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Journal

Environmental Research Letters, 16(6)

ISSN

1748-9318

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Publication Date

2021-06-01

DOI

10.1088/1748-9326/abfba1

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To cite this article: Md Abu Bakar Siddik *et al* 2021 *Environ. Res. Lett.* **16** 064017

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The environmental footprint of data centers in the United States

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Keywords: water scarcity, data center, water footprint, carbon footprint, water-energy nexus

Supplementary material for this article is available online

OPEN ACCESS

RECEIVED
21 January 2021

REVISED
20 April 2021

ACCEPTED FOR PUBLICATION
26 April 2021

PUBLISHED
21 May 2021

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Abstract

Much of the world's data are stored, managed, and distributed by data centers. Data centers require a tremendous amount of energy to operate, accounting for around 1.8% of electricity use in the United States. Large amounts of water are also required to operate data centers, both directly for liquid cooling and indirectly to produce electricity. For the first time, we calculate spatially-detailed carbon and water footprints of data centers operating within the United States, which is home to around one-quarter of all data center servers globally. Our bottom-up approach reveals one-fifth of data center servers direct water footprint comes from moderately to highly water stressed watersheds, while nearly half of servers are fully or partially powered by power plants located within water stressed regions. Approximately 0.5% of total US greenhouse gas emissions are attributed to data centers. We investigate tradeoffs and synergies between data center's water and energy utilization by strategically locating data centers in areas of the country that will minimize one or more environmental footprints. Our study quantifies the environmental implications behind our data creation and storage and shows a path to decrease the environmental footprint of our increasing digital footprint.

1. Introduction

Data centers underpin our digital lives. Though relatively obscure just a couple of decades prior, data centers are now critical to nearly every business, university, and government, as well as those that rely on these organizations. Data centers support servers, digital storage equipment, and network infrastructure for the purpose of large-scale data processing and data storage [1]. Increasing demand for data creation, processing, and storage from existing and emerging technologies, such as online platforms/social media, video streaming, smart and connected infrastructure, autonomous vehicles, and artificial intelligence, has led to exponential growth in data center workloads and compute instances [2].

The global electricity demand of data centers was 205 TWh in 2018, which represents about 1% of total global electricity demand [3]. The United States houses nearly 30% of data center servers, more than any other country [3–5]. In 2014, 1.8% of US electricity consumption was attributable to data centers, roughly equivalent to the electricity consumption of New Jersey [1]. Previous studies found power densities per floor area of traditional data centers almost 15–100 times as large as those of typical commercial buildings [6], and data center power density has increased with the proliferation of compute-intensive workloads [7]. Though the amount of data center computing workloads has increased nearly 550% between 2010 and 2018, data center electricity consumption has only risen by 6% due to dramatic improvements in energy efficiency and storage-drive density across the industry [1, 3]. However, it is unclear whether energy efficiency improvements can continue to offset the energy demand of data centers as the industry is expected to continue its rapid expansion over the next decade [8].

The growing energy demand of data centers has attracted the attention of researchers and policymakers not only due to scale of the industry's energy use but because the implications the industry's

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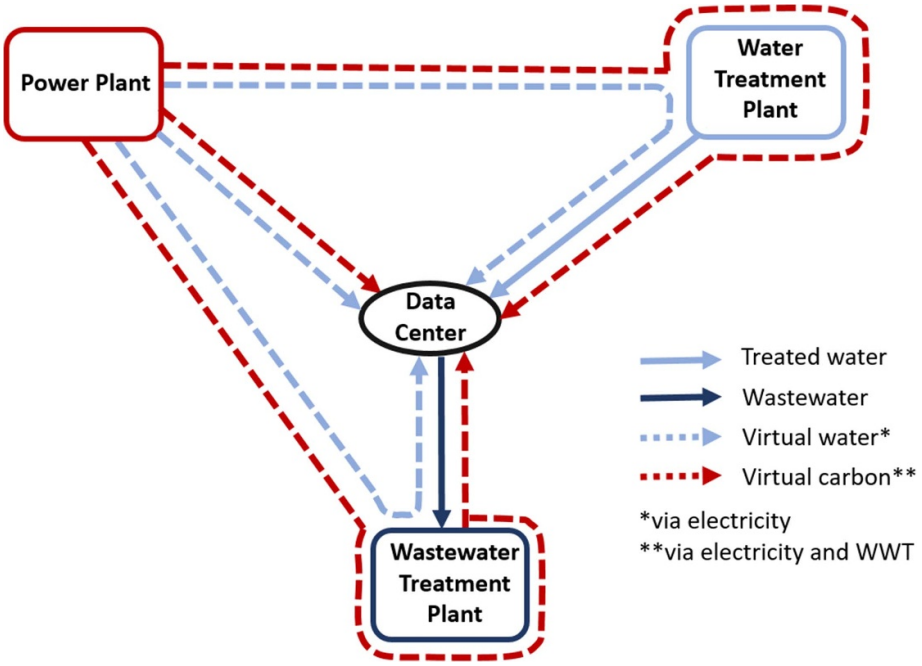


Figure 1. The system boundaries and interlinkages defining the operational water and carbon footprints of data centers. Specific power plants, water utilities, and wastewater treatment (WWT) utilities are connected to each data center through their provisioning of electricity and water. Power plants emit GHGs and consume water in the production of electricity. These environmental impacts are attributed to data centers in proportion to how much electricity the data center uses (red and blue dashed lines connecting facilities). The GHG emissions and water consumption associated with the provisioning of treated water and disposal of wastewater, including the GHGs and water consumed in the generation of the electricity supplied to these facilities, are also attributed to data centers in proportion to their use of these utilities. Data centers do not directly emit GHGs but they do directly consume water to dissipate heat. All these facilities work together to keep data centers operational and contribute to the water and carbon footprint of data centers.

energy consumption has on greenhouse gas (GHG) emissions and water use. Data centers directly and indirectly consume water and emit GHG in their operation. Most data centers' energy demands are supplied by the electricity grid, which distributes electricity from connected power plants. Electricity generation is the second largest water consumer [9] and the second largest emitter of GHGs in the US [10]. These environmental externalities can be attributed to the place of energy demand using several existing approaches [11, 12].

In addition to the electricity consumed directly by data centers, electricity is used to supply treated water to data centers and treat the wastewater discharged by data centers. Like data centers, water and wastewater facilities are major electricity consumers, responsible for almost 1.8% of total electricity consumption in the US in 2013 [13]. The electricity required in the provisioning and treatment of water and treatment of discharged wastewater also emits GHGs that can be attributed to data centers. Likewise, water used to generate the electricity used by water and wastewater utilities in their service of data centers contributes to the water footprint of these data centers. Water is also used directly within a data center to dissipate the immense amount of heat that is produced during its operation.

The geographic location [14, 15] and the local electricity mix [16] are strong determinants of a data center's carbon footprint, though these spatial details are often excluded in data center studies. A preliminary water footprint assessment of data centers by Ristic *et al* [17] provided a range of water footprints associated with data center operation. Although Ristic *et al* provided general estimates based on global average water intensity factors, their study highlights the importance of considering both direct and indirect water consumption associated with data center operation. Moreover, Ristic *et al* highlights the importance of considering the type of power plants supplying electricity to a data center and the type/size of a data center, as each of these factors can significantly impact energy use and indirect water footprint estimates.

In this study we utilize spatially-detailed records of data center operations to provide the first subnational estimates of data center water and carbon footprints. Here, water footprint is defined as the consumptive blue water use (i.e. surface water and groundwater). The carbon footprint of a data center, expressed as equivalent CO_2, is used to represent its global warming potential. Our assessment focuses on the operational environmental footprint of data centers (figure 1), which includes the power plant(s), water supplier, and wastewater treatment plant servicing the data center. The non-operational stages of a data center's life cycle (e.g. manufacturing of servers) consume relatively much less energy [18] and

are excluded in this study. The spatial detail afforded by our approach enables more accurate estimates of water consumption and GHG emissions associated with data centers than previous studies. Moreover, we evaluate the impact of data center operation on the local water balance and identify data centers located in, or indirectly reliant upon, already water stressed watersheds. We investigate the following questions: (i) What is the direct and indirect operational water footprint of US data centers? (ii) Which watersheds support each data center's water demand and what portion of these watersheds are water stressed? (iii) How much GHG emissions are associated with the operation of data centers? (iv) To what degree can strategic placement of future data centers within the US reduce the industry's operational water and carbon footprints?

2. Methods

We utilize spatially detailed records on data centers, electricity generation, GHG emissions, and water consumption to determine the carbon footprint and water footprint of data centers in the US. Our approach connects specific power plants, water utilities, and wastewater treatment plants to each data center within the US. All data used in this study are for the year 2018, the most recent year where all data are publicly available. A visual summary of our methods is shown in supplementary figure S1 (available online at stacks.iop.org/ERL/16/064017/mmedia).

2.1. Data center location and energy use

Information availability on data center location and size varies depending on its type and owner. Ganeshalingam *et al* [4] reports likely locations of in-house small and midsize data centers, which house approximately 40% of US servers. Detailed information on colocation and hyperscale data centers is derived from commercial compilations [19–21] that get direct support and input from data center service providers.

We classified data centers based on the International Data Corporation classification system (summarized in table S1) and estimated the electricity use based on data center floor space. We used IT load intensity values (IT_s in watt/ft^2) for different data center types (s) from Shehabi *et al* [22] to estimate the total energy requirements (DC_E_{total}; in MWh) of colocation and hyperscale data centers as follows:

$$DC_E_{\text{total}} = IT_s \times PUE_s \times A \quad (1)$$

where PUE_s is the power usage effectiveness of space type s, and A is the floor area of data center in ft^2. We account for potential overstatement of data center capacity [4], a lack of distinction between gross and raised floor area, and unfilled rack capacity by scaling our server counts to match the 2018 estimate of servers by data center type [3], as shown in table 1 and figure S2. Scaled server estimates are then spatially distributed in proportion to the current spatial distribution of installed server bases. The number of servers by state is shown in figure S2.

Power usage effectiveness (PUE) is a key metric of data center energy efficiency [23]. A value of 1.0 is ideal as it indicates all energy consumed by a data center is used to power computing devices. Energy used for non-computing components, such as lighting and cooling, increases the PUE above 1.0 (see equation (2)). Generally, a data center's PUE is inversely proportionate to its size since larger data centers are better able to optimize their energy usage. Average PUE values and energy use by data center type were taken from Masanet *et al* [3] and shown in table 1 and table S1.

$$PUE = \frac{\text{Total power supplied to the data center}}{\text{Power consumed by the IT equipment}}. \quad (2)$$

2.2. Electricity generation, water consumption, and GHG emissions

Power plant-specific electricity generation and water consumption data come from the US Energy Information Administration (EIA) [24]. Of the approximately 9000 US power plants, the EIA requires nearly all power plants report electricity generation. However, only power plants with generation capacity greater than 100 MW (representing three-fourths of total generation) must report water consumption. We assigned national average values of water consumption per unit of electricity generation by fuel type (i.e. water intensity; m^3 MW h^{-1}) to all power plants with unspecified water consumption. Operational water footprints of solar and wind power were taken from Macknick *et al* [25]. Following Grubert [26], we assign all reservoir evaporation to the dam's primary purpose (e.g. hydropower). We connected hydroelectric dams with their respective power plants using data from Grubert [27]. Reservoir specific evaporation comes from Reitz *et al* [28].

The U.S. Environmental Protection Agency's eGRID database [29] provided GHG emissions associated with each power plant. GHG emissions are converted to an equivalent amount of carbon dioxide (CO_2)-eq with the same global warming potential so to derive a single carbon footprint metric [30]. Direct GHG emission during the operation of data centers are negligible [18] and therefore not considered in this study.

Data centers, water suppliers, and wastewater treatment plants typically utilize electricity generated from a mix of power plants connected to the electrical grid. Within the electrical grid, electricity supply matches electricity demand by balancing electricity generation within and transferred into/out of a power control area (PCA). Though it is infeasible to trace an electron generated by a particular power

Table 1. Combined direct and indirect water consumption and GHG emissions (carbon equivalence) by data center type. Water intensity and carbon intensity are reported per MWh of electricity used and per computing workload. Better energy utilization, more efficient cooling systems, and increased workloads per deployed server has increased the water efficiency of larger data centers. Computing workloads in hyperscale data centers are almost six times more water efficient compared to internal data centers. Workload estimates are based on traditional and cloud workloads from [2, 3].

Category	Energy use (million MWh)	Computing workloads (million)	Water intensity (m^3 MWh^{-1})	Carbon intensity (ton CO_2-eq MWh^{-1})	Water intensity (m^3/workload)	Carbon intensity (ton CO_2-eq/ workload)
Internal	26.90	16	7.20	0.45	12.15	0.75
Colocation	22.40	41	7.00	0.42	3.85	0.25
Hyperscale	22.85	76	7.00	0.44	2.10	0.15

plant to the final electricity consumer, there are several approaches to relate electricity generation to electricity consumption (Siddik *et al* [31] summarizes the most common approaches).

Here, we primarily rely on the approach used by Colett *et al* [32] and Chini *et al* [33] to identify the generative source of electricity supplied to any given data center. This approach assesses electricity generation and distribution at the PCA level where it is primarily managed. PCA boundaries are derived from the Homeland Infrastructure Foundation level data [34] and crosschecked against Form EIA-861 [35], which identifies the PCAs operating in each state. Annual inter-PCA electricity transfers reported by the Federal Energy Regulatory Commission [36] are also represented within this approach. A data center (as well as water and wastewater utilities) draws on electricity produced within its PCA, unless the total demand of all energy consumers within the PCA exceeds local generation, in which case electricity imports from other PCAs are utilized. If a PCA's electricity production equals or exceeds the PCA's electricity demand, it is assumed all electricity imports pass through the PCA and are re-exported for utilization in other PCAs. Siddik *et al* [31] notes that water and carbon footprints are sensitive to the attribution method used to connect power plants to energy consumers. Therefore, we conduct a sensitivity analysis (see the supporting information for additional details) to test the degree to which our electricity attribution method affects our results. Additionally, we also test different assumptions regarding the water footprint of hydropower generation, as this too is a key source of uncertainty.

We focus on the annual temporal resolution and assume an average electricity mix proportional to the relative annual generation of each contributing power plant. Though the electricity mix within a PCA can fluctuate hourly depending on balancing measures, these intra-annual variations will not significantly impact our annual-level results. While it is infeasible to determine the precise amount of electricity each power plant provides to each data center, water utility, and wastewater treatment plant, our approach will enable us to estimate where each facility is most likely to draw its electricity. The dependency of a data center on local and imported electricity from other PCAs was calculated using equations (3) and (4).

$$DC_E_{p,l} = DC_E_p \times \left(1 - \sum_i r_i\right). \tag{3}$$

$$DC_E_{p,im} = DC_E_p \times \sum_i r_i \tag{4}$$

where $DC_E_{p,l}$ and $DC_E_{p,i}$ are the local (l) and imported (im) electricity (MWh) to a data center from PCA p, respectively. DC_E_p is the total electricity consumption of the data center, whereas r_i represents the electricity contribution of each PCA i to PCA p as follows:

$$r_i = \begin{cases} \dfrac{Import_{con}}{Generation_p + \sum Import_p - \sum Export_p}, & \text{if PCA } p \text{ is net importer} \\ 0, & \text{if PCA } p \text{ is net exporter} \end{cases}$$

where $Import_{con}$ is defined as the electricity from a linked PCA i that was consumed within PCA p. Any imported electricity not consumed with PCA p is re-exported.

Adjusted electricity consumption from the PCAs were assigned to the power plants using equation (5).

$$DC_E_{p,k} = DC_E_{p,adj} \times \frac{PP_k}{\sum_{k=1}^{n} PP_k} \tag{5}$$

where $DC_E_{p,k}$ is the total energy directly consumed [MWh/y] by data centers from power plant k that is attributed to PCA p, $DC_E_{p,adj}$ is the total electricity

consumption of the data center from PCA p after adjusting for the inter-PCA electricity transfers, PP_k is the net generation by a specific power plant in MWh/y, and n is the number of power plants within PCA p. A similar approach was taken to connect power plants to water and wastewater utilities, with their electricity usage (and associated environmental footprints) then linked to the data center they service. Boiler feed pumps require an insignificant amount of electricity to provide water to power plants. Therefore, we truncate our analysis at this point.

2.3. Water consumption and GHG emissions associated with data centers

The indirect water and carbon footprint of each data center consists of water consumption or GHG emissions associated with the generation of (i) electricity utilized during data center operation, (ii) electricity used by water treatment plants for treatment and supply of cooling water to data centers, and (iii) electricity used by wastewater treatment plants to treat the wastewater generated by a data center. The GHG emissions or water consumption of a power plant supplying electricity to a data center is attributed to the data center as follows:

$$DC_IF_k = DC_E_k \times F_k \tag{6}$$

where DC_IF_k is the indirect footprint (water or carbon) associated with electricity used during the operation of a data center from power plant k and DC_E_k is the total energy used [MWh/y] by a data center from power plant k (from equation (5)). When calculating the indirect water footprint, F_k is the water consumption per unit of electricity generated by power plant k in m^3 MWh^{-1}. When calculating the indirect carbon footprint, F_k is the GHG emitted per unit of generated electricity by power plant k (tons CO_2-eq MWh^{-1}).

Although the IPCC does not consider water treatment a notable emitter of GHGs [37], wastewater treatment plants are a major source of GHG emission [38, 39]. In 2017, total GHG gas emission from wastewater treatment plants was estimated to be 20 million metric tons, with a direct emission rate of 0.3 kg CO_2-eq/y per m^3 of wastewater treated [38, 39]. In absence of facility specific emission data, we have used the average emission rate for treating wastewater for all wastewater generated from data center operation [39]. No direct GHG emissions are assumed to be associated with data center operation at the facility [18].

The EPA Safe Drinking Water Information System contains information on the location, system type, and source of water for each public water and wastewater utility [40, 41]. We assumed the nearest non-transient water treatment plant and wastewater treatment plant services a data center's water demand and wastewater management, respectively. After calculating the water supply requirement of a data center (discussed later in this section), the electricity needed for treatment and distribution of cooling water can be calculated using the data from Pabi *et al* [13] (see table S2). Water and wastewater treatment plants were linked to power plants (as described previously) to estimate the indirect water footprint associated with electricity required to distribute and treat water and wastewater used by a data center. We then sum the water consumed by each power plant to directly or indirectly service a data center to determine the total indirect water footprint of that data center. The indirect water footprint associated with each power plant was also aggregated within watershed boundaries to determine which water sources each data center was reliant upon.

Direct water consumption of a data center can be estimated from the heat generation capacity of a data center [42], which is related to the amount of electricity used [43]. Estimates of data center specific electricity demand were multiplied by the typical water cooling requirement [1]—1.8 m^3 MWh^{-1}—to estimate the direct water footprint of each data center. The direct water consumption is assigned to the watershed where the water utility supplying the data center withdraws its water.

Data center wastewater is largely comprised of blowdown; that is, the portion of cooling water removed from circulation and replaced with freshwater to prevent excessive concentration of undesirable components [44]. We assume all data centers utilize potable water supplies and cycle this water until the concentration of dissolved solids is roughly five times the supplied water [44]. We calculate blowdown from data center cooling towers using the following commonly employed approach [45]:

$$R_{\text{Blowdown}} = \frac{1}{C-1} \times R_{\text{Evaporation}} \tag{7}$$

where R_{Blowdown} is the blowdown rate required for a cooling tower (m^3 MWh^{-1}), C is the cycle of concentration for dissolved solids (assumed here as 5), and $R_{\text{Evaporation}}$ is the rate of evaporation (m^3 MWh^{-1}).

2.4. Water scarcity footprint

The water scarcity footprint (*WSF*; as defined by ISO 14046 and Boulay *et al* [46]) indicates the pressure exerted by consumptive water use on available freshwater within a river basin and determines the potential to deprive other societal and environmental water users from meeting their water demands. We quantified the *WSF* of data centers using the AWARE method set forth by Boulay *et al* [46] (see the Supportive Information for more details). Other societal and environmental water use data, as well as data on natural water availability within each US watershed, come from [47–49].

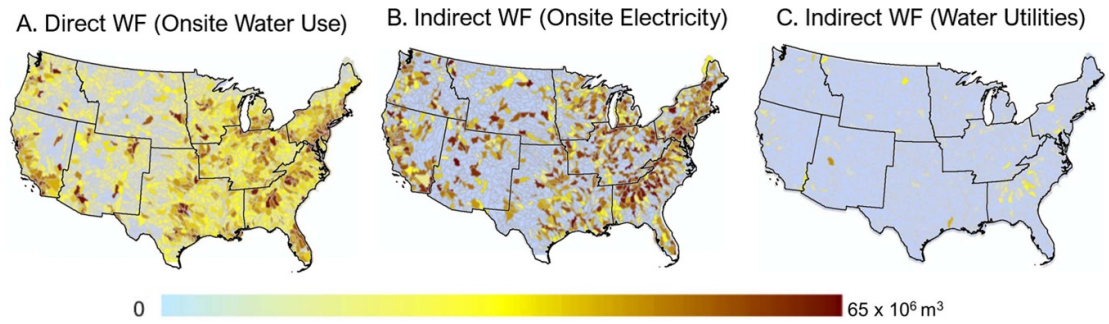


Figure 2. The blue water footprint (m^3) of US data centers in 2018, resolved to each subbasin (8-digit Hydrologic Unit Code). (A) Direct water footprint of data centers, (B) indirect water footprints associated with electricity utilization by data center equipment, and (C) indirect water footprints associated with treatment of supplied cooling water and treatment of generated wastewater.

3. Results

3.1. The water footprint of data centers

The total annual operational water footprint of US data centers in 2018 is estimated at 5.13×10^8 m^3. Data center water consumption is comprised of three components: (i) water consumed directly by the data center for cooling and other purposes (figure 2(A)), (ii) water consumed indirectly through electricity generation (figure 2(B)), and (iii) water consumed indirectly via the water embedded with the electricity consumption of water and wastewater utilities servicing the data center (figure 2(C)). The data center industry directly or indirectly draws water from 90% of US watersheds, as shown in figure 3(A).

Roughly three-fourths of US data centers' operational water footprint is from indirect water dependencies. The indirect water footprint of data centers in 2018 due to their electricity demands is 3.83×10^8 m^3, while the indirect water footprint attributed to water and wastewater utilities serving data centers is several orders of magnitude smaller (4.50×10^5 m^3). Nationally, we estimate that 1 MWh of energy consumption by a data center requires 7.1 m^3 of water. However, this national average masks the large spatial variation (range 1.8–105.9 m^3) in water demand associated with a data center's energy consumption. Data centers are indirectly dependent on water from every state in the contiguous US, much of which is sourced from power plants drawing water from subbasins in the eastern and western coastal states. Less than one-fifth of the industry's total electricity demand is from data centers in the West and Southwest US (regions as defined by NOAA [50]; see outlined areas in figures 2–5, and figure S4 for region identification), yet nearly one-third of the industry's indirect water footprint is attributed to data centers in these regions. Indirect water consumption associated with energy production in Southwest subbasins is particularly high, despite relatively low electricity supplied from this region, due to the disproportionate amount of electricity from water-intensive hydroelectricity facilities and the high evaporative potential in this arid region. Conversely, the Southeastern region consumes one-quarter of the electricity used by the industry but only one-fifth of the indirect water since data centers in this region source their electricity from less water-intensive sources.

On-site, direct water consumption of US data centers in 2018 is estimated at 1.30×10^8 m^3. Collectively, data centers are among the top-ten water consuming industrial or commercial industries in the US [47]. Approximately 1.70×10^7 m^3 of water directly consumed by data centers are sourced from a different subbasin than the location of the installed servers. Large direct water consumption in the Northeast, Southeast, and Southwest regions indicate clustering of servers in these regions. Combined direct and indirect water and carbon intensities are broken down by data center type in table 1.

3.2. Reliance of data centers on scarce water supplies

The WSF of data centers in 2018 is 1.29×10^9 m^3 of US equivalent water consumption, which is more than twice that of the volumetric water footprint reported in the previous section. The WSF (including both direct and indirect water requirements) per unit of energy consumption is 17.9 m^3 US-eq water MWh^{-1}, more than double the nationally averaged water intensity (7.1 m^3 MWh^{-1}) that does not account for water scarcity. WSFs that are larger than volumetric water footprints suggest that data centers disproportionately utilize water resources from watersheds experiencing greater water scarcity than average.

Only one-fourth of the volumetric water footprint of data centers resulted from onsite water use. Yet, more than 40% of the WSF is attributed to direct water consumption. This indicates that direct water consumption of data centers, which occurs close to where the data center is located, is skewed toward water stressed subbasins compared to its indirect water consumption, which is distributed

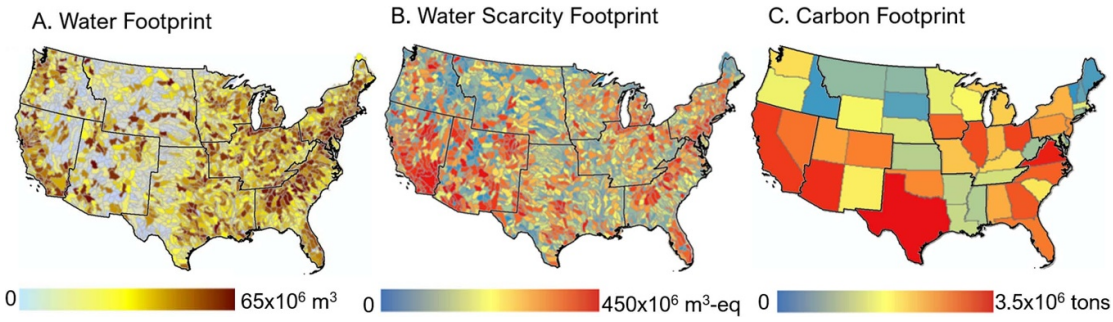


Figure 3. The subbasin or state of direct and indirect environmental impact associated with data center operation. (A) Water footprint (m^3). (B) WSF (m^3 US-eq water). (C) Carbon footprint (tons CO_2-eq/y).

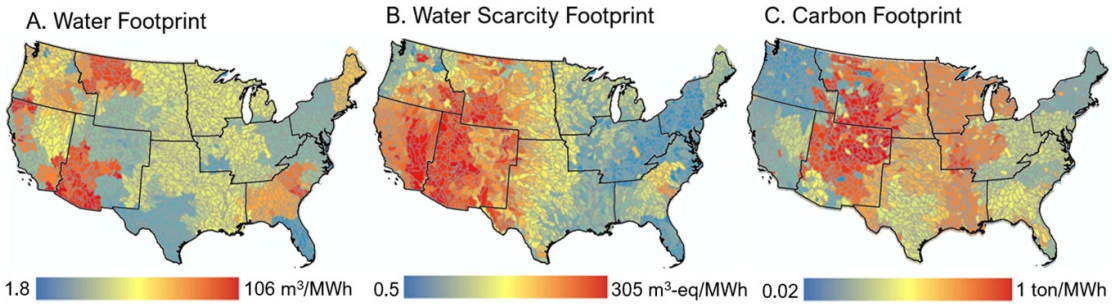


Figure 4. A data center's environmental footprint is highly contingent on where it is located. The (A) water intensity (m^3 MWh^{-1}), (B) water scarcity intensity (m^3 US-eq MWh^{-1}), and (C) GHG emissions intensity (tons CO_2-eq MWh^{-1}) of a hypothetical 1 MW data center placed in each of the 2110 subbasins of the continental United States.

more broadly geographically. We find that most of the watersheds that data centers draw from, particularly those in the Eastern US, face little to no water stress on average. In contrast, many of the watersheds in the Western US exhibit high levels of water stress, which is exacerbated by data centers direct and indirect water demands. Combined, the West and Southwestern watersheds supply only 20% of direct water and and 30% indirect water to data centers, while hosting approximately 20% of the nation's servers. Yet, 70% of the overall WSF occurs in these two regions (figure 3(B)), which indicates a disproportionate dependency on scarce waters in the western US.

3.3. GHG emissions attributed to data centers

Total GHG emissions attributed to data centers in 2018 was 3.15×10^7 tons CO_2-eq, which is almost 0.5% of total GHG emissions in the US [10]. A little over half (52%) of the total emissions of data center operations are attributed to the Northeast, Southeast, and Central US, which have a high concentration of thermoelectric power plants, along with large number of data centers (figure 3(C)). Almost 30% of the data center industry's emissions occur within the Central US, which relies heavily on coal and natural gas to meet its electricity demand. Yet, only 10% the industry's energy demand comes from the Central US, and just 9% of the water consumption associated with data centers operation occurs in this region. Moreover, the Central region is a net exporter of electricity to other regions, providing electricity for data centers located in the Northeast and Southeast regions, which houses almost one-third of servers. Yet, the generation of less carbon intensive electricity in the Northeast (hydroelectricity) and Southeast (wind/solar) regions means that while their electricity consumption comprises 34% of data centers' national electricity demand, these regions only constitute 23% of the industry's GHG emissions. The GHG emissions from treating the wastewater generated from data centers is around 550 tons/y (0.002% of total GHG emissions associated with data centers).

3.4. Where to locate data centers to minimize water and carbon footprints

Our results indicate significant variability of environmental impacts depending on where a data center is located. Here we explore how the geographic placement of a data center can lead to improved environmental outcomes. We find that the total water intensity of a data center can range from 1.8–106 m^3 MWh^{-1}, the water scarcity intensity from 0.5 to 305 m^3 US-eq MWh^{-1}, and the carbon intensity from 0.02 to 1 ton CO_2-eq MWh^{-1} depending on where the data center is placed (figure 4). Data center placement decisions are complicated by

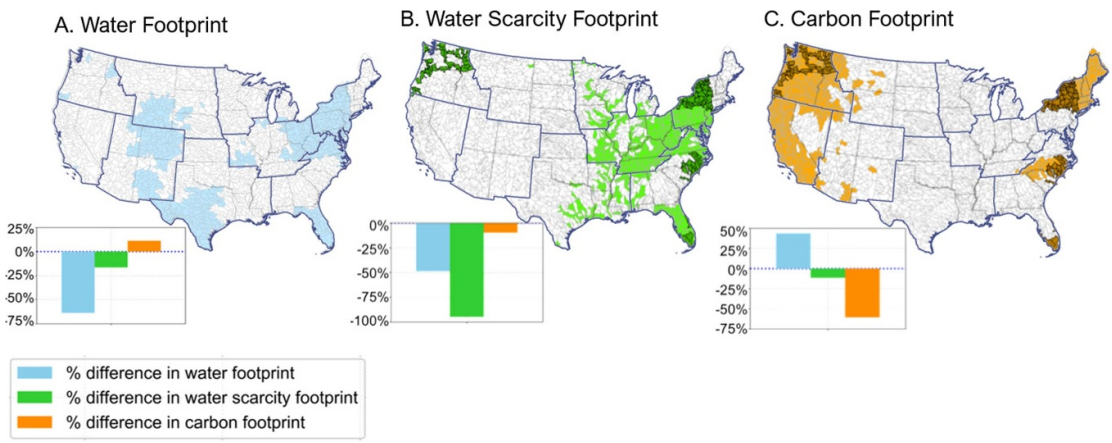


Figure 5. The (A) water footprint, (B) WSF, and (C) carbon footprint of data centers can be reduced by placing them in subbasins with the smallest footprint (top quartile of all subbasins), as denoted by the shaded subbasins in each panel. The bar graphs represent the percent reduction/increase of each environmental footprint within the shaded subbains compared to the national average data center environmental footprint. Hatched areas indicate subbasin that are among the most (top quartile) environmentally favorable locations for both water scarcity and GHG emissions.

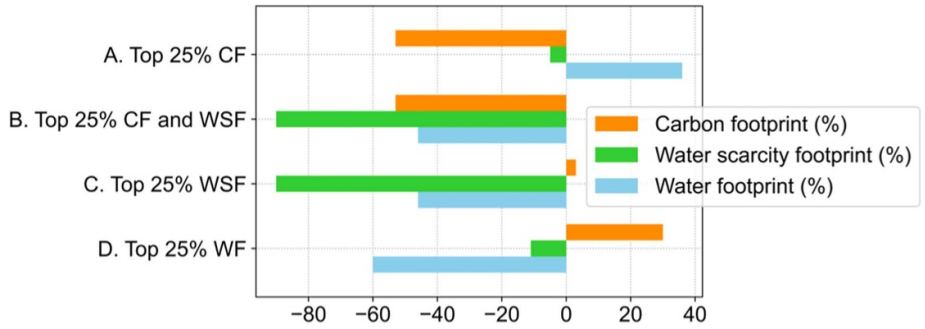


Figure 6. Percent change in environmental footprints associated with new data center servers compared to the 'business-as-usual' scenario. While the business-as-usual scenario assumes new servers will be placed in proportion to historical server locations, alternative scenarios explicitly consider the environmental implications of data center placement. Scenario A places data center servers in subbasins within the top quartile of all subbasins in environmental performance for both carbon (CF) and water scarcity (WSF) footprints. Scenario B represents server placement within subbasins in the top quartile for carbon footprints, while scenario C and D represent the best (top 25%) subbasins to place data center servers with respect to minimizing WSFs and water footprints (WF), respectively.

the electricity grid, which displaces environmental impacts from the physical location of a data center.

Figure 5 depicts subbasins in the top quartile of environmental performance as it relates to water footprint (5(A)), WSF (5(B)), and carbon footprint (5(C)) per MWh of electricity used by a hypothetical data center located within each subbasin. Less than 5% of subbasins are in the top quartile of environmental performance for both WSF and carbon footprint (hatched areas in figures 5(B) and (C), meaning that 40% of subbasins will require making a trade-off between reducing WSFs and carbon footprints. The remaining 55% of subbasins (white areas shared by figures 5(B) and (C) are not among the best locations to place a data center for either water or GHG reduction. Though the water footprint and WSF are related concepts, we show that nearly one-fifth of subbasins that were in the top quartile with respect to the water footprint are in the bottom quartile for WSF. In other words, a data center placed in these basins would use less water than 75% of potential sites, but it would draw that water from subbasins facing higher levels of water scarcity. In general, locating a data center within the Northeast, Northwest, and Southwest will reduce the facilities carbon footprint, while locating a data center in the Midwest and portions of the Southeast, Northeast, and Northwest will reduce its WSF.

In the coming years, cloud and hyperscale data centers will replace many smaller data centers [3]. This shift will lower the environmental footprint in some instances but introduce new environmental stress in other areas. Assuming added servers employ similar technology as existing servers and are placed in cloud and hyperscale data centers in proportion to the current spatial distribution of data centers (i.e. business-as-usual scenario), these new data center servers will have a collective water footprint of 77.77 $\times$ 10^6 m^3 (15% of the current industry total), WSF of 170.56 $\times$ 10^6 m^3 US-eq (9%), and 4.36 $\times$ 10^6 tons CO_2-eq (14%). However, if these new servers are

strategically placed in areas identified to have a lower environmental footprint, their water and carbon burden could be significantly reduced.

The WSF and carbon footprint of new data centers can be reduced by 153.00 × 10^6 m^3 US-eq (90% less than business-as-usual expansion) and 2.34 × 10^6 tons CO_2-eq (55%), respectively (figure 6(A)) if they are placed in areas with the lowest carbon and WSFs (hatched areas in figure 5). However, placing all new data centers within a small area may strain local energy and water infrastructure due to their collective water and energy demands. Data centers can be dispersed more broadly in areas that are favorable with respect to water footprint (figure 5(A)), WSF (figure 5(B)), or carbon footprint (figure 5(C)). However, only considering one environmental characteristic can lead to environmental trade-offs (figure 6).

4. Discussion and conclusion

The amount of data created and stored globally is expected to reach 175 Zettabytes by 2025, representing nearly a six-fold increase from 2018 [51]. The role of data centers in storing, managing, and distributing data has remained largely out of view of those dependent on their services. Similarly, the environmental implications of data centers have been obscured from public view. Here, for the first time, we estimate the water and carbon footprints of the US data center industry using infrastructure and facility-level data. Data centers heavy reliance on water scarce basins to supply their direct and indirect water requirements not only highlight the industry's role in local water scarcity, but also exposes potential risk since water stress is expected to increase in many watersheds due to increases in water demands and more intense, prolonged droughts due to climate change [52–54]. For these reasons, environmental considerations may warrant attention alongside typical infrastructure, regulatory, workforce, customer-/client proximity, economic, and tax considerations when locating new data centers.

The data center industry can take several measures to reduce its environmental footprint, as well as minimize its water scarcity risks. First, the industry can continue its energy efficiency improvements. The ongoing shift to more efficient hyperscale and co-location data centers will lower the energy requirements per compute instance. Software and hardware advances, as well as further PUE improvements, can continue to reduce energy requirements, and thus environmental externalities. For instance, quarterly PUE of as low as 1.07 has been reported by Google for some of their data centers [55]. Liquid immersion cooling technologies show promise of further reductions in PUE, with one study reporting a PUE below 1.04 [56]. The prospect of recovering low-grade heat (i.e. low temperature or unstable source of heat) from data centers for space or water heating is limited; however, approaches such as absorption cooling and organic Rankine cycle are promising technologies for generating electricity from waste heat [57].

Second, the data center industry can make investments in solar and wind energy. Directly connecting data center facilities to wind and solar energy sources ensures that water and carbon footprints are minimized. Purchasing renewable energy certificates from electricity providers does not necessarily reduce the water or carbon footprints of a data center. However, these investments gradually shift the electrical grid toward renewable energy sources, thus lowering the overall environmental impact of all energy users. Data center workloads can be migrated between data centers to align with the portion of the grid where renewable electricity supplies exceed instantaneous demand [58].

Third, as we show in this study, strategically locating new data centers can significantly reduce their environmental footprint. Climatic factors can make some areas more favorable due to lower ambient temperatures, thereby reducing cooling requirements. Lower cooling requirements reduces both direct and indirect water consumption, as well as GHG emissions, associated with data center operation. Since most data centers meet their electricity demands from the grid, the composition of power plants supplying electricity to a data center plays a significant role in a data center's environmental footprint. For an industry that is centered on technological innovation, we show that real estate decisions may play a similar role as technological advances in reducing the environmental footprint of data centers.

Data availability statement

Data center locations come from [4, 19–21]. Power plant electricity generation, water consumption, and GHG emission data come from [35, 59, 60]. Location of public water utility and wastewater treatment data comes from [40, 41]. Study data and code can be found in the Supporting Information, as well as at https://doi.org/10.7294/14504913. The DOI contains relevant shapefiles, tabular data, and scripts to help replicate and extend our work. All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

L M acknowledges support by the National Science Foundation Grant No. ACI-1639529 (INFEWS/T1: Mesoscale Data Fusion to Map and Model the US Food, Energy, and Water (FEW) system). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of

the National Science Foundation. Lawrence Berkeley National Laboratory is supported by the Office of Science of the United States Department of Energy and operated under Contract Grant No. DE-AC02-05CH11231.

Author contributions

L M conceived and designed the study. M A B S conducted the analysis. A S provided data and fundamental concepts regarding the analysis. All authors contributed to the writing of the manuscript.

Conflict of interest

The authors declare that they have no competing financial interests.

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