_{res}) applies to other electricity consumers, unmatched data-center electricity, and desalination electricity. Total emissions attributed to non-data-center consumers, data-center site electricity, and desalination electricity are calculated using **Eqn. (6)**.

$$(6) \quad M_{\text{system}} = f_{\text{match}}E_{\text{site}}I_{\text{clean}} + (1 - f_{\text{match}})E_{\text{site}}I_{\text{res}} + E_{\text{nonDC}}I_{\text{res}} + \epsilon_d W_{\text{direct}}I_{\text{res}}$$

Matching therefore reallocates attributed emissions between consumers without changing physical electricity demand, generation, or system-wide GHG emissions. Separately, the increase in system-wide electricity GHG emissions from expansion is calculated within each realization relative to a No Data-Center Expansion scenario, which retains the modeled 2025 data-center sector under the same background national electricity demand and grid scenario. With clean-electricity generation fixed within each grid scenario, the system-wide emissions increment equals the increase in natural-gas generation multiplied by its assumed emission factor, whereas **Eqn. (4)** attributes emissions to the full data-center fleet using the national-average emission factor.⁶⁷

Additional clean-electricity requirements are evaluated for maintaining the No Data-Center Expansion reference clean-generation share, reaching the UAE's 35% clean-generation benchmark^{29,30} (used as common benchmark across all grid and expansion scenarios), and avoiding additional natural-gas generation. Additional clean-electricity generation is also converted to solar PV-equivalent capacity assuming annual displacement of natural-gas generation. Grid parameters, scenario definitions, calibration, and detailed calculations are provided in SI Section S4 and Supplementary Data Sheet S4.

2.6 Uncertainty and sensitivity analysis

SA-MCs^{40,41} separates parameter uncertainty from the nine discrete capacity–grid scenarios, using common draws for inputs shared across scenarios. One-at-a-time sensitivity tests evaluate model parameters and design assumptions. For parameter tests, OCF and fill rates are fixed at their distribution bounds across archetypes and capacity groups, respectively. PUE, WUE, and non-data-center electricity demand are fixed at their modeled or sampled 5th and 95th percentiles, with PUE and WUE varied separately.

Design comparisons vary the AI training share (35–65%), cooling-configuration mixes, and supply-air temperature and dew-point limits. Cooling-technology comparisons separately identify the configurations yielding the lowest and highest median electricity and water demand among the different fleet-level configuration combinations, retaining paired PUE-WUE values. Other inputs retain their sampled values. Grid emission and freshwater intensities are recalculated in each comparison based on the resulting electricity demand and generation mix. Percentage changes between medians of total electricity, attributed GHG emissions, and water demand are quantified relative to each capacity–grid combination's reference case. For selected cooling alternatives, changes in system-wide GHG emissions and additional electricity per unit of water demand avoided are also calculated within paired realizations. Additional sensitivity tests examine alternative national electricity-demand envelopes. Detailed sensitivity analysis descriptions and results are provided in SI Section S5 and Supplementary Data Sheet S5.

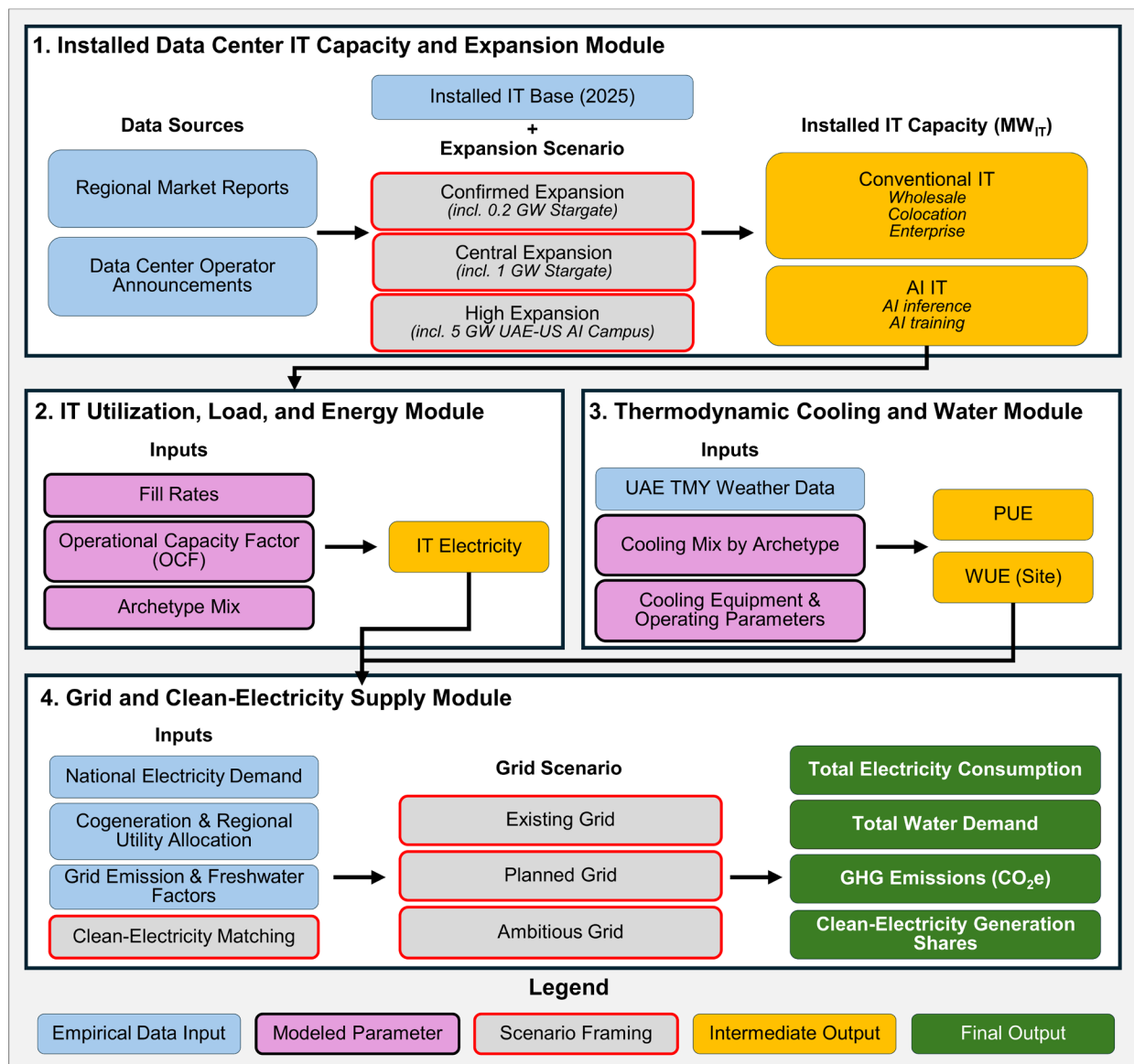


Figure 1. Modeling framework for the UAE data-center assessment. Schematic showing four linked modules combining the estimated 2025 installed IT capacity and announced additions with operating loads, thermodynamic cooling performance, and electricity and water supply assumptions to estimate annual electricity demand, water

demand, and greenhouse gas (GHG) emissions. Three cumulative capacity-expansion scenarios (Confirmed, Central, and High Expansion) are combined with three clean-generation scenarios (Existing Grid, Planned Grid, and Ambitious Grid), yielding nine capacity–grid combinations. Clean-electricity matching and additional generation requirements are evaluated separately within the grid module. Blue boxes show empirical data inputs, pink boxes show modeled parameters, grey boxes show scenario choices, yellow boxes show intermediate outputs between modules, and green boxes show the final electricity, water, emission, and clean-electricity generation outputs.

3. Results

3.1 Installed IT capacity, load, and cooling performance

Installed IT capacity increases from the modeled 2025 base of 0.411 GW_{IT} to 1.06, 2.16, and 7.42 GW_{IT} under Confirmed, Central, and High Expansion, respectively (**Figure 2A**). Apart from scale, expansion also changes the fleet composition, with AI IT accounting for approximately 18%, 54%, and 78% of installed capacity across the three scenarios. Wholesale capacity increases from 0.776 GW_{IT} under Confirmed Expansion to 1.36 GW_{IT} under High Expansion, while colocation and enterprise together remain below 0.20 GW_{IT}. High Expansion reaches approximately 18 times the 2025 installed capacity, with the 5 GW AI campus providing the largest addition.

Figure 2C–D summarizes the assumed OCF and fill-rate distributions used to convert installed capacity to operating IT load. Median OCFs are 0.68 for wholesale, 0.57 for colocation, and 0.48 for enterprise, reflecting differences in modeled computational utilization.^{2,3} AI training has a higher median OCF than inference (0.63 versus 0.41), with inference also having the widest uncertainty interval (0.32–0.47) due to fleets being provisioned for peak demand but operating at lower utilization outside peak periods.^{2,3,14} Median fill rates are 0.84 for the 2025 base^{43,47,54,68}, 0.89 for other announced additions^{55,68–70}, and 0.92 for the initial 0.2 and 1 GW Stargate phases. The 5 GW campus has a lower and wider fill distribution than the initial Stargate phases (median 0.84 [0.74–0.91]), reflecting higher uncertainty in equipment deployment beyond the initial announced capacity^{51,71}.

Modeled cooling performance under the assumed reference configurations differs across archetypes (**Figure 2E–G**). Median PUEs of 1.22 are estimated for both AI training and inference, and 1.26 for wholesale, reflecting the assumed use of economizers, liquid cooling in AI facilities, and lower electrical losses. Higher PUEs are estimated for colocation (1.62) and enterprise (1.80), reflecting greater reliance on chillers without economizers and, for enterprise, direct expansion. However, lower PUE does not necessarily translate into lower WUE. Median WUE ranges from 1.97 to 2.11 L kWh_{IT}^{−1} across wholesale, colocation, and AI due to their use of evaporative heat rejection, compared with 0.65 [0.13–1.73] L kWh_{IT}^{−1} for enterprise. In the assumed central cooling mixes (**Figure 2G**), dry heat rejection serves 75% of enterprise and 30% of colocation IT electricity, requiring water only for humidification. Sampled cooling-share distributions are provided in **Figure S1**.

Together, capacity, loading, and cooling performance yield median annual site electricity of 6.62 [6.02–7.27], 12.4 [11.4–13.5], and 37.8 [33.6–42.0] TWh yr^{−1} under Confirmed, Central, and High Expansion, respectively (**Figure 2B**). These estimates are 2.6, 4.8 and 14.6 times the modeled 2025 base of 2.59 [2.20–3.04] TWh yr^{−1}. AI IT accounts for 15%, 48%, and 72% of site electricity. Under High Expansion, AI training alone requires 17.3 TWh yr^{−1} compared with 9.93 TWh yr^{−1} for inference despite similar installed capacities, reflecting the higher OCF of training workloads. Lower AI OCFs and PUEs, together with the lower assumed fill of the 5 GW campus, moderate electricity growth relative to the 18-fold increase in installed capacity.

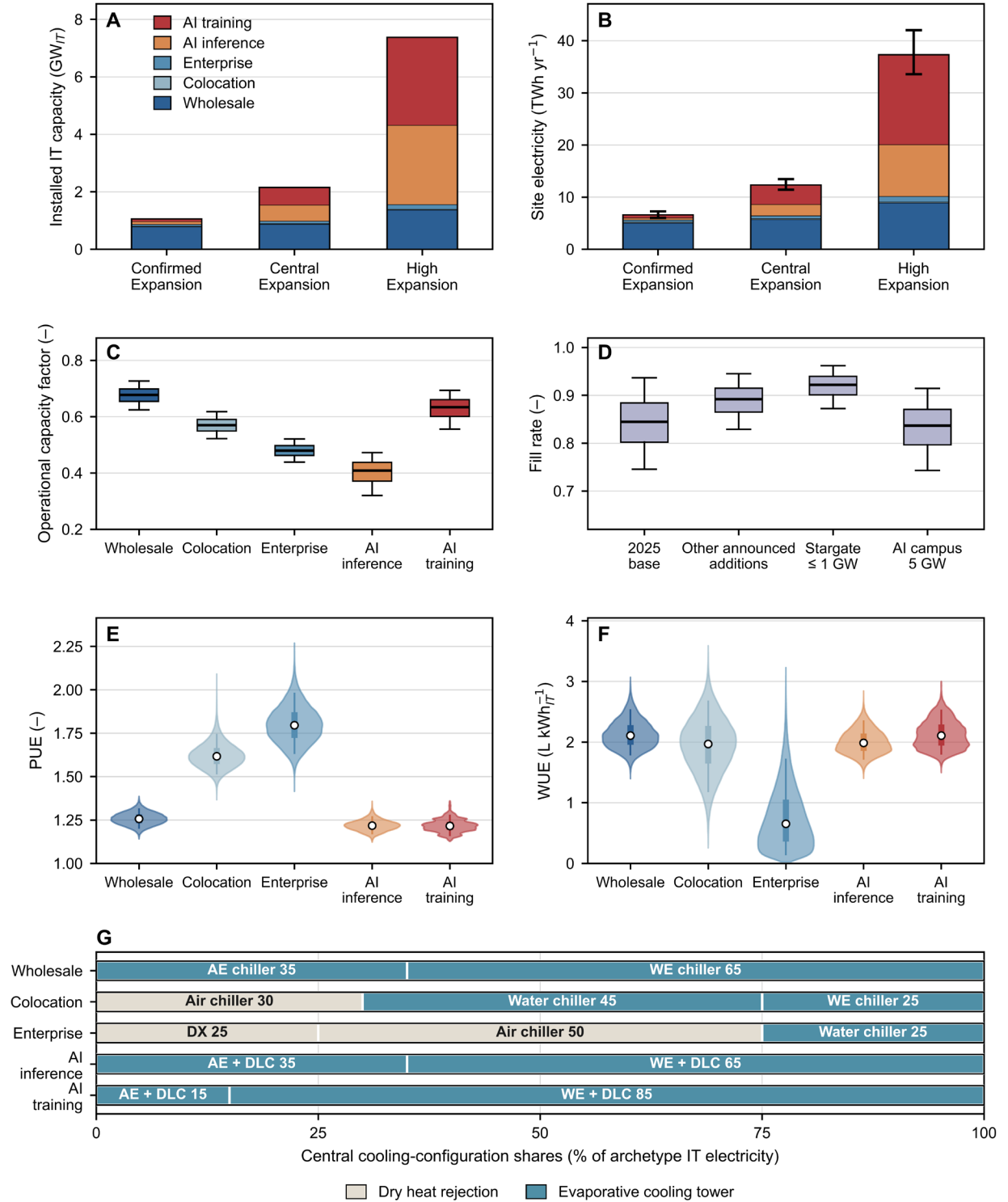


Figure 2. Installed IT capacity, operating-load assumptions, and cooling performance by IT archetype. Plots showing (A) installed IT capacity (GW_{IT}) and (B) annual site electricity (TWh yr^{-1}) under Confirmed, Central and High Expansion. Bar charts show per-archetype medians. Whiskers in (B) indicate the 5th–95th percentile interval of total site electricity. (C) Assumed operational capacity factors (OCF) by archetype and (D) assumed fill rate by capacity group. Box plots show medians, interquartile ranges and 5th–95th percentile whiskers. The fill rates are

weighted by capacity type within each archetype. **(E)** Modeled annual power usage effectiveness (PUE) and **(F)** site water usage effectiveness (WUE) across 100,000 Monte Carlo realizations. White dots indicate medians, thick bars interquartile ranges and thin whiskers 5th–95th percentile intervals. PUE and WUE are averaged across configurations using the same sampled cooling shares within each realization. **(G)** Assumed central cooling-configuration shares of each archetype’s IT electricity. Sampled cooling-share distributions are provided in **Figure S1**. Blue shades denote conventional IT, while orange and red denote AI inference and training, respectively. Abbreviations: DX: direct expansion; AE: airside economizers; WE: waterside economizers; and DLC: direct liquid cooling. Colocation and wholesale WE chillers use different equipment parameter sets. Site electricity excludes water-supply electricity and does not vary across grid scenarios.

3.2 Greenhouse gas (GHG) emissions and water demand

Annual GHG emissions attributed to data-center site and cooling-water desalination electricity increase with capacity expansion and vary across grid scenarios (**Figure 3A**). Under the Existing Grid, median emissions reach 3.01 [2.73–3.33], 5.69 [5.19–6.19], and 17.6 [15.6–19.7] Mt CO₂e yr⁻¹ for the Confirmed, Central, and High Expansion scenarios, respectively. Relative to the Existing Grid, median emissions are 12–13% lower under the Planned Grid and 28–32% lower under the Ambitious Grid across the three expansion scenarios. For Central Expansion, emissions decline to 4.96 [4.47–5.45] and 3.94 [3.38–4.45] Mt CO₂e yr⁻¹, respectively. Even under the Ambitious Grid, High Expansion produces 12.7 [10.8–14.6] Mt CO₂e yr⁻¹. Natural gas remains the largest source of national generation, accounting for approximately 80–82%, 68–71%, and 52–57% of national generation under the Existing, Planned, and Ambitious Grid scenarios across the three capacity scenarios. **Figure 3A** also shows the increase in system-wide GHG emissions relative to No Data-Center Expansion, which only retains the modeled 2025 data-center sector. These increases reach 2.27 [2.08–2.47], 5.55 [5.06–6.04], and 19.9 [17.5–22.3] Mt CO₂e yr⁻¹ under Confirmed, Central, and High Expansion, respectively, and are the consequence of increased natural gas supply for the additional electricity demand under the modeled annual balance.

Total water demand reaches 10.6 [9.02–12.6], 20.4 [17.8–23.3], and 63.1 [54.0–73.7] Mm³ yr⁻¹ under Confirmed, Central, and High Expansion, respectively (**Figure 3B**). Direct cooling make-up accounts for more than 99% of this demand, with indirect freshwater consumption from electricity generation contributing only 0.6–0.8%. Consequently, total water demand scales primarily with IT electricity and changes by less than 0.2% across grid scenarios.

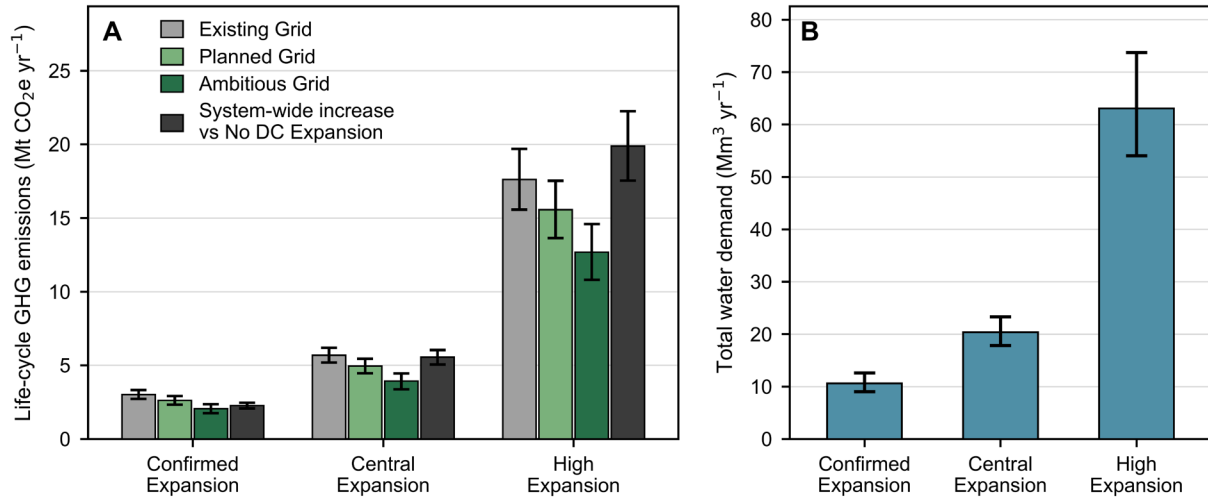


Figure 3. Greenhouse gas (GHG) emissions and water demand across capacity and grid scenarios. Plots showing (A) total annual data-center electricity-related GHG emissions (Mt CO₂e yr⁻¹) and (B) annual total water demand (Mm³ yr⁻¹) under Confirmed, Central, and High Expansion. Panel (A) includes emissions attributed to site electricity and electricity required to desalinate cooling make-up water for the full modeled data-center fleet and compares emissions from the Existing Grid, Planned Grid, and Ambitious Grid scenarios. Dark bars show the increase in system-wide electricity GHG emissions due to increased natural-gas generation relative to No Data-Center (DC) expansion, which retains the modeled 2025 data-center sector. Panel (B) shows water demand for the Existing Grid only, as median water demand differs by less than 0.2% across grid scenarios. Bars show medians across 100,000 Monte Carlo realizations, and whiskers indicate 5th–95th percentile intervals.

3.3 Clean-electricity generation requirements and emissions attribution

Within each grid scenario, higher data-center expansion reduces the national clean-electricity-generation share (**Figure 4A**). Under the Planned Grid, the No Data-center Expansion reference already requires a median of 9.4 TWh yr⁻¹ of additional clean generation to reach the UAE's 35% national clean-generation benchmark, equivalent to 4.7 GW of solar PV. Under Confirmed, Central, and High Expansion, the additional clean-generation requirement increases to 10.8, 12.9, and 21.8 TWh yr⁻¹, respectively, representing incremental PV-equivalent capacity requirements of 0.7, 1.7, and 6.1 GW relative to no expansion. Under the assumed demand and generation distributions, the Planned Grid reaches the 35% benchmark in approximately 13.6%, 10.1%, 6.2%, and <1% of Monte Carlo realizations under No Data-Center Expansion, Confirmed, Central, and High Expansion, respectively. Holding the No Data-Center Expansion clean share under Central Expansion requires 3.1 [2.7–3.7] TWh yr⁻¹ of additional clean generation (approximately 1.6 GW PV-equivalent), whereas avoiding an increase in natural-gas generation requires 9.9 [9.0–10.8] TWh yr⁻¹ of additional clean-electricity generation.

Under the Ambitious Grid scenario, national clean-electricity generation shares remain above 35% at the median across all three expansion scenarios (**Figure 4A**). However, the median share declines from 48.1% under No Data-Center Expansion to 42.9% under High Expansion. Despite remaining above the benchmark, High Expansion increases annual natural-gas generation by 35.4 [31.2–39.6] TWh relative to No Data-Center Expansion, with the corresponding increase in system-wide GHG emissions shown in **Figure 3A**.

Clean-electricity matching for data centers also changes the emissions attributed to remaining consumers (**Figure 4B**). Relative to the corresponding grid-average emission factors without matching (approximately 0.31–0.46 t CO₂e MWh⁻¹ across scenarios), the factor attributed to data-center site electricity falls to 0.23–0.34, 0.089–0.12, and 0.020–0.033 t CO₂e MWh⁻¹ at 30%, 80%, and 100% matching, respectively. Conversely, the residual-mix factor applied to other consumers and unmatched data-center and water-supply electricity increases. At full matching, the residual-mix factor exceeds the corresponding grid-average factor without matching by 3.8–4.1% under Central Expansion and 11.7–12.4% under High Expansion. To illustrate the magnitude in attributed emissions that are claimed to be reduced, under Central Expansion and Existing Grid, annual emissions attributed to data-center site electricity fall from 5.65 to 0.25 Mt CO₂e at full matching, while physical generation and system-wide GHG emissions remain unchanged.

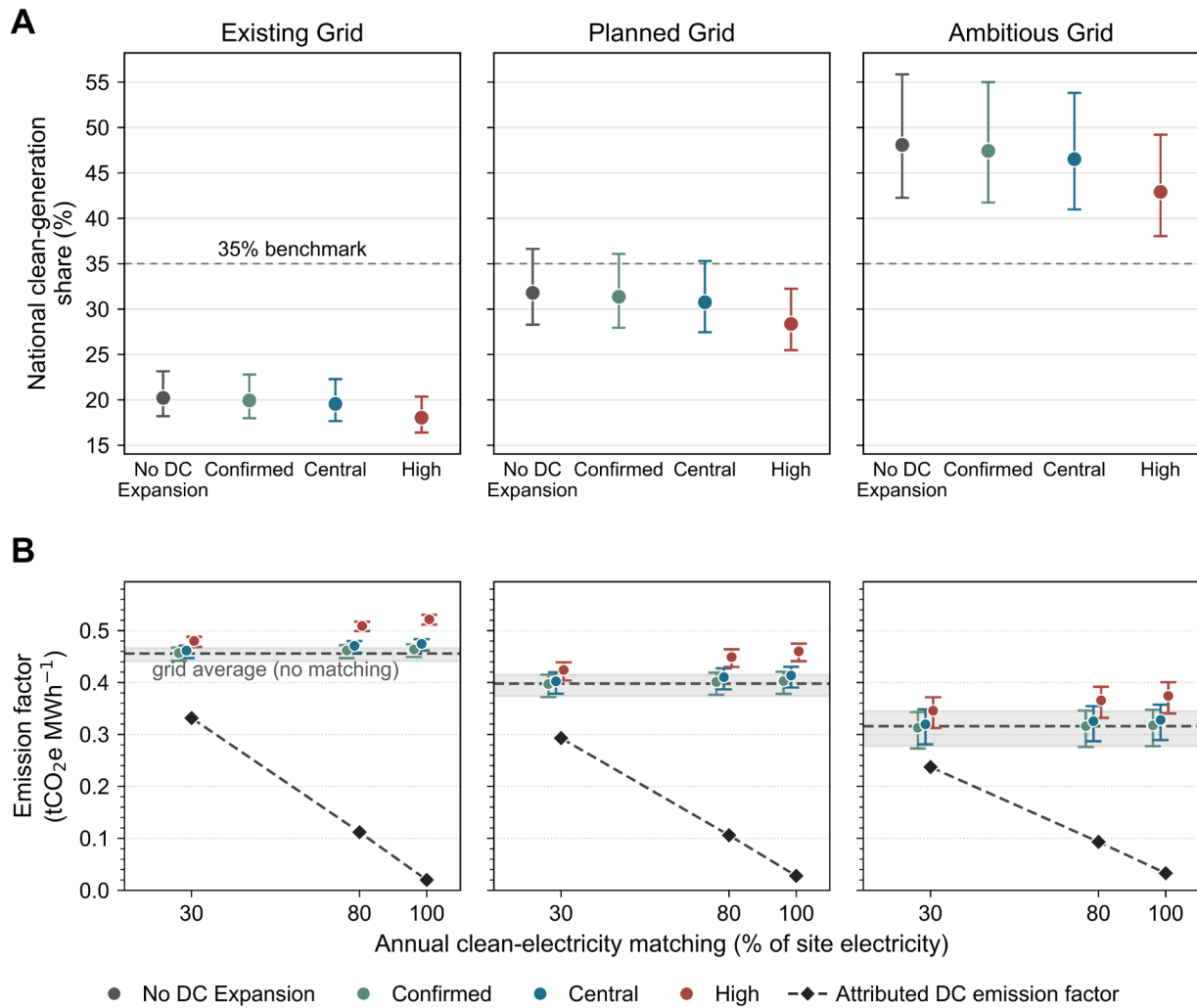


Figure 4. National clean-electricity-generation share and emission attribution. Plots showing (A) the national clean-generation share under No Data-center Expansion, Confirmed, Central, and High Expansion, and (B) residual-mix and data-center attributed emission factors at annual matching levels of 30%, 80% and 100% of site electricity.

Columns represent Existing, Planned, and Ambitious Grids. In panel (A), No Data-Center (DC) Expansion represents the modeled 2025 data-center sector without additional capacity expansion, and the horizontal dashed line indicates the 35% national clean-generation benchmark. Points show medians across 100,000 Monte Carlo

realizations with 5th–95th percentile whiskers. In panel **(B)**, colored points show residual-mix emission factors, while black diamonds show the mean across capacity scenarios of median attributed data-center emissions divided by median site electricity. Horizontal dashed lines and grey bands indicate grid-average emission factors without matching and their 5th–95th percentile intervals.

3.4 Sensitivity analysis

The two load parameters (OCF and fill rate) yield the largest changes in electricity and attributed GHG emissions among the tested parameters (**Figure 5**, showing results for Central Expansion under the Planned Grid). Setting archetype-specific OCFs to their distribution bounds changes electricity by –16.7% to +14.3%, while setting fill rates to their bounds changes it by –10.4% to +9.5%. GHG emissions and water demand respond approximately in proportion because both scale with IT electricity.

When varied separately, PUE and WUE primarily affect electricity and water demand, respectively. Across the modeled 5th–95th percentile PUE bounds, electricity and emissions change by up to –4.9% to +5.3%, while water demand changes by approximately 0.1% through indirect grid freshwater use. The corresponding WUE bounds change water demand by –16.4% to +20.9%, but electricity and emissions by 0.1% through water-supply electricity, which accounts for 0.6% of site electricity.

Unlike the individual PUE and WUE parameter tests, cooling-design comparisons vary both metrics together. Cooling technology produces the largest change in water demand. An all-dry cooling fleet reduces total water demand by 98.2% (from 20.4 to 0.36 Mm³ yr^{–1} under Central Expansion), because only humidification water and indirect grid freshwater demand remain. However, electricity and attributed GHG emissions increase by 11.4% and 11.6%, equivalent to 1.40 [0.71–2.28] TWh yr^{–1} and 0.57 [0.29–0.93] Mt CO_{2e} yr^{–1}, respectively. This also corresponds to a system-wide emissions increase of 0.79 [0.40–1.28] Mt CO_{2e} yr^{–1}. The net additional electricity requirement is approximately 70 [35–116] kWh m^{–3} of water avoided. Conversely, an all-evaporative fleet increases water demand by 11.9% while reducing electricity by only 0.7%, since the assumed reference cooling mix already relies heavily on evaporative heat rejection. Shifting archetype cooling mixes toward low-water or low-energy configurations changes water demand by –7.2% and +3.5%, respectively, while electricity changes by less than 0.4%. The response is asymmetric because the assumed central shares already favor evaporative heat rejection.

Widening the supply-air temperature range for wholesale hyperscale and AI facilities from 18–27 °C to 10–35 °C together with raising the upper dew-point limit from 17 to 21 °C (informed by the ASHRAE A2 allowable range)⁷² lowers median PUE from 1.26 to 1.19 for wholesale and from 1.22 to 1.14–1.15 for AI. These changes reduce total electricity by 5.3%, attributed GHG emissions by 5.4%, and water demand by 12.4% through greater economizer operation and reduced mechanical cooling and evaporative water requirements. The reductions assume that equipment can operate within the wider supply-air temperature and dew-point limits.

Changing the AI training share to 35% or 65% changes electricity, GHG emissions, and water demand by up to –3.8% to +3.9%, reflecting the higher modeled OCF of training compared with inference. Non-data-center electricity demand primarily affects GHG emissions. Setting demand at its 5th and 95th percentiles changes emissions by –5.5% and +4.3% under the Planned Grid, respectively, because the same clean-electricity generation supplies a different share of total demand. In separate alternative-demand scenarios, the fraction of realizations reaching the 35% clean-generation benchmark under Central Expansion and the Planned Grid ranges from 85.6% under a lower-background-demand case to no realizations meeting the benchmark under a higher-background-demand case, compared with 6.2% in the reference-case. These differences show the sensitivity of benchmark outcomes to the assumed national demand projections.

Across all nine capacity–grid combinations, the GHG response to non-data-center demand increases with the grid's clean-electricity generation share, from $-3.1\%/+2.4\%$ under the Existing Grid to $-10.5\%/+7.9\%$ under the Ambitious Grid. Under High Expansion and the Planned Grid, electricity responses widen to $-19.3\%/+16.0\%$ for OCF and $-14.1\%/+12.8\%$ for fill rate, while the all-dry cooling electricity penalty reaches 12.7%. Other sensitivity responses remain broadly similar across grid scenarios. Complete results are provided in Supplementary Data Sheet S5.

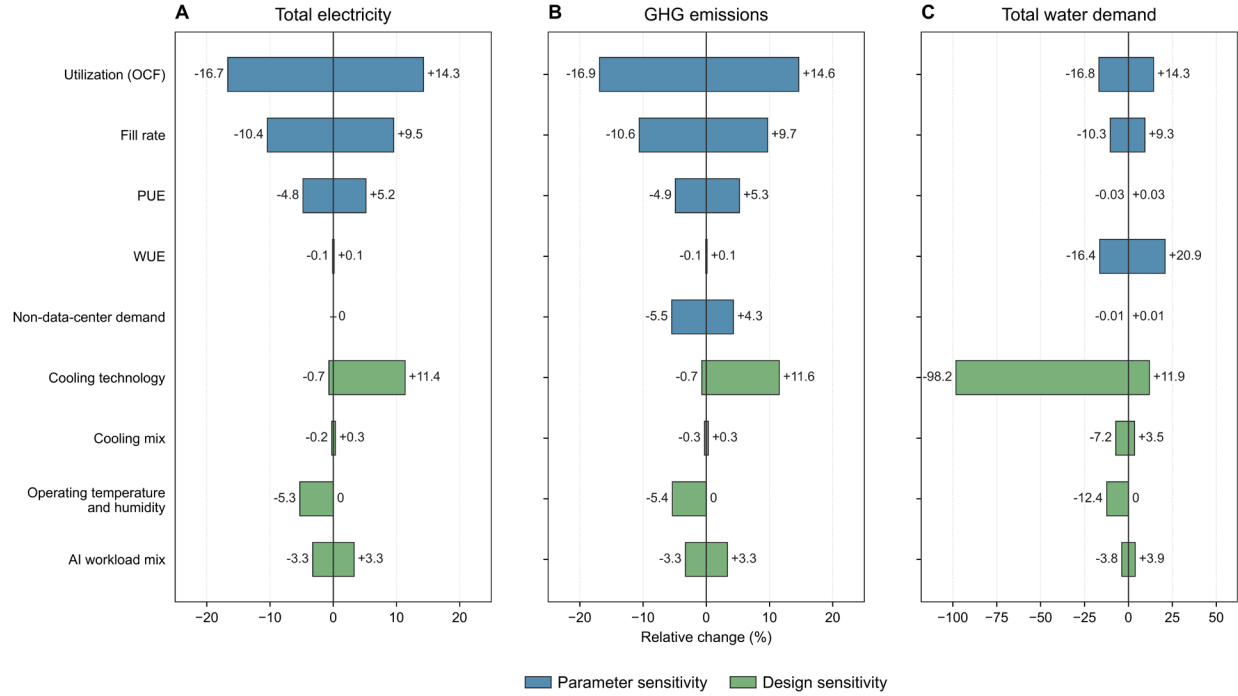


Figure 5. Sensitivity analysis of electricity, greenhouse gas (GHG) emissions, and water demand. Tornado plots showing relative changes in median (A) total electricity consumption, (B) GHG emissions, and (C) total water demand relative to Central Expansion under the Planned Grid (12.5 TWh yr^{-1} , $4.96 \text{ Mt CO}_2\text{e yr}^{-1}$, and $20.4 \text{ Mm}^3 \text{ yr}^{-1}$). GHG emissions include site electricity and electricity required for desalination. Each comparison varies one parameter group or design assumption while other inputs retain their sampled values. OCF and fill rates are set to their distribution bounds across archetypes and capacity groups, respectively. PUE, WUE, and non-data-center demand are set to their modeled or sampled 5th and 95th percentiles, with PUE and WUE varied separately. The cooling-technology bars show the minimum- and maximum-water configurations selected from 243 fleet-level combinations, corresponding to all-dry and all-evaporative fleets. Cooling-mix comparisons shift configuration shares toward lower-water or lower-energy mixes. The operating-temperature comparison expands the supply-air range from 18–27 °C to 10–35 °C and the upper dew-point limit from 17 to 21 °C for wholesale hyperscale and AI facilities. The AI workload comparison sets the training share to 35% or 65%. Cooling-design comparisons retain paired PUE-WUE values. Grid emission and freshwater intensities are recalculated in each comparison.

4. Discussion

Results show that the announced data-center expansion in the UAE would require substantial electricity and cooling water. Under Central and High Expansion, median annual total electricity demand reaches 12.5 and 38.0 TWh (4.1% and 11.5% of modeled national generation), while direct cooling make-up reaches 20.2 and 62.7 Mm³ (5.3% and 16.6% of reported UAE commercial water use⁷³). These

requirements arise despite the assumed adoption of advanced cooling technologies that yield modeled PUEs near 1.22 for new AI facilities. Total demand still depends on how much IT capacity is populated and operated, while evaporative heat rejection maintains substantial cooling-water requirements. Comparable growth is projected elsewhere in the Gulf: Alshehri et al.²⁰ estimate Saudi data-center electricity demand of 10.2–42.2 TWh annually by 2030 across deployment scenarios (2.8–11.6% of projected national electricity demand). Although their assumptions and time horizons differ, both assessments indicate that rapid data-center expansion can create substantial national electricity requirements even with relatively low facility overheads.

Data-center expansion also has implications for national electricity-related GHG emissions. Under the Existing Grid, annual emissions attributed to data-center site and desalination electricity reach 5.69 and 17.6 Mt CO₂e under Central and High Expansion, respectively. Increasing clean-electricity generation supply lowers these totals by 12–13% under the Planned Grid and 28–32% under the Ambitious Grid across the three expansion scenarios. For comparison, Xiao et al.¹⁴ project mid-case annual averages of 174 TWh yr⁻¹ of electricity demand and 26.8 Mt CO₂e yr⁻¹ of operational emissions for US AI servers by 2030. Under High Expansion, the modeled UAE fleet represents approximately 22% of that electricity demand but emits 41–58% of those attributed operational emissions across the three grid scenarios.

Higher clean-electricity generation reduces overall system-wide GHG emissions, but the additional emissions caused by data-center expansion remain nearly identical across the modeled grid scenarios (**Figure 3A**). This is because clean generation is held fixed within each portfolio, with natural gas supplying the additional demand. The assumed natural-gas life-cycle emission factor is approximately 0.56 t CO₂e MWh⁻¹, compared with a national-average grid factor of approximately 0.40 t CO₂e MWh⁻¹ under Central Expansion and the Planned Grid. Relative to No Data-Center Expansion, Central and High Expansion increase annual natural-gas generation by approximately 9.9 and 35.4 TWh, respectively. This corresponds to increases in annual system-wide GHG emissions of 5.6 and 19.9 Mt CO₂e, equivalent to 4.2–6.1% and 15–22% of the No Data-Center Expansion reference across the three grid scenarios, respectively. This increase is comparable in relative magnitude to the 13–28% increase US power-sector CO₂ emissions projected by Johnson et al.⁹ from data-center and cryptocurrency growth by 2030, where additional fossil generation drives the increase in both studies. Accommodating this additional load without increasing system-wide GHG emissions would therefore require additional clean-electricity supply to respond to this growing demand or deeper emission reductions elsewhere.

This distinction is relevant to the announced UAE-US AI campus, for which G42 describes nuclear, solar, and natural gas as intended electricity sources without specifying their shares or whether additional clean-electricity generation will be built.⁵² In the UAE, utilities can issue clean-energy certificates that assign attributes from existing nuclear and solar generation to buyers.^{37,38,58,74–76} Under the GHG Protocol's accounting approach, claimed clean-generation attributes should be excluded when calculating the residual-grid-mix emission factor for other consumers.⁶⁶ Under full annual matching, Central and High Expansion would claim 21% and 64% of eligible clean-electricity generation under the Existing Grid (13% and 40% under the Planned Grid; 9% and 27% under the Ambitious Grid), without accounting for existing claims by other consumers. Consequently, the residual-grid-mix emission factor increases by 3.8–4.1% and 11.7–12.4%, respectively, across the three grid scenarios. Excluding nuclear further constrains the eligible clean sources, with renewable generation becoming insufficient for full matching under certain grid-expansion scenarios. Matching existing attributes therefore reduces emissions attributed to data centers while increasing the residual-mix emission factor for other consumers, without changing system-wide GHG emissions. Previous studies similarly indicate that annual matching with existing generation may add little additional clean-electricity supply^{77–80}, allowing reported emissions reductions to exceed actual reductions in system-wide emissions^{81,82}.

At the scale of the announced expansion, clean-electricity claims from existing generation should be distinguished from commitments to additional supply. The UAE has announced a 35% clean-generation target by 2031, while EWEC's latest plans include 14 GW of solar capacity in Abu Dhabi by 2030 and more than 35 GW by 2035.^{25,26,83} These plans imply substantially greater clean-electricity supply, although previous changes to renewable-project schedules illustrate uncertainties in their delivery.^{84,85} It is also unclear to what extent utility planning accounts for the announced data-center buildout. For scale, the additional electricity demand under High Expansion relative to No Data-Center Expansion (35.4 TWh yr⁻¹) is comparable to the approximately 34 TWh yr⁻¹ increase in eligible clean generation between the Existing and Planned Grids. In parallel, a 1 GW gas-turbine plant and separate solar-plus-storage developments have been announced to help supply data-center projects, indicating that gas-fired generation is also part of the planned supply response for data centers.⁸⁶

Under the Planned Grid, the median national clean-electricity generation share declines from 31.8% under No Data-Center Expansion to 30.8% and 28.4% under Central and High Expansion, respectively. The 35% benchmark is reached in 13.6%, 6.2%, and <1% of modeled realizations, although these frequencies are sensitive to the assumed background national electricity-demand. Reaching the 35% clean-electricity generation benchmark requires a median of 4.7 GW of additional PV-equivalent capacity under No Data-Center Expansion, increasing to 6.4 and 10.8 GW under Central and High Expansion, respectively. The additional installation requirements under High Expansion (6.1 GW) are equivalent to almost all of the UAE's installed PV capacity at the end of 2025.⁸⁷ Under the Ambitious Grid, a larger modeled solar PV portfolio of approximately 41 GW, compared with 20 GW under the Planned Grid, maintains a median national clean-generation share of 42.9% under High Expansion, although this remains 5.2 percentage points below No Data-Center Expansion. This larger portfolio is approximately 6 times the UAE's installed PV capacity at the end of 2025, illustrating the scale of clean-generation expansion involved in accommodating growing electricity demand while pursuing national clean-generation goals.⁸⁷

Nevertheless, exceeding the 35% clean-electricity generation benchmark does not necessarily ensure progress toward the UAE's wider decarbonization objectives. The UAE seeks to reduce power-and-water-sector emissions by more than 50% relative to 2019 by 2035⁸⁸ and reach net-zero emissions in the electricity and water sector by 2050⁸³. Under the Ambitious Grid, the clean-electricity generation share remains above 35% even with High Expansion, yet annual system-wide GHG emissions increase by approximately 19.9 Mt CO₂e relative to the No Data-Center Expansion case. Maintaining a national clean-generation share differs from avoiding additional natural-gas generation. Under the modeled annual balance, the latter requires additional clean generation equal to the added load, roughly 3 times the amount needed to maintain the reference share under the Planned Grid. The pressure data centers are adding to decarbonization goals extends beyond the UAE: the IEA projects that coal and natural gas will supply more than 40% of additional global data-center electricity demand through 2030, despite major renewable expansion.⁸⁹

The UAE's climate and assumed cooling configurations produce substantial direct cooling-water requirements despite relatively low modeled facility electricity overheads. High temperatures and humidity constrain economizer operation under the modeled operating limits⁵⁷, while evaporative heat rejection assumed for wholesale and AI facilities reduces cooling electricity at the expense of make-up water. New AI and wholesale facilities require approximately 2.0–2.1 L kWh_{IT}⁻¹ of cooling make-up water, approximately 4–6 times average US fleet estimates of 0.36 L kWh_{IT}⁻¹ through 2023 and 0.45–0.48 L kWh_{IT}⁻¹ by 2028.² Direct cooling make-up accounts for more than 99% of modeled UAE water demand, whereas US assessments attribute roughly three-quarters of the US data-center consumptive freshwater footprint to electricity generation.^{10,14} Low indirect freshwater contribution in the UAE reflects the use of seawater for cooling in the modeled electricity supply, with seawater withdrawals excluded from the

freshwater accounting. Consequently, changing the generation mix across the three modeled grid scenarios alters total water demand by less than 0.2%, leaving facility cooling configuration as the principal means of reducing water requirements among the alternatives evaluated.⁹⁰

Desalinated cooling-water supply changes how data-center demand relates to local water scarcity. Rosa et al.⁹¹ identify 93% of UAE facilities to be in areas where modeled renewable freshwater availability is insufficient to meet existing consumption for at least part of the year, although their assessment does not explicitly account for desalination and other supply-management measures. Under the assumed municipal desalination supply, cooling demand places additional requirements on energy for water-production and distribution infrastructure rather than directly withdrawing scarce natural freshwater. Producing desalinated cooling make-up water requires approximately 3.8 kWh m⁻³ under the Existing Grid (7–9 times the energy reported for US surface-water and groundwater supply¹⁰). Nevertheless, desalination electricity accounts for only approximately 0.6% of data-center site electricity, meaning that desalination can support substantial cooling-water demand without dominating the fleet's electricity requirement. Cooling make-up under Central and High Expansion represents approximately 1.0% and 3.2% of UAE desalinated-water production⁹², although local production, storage, and distribution capacity determine supply reliability.⁹³ Desalinated water production also entails seawater intake and brine discharge, with potential marine impacts, while cooling-tower blowdown requires separate treatment or disposal.^{94–97} Reclaimed water can substitute for desalinated make-up where treatment and reliable supply are available, as reported for some facilities.^{98,99}

Cooling design determines the trade-off between water and electricity requirements. Under Central Expansion and the Planned Grid, an all-dry fleet reduces median total water demand by 98.2% (from 20.4 to 0.36 Mm³), while increasing median total electricity by 11.4% (1.40 TWh) and attributed GHG emissions by 11.6% (0.57 Mt CO_{2e}) annually. Under High Expansion, savings reach 62 Mm³ annually, with an additional electricity requirement of 4.83 TWh and 2.08 Mt CO_{2e} emitted annually. The net additional electricity requirement is approximately 70 and 77 kWh m⁻³ of total water demand avoided under Central and High Expansion, respectively, roughly 20 times the 3.62 kWh m⁻³ required to desalinate that water. Replacing evaporative heat rejection with dry cooling therefore nearly eliminates desalinated make-up requirements, but the additional cooling electricity far exceeds the desalination electricity avoided. Other studies show that increased electricity demand can also offset part of the water savings through additional freshwater consumption in electricity generation.^{35,100} However, this offset is small under the modeled UAE electricity supply, preserving nearly all of the water saving. By comparison, operating under wider supply-air temperature and dew-point limits can reduce electricity demand by 5.3% and water demand by 12.4% through greater economizer operation and reduced mechanical cooling requirements, although these savings depend on equipment compatibility and operating feasibility.

The magnitude of these projected impacts remains conditional on the extent to which announced capacity is developed and operated, especially the 5 GW AI campus. Some project announcements also do not distinguish IT capacity from total facility power, introducing uncertainty in the capacity estimates. Even for commissioned capacity, electricity and water requirements depend on the fraction populated with IT equipment and its average operating load. Accordingly, OCF and fill rate produce the largest changes in electricity demand among the operating parameters tested, while WUE and cooling technology strongly influence water requirements. Additional uncertainties arise from the assumed cooling configurations and operating conditions, the use of representative Abu Dhabi weather, and the lack of field validation of the adapted cooling model against UAE facilities. The national clean-generation results also depend on the assumed background electricity-demand, while the Planned and Ambitious Grids depend on the delivery of announced generation capacity. Within each grid scenario, clean-electricity generation is held fixed as data-center demand changes, so the analysis does not model additional utility investment in response to that demand.⁹ The annual electricity balance also does not resolve hourly

generation, dispatch, storage operation, curtailment, transmission constraints, or hourly clean-electricity matching. Resolving hourly balances could better capture temporal variations in electricity supply and demand and enable evaluation of additional mitigation strategies, such as shifting flexible data-center workloads toward periods of greater renewable availability.¹⁰¹ Reported uncertainty intervals reflect the sampled parameters and their assumed relationships, but do not capture all uncertainty in project completion or model structure. Greater disclosure of populated IT capacity, measured electricity demand, cooling configurations, and water make-up and sources would improve the accuracy of future assessments.

5. Conclusion

At the scale of announced UAE data-center expansion, the energy and environmental consequences depend not only on how efficiently facilities operate but also on how their additional electricity and cooling water are supplied. By linking installed IT capacity and operating loads to national electricity generation and desalinated-water supply, this study quantifies the additional clean-electricity generation required under different decarbonization objectives and the electricity-water trade-offs associated with cooling choices. The results distinguish reductions in emissions attributed to data centers from changes in system-wide GHG emissions and show why maintaining a national clean-electricity generation share does not necessarily prevent additional fossil-fuel generation. These findings show the need to shift the planning question from facility performance alone to the electricity and water infrastructure required to accommodate rapid expansion without increasing system-wide emissions or placing additional pressures on water supplies, especially in hot, water-scarce regions with gas-dominated power systems.

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Energy and environmental impacts of rapid data-center expansion in the United Arab Emirates – Supporting Information (SI)

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S1. Installed IT capacity and announced expansion

S1.1 Overview

The inventory was last updated in September 2026. All capacity is expressed as IT load in megawatts (MW_{IT}), representing the electrical capacity available to servers, storage, and network equipment. This common capacity basis is used to calculate IT electricity and cooling requirements in Sections S2 and S3. Although most capacity measures are reported as IT load, project capacities do not consistently distinguish IT load from total facility power in their announcements. The inventory covers facilities physically located in the UAE and has two components: a stochastic estimate of the 2025 Installed IT base and a set of announced capacity additions. Announced capacity is represented as conditional operating end states within 2030–2040 rather than forecasts for individual years. These scenarios assume the corresponding capacity is constructed and operated at the sampled fill rates and operational capacity factors (OCFs) (Section S2), under the electricity-supply and demand conditions described in Section S4. Where capacity is explicitly reported as IT load, the published value is used directly. Otherwise, reported MW values are treated as installed IT capacity under the assumption that they are consistent with industry reporting conventions. No facility-to-IT conversions are applied. It should be noted that this assumption may overestimate IT capacity where announced figures represent facility power. For example, at a PUE of 1.22–1.26, the IT equivalent would be approximately 18–21% below the reported facility-power value. This alternative interpretation is not included in the paper’s simulations. The reported basis for each project is documented in Supplementary Data Sheet S1.

The inventory excludes crypto-mining facilities because they are not represented in the market estimates used to establish the 2025 Installed IT base and have different operating characteristics from the data-center archetypes modeled here. To avoid double counting, cloud regions and GPU clusters hosted within facilities already represented in the inventory are not counted as separate capacity additions. Data-center project proposals without an identified developer or operator are also excluded. Every included facility along with its supporting parameters and sources is listed in the Supplementary Data Sheet S1.

S1.2 2025 baseline operating IT capacity

The 2025 Installed IT base is derived from published market sources of operating UAE data-center capacity.^{1–7} Announced additions are compiled from operator, government, utility, contractor, and trade-press sources, with primary operator or government sources preferred where available.

Published estimates of operating UAE data-center capacity in 2025 range from 350.6 to 507.7 MW_{IT} , with differences reflecting source definitions from the sourced reports. Rather than selecting a single estimate, total operating capacity is bounded and sampled through a distribution.

S1.3 Announced capacity additions

Twelve announced or under-construction projects identified as of September 2026 are represented using three cumulative capacity expansion tiers. The “Confirmed” tier includes projects under construction or with a stated completion date (448.2 MW_{IT}). The “Central” tier adds projects with a disclosed or reasonably inferred initial phase (748.2 MW_{IT}). The “High” tier includes all announced capacity and full project phases (2,013.2 MW_{IT}).

The Confirmed tier is dominated by Khazna's 400 MW of capacity under construction, treated as installed IT capacity in the model, including the disclosed AUH4, AUH8, and QAJ1 projects.^{8,9} The remaining Confirmed additions are Gulf Data Hub KIZAD (22 MW_{IT}), Equinix DX3 Phase 2 (7.2 MW_{IT}), and the Abu Dhabi Unified Government Data Centre (19 MW_{IT}).^{10–13} The Central tier additionally includes 25 MW of Moro Hub's 100+ MW Warsan campus¹⁴, 200 MW_{IT} of du's announced 1 GW AI Park¹⁵, the initial 29 MW DIEZ/VOLT phase¹⁶, Pure DC's 28 MW_{IT} Yas Island addition^{17,18}, and an estimated 18 MW for Gulf Data Hub Dubai 5¹⁰. High expansion replaces these Central-tier values with 100 MW for Moro Hub, 1 GW for du AI Park, and 129 MW for DIEZ/VOLT, including 100 MW of committed electrical power treated as IT capacity. It also includes an estimated 65 MW_{IT} for the du hyperscale facility with Microsoft as its principal tenant^{19,20}, VivoPower's 25 MW_{IT} project^{21,22}, and the 200 MW Microsoft–G42 expansion delivered through Khazna²³. Capacity estimates are used only where no MW value is disclosed and are documented in Supplementary Data Sheet S1.

Stargate UAE is treated separately from the general announced additions because its reported scale spans three distinct milestones. The program was announced in May 2025 as a 1 GW Stargate UAE cluster in Abu Dhabi, with 200 MW expected online in 2026, within a broader 5 GW UAE–US AI Campus^{24,25}. Therefore, 200 MW is assigned to the Confirmed tier, 1 GW to the Central tier, and 5 GW to High tier. The 200 MW Stargate milestone was expected to be ready in Q3 2026, while no completion date has been announced for the 1 GW cluster and the 5 GW campus represents a longer-term post-2030 potential buildout²⁶. At the time of writing, commercial operation of the first 200 MW had not been announced. U.S. export authorization for the associated computing hardware was granted in July 2026, while later reporting indicated that the broader campus may be developed as a network of data centers across the UAE rather than a single site^{27,28}. These developments affect project timing and siting but not the announced capacity milestones, which are retained in the analysis.

All data sources for these additional announcements can be found in Supplementary Data Sheet S1. Projects are included only when a MW capacity is publicly stated by the party expected to build, own, or operate the facility. Announcements without an identified project developer or operator are excluded from the inventory.

S1.4 Future capacity scenarios and archetype designation

Three future capacity scenarios combine the general expansion tiers with the corresponding Stargate UAE and the broader UAE–U.S. AI Campus milestones. The Confirmed Expansion scenario adds the 200 MW_{IT} Stargate milestone, the Central Expansion scenario adds the 1 GW_{IT} Stargate milestone, and the High Expansion scenario includes the entire 5 GW_{IT} buildout. These correspond to 648.2, 1748.2, and 7013.2 MW_{IT} of additional capacity, respectively, above the sampled 2025 base. Median installed IT capacity reaches 1.06, 2.16, and 7.42 GW_{IT} under Confirmed, Central, and High Expansion, respectively. Capacity is assigned to five load archetypes: wholesale hyperscale, retail colocation, enterprise and telecom, AI training, and AI inference. These are modeling classes used to assign OCF parameters (Section S2) and cooling, PUE, and WUE parameters (Section S3). Conventional announced projects are assigned to a single archetype based on operator descriptions, while the remaining 2025 base and AI-dedicated capacity are allocated through sampled archetype and workload shares, respectively. Project

assignments and sources are provided in Supplementary Data Sheet S1. The AI-dedicated projects (du AI Park, DIEZ/VOLT, Stargate) are treated as mixed AI workloads whose training and inference shares are sampled through distributions. Details are provided in Section S2.

S2. IT utilization, load, and energy

S2.1 Capacity fill rates

Fill rate represents the fraction of commissioned IT capacity that is populated with computing equipment and placed into operation. It is different from the OCF (Section S2.2), which describes the annual average equipment power as a fraction of rated power. The product of fill and OCF represents the overall IT load factor. Fill is sampled using triangular distributions for three capacity groups within each expansion scenario: the 2025 installed base, announced additions, and the corresponding Stargate milestone. Separate distributions are used for the initial Stargate milestones and the 5 GW full buildout. The 2025 Installed IT base uses a low, central, and high value of (0.70, 0.85, 0.98), while announced additions at steady state use (0.80, 0.90, 0.97). The 200 MW_{IT} and 1 GW_{IT} Stargate milestones use a higher assumed fill range of (0.85, 0.93, 0.98), reflecting the expected higher equipment population of dedicated AI facilities compared with multi-tenant facilities. The 5 GW Stargate case uses a lower and wider range of (0.70, 0.85, 0.95) because its deployment is staged and remains undated beyond the initial 200 MW_{IT}²⁴. The wider 5 GW range is also consistent with reported differences between contracted and operating AI capacity. For example, CoreWeave, a US-based AI-cloud provider, reported 1.5 GW of active power against 3.7 GW of contracted in 2026.²⁹ This comparison is used only to support greater uncertainty in large future deployments rather than as a direct estimate of fill. One fill value is sampled for each capacity group in every Monte Carlo realization and shared across archetypes. For archetypes containing capacity from multiple groups, the effective fill rate is calculated as the capacity-weighted average of the corresponding group values. Fill is sampled independently of capacity, OCF, PUE, and WUE. All fill-rate parameters and supporting evidence are summarized in Supplementary Data Sheet S2.

Fill rates are treated as modeling assumptions because directly comparable measurements of physical data-center fill were not identified. The effects of the assumed fill-rate ranges on the model results are evaluated in the sensitivity analysis (Section S5.2). Commercial occupancy, customer-use disclosures, and commissioning data are therefore used as supporting evidence for these ranges rather than direct measurements. The upper bound for the 2025 Installed IT Base is informed by reported occupancy and vacancy rates, including UAE vacancy of 2.4%^{1,2}, Abu Dhabi vacancy below 1%^{4,30}, reported UAE utilization of 98.7%⁵ (although the basis is not entirely clear), 97% global occupancy³¹, and North American vacancy of 1% – 1.4%^{32,33}. The lower bound is informed by a VNET (Chinese wholesale operator) report, that showed 70.1% customer utilization of wholesale capacity in service in 2025, compared to a 95.3% commitment rate.³⁴ This provides the closest published equivalent to the fill share. A colocation-sector comparison is relevant because approximately 95% of UAE data-center capacity is delivered through colocation providers.³⁵

For Announced Capacity Additions, reported pre-commitment and occupancy rates are used to bound the assumed fill-rate range. Capacity under construction has been reported as 74.3% to more than 80% pre-committed in North America³³, 77% globally³¹, approximately 89% when hyperscale self-build is included³⁶, and above 70% in Abu Dhabi³⁰. Projected UAE colocation occupancy of approximately 89% by 2029 is also consistent with the central assumption of the sampled range.⁶ Because pre-committed capacity may not be populated immediately, particularly given reported customer move-in periods of 3 – 12 months³⁰, these values are used as supporting evidence rather than direct estimates of fill rate. VNET's reported 93.1% utilization of mature wholesale capacity provides an additional estimate that the range

encompasses most likely fill-rate cases.³⁴ The 80% fill rate assumed for the 5 GW_{IT} Stargate campus by projection market reports⁵ falls within the wider adopted range. Fill uncertainty is propagated through the Monte Carlo simulation, and its effects on final results are examined in the sensitivity analysis (Section S5.2).

S2.2 Operational capacity factor (OCF)

The OCF is the annual average power drawn by populated IT equipment as a fraction of its rated peak power. Following the LBNL bottom-up model^{37,38}, average server power is represented as the utilization-weighted mean of idle and operational power as shown in the main text. For conventional servers, operational power is assumed to be equal to rated power. Because these parameters are derived for servers, they are applied as proxies for the full IT load, including storage and network equipment. For the conventional archetypes, p_{idle} is set to 0.36, which is the most recent estimated value in the LBNL model, for 2023.³⁷ The report then projects idle power to decline further over time, reaching 0.27 by 2028 due to improved power management³⁷, but is later updated to a minimum of 0.30³⁸, which places the 2025 value near 0.32. The projected decline reflects turnover of the US fleet toward newer servers and may not directly apply to the UAE installed base. Therefore, 0.36 is retained as a conservative value that does not assume future improvements in server power management. The updated trajectory value would lower the central OCFs by 0.02 – 0.03, within the adopted ranges sampled in the Monte Carlo simulation (MCs). LBNL also notes that available SPEC measurements show idle-power fractions remaining near 20% – 25% and that its projected decline may underestimate idle power draw, providing additional support for retaining the higher 2023 value.³⁷

Computational utilization values are also taken from the LBNL space-type trajectories^{37,38}. These translate to 0.186 for internal and small data centers, 0.328 for colocation, and 0.492 for hyperscale. The space types are mapped to the enterprise and telecom, retail colocation, and wholesale hyperscale archetypes, respectively. Using **Eqn. (1)** in the main text, these assumptions give central OCF values of 0.48, 0.57, and 0.68. The 2025 computational utilization values are held constant over the modeling horizon, consistent with the end-state framing of the analysis.

Low and high OCF bounds are set at approximately $\pm 12\%$ of the central values (0.42 – 0.54, 0.50 – 0.64, and 0.60 – 0.75), which define the triangular distributions sampled in the MCs. LBNL reports no uncertainty range for conventional server utilization.^{37,38} Through **Eqn. (1)** in the main text, the adopted OCF bounds correspond to computational-utilization ranges of 0.09 – 0.28, 0.22 – 0.44, and 0.38 – 0.61 for enterprise and telecom, retail colocation, and wholesale hyperscale, respectively. These ranges span the 2014-2027 LBNL utilization trajectory for each space type and extend beyond it in both directions. The range also contains the central OCF values obtained using the 2025 Update's idle-power minimum of 0.30. The wider adopted UAE ranges are accepted because UAE-specific computational utilization data are not available and the U.S. space types are used only as proxies for UAE facilities.

For the AI archetypes, **Eqn. (1)** in the main text is evaluated using two published sets of operating-power and utilization assumptions from Shehabi et al.³⁷ and Xiao et al.³⁹. Shehabi et al.³⁷ use an p_{idle} of 0.20, based on measurements of idle accelerated servers at Brookhaven National Laboratory, p_{op} (varied from 0.60 – 0.80, compared with a measured value of 0.74), and computational utilization of 0.80 (0.75 – 0.85) for AI training and 0.40 (0.375 – 0.425) for AI inference. These assumptions yield OCF values of 0.60 for training and 0.40 for inference. Xiao et al.³⁹ use an p_{idle} of 0.23 and p_{op} of 0.88, and 2024 utilization values of 0.72 for training and 0.25 for inference in their published model. This increases to 0.74 and 0.35 by 2030. This yields OCF values of 0.70 and 0.39 in 2024 and 0.71 and 0.46 in 2030 for training and inference, respectively. The two estimates therefore bound training OCF at approximately 0.60 – 0.70, with most of the difference resulting from their assumed operational-power fractions. Both

estimates give a similar OCF of approximately 0.40 in 2024 for inference. The 2025 LBNL Update³⁸ retains the same assumptions for training but revises inference utilization downward to the enterprise trajectory, reaching 0.20 by 2030, on industry feedback that inference fleets are provisioned for peak demand and run well below it on average. The Reference Case retains p_{idle} as 0.20, while the High Inference Energy case increases p_{idle} to 0.30 and utilization by 10 percentage points. The report also mentions an industry potential with p_{idle} as high as 0.50. Evaluated using **Eqn. (1)** in the main text, these three cases give inference OCF values of 0.30, 0.42, and 0.54, respectively.

Training OCF is assigned a central value of 0.65, the midpoint of the Shehabi et al.³⁷ and Xiao et al.³⁹ estimates of 0.60 and 0.70. The low bound of 0.52 is set slightly above the Shehabi et al. estimate evaluated at their lower operational-time and operational-power values (0.50), and the high bound of 0.72 slightly above the Xiao et al. 2030 estimate. Inference OCF is assigned a central value of 0.43, informed by the five estimates described above (0.30, 0.40, 0.42, 0.46, and 0.54). The high bound of 0.50 corresponds to high operational time combined with high operational power. The low bound of 0.28 is a sensitivity value for bursty inference workloads, in which servers spend long periods near idle between demand peaks, as observed in transient power measurements of AI clusters.⁴⁰ The dispersed global-average OCF of 0.26 reported by Shehabi et al.³⁷ is not used because it assumes inference power demand at one-half of training power demand, which does not represent the dedicated GPU clusters considered here. Both OCF distributions are triangular, with the resulting parameters summarized in Supplementary Data Sheet S2.

The product of fill rate and OCF gives the IT load factor and can be compared with published values. Across Monte Carlo realizations, the 2025 Installed IT Base has a median load factor of 0.55 (90% interval: 0.47 – 0.62). The IEA reports data-center load factors of 46% for the Middle East and 49% globally in 2024,⁴¹ while LBNL assumes an average capacity utilization of 50% when converting electricity demand to interconnection capacity.^{37,38} Reports also indicate that one in four facilities typically operates below 40% of its UPS capacity.⁴² The modeled median is slightly higher than the regional IEA value, consistent with the larger share of wholesale hyperscale capacity in the modeled UAE base compared with a regional fleet that also includes enterprise facilities. No measured load factor for an operating AI campus at comparable scale can be identified. The IEA projects Middle East and global data-center load factors of 45% and 48%, respectively, in 2030.⁴¹ For comparison, the modeled Confirmed, Central, and High Expansion scenarios have load factors of approximately 0.56, 0.52, and 0.47, respectively, calculated as the ratio of median annual IT electricity to median installed IT capacity multiplied by 8,760 hours. The IEA also reports accelerated-server utilization of approximately 90%⁴¹ which corresponds through **Eqn. (1)** in the main text to an OCF of 0.65.

S2.3 Archetype mix and designation

Each unit of IT capacity is assigned to one of five load archetypes:

1. wholesale hyperscale
2. retail colocation
3. enterprise and telecom
4. AI training
5. AI inference

The archetypes follow the data-center space types of the LBNL model.³⁷ Wholesale hyperscale comprises large-scale facilities built by major colocation companies for wholesale leasing as well as facilities built

by companies deploying internet services and platforms at massive scale. In the UAE these two categories coincide, since the large wholesale providers host hyperscale tenants. Retail colocation comprises facilities built by local colocation companies providing retail leasing at smaller scale. Enterprise and telecom comprises data centers run by enterprises for their own use and by telecommunications companies to support their own services. AI training and AI inference are not space types but workload classes for accelerated servers, distinguished because their power draw differs.

The archetype determines the OCF distribution (Section S2.2) and the cooling mix used to obtain PUE and WUE (Section S3). Archetype assignment differs between the 2025 installed base, announced conventional projects, and AI-dedicated projects. For the 2025 base, archetype shares are sampled. For the expansion, each announced conventional project is assigned a single archetype while AI-dedicated capacity is divided into sampled workload shares.

For the 2025 Installed IT Base, the 320.2 MW_{IT} wholesale capacity (Section S1.2) is assigned entirely to the wholesale hyperscale archetype. Capacity above this fixed component is divided among the five archetypes using shares drawn from a constrained uniform distribution, where each share lies within a prescribed range and the five shares sum to one. The ranges are 0 – 40% for wholesale hyperscale, 5 – 30% for retail colocation, 20 – 60% for enterprise and telecom, 0 – 8% for AI inference, and 0 – 2% for AI training. Ranges are used rather than point estimates because no MW-weighted breakdown of UAE operating capacity by facility type is publicly available. The data ranges are informed by several observations of the current UAE data-center market. First, Khazna and Gulf Data Hub together account for approximately 75% of built UAE IT capacity,⁴³ which is already captured in the fixed wholesale component. No other wholesale operator of comparable scale has been identified, so additional wholesale hyperscale capacity is limited. Second, approximately 95% of UAE capacity is delivered through colocation providers³⁵, and the operators outside Khazna and Gulf Data Hub are predominantly telecom, government, and enterprise facilities at smaller scale. Therefore, the remaining mix distribution is expected to be dominated by the enterprise and telecom and retail colocation archetypes rather than by further wholesale hyperscale capacity.⁵ Third, wholesale capacity can be leased through multiple layers. As an example, Gulf Data Hub space is leased to Etisalat under a wholesale agreement, while Equinix operates within Khazna facilities.¹⁰ These tenants are already counted in the fixed wholesale capacity. Retail colocation and enterprise shares of the remaining mix therefore represent only facilities operated by those providers, which justifies lower bounds above zero but small. At the median across MCs realizations, the resulting 2025 Installed IT Base is approximately 84% wholesale hyperscale, 10% enterprise and telecom, 5% retail colocation, and 1% AI.

AI-dedicated projects, including the three Stargate milestones, du AI Park, and the DIEZ/VOLT development, are not assigned to a single archetype. Their capacity is divided among AI training, AI inference, and non-accelerated IT sampled through distribution shares. Non-accelerated IT includes external storage, networking, and management racks that are not included in the accelerated-system rack power and is assigned to the wholesale hyperscale archetype. The assumed mean workload split is 50% AI training, 45% AI inference, and 5% non-accelerated IT, respectively. The inclusion of non-accelerated IT is informed by published GPU-cluster reference designs, which show that external networking alone can account for approximately 9% of total cluster IT power.⁴⁴ Components already included within the reported GPU-rack power, such as CPUs, switch trays, and fans, are not counted again.^{45,46} The assumed distributions allow the training and inference shares to vary around the assumed 50/45/5 mean split. The selected parameters yield a training share range of approximately 0.32 – 0.68 for the AI based projects. The central training/inference split is treated as a scenario assumption because UAE operators do not publish the projected workload split of their AI capacity. However, some evidence from market reports and public announcements inform the adopted ranges. First, public statements for the UAE projects emphasize both regional inference and large-scale compute rather than training alone, including Stargate

UAE, suggesting that a substantial share of the capacity will support inference.^{24,25,47} Second, published estimates generally place training at or below approximately one half of AI activity, although they use different bases. Reported values include 30% of AI computing capacity³⁹, 20% – 53% of U.S. AI-server electricity^{37,38}, two-fifths of machine-learning energy at Google⁴⁸, and roughly equal shares of AI power demand across training, experiments, and inference⁴⁹. These values support a central split in which neither training nor inference strongly dominates. Third, dedicated frontier campuses are often described primarily as training clusters. Examples include Meta's Hyperion⁵⁰, AWS's Project Rainier⁵¹, and xAI's Colossus⁵². This supports allowing a higher training share for large dedicated campuses than would be expected from national or global fleet averages. A common central training share of 0.50 is therefore retained across AI projects, with the project-specific distributions allowing both training- and inference-dominant operating cases.

All fill rate, OCF, and archetype distribution parameters can be found in Supplementary Data Sheet S2.

S3. Thermodynamic cooling model

S3.1 Scope, definitions, and boundaries

Cooling performance is represented by two annual metrics. Power usage effectiveness (PUE) is the ratio of total annual facility electricity to annual IT electricity and is dimensionless. Water usage effectiveness (WUE) is the annual on-site cooling water demand per unit of IT electricity, expressed in liters per kilowatt-hour of IT electricity (L/kWh_{IT}). Both metrics are simulated using physics-based cooling models^{39,53} rather than taken directly from published figures, which are limited and do not consistently specify operating conditions or accounting boundaries. This also allows the cooling estimates to be combined with the capacity and load model of Sections S1 and S2 on a consistent basis with clearly specified operating conditions and accounting boundaries. Each cooling-case realization is therefore evaluated using an explicitly specified cooling configuration and UAE-specific weather data described in Section S3.2.

The modeled PUE boundary comprises IT load along with the following cooling electricity terms, where applicable to each configuration:

- computer-room air-handler fans
- humidification pumps or electric humidification
- direct-expansion (DX) refrigeration or chillers
- chilled-water pumps
- water-side economizer pumps
- coolant pumps for direct liquid cooling
- and cooling-tower pumps and fans for evaporative heat rejection

Non-cooling loads include uninterruptible power supply (UPS) losses, power-distribution losses, and lighting. No separate terms are included for transformer losses or electricity used by humidifier standby, controls, building management, offices, and security. In the liquid-cooling cases, UPS losses and lighting are included in PUE but excluded from the cooling load under an inherited modeling convention. All electricity generation is also assumed to be generated off-site and supplied from the grid. For the liquid-cooling configurations, a residual room-air fraction of 10% is assumed, informed by published GB300

NVL72 equipment specifications.⁵⁴ In the reference liquid-cooling configurations, this fraction scales computer-room air-handler fan electricity, while the economizer, chiller, and heat-rejection calculations retain the full modeled heat load. The dry liquid-cooling comparison instead explicitly separates the air- and liquid-cooled heat loads. This approach approximates liquid cooling without independently resolving the equipment-side coolant and residual-air thermal paths. The WUE boundary accounts for on-site cooling water demand, which includes humidifier makeup, cooling-tower evaporation, tower drift, and the blowdown required to maintain the sampled cycles of concentration. Because blowdown is discharged rather than evaporated, this quantity represents water supplied across the facility boundary rather than net water consumption. Water associated with electricity generation is excluded from WUE and treated as the indirect term in Section S4, following the distinction between direct and indirect water requirements.⁵⁵ Water quality and on-site water and wastewater treatment are not represented in the cooling model.

For each cooling case, annual PUE and WUE are sampled as a matched pair from the same simulated realization. When cooling cases are combined, the same sampled technology shares are applied to both metrics (Section S3.3). This preserves their dependence on the cooling configuration, weather, and equipment parameters. As an example, evaporative rejection lowers chiller electricity and raises water demand, whereas dry rejection does the reverse. Sampling PUE and WUE independently would incorrectly disregard these types of relationships/dependencies and could combine electricity and water requirements from incompatible simulated conditions, misrepresenting the energy-water trade-off.

Both metrics are annual, hour-weighted averages over the binned weather data described in Section S3.2. Within each thermal-model realization, IT power is held constant while cooling electricity and water demand are evaluated across the weather bins. Weighting each bin by its represented hours therefore gives the annual electricity and water ratios defined above. These should not be taken as design-point or peak-condition values. A facility whose plant is briefly inefficient during the hottest hours may still have a low annual PUE. Comparisons with operator disclosures therefore require consistent reporting periods and accounting boundaries.

S3.2 Simulating annual PUE and WUE

PUE and WUE are generated in two stages. In the first stage, a thermal model of each cooling configuration is evaluated under UAE weather conditions using sampled equipment and operating parameters. This produces an empirical distribution of paired annual PUE and WUE values for each cooling case and applicable data center archetype. These distributions are then sampled within the MCs in the second stage. The stages are separated because the thermal calculations are computationally expensive relative to the rest of the model. This allows the cooling distributions to be generated and inspected independently and then reused across capacity and load scenarios without repeating the thermal calculations.

The physics-based cooling model is built from two published sources: conventional configurations follow the data-center cooling model of Lei and Masanet⁵³, while the liquid-cooling cases adapt the implementation used by Xiao et al.³⁹ for AI servers. Readers are referred to these sources for the underlying energy and water balance equations. Source code for both model implementations is adopted and implemented using the UAE weather data, cooling-case assignments, parameter ranges and operating limits. Moist-air properties, including humidity ratio, enthalpy, dew-point temperature and wet-bulb temperature, are calculated using the CoolProp humid-air property library.⁵⁶ The same library is used by both source implementations, so retaining it preserves numerical comparability and compatibility with the published models.

Weather is represented by a typical meteorological year for Abu Dhabi International Airport (WMO station 412170; 24.433° N, 54.651° E, 26.8 m), taken from the TMYx series for the 2007–2021

observation window, containing 8,760 hourly observations of dry-bulb temperature, relative humidity and atmospheric pressure.⁵⁷ It is assumed that this weather file is representative of all facilities in the country. Differences between locations within the UAE, including inland conditions, are not modeled. Due to the high computational needs of this approach, hours are grouped into bins 2 °C wide in dry-bulb temperature and 5 percentage points wide in relative humidity, giving 255 occupied bins. Each bin is represented by the mean temperature, relative humidity and atmospheric pressure of its member hours, and is weighted by the number of hours it represents. The weights therefore sum to the full 8,760-hour year. Because cooling electricity, humidification and economizer operation respond nonlinearly to weather, evaluating the model at the mean conditions of a bin can give a different result from evaluating every hour separately. Therefore, binning approximates the hourly weather conditions within each group. The direction and magnitude that this difference may introduce have not been quantified for the present model, so no numerical bound on binning error is assumed.

Following Lei and Masanet⁵³, equipment and operating parameters are sampled using Latin hypercube sampling with uniform marginal distributions over the specified ranges. This method distributes samples across each parameter's range while limiting the number of computationally expensive thermal simulations. 300 draws are used for each applicable cooling case-archetype combination. Depending on the configuration, sampled parameters include UPS efficiency, power-distribution loss, lighting fraction, air temperature rise, fan and pump pressures and efficiencies, heat-exchanger effectiveness, chilled-water temperature difference, cooling-tower approach, tower drift fraction, cycles of concentration, chiller load fraction and the coefficient-of-performance uncertainty multiplier. The UPS efficiency range is assigned by archetype, while a common reference operating range is applied to all cooling configurations, as described in Section S3.4. Each draw represents one assumed facility design and operating scenario evaluated across the weather year. Sampled parameters therefore remain fixed across weather bins, while calculated cooling performance responds to the changing weather conditions. The chiller load fraction is sampled separately from the IT load factor.

Refrigeration performance is represented by three previously fitted regressions supplied with the source model⁵³ which are used to estimate coefficient of performance (COP) values. For water-cooled chillers, condenser-water temperature is calculated as ambient wet-bulb temperature plus the sampled cooling-tower approach, allowing the regression to respond to both outdoor temperature and humidity. A COP multiplier is sampled uniformly between 0.89 and 1.11 for each realization and applied throughout the weather year to represent uncertainty around the fitted performance.⁵³ For DX, the source implementation replaces the regression prediction with a base COP of 2.8 at outdoor temperatures at or below 15 °C, with the same uncertainty multiplier applied. Regression-based COP values are constrained to a minimum of 1.0 after applying the uncertainty multiplier which safeguards against low extrapolated predictions.

Each parameter draw is evaluated across all 255 weather bins, and the resulting PUE and WUE values are weighted by the hours represented in each bin to obtain the annual ratios defined in Section S3.1. One draw therefore yields one paired annual PUE and WUE value, and 300 draws form the empirical joint distribution for that cooling case and archetype. Stage 2 samples paired values directly from these stored distributions without fitting a parametric distribution. When cooling cases are combined, the same sampled technology shares are applied to both metrics.

S3.3 Cooling mix by archetype

Each archetype is represented by a mix of cooling configurations to account for differences in facility design. The following central shares represent the fraction of each archetype's IT electricity assigned to each configuration:

- Enterprise and telecom: Direct expansion: 25%; air-cooled chiller: 50%; water-cooled chiller: 25%
- Retail colocation: Air-cooled chiller: 30%; water-cooled chiller: 45%; water-cooled chiller with waterside economizer: 25%
- Wholesale hyperscale: Airside economizer with water-cooled chiller: 35%; waterside economizer with water-cooled chiller: 65%
- AI inference: Liquid cooling with airside economizer: 35%; liquid cooling with waterside economizer: 65%
- AI training: Liquid cooling with airside economizer: 15%; liquid cooling with waterside economizer: 85%

The selection of configurations is informed by the distinctions between facility types outlined in Shehabi et al.³⁷ Enterprise and telecom facilities are represented using direct expansion and chiller systems, retail colocation using chiller systems with and without economization, and wholesale hyperscale using configurations with economizers. AI facilities are represented using liquid-cooling configurations, with a greater assumed share assigned to waterside economization. UAE operator disclosures provide additional support for including adiabatic free cooling in hyperscale facilities and liquid cooling in AI facilities.^{9,10,15} These disclosures establish the relevance of the technologies, and are treated as modeling assumptions since they do not identify their shares across the UAE fleet or whether facilities use dry or evaporative heat rejection.

Given that these numerical shares are modeling assumptions informed by these sources rather than measured UAE adoption rates, each Monte Carlo realization samples a new set of shares around the central mix using a Dirichlet distribution to represent uncertainty in these assumptions and consider configurations with either lower water demand or lower electricity demand. The resulting distributions of the sampled shares for each archetype and configuration are shown in **Figure S1**. Within each realization, the same shares are applied to the paired PUE and WUE results, preserving their relationship. Both central configurations for wholesale hyperscale and the AI archetypes include evaporative heat rejection, so varying their shares alone cannot represent a fully dry cooling design. Two additional configurations with dry heat rejection, for wholesale and AI facilities, are evaluated only in the cooling-design comparisons (Section S5.2 and Supplementary Data Sheet S3).

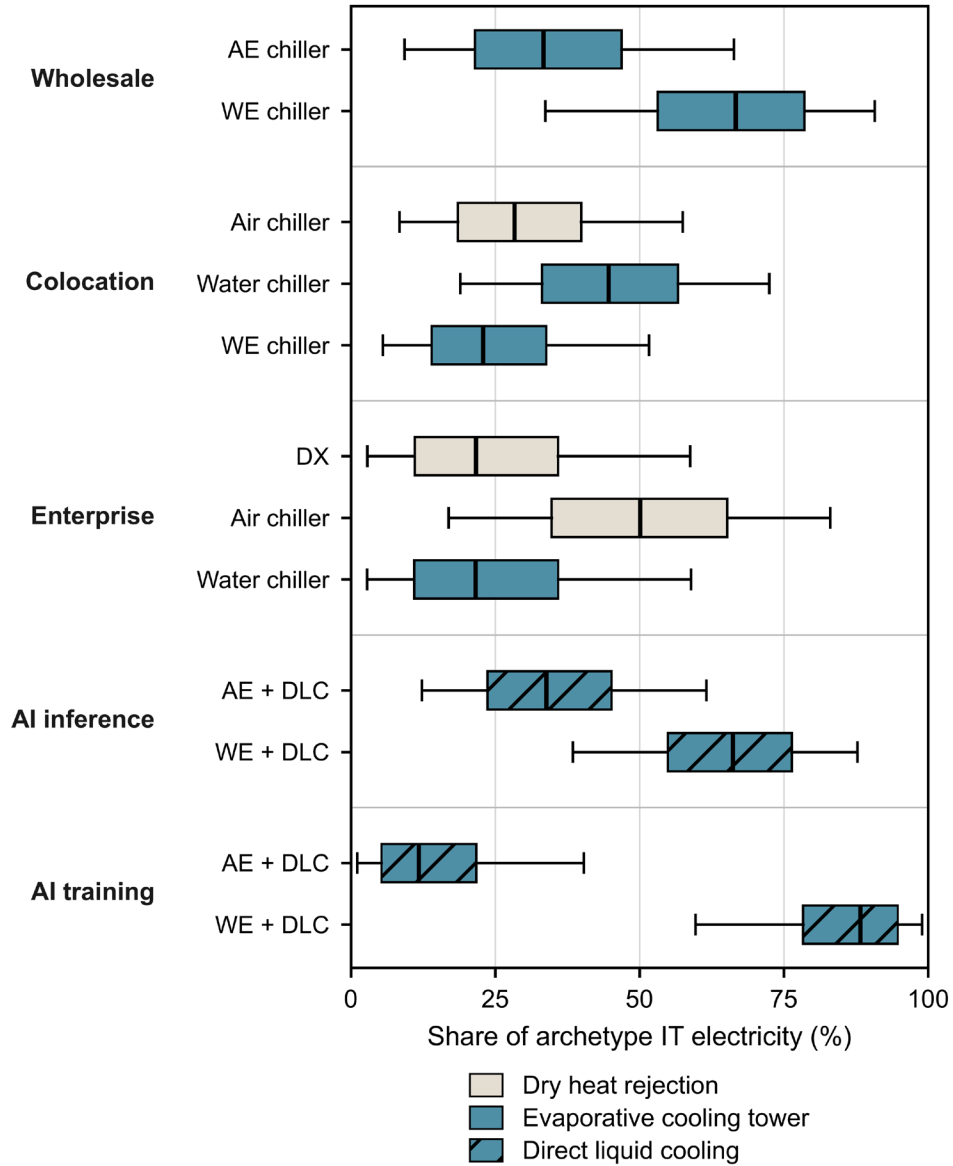


Figure S1: Sampled cooling-configuration shares by archetype. Box plots showing the share of each archetype's IT electricity assigned to each cooling configuration across the 100,000 Monte Carlo realizations, drawn from a distribution centered on the shares listed in Section S3.3. Black lines show medians, boxes interquartile ranges and whiskers 5th–95th percentile intervals. The shares of an archetype are drawn jointly and sum to one in each realization. Grey denotes dry heat rejection, blue evaporative cooling towers and hatching direct liquid cooling (DLC). Abbreviations: DX: direct expansion; AE: airside economizers; WE: waterside economizers; and DLC: direct liquid cooling.

S3.4 Cooling operating conditions

Cooling requirements depend on outdoor conditions and the temperature and humidity maintained inside the facility. In this study, the reference model uses a common 18 – 27 °C supply-air temperature range with explicitly specified humidity limits. A warmer operating range is evaluated separately for wholesale

hyperscale and AI as a sensitivity. It should be noted that these are assumed operating policies, not measured UAE conditions as that information is not disclosed publicly.

The reference model temperature limits match the ASHRAE recommended range for equipment classes A1–A4.⁵⁸ Dew-point limits of –12 to 17 °C and relative-humidity limits of 20 – 80% are retained from the model and differ from the ASHRAE recommended humidity limits. This operating range is applied to all reference configurations, including the dry cooling designs. The recommended temperature range is adopted as a more conservative reference for modeled cooling electricity.

In the warmer sensitivity, wholesale hyperscale and both AI archetypes are evaluated using supply-air limits of 10 – 35 °C, dew-point limits of –12 to 21 °C and relative-humidity limits of 20 – 80%. The temperature limits match the ASHRAE A2 allowable range.⁵⁸ Enterprise and telecom and retail colocation retain the reference range. Identical equipment-parameter draws, cooling-technology shares and weather data are used to compare the two policies.

In the modeled waterside-economizer configurations, the upper supply-air temperature limit is used by the controller. This translates to 27 °C under the reference policy and 35 °C for the affected configurations under the warmer sensitivity. The higher ceiling permits warmer modeled cooling water and greater economizer use, reducing chiller electricity requirements. Mechanical cooling supplies the demand that cannot be met by the economizer.

In the liquid-cooling cases, air and water temperatures are not independently controlled, so the policy sensitivity represents changes in the coupled model rather than an isolated change in room-air temperature. The sensitivity changes cooling electricity and water demand while holding IT power constant. Temperature-dependent server-fan power, leakage, and performance throttling are not modeled. The estimated savings therefore assume that the IT equipment can operate within the supply-air temperature and dew-point limits.

S3.5 PUE and WUE results by archetype

For each archetype, the paired annual PUE and WUE distributions are combined using the sampled cooling-technology shares described in Section S3.3. Each Monte Carlo realization draws one paired observation from each applicable cooling configuration and averages these observations using the sampled shares of IT electricity. The same shares are applied to PUE and WUE, preserving their dependence on the cooling mix. Observations are sampled independently across configurations, while PUE and WUE remain paired within each configuration.

The resulting distributions represent aggregate cooling performance within each archetype and are used in the subsequent electricity and water calculations. **Table S3.1** shows the median and 5th – 95th percentiles across the 100,000 realizations used in the final model run. Lower PUE does not consistently coincide with lower WUE. Both AI archetypes have a median PUE of 1.22 at the reported precision, while enterprise and telecom has the lowest median WUE and the highest median PUE. These differences reflect the assumed cooling configurations, equipment parameters and operating conditions.

Table S3.1 Paired annual PUE and WUE distributions for the different data center archetypes under the assumed reference cooling mix. Values are medians, with 5th – 95th percentiles in brackets.

Archetype	PUE [-]	WUE [L/kWh _{IT}]
Enterprise and telecom	1.80 [1.63–1.98]	0.65 [0.13–1.73]
Retail colocation	1.62 [1.51–1.75]	1.97 [1.18–2.68]
Wholesale hyperscale	1.26 [1.20–1.32]	2.11 [1.78–2.54]
AI training	1.22 [1.16–1.28]	2.11 [1.79–2.54]
AI inference	1.22 [1.17–1.27]	1.99 [1.71–2.36]

Under the warmer operating-policy sensitivity, median PUE values are reduced to 1.19 for wholesale hyperscale, 1.14 for AI training and 1.15 for AI inference. The corresponding median WUE values are 1.81, 1.89 and 1.71 L/kWh_{IT}. Enterprise and telecom and retail colocation are unchanged because their operating range is held fixed. For the liquid-cooling cases, these differences reflect changes in the coupled air-and-water representation described in Section S3.4.

S3.6 Comparison with published performance and model limitations

The cooling model performance is evaluated through checks against the published implementations and comparisons with reported facility performance. It should be noted that published comparisons support the underlying modeling approach but do not establish the accuracy of the UAE adaptation. In their earlier study, Lei and Masanet⁵⁹ compared modeled annual mean PUE with reported values from 17 Google and Facebook hyperscale facilities, including Singapore, and reported relative errors within approximately 4%. The subsequent PUE/WUE study⁵³ found that reported annual values for five facility cases fell within the modeled best-to-poor-practice ranges. Validation of the adapted model against measured UAE facility performance has not been established due to the limited availability of that data. Modeled values were also compared with published facility and regional values (**Table S3.2**). Published benchmarks were selected to provide regional and climatic context, prioritizing the UAE and neighboring Gulf countries, locations with hot and humid or hot and dry conditions, and regional survey and global fleet averages. These comparisons provide context and order of magnitude estimate comparisons because cooling systems, equipment loading, operating conditions and accounting boundaries differ across sources.

Table S3.2 Published PUE and WUE benchmarks used to assess the modeled results.

Source	Location	Year	Scope	PUE [-]	WUE [L/kWh _{IT}]
AWS ⁶⁰	UAE	2025	Regional operator average	1.25	--
AWS ⁶⁰	Bahrain	2025	Regional operator average	1.33	--
Pure DC ⁶¹	Abu Dhabi	Not Specified	Site	1.38	--
Uptime Institute ⁶⁶	Middle East and Africa	2025	Regional operator average	1.68	--
AWS ⁶⁰	Singapore	2025	Regional operator average	1.30	1.57
AWS ⁶⁰	Jakarta, Indonesia	2025	Regional operator average	1.29	2.85
Google ⁶³	Singapore	2024	Site	1.13	--
Google ⁶³	Singapore	2024	Site	1.15	--
Microsoft ⁶⁴	Singapore	2022	Regional operator average	1.36	2.06
Microsoft ⁶⁴	Arizona	2022	Regional operator average	1.22	2.24
Google ⁶³	Nevada	2024	Site	1.09	--
Equinix ⁶⁵	Global sites using evaporative cooling	2024	Operator report	--	1.55

Uptime Institute ⁶²	Global	2025	Global survey average	1.54	--
Google ⁶³	Global fleet	2024	Operator fleet average	1.09	--
AWS ⁶⁰	Global fleet	2025	Operator fleet average	1.14	0.12

The modeled wholesale hyperscale median PUE is 1.26, slightly above the AWS UAE value of 1.25 and below the AWS Bahrain and Pure DC Abu Dhabi values of 1.33 and 1.38, respectively. Both modeled AI medians are 1.22, below these UAE and Bahrain benchmarks but above Google’s Singapore values of 1.13 – 1.15. Lower PUE values are also reported for Nevada and Google’s global fleet. These comparisons place the modeled estimates within the range of published performance.

The direction of the modeled energy-water trade-off also agrees with a study of two Phoenix-area colocation facilities.⁶⁷ The facility using air-cooled chillers had approximately 13% higher average PUE and 66% lower source WUE than the facility using water-cooled chillers and evaporative cooling. Source WUE includes water associated with electricity generation, so that percentage is not directly comparable with differences in the on-site WUE modeled here. Enterprise and telecom and retail colocation have higher modeled medians of 1.80 and 1.62, respectively, above the 1.54 global survey average. The modeled retail colocation, wholesale hyperscale and AI median WUE values of 1.97–2.11 L/kWh_{IT} fall between AWS’s Singapore and Jakarta values of 1.57 and 2.85 L/kWh_{IT}. However, substantially lower WUE is reported for AWS’s global fleet, and Equinix’s evaporatively cooled sites average 1.55 L/kWh_{IT}. No comparable annual UAE WUE was identified in the sources reviewed. Differences in water-accounting boundaries also limit direct comparisons between published and modeled values.

Some modeling limitations that may lead to these observed differences include assumed cooling mixes, simplified cooling-system operation, a single coastal weather year and refrigeration regressions used beyond their training ranges. The reported uncertainty intervals do not capture all model limitations or alternative designs.

S4. Grid and clean-electricity supply

S4.1 Scope and boundaries

The grid and water supply module uses the site electricity and direct cooling-water demand from Section S3 to estimate total electricity consumption, total water demand, GHG emissions, national clean-generation shares, and clean-electricity matching outcomes. Total electricity includes site electricity and the electricity required to desalinate the direct cooling water (Section S4.4). Total water combines direct cooling demand with indirect freshwater used to generate site electricity, following the direct and indirect framework of Siddik et al.⁵⁵ Life-cycle-adjusted emissions (CO₂e) are calculated for total electricity consumption, including water-supply electricity, using operational emission factors supplemented by literature-based life-cycle additions. Operational emissions are calculated separately and compared with utility-reported 2025 emission intensities using the allocation methods described in Section S4.3. Annual totals are calculated within each Monte Carlo realization before medians and percentile intervals are obtained.

Grid conditions are represented as end states of the 2030 decade (Section S1.1). Three grid scenarios (Existing Grid, Planned Grid, and Ambitious Grid) specify annual clean-electricity generation. The Existing Grid retains reported 2025 generation, while the Planned and Ambitious Grids represent generation portfolios informed by announced utility expansion for 2030 and 2035, respectively.^{68–71} In

each realization, non-data-center demand is obtained by subtracting an assumed data-center load from the sampled national total-demand estimates. Modeled data-center site electricity and electricity required for cooling-water desalination are then added to obtain total national demand. Once available clean generation is used in full, it is assumed that natural-gas generation meets any remaining demand. Carbon and water intensities are calculated from the same generation mix, maintaining consistency between the two.

National-average life-cycle emission factors are used to calculate emissions attributed to data-center electricity. Changes in physical system emissions from expansion are calculated separately relative to the No Data-Center Expansion reference, which retains the modeled 2025 data-center sector. Annual clean-electricity matching reallocates attributed emissions without changing physical electricity generation or total system emissions.

The analysis assumes an annual energy balance, meaning that year-by-year trajectories, dispatch and transmission constraints are not modeled and outside the scope of the study. The additional clean-electricity generation required under alternative decarbonization objectives is evaluated separately (Section S4.5). Intensities are expressed per unit of gross generation and applied without adjustment for transmission and distribution losses. Indirect water includes freshwater used in generation, whereas seawater used for condenser cooling and desalination feed is excluded.

S4.2 The UAE electric grid and clean-electricity supply scenarios

The UAE national grid^{70,71} is represented using 2025 generation data for Emirates Water and Electricity Company (EWEC), Dubai Electricity and Water Authority (DEWA), and the Northern Emirates. EWEC generation is estimated at 118,320 GWh, comprising 107,847 GWh reported in its 2025 Statistical Report and 10,473 GWh inferred for Fujairah F3, which falls within the EWEC-contracted generation boundary. DEWA reported 62,209 GWh, while Northern Emirates own generation is assumed at 10,000 GWh. These values establish fixed system weights of 62.1%, 32.7%, and 5.3%, respectively, for constructing national factors. The reconstructed national total of 190.5 TWh which matches officially reported 2025 national generation. The adopted regional emission factors give a national fossil-fleet factor of 0.5018 t CO₂e/MWh, with the unit reflecting the source-specific operational emission reporting conventions. The regional factors, reporting boundaries and cogeneration parameters are documented in Supplementary Data Sheet S4. Comparisons with utility-reported operational intensities use the fitted cogeneration allocation described in Section S4.3.

Three scenarios characterize annual clean generation. The Existing Grid retains reported and reconstructed 2025 generation quantities, including 42.38 TWh of nuclear and 16.79 TWh of solar PV and CSP generation. Waste-to-energy contributes another 1.25 TWh to physical non-gas supply but is excluded from the modeled clean-generation pool. The Planned Grid represents announced utility expansion for 2030, including EWEC's 14 GW cumulative solar PV capacity and 5.96 GW of identified DEWA PV capacity. Nuclear generation is held at 44 TWh, consistent with EWEC's expected output from the four Barakah units.⁷² This portfolio provides a median of 93.4 [89.2–97.5] TWh of eligible clean generation. The Ambitious Grid represents a larger portfolio informed by EWEC's announcement of more than 35 GW of solar capacity by 2035, using 35 GW as the modeled reference alongside the same DEWA PV capacity. This produces 141.2 [132.1–150.3] TWh of eligible clean generation. Future solar PV generation is calculated using an assumed effective capacity factor sampled uniformly between 0.23 and 0.29, which is an assumed range informed by observed 2025 utility-scale solar output.^{70,71} EWEC's PV facilities operating throughout 2025 retain their reported generation of 6.426 TWh, while additional EWEC capacity and DEWA's identified PV capacity are converted to annual

generation using the sampled factor. The same factor is shared across scenarios within each Monte Carlo realization.

National total electricity demand is sampled from a PERT distribution with minimum, mode and maximum values of 240, 307 and 352 TWh yr⁻¹.^{70,71,73,74} These values are informed by reconstructed national electricity-demand paths spanning the 2030–2040 period. To account for data-center electricity already accounted for in these national demand estimates, an allocation is sampled from a triangular distribution (6, 12.4, 20 TWh yr⁻¹).^{5,75} The bounds are source-informed assumptions, while the central value is based on the modeled Central Expansion electricity requirement. Subtracting the sampled embedded data-center allocation gives non-data-center demand of 291.2 [254.1–323.9] TWh yr⁻¹. Demand is sampled directly, without assigning commissioning years, and the same background-demand draws are used across all nine capacity-grid combinations. In each realization, both modeled site electricity and cooling-water-supply electricity are subsequently added to this demand, and natural-gas generation supplies the remainder after the fixed generation quantities. The influence of these demand estimates on the results is assessed separately in Section S5.

Data-center capacity relative to national peak demand is estimated by summing nameplate IT capacity multiplied by the annual-average PUE for each archetype. National peak demand is inferred from total annual generation combined at an assumed national load factor of 0.72 derived from the utilities' 2030 forecasts.^{70,71}

Table S4.1 Clean-supply generation and resulting grid factors for the Central Expansion scenario. Derived factors are medians with 5th – 95th percentiles across all MCs realizations.

	Existing Grid	Planned Grid	Ambitious Grid
Nuclear generation (TWh)	42.38	44.0	44.0
Solar PV generation (TWh)	13.79	46.11 [41.99–50.25]	93.92 [84.84–103.05]
CSP generation (TWh)	3.00	3.00	3.00
Wind generation (TWh)	0.25	0.25	0.25
Waste-to-energy generation (TWh)	1.25	2.00	2.00
Total non-gas generation (TWh)	60.67	95.36 [91.24–99.50]	143.17 [134.09–152.30]
Eligible clean generation (TWh)	59.42	93.36 [89.24–97.50]	141.17 [132.09–150.30]
Desalination mix, MSF / MED / RO	0.626 / 0.036 / 0.338	0.261 / 0.012 / 0.727	0.246 / 0.009 / 0.745
National clean-generation share (%)	19.6 [17.7–22.3]	30.8 [27.4–35.3]	46.5 [41.0–53.8]
Life-cycle-adjusted emission intensity (t CO ₂ e/MWh)	0.456 [0.441–0.466]	0.398 [0.374–0.415]	0.316 [0.278–0.345]
Operational emission intensity (t CO ₂ e/MWh)	0.404 [0.390–0.413]	0.348 [0.325–0.364]	0.269 [0.232–0.296]
Grid freshwater intensity (L/kWh)	0.0104 [0.0101–0.0108]	0.0114 [0.0105–0.0126]	0.0128 [0.0109–0.0153]

The modeled generation portfolios apply to all capacity scenarios. Within each grid scenario, generation quantities are held fixed with respect to additional data-center demand, while the Planned and Ambitious Grids also vary with the sampled solar yield. Derived grid factors vary because additional data-center electricity increases fossil generation and reduces the clean-generation share. Central results are shown here, while all nine capacity-grid combinations are reported in Supplementary Data Sheet S4. Emissions accounting and desalination assumptions are described in Sections S4.3 and S4.4, respectively.

S4.3 Emissions accounting

Emissions are calculated on operational and life-cycle-adjusted bases. Life-cycle-adjusted CO₂e emission factors are used to characterize total electricity-supply emissions, while combustion-based operational CO₂e is quantified for comparison with utility reported emission intensities. Embodied carbon of the manufacturing of the IT equipment and data-center construction is not accounted for.

The operational grid intensity in each realization is calculated from the fossil-generation share multiplied by the national fossil-fleet factor of 0.5018 tCO₂e/MWh (in addition to a waste-to-energy share multiplied by 0.540 tCO₂e/MWh derived from DEWA's reported emissions and electricity received from the Warsan power plant⁷⁰). Nuclear and renewable generation do not carry any operational emissions. The fossil-fleet factor uses an all-to-power allocation, assigning the represented fuel emissions from joint electricity and water production entirely to electricity. National-average grid intensities are applied to calculated electricity-related attributed emissions.

An alternative allocation between electricity and water is considered in utility comparisons and the operational sensitivity analysis. The utility reconciliation uses a short-run marginal cost (SRMC) representation informed by EWEC's published allocation method to distribute cogeneration fuel emissions between electricity and desalinated water.^{71,72} DEWA's allocation share is fitted to its reported Category 1 electricity intensity.⁷⁰ For the future grid scenarios, the proportion of fossil generation associated with cogeneration is assumed to decrease in proportion to the thermal-desalination share relative to 2025. This reduces the share of fuel emissions assigned to water. Under these allocation schemes, the modeled 2025 emission intensities match the utility-reported values: 0.187 t CO₂e/MWh for EWEC and 0.3833 t CO₂e/MWh for DEWA.^{70,71} The utility-consistent factors are used to ensure agreement with utility reporting conventions, while the all-to-power factors are retained for national grid-emissions-intensity comparisons. Parameters and reporting boundaries are documented in Supplementary Data Sheet S4.

The life-cycle-adjusted emission intensities add an assumed additional natural gas supply-chain contribution of 0.060 tCO₂e per MWh of natural-gas-based generation, representing extraction, processing, transport and methane leakage.^{76,77} Generation-weighted life-cycle factors are also included for solar PV at 0.043 tCO₂e/MWh⁷⁸, CSP at 0.027, wind at 0.011, nuclear at 0.012,⁷⁶ and an additional 0.050 tCO₂e/MWh for waste-to-energy⁷⁹. These parameters and sources are documented in Supplementary Data Sheet S4.

For each scenario, emissions attributed to total data-center electricity use are calculated within each realization by multiplying the corresponding national-average life-cycle grid intensity by total electricity consumption, including site electricity and water-supply electricity (Section S4.4). Changes in physical electricity-system emissions from further data-center expansion are calculated separately relative to the No Data-Center Expansion reference, which retains the modeled 2025 data-center sector under the same clean-electricity supply and background demand. Reported totals are medians of the within-realization sums, meaning that component medians need not sum to the median total.

S4.4 Water supply and associated electricity consumption

Total modeled water demand combines direct cooling make-up water supplied to facilities and indirect freshwater consumption from electricity generation. Direct demand is calculated by multiplying WUE by IT electricity consumption, as described in Section S3. Indirect use is calculated by multiplying grid freshwater intensity by site electricity consumption. Seawater used for condenser cooling and desalination feed is excluded.

Electric grid freshwater intensity is calculated in each realization by weighting technology-specific factors by their generation shares. Electric-generation water consumption factors are included for fossil generation, nuclear generation, dry-cooled CSP, and waste-to-energy. Freshwater use for PV panel washing is also accounted for.⁸⁰ Sources and limitations of these factors are documented in Supplementary Data Sheet S4.

Direct cooling water is assumed to be supplied by the desalinated municipal network. Water-supply electricity is calculated by multiplying direct water demand by the electricity intensity of the scenario's desalination mix. Adopted intensities for multi-stage flash (MSF), multi-effect distillation (MED), and reverse osmosis (RO) are accounted for, which correspond to 4.0, 2.5, and 3.5 kWh per m³, respectively.^{81,82} The mixes in **Table S4.1** are scenario assumptions informed by utility production, capacity and expansion information (mostly towards RO desalination).^{70–72} Their composition and weighting are documented in Supplementary Data Sheet S4.

Water-supply electricity is added to site electricity and included in the national electricity-generation balance, with associated emissions calculated using the same realization's grid emission factors. Thermal energy used by MSF and MED is not added as a separate energy input because it is assumed to be supplied through cogeneration, with the associated fuel emissions assigned to electricity under the all-to-power convention (Section S4.3). Municipal distribution electricity and network losses are not modeled. Indirect freshwater use is calculated for site electricity only.

S4.5 Clean-electricity matching and new supply requirements

Annual clean-electricity matching is evaluated at 0, 30, 80 and 100% of data-center site electricity. Matching represents a claim on the emission reduction attributes of existing clean generation, without assuming that the purchase creates additional supply.⁸³ The assumed eligible sources of clean electricity include nuclear, solar PV, CSP and wind generation, totaling 59.4, 93.4 and 141.2 TWh under the Existing, Planned and Ambitious Grids, respectively. A renewables-only scenario excludes nuclear, leaving 17.0, 49.4 and 97.2 TWh, respectively, at the median. Matching applies to site electricity and excludes water-supply electricity. The total amount of requested clean energy is the product of the matching fraction and total site electricity demand, subject to the available eligible generation. Existing clean-electricity claims by other consumers are not modeled. The remaining eligible clean generation available after the modeled data-center claims is also quantified.

Additional clean-generation requirements are evaluated for three objectives: (1) preserving the national clean-generation share of the No Data-Center Expansion reference, (2) reaching the UAE's 35% clean-generation benchmark, and (3) avoiding additional natural-gas generation from further data-center expansion. For the first, the clean-generation share of the No Data-Center reference is maintained under the expanded electricity demand. For the second, the additional generation requirement is calculated as the positive difference between 35% of total national generation and the available eligible clean generation. The 35% objective is used as a common benchmark across the 2030–2040 operation. For the third, additional non-gas generation is calculated to offset the increase in residual natural-gas generation relative to the No Data-Center reference, with the modeled generation portfolio held fixed. These requirements are converted to PV-equivalent installed capacity. Further calculations and results are provided in Supplementary Data Sheet S4.

Life-cycle-adjusted emission factors are used to calculate the residual-mix emission factor after allocating the attributes of matched clean generation to data centers (**Eqns. (5)–(6)** in the main text). The remaining emissions are attributed to non-data-center consumers, unmatched data-center site electricity and desalination electricity. Matching existing generation therefore redistributes attributed emissions without changing physical electricity demand, generation, or total system emissions.

S5. Uncertainty and sensitivity analysis

S5.1 Scenario-aware Monte Carlo simulation

Uncertainty is propagated using scenario-aware MCs (SA-MCs)⁸⁴, which separates parameter uncertainty from scenario uncertainty. Parameter uncertainty covers inputs that are uncertain within each scenario and are represented by the distributions described in Sections S1 to S4. These include current installed IT capacity, archetype and workload shares, fill rate, OCF, PUE and WUE, cooling-technology shares, non-data-center background electricity demand (including the subtracted data-center demand share from national estimates), effective solar yield for future PV generation, and the freshwater factor of solar generation. Scenario uncertainty covers choices that define distinct futures that cannot coexist. These are represented by the three capacity expansion scenarios and the three grid scenarios evaluated as nine separate combinations. This allows the effects of the scenario choices to be distinguished. The grid module is calibrated against utility-reported 2025 operational emission intensities (Section S4.3), while PUE and WUE are derived from the thermodynamic cooling model (Section S3). Uncertainty associated with model structure and assumptions is not fully captured by the sampled parameter distributions and is evaluated through selected sensitivity comparisons.

Each realization samples the specified input distributions and computes the annual balances. Shared inputs use the same sampled values across scenario combinations, including the national demand and solar-yield draws used for paired comparisons across scenarios and counterfactuals. Reported medians and 5th–95th percentile intervals are computed over $N = 100,000$ realizations per combination. Parameter distributions, ranges and sources are given in Supplementary Data Sheets S1 to S4.

S5.2 Sensitivity analysis

The sensitivity of the main results to individual inputs and design assumptions is examined by varying one parameter group or design assumption at a time while other inputs retain their sampled values. Each comparison is evaluated for all nine capacity–grid combinations. Percentage changes are calculated between the median output at each alternative setting and the corresponding reference median for total electricity consumption, GHG emissions, and total water demand. Grid emission and freshwater intensities are recalculated in every comparison based on the resulting electricity demand and generation mix.

OCF and fill rate are set to their lower and upper distribution bounds across all archetypes and capacity groups, respectively (Section S2). PUE and WUE are set to each archetype’s modeled 5th and 95th percentiles (Section S3), and non-data-center demand to its sampled 5th and 95th percentiles (254.1 and 323.9 TWh yr⁻¹). PUE and WUE are varied separately, with the other retaining its sampled values. These settings differ in how they are selected and do not represent a common probability interval. Design comparisons set the training share to 35% or 65% in every project with sampled workload shares, retaining a 5% non-accelerated IT share and assigning the remainder to inference. Cooling shares are centered on the low-water and low-energy mixes described in Section S3.3. The warmer operating-policy comparison applies the temperature and humidity limits described in Section S3.4 to wholesale hyperscale and both AI archetypes, while enterprise and colocation retain their reference limits. PUE and WUE vary together in the cooling-mix and operating-policy comparisons.

Cooling-technology comparisons identify the lowest and highest median electricity and water demands among 243 configuration combinations. Each combination assigns one configuration to each archetype, retaining paired PUE and WUE values and equipment-performance uncertainty, and uses the

same sampled inputs. Additional dry configurations for wholesale hyperscale and AI are included (Section S3.3).

Separate sensitivity runs evaluate lower and higher national total-demand envelopes using beta-PERT distributions of (211, 246, 292) and (288, 325, 373) TWh yr⁻¹, respectively. The same sampled embedded data-center allocation is subtracted in each case, while other inputs use the same Monte Carlo draws as the reference. Under Central Expansion and the Planned Grid, the 35% clean-generation benchmark is reached in 85.6% and 0% of realizations under the lower- and higher-demand envelopes, respectively, compared with 6.2% in the reference case. Settings and outputs for the sensitivity comparisons are documented in Supplementary Data Sheet S5.

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