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Original Research

Global data–water symbiosis reduces AI infrastructure's carbon and water footprint

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A B S T R A C T

Data centres support artificial intelligence (AI) development but place rapidly increasing demands on electricity and freshwater resources, with cooling representing a significant portion of their total energy consumption. Wastewater treatment plants (WWTPs) discharge large volumes of treated effluent with substantial cooling potential; however, their integration with data centre infrastructure has not been evaluated. Here we construct a global geodatabase of over 4775 data centres and 57,547 municipal WWTPs across 98 countries, integrating spatial analysis, engineering systems modelling, optimisation, and life-cycle assessment to quantify the benefits of combining treated water reuse with bidirectional thermal recovery. The analysis reveals a strong global spatial co-occurrence between data centres and WWTPs, enabling optimized national-scale pairings in which treated effluent is used for data centre cooling and the return heat is recovered to support sludge drying and anaerobic digestion. This symbiotic approach reduces greenhouse gas emissions by approximately 84 million tonnes of CO_2 equivalent annually, conserves approximately 1300 million m^3 of freshwater, and provides net annual cost savings of approximately US$95.4 billion. The greatest mitigation and water-saving potential lies in the United States, Japan, China, the Netherlands, and the United Kingdom. These findings establish data–water symbiosis as a readily scalable infrastructure solution that decouples AI from its carbon and water footprints. WWTPs are poised to evolve from disposal facilities into critical energy-coupling hubs, enabling efficient thermal and water exchange across urban systems and accelerating progress towards multiple Sustainable Development Goals.

1. Introduction

Data centres provide the foundational infrastructure for the development of artificial intelligence (AI) [1], emerging as gluttons of electricity and water for the coming decades [2–4]. The advancement of green data centres, which deploy advanced technologies to maximise energy efficiency while minimising their environmental externalities [5,6], is critical for triple-bottom-line sustainability in AI development [7]. Notably, the average modern data centre uses around 40% of its power for cooling [8]. Current data centre cooling technologies mainly include air cooling and liquid cooling. Air cooling is simple to operate and remains widely used, but its heat transfer efficiency can be constrained under high-density computing loads. By contrast, liquid cooling dissipates heat more effectively and is becoming increasingly relevant

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for AI-oriented facilities with intensive cooling demands [9]. AI drives the increase in greenhouse gas (GHG) emissions from industrial activities, and carbon emissions are expected to exceed 2.5 billion tonnes of CO_2 eq in 2030, accounting for 8% of the global total emissions. Meanwhile, the increased power demand caused by generative AI triggers severe water shortages and inequities in access to electricity worldwide, partly due to the demand for freshwater in the data centres' cooling sector [10]. Decoupling data centres and GHG emissions is important to achieve climate mitigation goals. Moreover, identifying and implementing water reuse opportunities will be essential to addressing the challenges associated with water management and shortages. In this context, treated wastewater from WWTPs is particularly attractive for liquid cooling because it can substitute for freshwater and carry recoverable low-grade heat. Compared with conventional freshwater cooling, it reduces dependence on potable water resources; compared with desalinated seawater or groundwater [11,12], it may pose lower ecological risks. It also enables bidirectional resource recovery between data centres and WWTPs.

Wastewater treatment plants (WWTPs), as essential environmental infrastructure [13], produced about 41 billion tonnes of treated wastewater in 2021 [14]. Considering that 83.5% (48,052) of WWTPs operate in regions with an annual average temperature below 20 °C [14,15], the cooling energy potential associated with their discharge into reservoirs is substantial. The recovery of energy from WWTPs is emerging as a promising approach [16], and treated water is increasingly utilised as cooling water in power plants [17]. However, the potential benefits of utilising the cooling energy present in wastewater for data centres have been largely neglected. Consequently, a collaborative symbiosis between data centres and WWTPs can be the right way to realise synergistic benefits by WWTPs supplying substantial, cost-effective and sustainable cooling for data centres and by data centres delivering their waste heat to WWTPs—the ultimate recipient of energy—thereby reducing the energy consumption of sludge drying and anaerobic digestion [18]. The recycling of thermal energy, both heat and cooling energy, between data centres and WWTPs paves the way for developing symbiotic infrastructure systems.

Infrastructure symbiosis facilitates efficient use of energy, water and other resources [19], but previous studies about green data centre operations have largely addressed these issues in isolation: hardware upgrades [20], migrating workloads between data centres to mitigate carbon emissions [21], the integration of renewable energy sources into data centres to curb carbon footprints [22], while others have optimized traditional cooling systems for enhanced efficiency [23]. Meanwhile, wastewater reuse for industrial cooling has been investigated in regional case studies [24], demonstrating the potential for symbiosis between data centres and WWTPs. However, integrated frameworks that explicitly optimise data centres and WWTPs remain scarce.

To what extent can a globally optimized data—water symbiosis improve environmental and economic benefits, considering regional variability? Here we develop a global data—water infrastructure symbiosis geodatabase that covers more than 4775 data centres and 57,547 WWTPs across 98 countries. Our analytical framework combines engineering systems modelling, optimisation-based pairing, and life-cycle assessment (LCA). The existing configuration of data centres and WWTPs in 2023 is used as the baseline scenario. We then construct a symbiotic scenario in which data centres adopt enhanced energy recycling and use treated wastewater. In this setting, the model identifies data centre–WWTP pairings with the greatest potential to reduce GHG emissions and save water. We also evaluate how the symbiosis affects GHG emissions and freshwater conservation.

2. Materials and methods

2.1. Geodatabase of global data centres and WWTPs

Data centre facility records were compiled from publicly available geospatial databases, official cloud-provider location pages, and peer-reviewed literature. Public geospatial sources included OpenStreetMap [25], the IM3 Open Source Data Center Atlas [26], and the Epoch AI Frontier Data Centres database [27]. OpenStreetMap and IM3 were used primarily for facility locations and spatial footprints, whereas the Epoch AI database was used to supplement information on large AI-oriented facilities. Facility size, site area, listed Power Usage Effectiveness (PUE), and other technical attributes were first assembled from directory sources where available and then harmonised through standardised name, address, and power-capacity fields. Geographic coordinates, administrative units, and building footprints were further cross-checked against OpenStreetMap, and elevation was assigned using the SRTM-90 digital elevation model [28].

To improve coverage of hyperscale and public-cloud infrastructure, facility records were further supplemented using the official location pages of major cloud providers, including AWS [29], Azure [30], Meta [31], Oracle Cloud [32], IBM Cloud [33], and Google Data Centres [34,35].

Further supplementation was guided by peer-reviewed bottom-up studies that have spatially characterised data centre infrastructure and associated environmental attributes, thereby improving coverage of both large commercial facilities and smaller in-house sites [36]. For the United States, peer-reviewed CBECS-based bottom–up analyses were used to benchmark the aggregate structural and technical characteristics of small and midsize data centres, rather than to define facility-level records, thereby improving representation of smaller in-house sites [37,38].

Metadata for WWTPs were assigned to HydroBASINS level-06 sub-basins and first-level administrative units defined by GADM v4.1 [39]. Water stress index conditions were characterised using WRI Aqueduct 4.0 [40], temperature conditions were assigned using NOAA observational and climatological datasets [41], and elevation was derived from the SRTM-90 digital elevation model [28].

The geodatabase also includes the geographical coordinates (latitude and longitude) of both data centres and WWTPs, which we obtained from Google Maps. We generated a matrix of distances between WWTPs and data centres by calculating the distance between each pair, leveraging the open application programming interface (API) of Google Maps. The geodatabase was further used to determine the inter-facility distance between each data centre and WWTP pair, which served as a key spatial parameter in the optimisation of candidate linkages (Supplementary Note 1.1).

Using this geodatabase, we first quantified the geographic proximity between data centres and WWTPs in each country (Supplementary Note 2.1), and then estimated the cooling demand of data centres and the cooling supply potential of WWTPs at the national level (Supplementary Note 2.2). We calculate GHG emissions, energy demands for recycling, and freshwater consumption. We also quantify treated water volumes from WWTPs, considering a range of technologies and operational conditions. GHG emissions are measured in tonnes of CO_2 eq, with detailed calculations provided (Supplementary Note 2.3-2.9).

2.2. Scenarios and optimisation

We present an integrated analysis of the symbiotic relationship between data centres and WWTPs. For this analysis, we employ a counterfactual approach with 2023 as the baseline year. Our geodatabase includes data on data centres from 2024 and WWTPs from 2022, spanning multiple regions globally. The baseline scenario for 2023 is defined as the "original wastewater treatment mix of WWTPs" and the "original energy consumption mix of data centres." In contrast, the counterfactual symbiotic scenario envisions "enhanced energy recycling and treated water use in data centres." Detailed descriptions of the baseline energy recycling and water consumption mix are provided in the Results section. The symbiotic scenario necessitates additional infrastructure investments, including advanced wastewater treatment, new water pipelines, and upgraded wastewater treatment to meet energy consumption and carbon emission standards. It also leads to reductions in electricity consumption, as well as freshwater extraction and usage. In this framework, we compare the infrastructure configurations of the baseline and symbiotic scenarios to quantify the resulting environmental and economic benefits.

In the symbiotic scenario, candidate linkages between data centres and WWTPs are explicitly represented, and the associated benefits of energy recovery and reclaimed-water reuse are evaluated. On this basis, a tailored techno-economic optimisation routine is constructed to determine the optimal matching configuration between data centres and WWTPs. The scale of optimized pairing is limited within each country, meaning data centres will be paired only with domestic WWTPs. The goal is to maximise GHG mitigation and water reuse under economic cost constraints (Supplementary Note 1.1). We formulate the optimisation function as equations (1) and (2):

$$\textit{Minimize GHG emissions of the symbiotic scenario} \tag{1}$$

$$\textit{Subject to } \Delta \textit{economic costs of each linkage} \leq 0 \tag{2}$$

where Δ represents the annual cost difference between the symbiotic scenario and the baseline scenario. Freshwater consumption is defined as the share of freshwater withdrawal that is not returned to its original natural source; therefore, greater use of reclaimed water reduces freshwater consumption.

The economic constraints on linking treated water between WWTPs and data centres include cost savings from reduced electricity and water use, additional pipeline infrastructure costs, and the costs associated with avoided sludge treatment and advanced wastewater treatment. The feasibility of each pairing is determined by these economic constraints. To maximise GHG mitigation and water reuse, we prioritise the use of treated water from WWTPs by nearby data centres, thereby minimising the environmental impact of transportation. The model permits one-to-many and many-to-one linkages, allowing one WWTP to supply multiple data centres where this improves the objective.

As reclaimed water from some water-scarce areas needs to be replenished for groundwater [42] and farmland irrigation [43], we augmented the optimisation model to internalize local water scarcity by introducing an administrative-unit water stress index (WSI) that both weights the objective and acts as a feasibility constraint (treating WSI >0.4) while the minimum-cost flow model continues to minimize GHG. To construct the WSI, we combined HydroBASINS Level-06 sub-basins [44], GADM 4.10 first-level administrative units [39] and Aqueduct 4.0 baseline water stress (BWS) [40]. After spatial reprojection, each sub-basin polygon was intersected with each administrative unit to generate a set of 'basin × admin' fragments. For each unit, area weights were defined as the ratio of a fragment's area to the unit's total area, and unit-level BWS was computed as the area-weighted mean across its fragments. The resulting global Admin-1 WSI informs each WWTP's cooling potential and prioritises data–water symbiosis in low WSI regions, thereby avoiding proximity-driven siting choices that could otherwise exacerbate competition for limited freshwater in arid areas (Supplementary Note 1.2).

Because once-through systems generally rely on direct withdrawals of surface water or seawater, and seawater incurs no raw-water charge, replacing these supplies with treated effluent would be economically unattractive. We therefore restrict the analysis to cases in which reclaimed wastewater substitutes for freshwater in data centres that use liquid-cooling systems. The water quality required for these applications can be obtained by upgrading WWTP effluent through tertiary treatment. Within this scope, the model selects WWTP–data centre pairings that satisfy spatial, engineering, and cost constraints. The optimisation procedure and parameter settings are provided in Supplementary Note 1.

2.3. Life-cycle assessment

We conduct an attributional gate-to-gate LCA and life-cycle cost (LCC) to evaluate the environmental benefits of the data-water infrastructure symbiosis relative to a baseline scenario, following the general steps outlined in ISO 14040 (Simapro 9.6.0.1, Supplementary Note 2.3). We quantify the changes in GHG emissions and freshwater consumption associated with the symbiotic configuration. Here, the primary system boundary is defined by the processes modified through infrastructure integration, and the main analysis is therefore conducted using a gate-to-gate framework, while cradle-to-grave results are additionally provided in the Supplementary Information to facilitate interpretation and use across disciplinary backgrounds. Within the gate-to-gate system boundary, these processes comprise resource-recovery activities, including energy recycling, sludge dehydration and anaerobic digestion, and treated water use; displaced conventional activities, namely freshwater extraction and treatment; and additional requirements introduced by reuse, including advanced wastewater treatment and the manufacture, installation, and operation of cooling water pipelines [45]. The LCA boundaries of the baseline scenario and the symbiotic scenario, as well as all the computational details, are provided (Supplementary Note 2.4–2.6). All components of the LCC analysis are fully described in correspondence with the LCA framework (Supplementary Note 2.4–2.9). Using this framework, the baseline and symbiotic scenarios can be assessed consistently in terms of environmental impacts and economic costs (Fig. 1).

The functional unit was 1 kWh of IT load; results were normalised accordingly. To facilitate interpretation of the wastewater-side inventories, the Supplementary Information provides a thermodynamically derived conversion relationship between 1 kWh of IT load and the corresponding volume of treated water required for cooling for each data centre–WWTP linkage. This relationship was used only to convert wastewater-side inventories that were originally compiled per unit volume of treated water into the single IT-based functional unit adopted in this study, and does not introduce a second functional unit into the main analysis (Supplementary Note 2.5). Infrastructure, operation, and end-of-life were modelled using Ecoinvent 3.10; country-level electricity, water prices and emission factors were parameterised for the foreground models. Data centre electricity was derived from IT load via PUE; refrigerant leakage and scheduled replacements were included. Regarding the avoided burdens of freshwater extraction, in the baseline scenario, the data centre is supplied by conventional municipal freshwater, modelled using attributional datasets for abstraction, treatment, and distribution. In the symbiotic scenario, the data centre is supplied by treated wastewater, and therefore no longer requires the municipal freshwater supply. Here, we assume that the treated water used for cooling has only undergone one

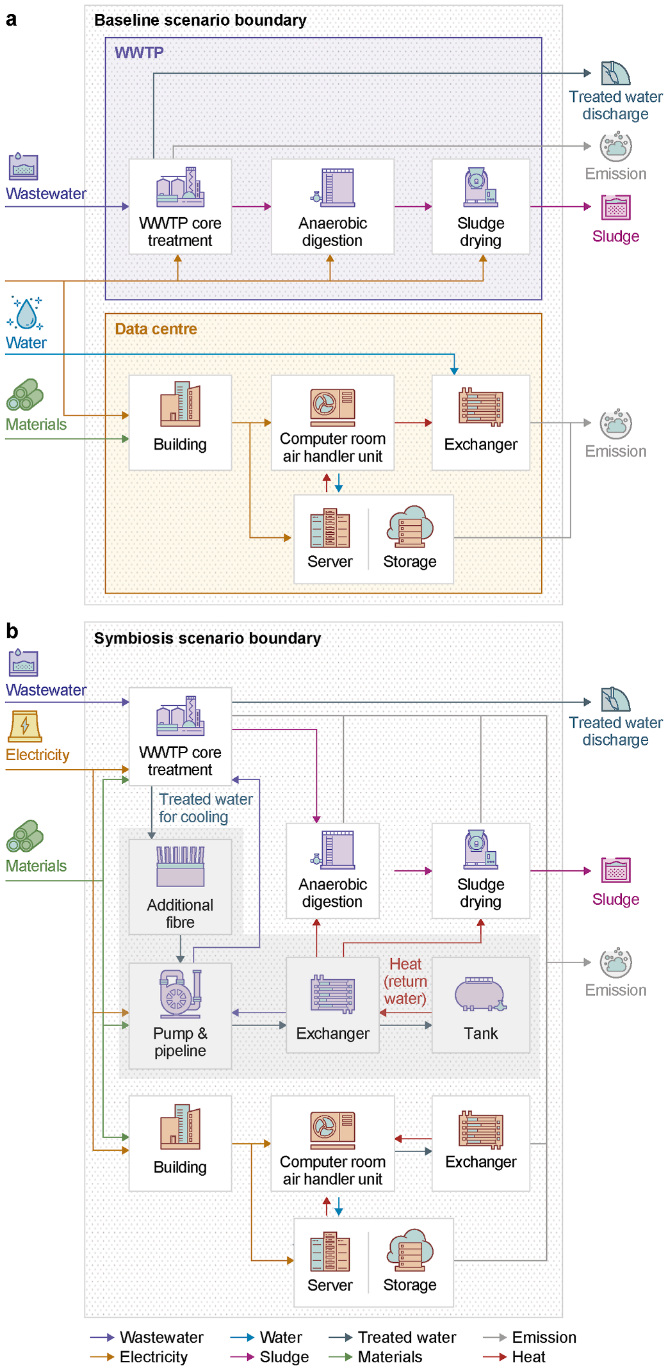

Fig. 1. | Life-cycle assessment boundary for the data centre and wastewater treatment plant (WWTP) in the baseline and symbiosis scenario. a, Baseline scenario; **b**, Symbiosis scenario. The baseline scenario shows the data centre and WWTP operating independently, with the data centre relying on a freshwater supply and the WWTP discharging treated effluent directly. The symbiosis scenario illustrates the integrated operations: (1) treated water from the WWTP undergoes tertiary treatment (additional filtration) to replace freshwater for the data centre cooling; (2) waste heat from the data centre is recovered via heat exchangers and returned to the WWTP to support anaerobic digestion and sludge drying. The grey shaded area represents the foreground infrastructure added to enable the symbiosis (e.g., pumps, pipelines, and exchangers). Colored arrows indicate the direction of water, electricity, materials, and heat flows between unit processes. This schematic illustrates a representative one-to-one pairing to highlight the coupling mechanism; actual matches in the study may involve one-to-many or many-to-one configurations. The assumed operational lifespan is 20 years, with a functional unit of 1 kWh of IT load.

cooling cycle. WWTP energy and chemicals followed unit-process inventories; sludge was routed to landfill, incineration or digestion with energy recovery. In the symbiosis scenario, data centre heat displaced WWTP thermal demand and reclaimed WWTP water displaced data centre freshwater; net impacts were computed as:

$$B_{\mathrm{net},i,k} = B_{\mathrm{symbio\_DC},i,k} + B_{\mathrm{symbio\_WWTP},i,k} - B_{\mathrm{baseline\_DC},i,k} - B_{\mathrm{baseline\_WWTP},i,k} \quad (3)$$

$B_{net,i,k}$ denotes the net benefit of type k attributable to linkage i between the data centre and the WWTP. Here, k represents the benefit category, including GHG, freshwater, and economic benefit. Because one data centre may be connected to multiple WWTPs and one WWTP may also serve multiple data centres, all benefit terms are defined on a linkage-attributed basis rather than as facility-level totals. Specifically, $B_{symbio\_DC,i,k}$ and $B_{symbio\_WWTP,i,k}$ denote the portions of benefit type k generated for the data centre and the WWTP, respectively, by linkage i under the symbiotic scenario. Correspondingly, $B_{baseline\_DC,i,k}$ and $B_{baseline\_WWTP,i,k}$ denote the baseline benefit portions associated with the same service volume, treatment load, cooling demand, or resource flow represented by linkage i when the two facilities operate independently. Therefore, $B_{net,i,k}$ quantifies the incremental benefit of type k generated by linkage i relative to the baseline scenario.

When attributional allocation was required, burdens were split according to the share of heat or cooling in the total energy exchanged. Environmental impacts were assessed using the ReCiPe 2016 Midpoint (H) method, and LCC included capital expenditures, operating expenditures, and end-of-life costs, applying a real discount rate of 3%. Uncertainty was evaluated via sensitivity analyses on data centre total power, WWTP capacity, cooling water temperature, WWTP sludge drying efficiency, WWTP anaerobic digestion efficiency, data centre PUE, data centre cooling energy recovery efficiency, and data centre water usage effectiveness (WUE) (Supplementary Note 3).

3. Results

3.1. Global distribution correlation analysis of data–water infrastructure

Globally, Moran's I was 0.67 ($p = 0.001$), where positive values indicate spatial clustering, values near 0 indicate a random pattern, and negative values indicate spatial dispersion. This value indicates strong positive spatial autocorrelation [46], suggesting that data centres and WWTPs are located closer together and in more geographically clustered patterns than expected under spatial randomness (Fig. 2; Supplementary Note 2.1). This positive spatial association was consistently supported by analyses using different spatial weight matrices (Supplementary Data). Ripley's K-function returned a mean value of 0.00065, further confirming that the global point pattern is clustered rather than random or dispersed [47]. The spatial distribution of cooling energy demand among data centres globally is notably uneven (Supplementary Fig. S30a). Data centres in the United States, Japan, the Netherlands, Australia, Finland, and China account for approximately 98.70% of the global total, whereas those in the Democratic Republic of the Congo, Venezuela, and Senegal together contribute only 0.0001%. This pronounced imbalance mainly reflects differences in the number of data centres among countries and regions. Meanwhile, energy spatial analysis reveals that the global cooling energy potential distribution is also highly uneven (Supplementary Fig. S30b). The

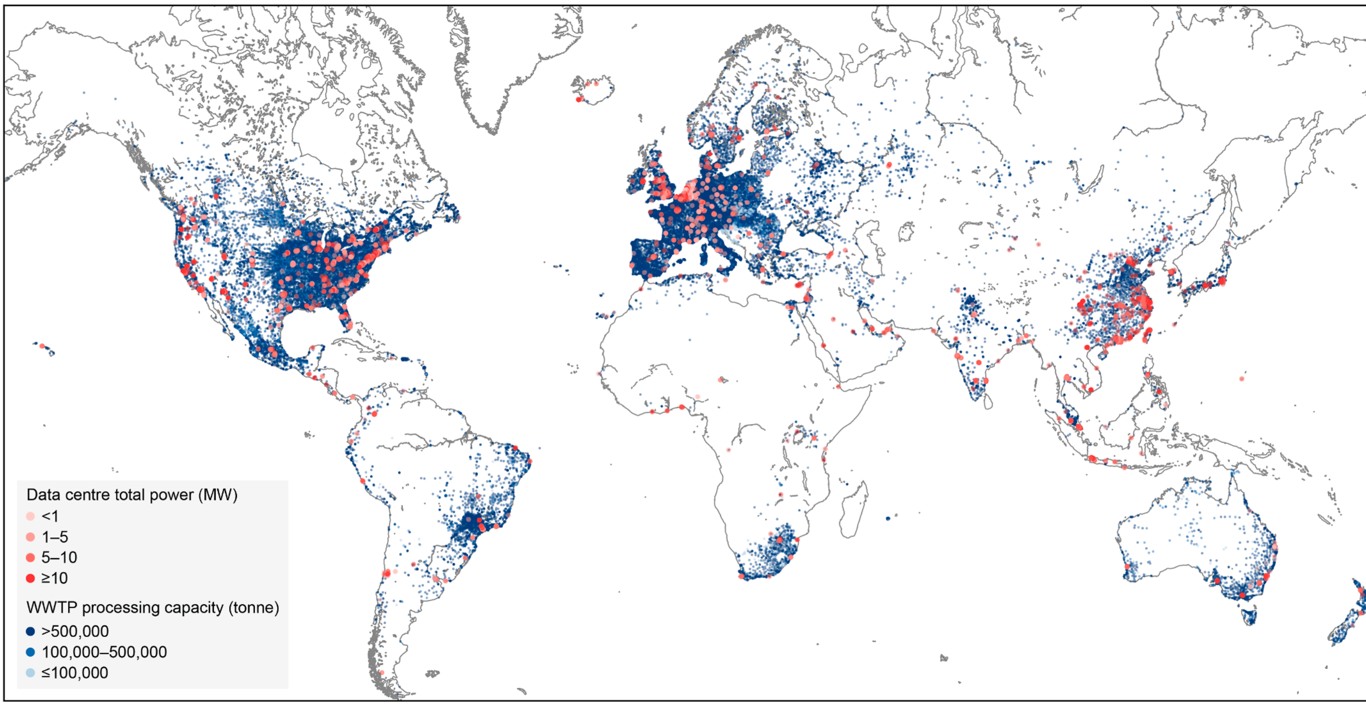

Fig. 2. Global distribution and size of data centres and WWTPs. Locations of 4,775 data centres and 57,547 WWTPs worldwide are shown. Symbol size indicates facility capacity for data centres and treatment capacity for WWTPs. The map was created in Python 3.9 using the Basemap toolkit in Mercator projection.

WWTPs located in the United States, China, Germany, Canada and the United Kingdom contribute 58.90% of the total cooling energy potential, whereas those in Rwanda, Djibouti, and Zambia account for 0.0013%. The uneven distribution of cooling energy potential is attributed to factors such as the number and capacity of WWTPs and local temperature conditions. Furthermore, this suggests that average annual temperature has a pronounced impact on the projected energy recycling potential.

3.2. Carbon mitigation and water saving

In the symbiosis scenario, treated effluent from the WWTPs is used as the cooling medium for the data centres, and the residual heat in the return flow is harvested to maintain the operating temperature of the anaerobic digesters and accelerate sludge drying. The symbiosis reduced both GHG emissions and freshwater consumption relative to the baseline (Table 1). Specifically, it could reduce GHG emissions by 84.3 million tonnes of CO_2 equivalent (Mt CO_2 eq), representing 16.30% of the total GHG emissions attributed to the global wastewater treatment sector (estimated at 524 Mt CO_2 eq [48]). Additionally, the symbiosis facilitates the conservation of approximately 1300 million m^3 of freshwater, which is equivalent to 798 times the amount of freshwater used by Google globally in 2021 [49]. For the purposes of this study, freshwater consumption is defined as the net loss of withdrawn freshwater relative to the originating natural water body; accordingly, water reused within recirculating cooling systems is not included (Table 1).

Based on the linkages identified by the optimisation model, 3362 out of the 57,547 municipal WWTPs and 4725 out of the 4775 data centres in the initial global inventory were retained in the final symbiotic network after applying spatial, cooling demand and cooling energy potential matching, water stress, and economic feasibility constraints. The available wastewater amounts to 18.2 billion tonnes per year, with a corresponding cooling energy potential of 593 million megawatt-hours (MWh). This indicates that nearly all data-centre cooling demand in the global inventory can be efficiently satisfied by WWTPs. Compared with the emissions from the information and communications technology (ICT) industry documented in our inventory, which total 750 Mt CO_2 eq, implementing symbiotic practices can lead to an 11.4% annual reduction in GHG emissions.

Table 1
| Changes in GHG emissions and freshwater consumption resulting from energy recycling and treated water reuse.

Process	GHG (Mt CO_2 eq)	Freshwater (million m^3)
Data centre cooling energy utilisation	−97.50	−1302.02
Anaerobic digestion	−1.87	−1.01
Sludge dehydration	−1.99	−1.96
Data centre advanced wastewater treatment	0.03	−76.40
Cooling water pipeline construction including installation	5.15	98.12
Cooling water pipeline operation	11.19	0.13
Cooling water tank and filter	0.70	−17.11
Net change	−84.3	−1300.2

Note: Cooling water from the data centre's advanced water treatment is not reused as cooling water but is instead discharged to natural water bodies (ReCiPe 2016, freshwater consumption [50]).

GHG emission reductions from utilising cooling energy in data centres totalled 97.50 Mt CO_2 eq. Carbon emissions from routine recirculating cooling water operations in data centres are typically elevated due to filtration of the return cooling water (0.70 Mt CO_2 eq). Sludge-related activities, including sludge processing, dehydration, transportation, and resource recovery, are associated with a GHG reduction of 3.86 Mt CO_2 eq. In the water-reuse pathway, the combined effects of reduced freshwater withdrawal and treatment, together with additional emissions from pipeline construction and operation and from advanced wastewater treatment, correspond to a net GHG reduction of 15.26 Mt CO_2 eq. Although sludge dehydration and transportation, as well as pipeline construction, pipeline operation, and wastewater treatment for data centres, increase GHG emissions, these increases are outweighed by the substantial reductions achieved through cooling energy reuse. The resulting net impact of the process changes is therefore markedly lower overall. Energy recycling also helps preserve freshwater resources. Notably, the overwhelming majority of freshwater savings (99%, or 1,302 million m^3) stemmed from the use of treated effluent for data centre cooling (Table 1). Emissions associated with advanced wastewater treatment and pipeline construction were largely offset by other processes, resulting in a substantial net reduction in both greenhouse gas emissions and freshwater consumption.

The aggregate benefits of GHG mitigation and freshwater conservation were spatially allocated according to the locations where these effects were realised. We associate GHG mitigation and freshwater conservation with the countries hosting data centres and attribute changes in environmental impact to upstream processes, such as water pipeline construction and sludge resource management, rather than to the locations where these activities actually take place. At the national level, all analysed countries show net reductions in GHG emissions and freshwater use. Due to the high density and proximity of data centres and WWTPs, the United States (24.14%), Japan (18.14%), China (16.15%), the Netherlands (9.96%), and the United Kingdom (5.92%) together account for 74.31% of total GHG mitigation (Table 2, Supplementary Figs. S31 and 32). At the global first-level administrative region scale, data centres account for an average of 76.5% of total GHG mitigation (Supplementary Figs. S31 and 32). In the United States, the top states contributing to GHG mitigation include California, Texas, and Illinois, which together account for 57.03% of the United States' total contribution. In Japan, the leading prefectures are Tokyo, Osaka, and Kanagawa, which account for 96.24% of Japan's total contribution. In China, the top provinces contributing to GHG mitigation are Shanghai, the Hong Kong Special Administrative Region, and Guangdong, which together account for 63.04% of the national total. The United States (31.48%), the Netherlands (14.18%), Japan (8.58%), China (8.06%), and Canada (5.03%) together account for 67.33% of total freshwater conservation. At the first-level administrative scale, data-centre-side processes accounted for an average of 88% of total freshwater conservation (Supplementary Figs. S31 and 32). In the United States, the top contributing states to freshwater conservation are California, Texas, and Illinois, which together account for 61.57% of the total. In the Netherlands, the major contributors are North Holland, South Holland, and Gelderland, which account for 98.17% of the national total. In Japan, the most significant prefectures for freshwater conservation are Tokyo, Osaka, and Kanagawa, which together account for 96.63%. Major factors in GHG mitigation include cooling energy recycling in WWTPs, waste-heat energy recycling in data centres, avoided sludge treatment, and reduced refrigeration needs. Additionally, water savings in data centres are a predominant component of overall freshwater conservation efforts.

In the baseline scenario, 80% of the 1 m^3 of freshwater used by the data centre evaporates, 20% becomes wastewater, and a very small amount of drift water is ignored [51]. It is estimated that this hybrid approach will generate approximately 1.14 (1.11–1.21) kg CO_2 eq for each tonne of freshwater (Supplementary Data). While the baseline wastewater treatment includes energy recovery, the application of recycled water in data centres leads to net reductions in GHG emissions, rather than positive emissions associated with baseline treatment. This is primarily attributable to the ability of data centres to achieve higher thermal efficiency compared with air cooling through the use of liquid cooling systems, thereby facilitating a notable proportion of energy recovery from recycled water. The cooling water demand of the data centre accounts for only about 3% of the WWTP capacity (Supplementary Note 2) and therefore does not adversely affect daily operations. The wastewater from the data centre can be treated by the WWTP after filtration. Added filtration contributes only marginally to GHG emissions under the symbiotic scenario (Supplementary Note 2.6). In the symbiotic scenario, this wastewater can be conveyed through the return pipeline to the WWTP linked under the symbiosis scenario.

We assessed the plant-level capacity of data centres and estimated water consumption by data centre type, using the established water utilisation framework to determine annual usage for each facility type. Our findings indicate that optimising water reuse from WWTPs for data centres could enable the use of 1.64% (1300 million m^3) of the total treated effluent from WWTPs. Because the optimized symbiosis used 1.64% of total treated effluent, the remaining unused share in the inventory remained

Table 2
| Representative global cases of CO_2 and water co-benefits from data centre–WWTP symbiosis.

Country (Administrative division)		GHG mitigation (Mt CO_2 eq)	Data centre share	Freshwater saving (million m^3)	Data centre share
China	Shanghai province	−5.58	96.04	−100.79	99.07%
	Guangdong province	−0.56	84.98%	−5.34	92.94%
	Shandong province	−0.11	57.77%	−0.71	69.06%
United States	California	−4.58	99.44%	−150.86	99.95%
	District of Columbia	−0.01	60.58%	−0.16	99.90%
	West Virginia	−0.0030	0.00%	−0.001	0.00%
Germany		−2.42	99.57%	−29.29	96.87%
Greece		−0.09	97.13%	−1.39	85.14%
Japan		−15.51	96.61%	−112.39	97.87%
India		−2.11	98.50%	−22.62	100.00%
Indonesia		−1.19	98.64%	−10.78	99.97%
United Arab Emirates		−0.08	87.12%	−0.42	79.74%
South Africa		−1.26	99.13%	−7.87	99.29%
Nigeria		−0.04	97.67%	−0.15	95.79%
Brazil		−0.54	89.14%	−52.01	100.00%

large; however, the implications for ecosystem replenishment depend on local allocation priorities and should not be overstated [52]. Moreover, water reuse reduces GHG emissions, whereas the construction of cooling water pipelines increases freshwater consumption.

3.3. Economic benefits of data–water symbiosis

The symbiosis yields not only environmental advantages but also global economic benefits of US$95.4 billion annually relative to the baseline scenario, without accounting for the social cost of carbon. In the context of energy recycling, the costs associated with reduced cooling energy and freshwater consumption are estimated to decrease annual expenditures by US$112.65 billion (US$85.13–136.74 billion) and US$2.62 billion (US$0.52–5.24 billion), respectively. The processes of sludge dehydration and anaerobic digestion incur additional annual expenses of US$10.81 billion (US$6.86–12.51 billion) and US$7.49 billion (US$6.34–9.63 billion), respectively. However, the construction and operation of pipelines contribute additional costs of US$15.82 billion (US$11.21–18.96 billion) and US$20.70 billion (US$16.49–23.52 billion), respectively. Furthermore, advanced wastewater treatment incurs supplementary costs of US$5.55 billion (US$2.92–7.42 billion) annually.

We further analysed the cost changes resulting from energy recycling and water reuse at the national level. Our findings indicate that the United States, Japan, Germany, the Netherlands, Australia, Sweden, the United Kingdom and China experience annual cost savings of US$11.71 billion, US$8.82 billion, US$8.13 billion, US$8.07 billion, US$6.64 billion, US$5.71 billion, US$5.02 billion, and US$4.32 billion, respectively, which collectively accounts for 60.72% of the total cost reductions. These results suggest that policy support for the symbiosis should focus primarily on these eight countries, where most of the economic benefits can be realised. In the wastewater treatment sector, key economic gains would come from avoided sludge treatment costs and additional revenues from reclaimed water sales, although the need for tertiary treatment may raise overall costs. For the ICT sector, both energy recovery and reclaimed-water use would help reduce operating expenditures and, even more importantly, cut GHG emissions and freshwater use per megawatt-hour of electricity consumed. If evaluation and incentive schemes linked to the United Nations' carbon and water objectives give greater prominence to these environmental outcomes, data centres would have a stronger motivation to develop symbiotic links with nearby WWTPs.

The symbiosis's economic performance is strongly shaped by the spatial separation between the two facilities. At the linkage level, both sludge-transport distance and reclaimed-water conveyance distance are closely associated with the magnitude of cost savings. In total, we identify approximately 7000 energy-recycling linkages between WWTPs and data centres, with an average pipeline length of 17.49 km. Among all pipeline-based linkages, 87.80% are located within 40 km of the supplying WWTP, suggesting that urban planning should preferentially target cooling water reuse opportunities inside a 40 km service range. Greater use of sludge and reclaimed water is associated with greater economic gains (Fig. 3a and b). The same pattern indicates that stronger energy recycling and greater treated water substitution are associated with larger GHG reductions and freshwater savings, respectively, as well as additional cost benefits. On a per-linkage basis, energy recycling delivers an average GHG mitigation of 0.012 Mt CO_2 eq per year and is associated with a mean cost saving of US$583 million per year. For water-reuse linkages, the average freshwater conservation reaches 0.19 million m^3 per year, corresponding to an average cost saving of US$1.07 million per year.

Below a total power threshold of 21.44 MW, the cost saving per megawatt attributable to symbiotic energy-recovery infrastructure declines with pipeline length (negative slope). Beyond this threshold, the marginal effect of pipeline length is negligible, and pipeline construction costs constitute only a small fraction of the realised cooling cost savings. Accordingly, the savings from the data centre fully cover all symbiosis-related costs, yielding positive net benefits even for long-distance pipeline linkages (Fig. 3c). The pattern of water-reuse linkages spans pipelines of varying lengths, indicating that all selected connections remain economically viable. Within this feasible set, however, unit cost savings per m^3 of reused water decline as pipeline length and pipe diameter increase, so the shortest linkages deliver the greatest savings. The selection of pipe diameters is made to ensure sufficient treated water flux for each linkage, accounting for resulting cost variations (Supplementary Note 2.6). At the data centre–aggregated level—i.e., for each data centre, we sum the pipeline distances across all linkages—the average distance for pipeline construction is 26.20 km, accompanied by an average cost reduction of US$121.85 per megawatt of IT load; this economic behaviour is mirrored at the finer resolution of individual pipeline linkages. Below a linkage-specific threshold of 8.87 MW, the per-megawatt cost savings attributable to energy recovery decline as pipeline length increases. Beyond this 8.87 MW threshold, the marginal effect of pipeline length becomes negligible, as pipeline construction costs constitute only a minor fraction of the realised cooling cost savings. At this individual linkage level, the average construction distance is 17.49 km, yielding an average cost reduction of US$120.60 per megawatt (Fig. 3d).

At the WWTP-aggregated level (summing distances across all linkages per WWTP), the average cumulative pipeline distance per WWTP is 36.81 km, with an average cost reduction of US$0.27 per m^3 of treated water (Supplementary Fig. S33a). At the individual pipeline level, the average construction distance is 17.49 km, with an average cost reduction of US$0.21 per m^3 of treated water (Supplementary Fig. S33b). On the data centre side, cost savings per m^3 of cooling water decrease as transportation distance increases. For WWTPs, however, the utilisation of waste heat from data centres provides a modest compensatory benefit that partially offsets the cost penalty associated with longer pipeline distances.

Therefore, although longer pipeline distances reduce the magnitude of economic benefits on the data-centre side, pipeline expenses remain small relative to the realised savings, so extended-distance connections still yield positive net benefits overall. Although sludge resource utilisation generates additional carbon emissions, its effect on the overall economic balance is relatively small. Furthermore, increasing pipeline distance tends to reduce the magnitude of overall net benefits, even though those benefits remain positive within the feasible set.

3.4. A simulated case study

Here, we simulated the symbiosis between a data centre and a WWTP in Shenzhen, a major city in China, using two years of actual operational data from the WWTP (Fig. 4). This simulation was chosen to account for the seasonal influence of the computer room air handler (CRAH) in the data centre and the long start-up cycle of the anaerobic digestion unit in the WWTP. Although the WWTP in this study does not include a data centre, we used a scenario that maximises carbon reduction benefits to assess the feasibility of co-constructing these systems. The co-construction scenario was modelled and simulated using SUMO 24.0.1 and

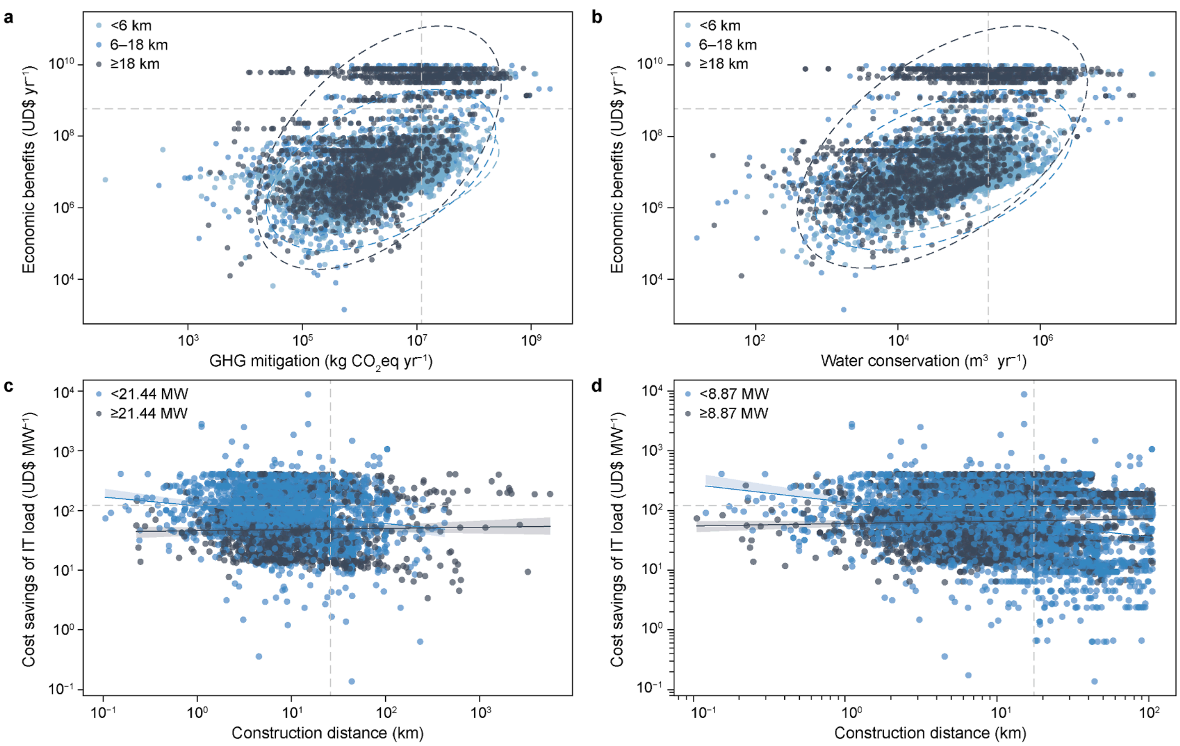

Fig. 3. | The impact of co-construction on the environment and economy. a–**b**, Greenhouse gas (GHG) mitigation (**a**) and freshwater conservation (**b**) versus cost reductions of each energy recycling linkage. **c**, Data centre-aggregated cumulative pipeline length versus cost reductions per megawatt (MW) IT load. **d**, Pipeline-level length versus cost reductions per MW IT load. The points representing GHG, freshwater conservation, and cost linkages are categorised by the distance between data centres and WWTPs. Horizontal and vertical grey dashed lines indicate the mean values of the variables on the y and x axes, respectively, in each panel. In a and b, dashed ellipses indicate the 95% covariance ellipses of linkage-level observations for the three pipeline-distance groups (<6 km, 6–18 km, and ≥18 km), calculated in log-transformed space and shown on log-scaled axes. They summarize the group-specific centroid, spread, and orientation of the bivariate distribution. In c, the solid lines show how the relationship between cumulative pipeline length and cost savings per MW of IT load varies across different capacity classes at the data centre level; in d, the solid lines show the corresponding relationship at the individual pipeline level. Shaded bands indicate the 95% confidence intervals of the fitted relationships. The benefit per m^3 of wastewater recovered represents the net cost reduction after accounting for sludge dewatering and anaerobic digestion; the cost reduction per megawatt of computing power represents the net cost reduction after accounting for changes in industrial water use, water pipeline construction and operation, and data centre advanced wastewater treatment costs.

TRNSYS 18, with dynamic simulations of key system components.

The wastewater containing waste heat from the data centre will be divided into three streams, each serving distinct purposes: one will enter the Anaerobic/Oxic/Anoxic (AOA) unit, another will be used for insulation of the anaerobic digestion unit, and the third will provide heat for sludge dewatering (Supplementary Fig. S34). Upon entering the AOA unit, the wastewater will undergo significant dilution, reducing its temperature almost to baseline levels. At the modelled dilution ratio, the concentrations of corrosion inhibitors and antibiotics were reduced by approximately three orders of magnitude to below 1 μg L−1, suggesting that their effects on AOA performance would likely be limited. In addition, the slight temperature increase may be beneficial to biological treatment efficiency. The second stream of wastewater, containing waste heat, will be directed to the anaerobic digestion unit. This unit typically requires heating and insulation to maintain optimal treatment efficiency, and the waste heat will help compensate for its thermal deficit. Finally, the third stream will supply the necessary heat for efficient sludge dewatering.

The sludge drying processes resulted in a 15.40 MWh d^{-1} reduction (3.53–56.06 MWh d^{-1} operational variation) in energy consumption, representing a 22.70% efficiency improvement (21.48–50.78% system tolerance) (Fig. 4a). This optimisation stems from the implementation of waste heat recovery from data centre cooling systems, where the elevated temperature of return water accelerates moisture evaporation through (1) lowering water viscosity and (2) increasing vapor pressure differentials, as described in the modified Darcy's law for thermal-assisted dewatering. The co-construction project has resulted in a 29.51 m^3 d^{-1} (−190.64 to 378.02 m^3 d^{-1}) increase in methane production at the WWTP, corresponding to a 6.81% relative enhancement (5.37–10.77% confidence interval) (Fig. 4b). This improvement can be attributed to the enhanced efficiency of anaerobic digestion processes under elevated temperature conditions, which is theoretically supported by the anaerobic digestion model [53]. The synergistic effects are particularly evident in the data centre operations (Fig. 4c and d). The chiller-less cooling system achieved a 6.31 MW (−3.15 to 15.61 MW load fluctuation) reduction in CRAH power consumption, translating to 4.30% energy savings (0.62–6.78% depending on workload). Concurrently, the server room temperature decreased by 5.35 °C (−8.80 to 11.7 °C seasonal variation).This study demonstrates the benefits of co-construction of the data centre with the WWTP to optimise energy use and improve operational efficiency. Overall, this co-construction approach offers a sustainable solution for energy recovery, operational optimisation, and environmental benefits.

4. Discussion

Efficient energy and water use remain central to urban sustainability, yet approaches that address individual infrastructure sectors in isolation have shown limitations in meeting the rapidly growing demands of AI. This study demonstrates that symbiosis between cooling-intensive data centres and water-rich WWTPs

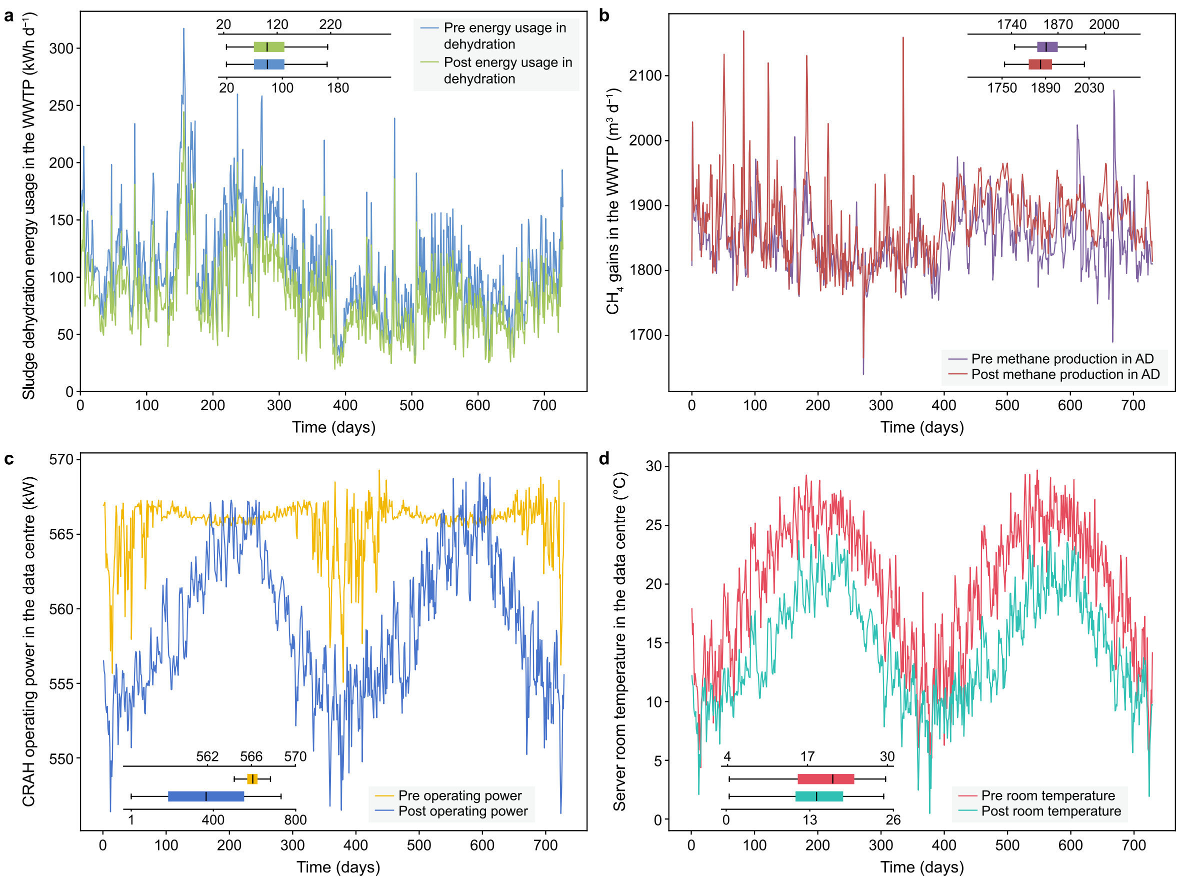

Fig. 4. | Long-term performance of the co-construction of the data centre and WWTP process configuration. This configuration comprises four interlinked technological components CRAH, AOA unit, anaerobic digestion and sludge dehydration) to enable smooth operation and maintenance. The data centre's CRAH generates a significant volume of heated water, which is then directed to the WWTP's anaerobic digestion unit and the sludge dehydration heat exchanger. **a**, Time-series variation in sludge-drying energy consumption, showing the reduction achieved under the co-construction scenario relative to the baseline scenario. **b**, Time-series variation in methane production from the WWTP, showing the enhancement associated with thermally supported anaerobic digestion. **c**, Time-series variation in CRAH power demand, showing the reduced cooling energy demand under the chiller-less co-construction configuration. **d**, Time-series variation in server-room temperature, showing the thermal response and stability of the data-centre operation under the co-construction scenario. Insets in a–d summarize the mean and variance of the corresponding colored traces in each panel. The inset y axis represents the same variable as that in the corresponding main panel, and the unit is identical to that of the corresponding main-panel y axis.

provides a practical pathway for integrated resource management. By establishing bidirectional exchanges of treated effluent for data centre cooling and low-grade waste heat for sludge drying and anaerobic digestion, the data–water infrastructure symbiosis reduces GHG emissions and freshwater consumption while generating net economic benefits, thereby supporting more coordinated urban infrastructure planning.

From an engineering perspective, the proposed symbiosis is feasible. Treated wastewater can serve as cooling water once subjected to tertiary treatment and conventional conditioning. Operational concerns such as corrosion, scaling and biofouling [54], can be effectively managed through established measures, including additional filtration [55], disinfection, corrosion-resistant materials [56], hydraulic separation via heat exchangers, and continuous water-quality monitoring. The analysis adopts a single-pass cooling configuration, limiting the withdrawal to approximately 3% of typical WWTP capacity on average. These boundary conditions indicate that the symbiosis constitutes a practical infrastructure solution rather than a purely conceptual one.

Realising these benefits requires coordinated action among stakeholders. A clear roadmap should assign responsibilities, align regulations, and foster collaboration between regulatory authorities, water utilities, data centre operators and civil society [57,58]. Operationally, the exchange can be structured as a third-party heat-supply agreement—consistent with established district-heating models [59].—in which WWTPs supply cooling water and recover heat, while data centres act as customers. Formal contracts can define service payments and the trading of carbon and water-reuse credits. Capital costs for shared infrastructure (pipelines and heat exchangers) should be apportioned according to anticipated benefits, with transparent public reporting.

Government support can accelerate adoption by funding pilot projects, removing regulatory barriers, offering tax credits or tradable certificates, and establishing harmonised standards for treated water. Emphasis on transparency and public access to project information will further build trust and accountability.

Several limitations should be acknowledged. The geodatabase represents the most up-to-date plant-level information available, yet the 2023 baseline analysis treats all WWTPs as fully operational and applies a 20-year retirement schedule to data centres; future growth in both sectors is therefore expected to expand the potential benefits [60,61]. The study employs an attributional gate-to-gate LCA that includes pipeline construction and pumping energy but excludes site-specific relocation, redesign or broader supporting infrastructure. A consequential LCA coupled with explicit market modelling would better capture dynamic interactions and long-term systemic effects, consistent with established best practices for applying LCA to wastewater treatment systems [62]. While the present analysis provides a robust technology-based estimate of first-order mitigation potential, such extensions remain important for future project-level planning and policy development.

Through data–water symbiosis, this work directly advances sustainable development goals 6, 9 and 13 by promoting efficient resource cycling and integrated urban infrastructure. Policies that incentivise the co-location and thermal–hydraulic coupling of data centres with WWTPs could therefore play a cost-effective role in achieving global climate and water sustainability objectives.

5. Conclusions

Coupling data centres with WWTPs through treated water reuse and bidirectional thermal recovery offers a practical, globally scalable pathway to substantially reduce the carbon and water footprints of AI infrastructure. The optimized symbiosis delivers meaningful GHG mitigation, freshwater conservation and net economic benefits while concentrating advantages in regions where the two infrastructures already exhibit strong spatial co-location, notably the United States, Japan, China, the Netherlands and the United Kingdom. Beyond enhancing the operational efficiency of individual facilities, this framework repositions WWTPs as active urban resource hubs for water and heat exchange. As AI-driven computing demand continues to expand, data–water symbiosis provides a readily implementable infrastructure solution that supports more coordinated urban planning and contributes to the decoupling of digital growth from escalating environmental pressures.

CRediT authorship contribution statement

Aijie Wang: Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization. **Congchao Zhang:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Tiefu Xu:** Writing – review & editing, Conceptualization. **Dragan Savic:** Writing – review & editing. **Jingjing Jiang:** Writing – review & editing, Investigation. **Peng Xiao:** Methodology. **Chuan He:** Visualization. **Yu Tao:** Writing – review & editing, Resources, Investigation, Funding acquisition, Conceptualization. **Glen Daigger:** Writing – review & editing. **Nanqi Ren:** Writing – review & editing, Supervision.

Code availability

The codes that support the findings of this study are available at: https://github.com/UrbanWaterHIT/Data_Water_Symbiosis.

Declaration of competing interest

The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for this journal and was not involved in the editorial review or the decision to publish this article.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Aijie Wang is the Executive Editor, Nanqi Ren is the Editor-in-Chief, and Yu Tao is the Managing Editor for this journal and were not involved in the editorial review or the decision to publish this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ese.2026.100702.

Data availability

The data for this research work, which support all figures and provide detailed data on data centres and WWTPs, are provided as Supplementary Data. All data used for this study are provided or available from publicly accessible sources cited, including HydroBASINS L06 sub-basins; GADM v4.1 first-level administrative boundaries; WRI Aqueduct 4.0; NOAA observational/climatological datasets; SRTM-90 digital elevation model.

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