Characterizing Data Center Cooling System Water Stress in the United States

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ABSTRACT

Massive data center (DC) energy demands lead to water consumption concerns. This study quantifies on-site and off-site DC water consumption and its holistic impact on regional water availability. This study proposes a new DC sustainability metrics, Water Scarcity Usage Effectiveness (WSUE), that captures the holistic impacts of water consumption on regional water availability by considering electricity and water source locations and their associated water scarcity. We examine the water consumption of various DC cooling systems by tracking on-site water consumption along with the direct and indirect water transfers associated with electricity transmission at the contiguous U.S. balancing authority (BA) level. This study then applies the WSUE metric for different DC cooling systems and locations to compare the holistic water stress impact by large on-site water consuming systems (e.g., via cooling towers) versus systems with higher electrical consumption and lower on-site water consumption such as the conventional use of computer room air conditioner (CRAC) units. Results suggest that WSUE is strongly dependent on location, and a water-intensive cooling solution could result in a lower WSUE than a solution requiring no or less on-site water consumption. The use of the WSUE metric aids in DC siting decisions and DC cooling system design from a sustainability point of view.

INTRODUCTION

The growth in the size and quantity of data centers (DCs) increases concerns about the sector's growing energy usage and environmental impact. Jones (Jones, 2018) reported that DCs consume more than 200 TWh of electricity annually, which accounts for 1% of global electricity demand, and Bashroush and Lawrence (Bashroush and Lawrence, 2020) suggested that DCs may consume up to 500 TWh of electricity annually.

Numerous studies have focused on understanding and reducing DC carbon footprint (Belady, 2010; Qu et al., 2017; Marriott and Matthews, 2005; Yang and Agarwal, 2017; de Chalendar et al., 2019; Chen and Wemhoff, 2021a). However, carbon emissions are only one factor that contributes to DC environmental sustainability. Hadian and Madani (Hadian and Madani, 2015) affirmed that achieving a low carbon footprint is not enough to claim that an energy system is "green" until water and land footprints are also considered. Ristic et al. (Ristic et al., 2015) stated that "reporting will have to increase and be communicated more widely for a better understanding of not just DC energy efficiency, but their overall environmental footprint and sustainability."

Evaluating the embodied water consumption from purchased electricity in the U.S. is challenging due to the complexity of electricity transmission within interconnected power grids. Nonetheless, carbon emissions and water consumption are both embedded in electricity generation. The methods and models of tracking carbon emissions within power grids can also be applied to tracing water consumption. Ryan et al. (Ryan et al., 2016) compared models and methods to predict carbon emissions from electricity. Siddik et al. (Siddik et al., 2020) concluded that, generally, two types of data-driven attribution methods are used: (1) those based on grid infrastructure and (2) those based on geographical boundaries. The authors also recognized that methods based on grid infrastructure are difficult to implement because of data limitations. Kodra et al. (Kodra et al., 2015) employed an iterative method based on a network approach to track electricity interchanges and

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associated emissions transfers in the U.S. At each time step, each region transmits a portion of its available electricity to other regions. The iterations stop when the available electricity of each region diminishes. Following Kodra's work, Qu et al. (Qu et al., 2017) developed the quasi-input-output (QIO) model that improves the accuracy of the iterative method by utilizing input-output theory from economics. Chen and Wemhoff (Chen and Wemhoff, 2021a) extended the QIO model by proposing an emission factor translation approach that enables emission quantification at the U.S. county level.

This study applies results from the QIO model (Chen and Wemhoff, 2021b) to examine the impact of DC water usage on ecosystems, specifically how DC water consumption affects local and regional water availability. This study therefore proposes a Water Scarcity Usage Effectiveness (WSUE) metric that assesses the impacts of DC on-site and indirect water usage on regional water availability. This study applies computational models of various DC cooling systems and locations to demonstrate the significant variation in water usage effectiveness (WUE) and WSUE values due to regional water availability.

MATERIALS AND METHODS

Assessing DC water usage and its associated efficiency are complicated (Belady and Pouchet, 2011). Just as carbon emissions are embedded in the electricity that DCs consume (Belady, 2010), DCs consume enormous amount of water indirectly through off-site electricity generation processes. To better understand DC water consumption, one must consider both "site-based" and "source-based" water consumption. The Green Grid (Belady and Pouchet, 2011) defined the WUE as the volume of water in liters consumed on-site annually per kWh of IT load. The WUE is a site-based metric that measures the direct water consumed on-site for DC operation:

$$\mathrm{WUE} = \frac{W_{site}}{P_{IT}} \tag{1}$$

where W_{site} is the annual site water consumption, and P_{IT} is the annual IT equipment energy consumption. A variant of WUE is $\mathrm{WUE}_{\mathrm{source}}$, which includes water consumed on-site as well as water consumed off-site through the production of energy consumed on-site:

$$\mathrm{WUE}_{\mathrm{source}} = \frac{W_{site} + W_{off-site}}{P_{IT}} \tag{2}$$

where $W_{off\text{-}site}$ is the annual source energy water usage. By its definition, Eqn. (2) can be reformulated as:

$$\mathrm{WUE}_{\mathrm{source}} = [\mathrm{EWIF} \cdot \mathrm{PUE}] + \mathrm{WUE} \tag{3}$$

where EWIF is the energy water intensity factor, which measures the amount of water used to produce the energy consumed by the DC; and PUE is power usage effectiveness, which is a widely used DC energy efficiency metric defined as the ratio of total DC energy consumption (P_{tot}) to IT equipment energy consumption (P_{IT}). In Eqn. (3), the product of EWIF and PUE can be referred as the "off-site WUE" that focuses on measuring the water consumption in power generation processes. Practically, WUE is relatively easy to measure compared to $\mathrm{WUE}_{\mathrm{source}}$ (Belady and Pouchet, 2011), and the site-based WUE is also more easily reduced than off-site WUE through adjusting on-site operations. On the other hand, $\mathrm{WUE}_{\mathrm{source}}$, which provides a more holistic view of the environmental burden of the DC and its IT equipment, is designed for DC decision making regarding site selection and planning.

The site-based metric WUE along with source-based metric $\mathrm{WUE}_{\mathrm{source}}$ are principal environmental indicators in the DC industry. Shehabi et al. (Shehabi et al., 2016) estimated that over 660 million cubic meters of water was required by U.S. DCs' onsite operations in 2020. Nevertheless, Heslin (Heslin, 2016) reported that water conservation is ranked as a low priority among most DC operators. In fact, less than one-third of DC operators measure the water consumption or use the WUE metric (Heslin, 2016). Facebook is one of the few businesses who report WUE of their DCs. However, since WUE is a relatively new measure compared to PUE, there are currently no industry standards or baselines. Pegus et al. (Pegus et al., 2016) analyzed the computing load of the Massachusetts Green High-Performance Computing Center (MGHPCC) and its impact on multiple DC performance metrics, including WUE. However, only on-site water usage was documented and analyzed. The first preliminary DC water footprint accounting was performed by Ristic et al. (Ristic et al., 2015), who revealed that their DC water footprint, defined as the summation of direct water footprint (cooling systems) and indirect water footprint (energy source), ranges from 1,047 to 151,061 m^3/TJ. Their indirect water footprint was calculated using nationally averaged EWIF values for each power generation technology weighted with the fraction of regional energy generation from that technology. The authors acknowledged the existence of a large uncertainty in its water footprint accounting since EWIF varies geographically. In any case, the water transmission embedded in electricity transfers was not included in their water footprint calculations.

Assessing DC water usage and its impacts on water availability requires three steps:

1. Determine the EWIF for different power generation technologies in various regions and find the DC PUE since off-site WUE can be obtained once EWIF and PUE are known. Previous studies have proved that water footprint of electricity primarily depends on energy source and varies greatly by region (Mekonnen et al., 2015; Peer et al., 2019). It is worth noting that EWIF should account for the entire life cycle of power generation, so the water consumption in upstream electricity production (e.g., fuel extraction, processing, and transportation) should be included.
2. Consider the electricity interregional transmission and its associated water relocation because some electricity transfers occur between regions that have completely different power generation portfolios, which significantly alters regional EWIF.
3. Incorporate water scarcity metrics to investigate the impacts of DC water use on water availability.

Related work (Chen and Wemhoff, 2021a) derives the life cycle EWIF for different locations by following power generation from each source in each region's electricity generation portfolio. The QIO model is used to trace the electricity interregional transfers and their associated water relocation, enabling the definition and calculation of the scarce water index (SWI) metric that relates water scarcity to electricity consumption. Here, the WSUE metric is defined and calculated using SWI, PUE and WUE to analyze the impacts of DC water draws on regional water availability.

Assessing the Impacts of DC Water Consumption

The water scarcity footprint (WSF), recommended in ISO 14046 (*ISO 14046:2014*, 2014), is the metric that quantifies the potential environmental impacts related to water. By its definition, regional WSF can be calculated using:

$$\text{WSF} = \text{Water Consumption}[\text{m}^3] \times \text{Water Scarcity Indicator} \tag{4}$$

WSF represents the volume of water consumption that also accounts for water availability. It also enables comparison of water consumption in different regions. Recently, Lee et al. (Lee et al., 2019) developed an Available Water Remaining for the United States (AWARE-US) model at a refined spatial scale (i.e., the county-level) to quantify the water scarcity and impacts of water consumption in different regions within the contiguous U.S. Their AWARE characterization factor (AWARE CF) compares regional available water to a reference value:

$$\text{AWARE CF} = \frac{AMD_{ref}}{AMD} \tag{5}$$

where AMD indicates water availability minus demand, and AMD_{ref} is the reference value of AMD that is estimated as the weighted average of all regions. Note that AMD is relative to land area and must be positive since human water consumption plus environmental water required to sustain a riverine ecosystem cannot exceed natural runoff. AWARE CF is bounded between 0.1 to 100, and high AWARE CF values represent water scarce regions. Therefore, large WSF values, indicating more intense relationship between water consumption and regional water availability, can either be caused by high water consumption or high AWARE CF values.

Several regions in the U.S. are experiencing more frequent and longer durations of droughts due to climate change (Jones and van Vliet, 2018). For heavy water consuming facilities like DCs, it is necessary to quantify the impacts of its huge water consumption on regional water availability. WSUE, which is a metric that incorporates DC source-based water consumption and regional water availability, is designed for DC owners and operators to examine the impacts of DC water consumption on regional water scarcity. It is also a useful tool for identifying the most water friendly regions that are suitable for future DC construction. Per Eqn. (4), WSF quantification requires accurate measurement of water consumption. However, water consumed off-site through the production of energy is often ignored. This quantification of WSF that considers both on-site and off-site water consumption of *any* building is

$$\text{WSF} = (\text{AWARE CF})(W_{site}) + (\text{WSI})(P_{tot}) \tag{6}$$

where the AWARE CF value here is specific to the building location, and SWI quantifies the impact of electricity consumption on water availability. It follows that the WSF for a data center can be found using this equation in conjunction with the definition of PUE as

$$\text{WSF} = (\text{AWARE CF})(W_{site}) + (\text{SWI})(P_{site}) \tag{7}$$

Dividing both sides results in a definition for the water scarcity usage effectiveness:

$$\text{WSUE} = \frac{\text{WSF}}{P_{IT}} = (\text{AWARE CF})(\text{WUE}) + (\text{SWI})(\text{PUE}) \tag{8}$$

Therefore, the scarce water usage of a DC with known PUE and WUE values can easily be calculated based on the location-specific factors AWARE CF and SWI. Equation (8) shows that theoretically a water-intensive cooling solution (e.g., evaporative cooling) with a large WUE could result in a lower WSUE than a solution requiring no on-site water consumption if PUE and SWI are large. Here, AWARE CF and SWI are specific at the county and balancing authority (BA) levels, respectively, since AWARE CF is highly location dependent and SWI is based on regional electricity flows.

Measuring Water Consumption Impact of DC Cooling Systems

In this study, a generic DC with three individual cooling systems is computationally modeled at four different U.S. locations: Boston, Miami, Denver, and Phoenix. The three chosen cooling systems are (1) Computer Room Air Handling (CRAH)-based cooling, (2) Computer Room Air Conditioning (CRAC)-based cooling, and (3) pure evaporative cooling with airside economization. The computational modeling work in this study was performed using the Villanova Thermodynamic Analysis of Systems (VTAS) software, which is a flow network modeling tool for the thermodynamics, fluid mechanics, and heat transfer inherent to an entire DC system, including contributions by individual servers, the DC airspace, and the heating, ventilating, and air conditioning (HVAC) components (Wemhoff et al., 2013). VTAS provides a framework and component models where thermodynamics, fluid mechanics, and heat transfer physical equations are coupled and solved in a MATLAB based mathematical/computational scheme. Some validation of VTAS models of DC cooling systems has been achieved (Khalid and Wemhoff, 2019).

Figure 1 shows the schematic diagram of a DC with CRAH-based cooling system. The total heat output in the DC is modeled as 400 kW, and the cooling system contains four CRAHs, four chillers and four cooling towers in a parallel configuration. Further, the air supply temperature of CRAHs and water supply temperature from chillers are fixed at 20°C and 15°C, respectively. The air properties of the external environment is location-dependent, and the weather data is retrieved from TMY3 database (Wilcox and Marion, 2008, p. 3). The annualized PUE and WUE are calculated based on modeling the yearly weather data through ten equivalent days, which has been verified as sufficient for estimating these metrics.

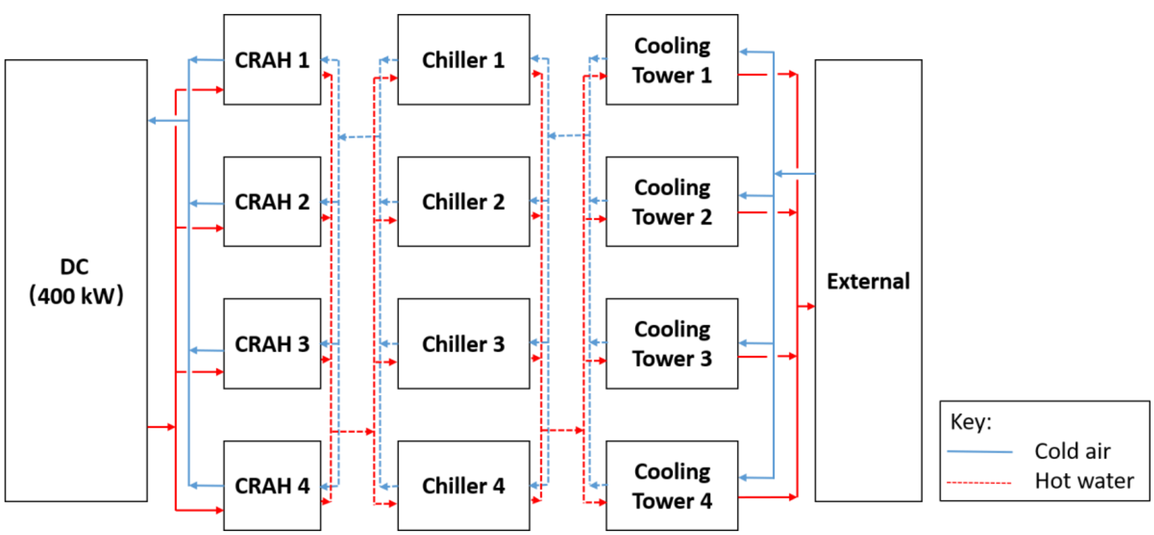

Figure 1 VTAS model of a DC containing a CRAH-based cooling system. A pump/fan is provided in the supply stream for each CRAH, chiller, and cooling tower, and for the outside air leaving the cooling tower. The make-up water lines for the cooling towers are not shown.

Figure 2 shows the schematic diagram of DCs with (a) CRAC-based cooling system and (b) evaporative cooling system. Similarly, the total heat output in the two DCs are designed to be 400 kW. In Fig. 2(a), the CRAC-based cooling system contains four CRAC units in a parallel configuration and the supply air temperature to the DC is set to be 20°C. In Fig. 2(b), the evaporative cooling system uses an adiabatic evaporative cooler, which has an efficiency η of 0.9. Note that the evaporatively-cooled system modeled here does not include any return air stream; all air leaving the DC is expunged to the external environment.

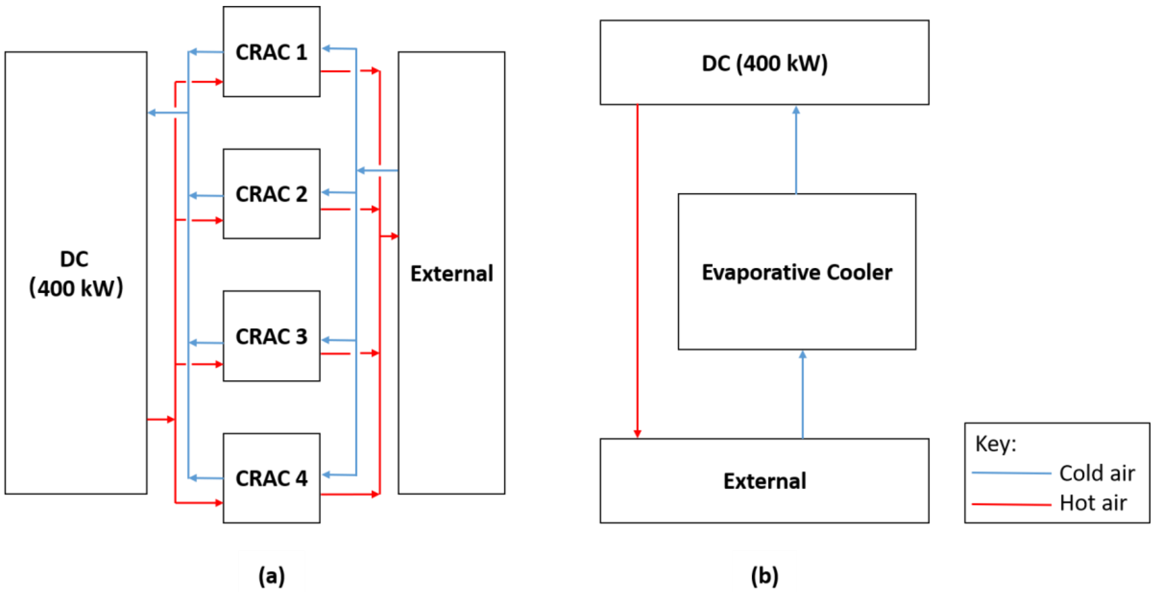

Figure 2 (a) Schematic diagram of a DC with CRAC-based cooling system and (b) schematic diagram of a DC with evaporative cooling system. A fan is provided in each airstream leaving the CRACs and in the supply air leaving the evaporative cooler.

The key to the PUE estimate for CRAC and CRAH cooling system configurations in different climate zones is the temperature dependence of the coefficient of performance (COP) of direct expansion units (CRACs and chillers). This dependence was determined through separate, secondary system models where single, more complex CRAC and chiller component models were adjusted to determine the COP under various conditions. In these separate system models, the CRAC and chiller are modeled via an ideal refrigeration cycle with a varying condenser saturation temperature. In the case of the CRAC unit, the cooling load (100 kW), indoor supply air temperature (20°C), indoor supply air flowrate (2.0 m^3/s), and outdoor air flowrate (4.0 m^3/s) are fixed and equivalent to the primary cooling system models in this study. For the CRAC secondary model, the outdoor air temperature is varied between -10°C and 40°C, and the condenser saturation temperature is calibrated to achieve a fixed condenser conductance (UA = 10,100 W/K) that satisfies the Second Law of Thermodynamics. The resultant data are used as a curve to approximate the COP variation with temperature under the above fixed conditions but with varying external air temperature. The chiller COP dependence on condenser water supply temperature was also determined using the same approach, where chilled and condenser water loop flowrates (0.001 m^3/s and 0.01 m^3/s, respectively), chilled water supply temperature (15°C), and chiller condenser conductance (UA = 160,000 W/K) are fixed and equivalent to those in the primary cooling system models in this study, and the condenser water supply temperature is varied. Figure 3 provides the resultant predicted variation in CRAC and chiller COP values under these conditions.

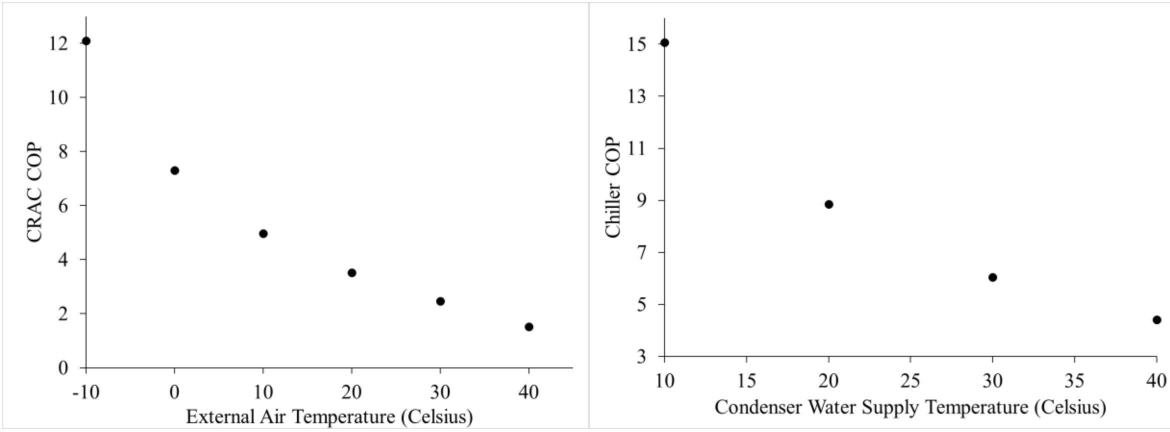

Figure 3 (a) CRAC unit COP T-dependence curve and (b) chiller COP T-dependence curve

For a system cooled by a single evaporative cooler, the mass flow rate of the external air through the evaporative cooler and into the DC is fixed at 8 m^3/s for consistency with the other systems, although this allows for an elevated supply air temperature. Table 1 provides the modeled maximum (worst case weather conditions) supply air temperature of the evaporatively-cooled system, which should be considered when comparing the metrics of the pure evaporatively-cooled system and the other two systems (Table 2). In fact, the only two locations that appears viable for evaporative cooling are Denver and San Francisco; the other entries are in red in Table 2 to signify that this cooling solution is not viable.

Table 1. Maximum Supply Air Temperature of the Evaporatively-Cooled System

Location	Maximum Supply Air Temperature (°C)
Boston	31.1
Denver	21.7
Miami	29.4
Phoenix	26.4
San Francisco	21.0

Results shown in Table 2 indicate that switching from a CRAC-based cooling system to a CRAH-based cooling system could significantly reduce the DC PUE due to the use of a cooling tower over a CRAC air-cooled condenser coil. Specifically, the DC PUE drops by 10.1-14.9% for the locations in this study, suggesting a relative independence on location. Results also show that a water-intensive cooling solution (e.g., CRAH-based cooling) with large on-site water usage could result in a lower WSUE than a solution requiring no or less on-site water consumption (e.g., CRAC-based cooling) if PUE and/or SWI values are large, which is the case in Phoenix and San Francisco. The general WSUE values for water-scarce Phoenix are much larger than those in water-rich Boston and Miami, regardless of cooling system type. However, CRAC-based cooling possesses a lower WSUE (40.83 L/kWh) than CRAH-based cooling (250.72 L/kWh) in Denver because the level of water shortage in that city (AWARE CF = 100) leads to a higher water scarcity impact from direct water usage comparing to indirect water usage (SWI = 24.16 L/kWh). Further, compared to other cities who possess relatively low SWI values, a much higher WSUE value is observed in Phoenix (1,673.76 L/kWh) for CRAC-based cooling system due to a high SWI (890.3 L/kWh), indicating the significance of water stress impact from indirect water consumption. Similarly, the evaporative cooling solution in San Francisco returns a higher WSUE (124.86 L/kWh) than in Denver (33.40 L/kWh) due to the higher SWI (123.6 L/kWh) in San Francisco, which again emphasizes the importance of indirect water consumption in water stress impact quantification. Finally, the evaporative cooling solution for Denver and San Francisco indicates a much lower PUE, WUE, and WSUE than the other cooling solutions, which is due to the use of airside economization (rather than heated return air) and the lack of a compressor within the cooling system.

The WSUE does contain limitations. First, the AWARE CF is bounded between 0.1 and 100, which could provide artificially lower values of WSUE in water scarce locations and potentially reduce the contribution of on-site water usage to the metric. Second, the physical meaning of WSUE is more obscure than the well-known PUE and WUE metrics since WSUE depends on a combination of water consumption in electricity generation (and their associated local water availability) and on-site water use compared to available water. A useful way to use the metric is to take the ratio of WSUE values for two locations, per Eq. (8), as

$$\frac{WSUE_1}{WSUE_2} = \frac{WSF_1}{WSF_2} \tag{9}$$

The above ratio of WSUE values is therefore the ratio of potential environmental impacts due to water per the WSF definition in Eq. (4). Therefore, per Table 2 a DC using CRAC cooling in Phoenix has roughly 1,881 times the potential holistic water environmental impact compared to the same DC in Boston, although that ratio may be even higher due to the capping of AWARE CF at 100 for Phoenix.

Table 2. Performance Metrics of DCs with Different Cooling Systems in Various Regions*

Location	AWARE CF (0-100)	SWI (L/kWh)	Cooling System	PUE	WUE (L/kWh)	WSUE (L/kWh)
Boston	0.27	0.53	CRAC cooling	1.69	0	0.89
			CRAH cooling	1.52	2.11	1.38
			Evaporative cooling	1.01	0.01	0.54
Denver	100	24.16	CRAC cooling	1.69	0	40.83
			CRAH cooling	1.52	2.14	250.72
			Evaporative cooling	1.01	0.09	33.40
Miami	0.67	0.91	CRAC cooling	1.86	0	1.69
			CRAH cooling	1.61	2.37	3.04
			Evaporative cooling	1.01	0.01	0.92
Phoenix	100	890.3	CRAC cooling	1.88	0	1,673.76
			CRAH cooling	1.6	2.44	1,668.48
			Evaporative cooling	1.01	0.30	929.20
San Francisco	0.96	123.6	CRAC cooling	1.71	0	211.36
			CRAH cooling	1.53	2.17	191.19
			Evaporative cooling	1.01	0.02	124.86

*The modeled evaporative cooling system supply air temperatures in Boston, Miami, and Phoenix are too high for practical comparison of metrics with other cooling systems.

CONCLUSION

The proposed metric WSUE provides a straightforward mechanism to evaluate the impact of a data center's location and cooling system type on regional water stress. The results suggest that location plays a more significant role in WSUE than cooling system type, although the WSUE can be significantly altered based on the DC cooling solution. This study suggests that WSUE can be considered along with other widely used DC performance metrics (i.e., PUE, CUE and WUE) when evaluating how efficient and how "green" a DC is. The metric also represents is also a useful mechanism for making decisions regarding DC siting and cooling solutions.

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NOMENCLATURE

AMD = Water availability minus demand

AWARE-CF = Available Water Remaining Characterization Factor

COP = Coefficient of performance

CUE = Carbon Usage Effectiveness, kg-CO_2e/kWh
EWIF = Energy Water Intensity Factor, L/kWh
P = Energy consumption, kWh
PUE = Power Usage Effectiveness
R = Ratio of water consumption to available water
UA = Overall heat transfer conductance, W/K
W = Water consumption, L
WSF = Water Scarcity Footprint, L
SWI = Scarce Water Index, L/kWh
WSUE = Water Scarcity Usage Effectiveness, L/kWh
WUE = Water Usage Effectiveness, L/kWh
WUE_{source} = Water Usage Effectiveness source, L/kWh

Subscripts

IT = IT equipment
ref = reference value
site = on-site
off-site = off-site
source = on-site plus off-site
tot = total

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