

The sustainability benefits of economization in data centers containing chilled water systems

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ARTICLE INFO

Keywords:

Sustainable data centers
Computer room air handler
Carbon usage effectiveness
Water usage effectiveness
Water scarcity footprint

This study provides the first known conservative estimates of reductions in carbon and water scarcity footprints when employing economization technologies in chilled water-based data centers (DCs) in the U.S. Specifically, a generic DC that employs a Computer Room Air Handling (CRAH)-based cooling system with a total IT load of 400 kW is computationally modeled at 925 locations in the U.S. with airside and/or water-side economization. The energy savings and environmental benefits are presented in terms of key DC performance metric reductions, including Carbon Usage Effectiveness (CUE) and Water Scarcity Usage Effectiveness (WSUE). The results suggest that implementing both water-side and airside economization schemes under conditions within the ASHRAE A1 Allowable envelope reduces the mean state-averaged PUE, WUE, CUE, and WSUE by 11%, 22%, 11%, and 15%, respectively. These results highlight the environmental benefits of economization technologies and provide guidance on economization strategies.

1. Introduction

Approximately 34.8% of the 3.8 trillion kilowatt-hours (kWh) of electricity consumed by the U.S. in 2020 was by the commercial sector (US EIA, 2021). According to the U.S. Department of Energy (DOE), the average power density for a commercial building is 242.2 kWh/m², which could be much higher for electricity intensive facilities such as data centers (DCs). The growth in the size and quantity of DCs increases concerns about the sector's growing energy usage and corresponding environmental impact (Bashroush and Lawrence, 2020). The two largest environmental concerns of DCs are their carbon dioxide equivalent (CO₂e) emissions (primarily due to electricity consumption) and water consumption. Approximately 0.5% of total CO₂e emissions in the U.S. can be attributed to DCs (Siddik et al., 2021). In addition, a large amount of water is consumed during DC operation, either directly in cooling systems through evaporative processes or indirectly for electricity production.

Two major and complementary methods to build sustainable DCs are: (1) involve "green" elements in the design process, and (2) "greenify" the process of DC operation (Wang and Khan, 2013). Many researchers have explored ways to enable DCs to operate in a "green" mode, such as server consolidation and virtualization (Hosseini Shirvani et al., 2020; Jin et al., 2012; Uddin et al., 2021), thermal-aware workload management, and cloud-assisted temperature control (Gupta et al.,

2021; Liu et al., 2016; MirhoseiniNejad et al., 2021).

One popular "green" element that can be implemented in the DCs is economization. Two main economization technologies are commonly used in DCs: airside economizers and water-side economizers. An airside economizer is a part of a building's cooling system that uses cool outdoor air to remove building cooling loads instead of operating the air conditioning compressor. It is an add-on feature to a Heating, Ventilation, and Air Conditioning (HVAC) air handler that mixes outdoor air with return air. On the other hand, one type of water-side economizer features a closed air-water heat exchanger to pre-cool return water in the chilled water loop to reduce chiller load. Both economization technologies have the potential to significantly reduce data center energy use and the corresponding environmental footprint.

Both airside and water-side economization technologies have been investigated extensively in terms of DC energy efficiency (Agrawal et al., 2016; Cho et al., 2012; Cho and Kim, 2016; Deymi-Dashtebayaz and Namanlo, 2019; Díaz et al., 2020; Lei and Masanet, 2020; Lui, 2010; Nadjahi et al., 2018; Ni and Bai, 2017; Park and Seo, 2018; Zhang et al., 2014). Notably, Nadjahi et al. (Nadjahi et al., 2018) reviewed different thermal management and innovative cooling strategies for DCs and concluded that the free cooling technology is the most suitable technology to improve energy efficiency, where airside economization uses free outdoor air to cool the DC and water-side economization removes heat using free cold water. However, no studies exist that investigate the reductions in carbon footprint and water stress impact by DCs when

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Nomenclature	
AA	ASHRAE Allowable (Class A1) envelope
A_{cf}	Regional water scarcity coefficient
AR	ASHRAE Recommended envelope
ASHRAE	American Society of Heating, Refrigerating, and Air Conditioning Engineers
AWARE	Available water remaining
COP	Coefficient of performance
CRAC	Computer room air conditioner
CRAH	Computer room air handler
CUE	Carbon usage effectiveness
DC	Data center
DOE	Department of Energy
EF	Emission factor
EIA	Energy Information Administration
EWIF	Energy water intensity factor
HVAC	Heating, ventilation, and air conditioning
NREL	National Renewable Energy Laboratory
P_{ch}	Chiller energy
P_f	Fan energy
P_{IT}	IT equipment energy
P_p	Pump energy
P_{site}	Total facility energy
PUE	Power usage effectiveness
RH	Relative humidity
SWI	Scarce water index
T_{ai}	Inlet air temperature
T_{ao}	Outlet air temperature
TMY	Typical Meteorological Year
T_{wb}	Wet bulb temperature
VTAS	Villanova Thermodynamic Analysis of Systems
W_{ct}	Cooling tower water loss
W_{evap}	Evaporative cooler water loss
$W_{offsite}$	Offsite water consumption
W_{site}	Onsite water consumption
WSF	Water scarcity footprint
WSUE	Water scarcity usage effectiveness
WUE	Water usage effectiveness
η	Efficiency

economizers are employed in chilled water-based systems. Our past study compared the DC performance with different cooling systems built in five locations in the U.S. (Chen and Wemhoff, 2022b). However, economization is examined as a standalone cooling system, but actual cooling systems contain economization as one of multiple modes of operation depending on outdoor air conditions. We further examined the air-cooled DC environmental performance with two operation modes (no economization and airside economization when applicable) in the continental U.S. (Chen and Wemhoff, 2022a). While the previous study provides a more reasonable depiction of the influence of cooling mode switching on DC performance and environmental metrics, only airside economization in DCs containing computer room air conditioning (CRAC) units was investigated.

This study builds upon previous research by providing the first known examination of how integrating economization into chilled water-based DCs can reduce Scope 3 operational carbon emissions and water scarcity footprint, that is the embodied emissions associated with the life cycle of the power generation process and electricity interchanges in the grid. This study examines these environmental benefits for various geographic locations and economization strategies. This work is important since chillers generally have higher coefficient of performance (COP) values than CRAC units (Tian et al., 2015) and therefore lead to the improved energy efficiency of data center cooling systems since direct expansion systems constitute a significant portion of cooling system energy consumption. Specifically, this study evaluates the performance of a DC at over 900 locations in the continental U.S. with six different operation modes for the chilled water system: (1) no economization, (2) airside economization under the ASHRAE Allowable (AA) envelope (Class A1), (3) airside economization under the ASHRAE recommended (AR) envelope, (4) water-side economization, (5) both airside and water-side economization under the AA envelope, and (6) both airside and water-side economization under the AR envelope. An evaporative cooler is used as the airside economizer to provide outdoor air to the server room when the ambient conditions are feasible per ASHRAE (*Air-Side Economizer Systems Guideline*). The water-side economizer is modeled as a standalone heat exchanger that precools the water coming out of the Computer Room Air Handling (CRAH) units prior to entering the chillers when outdoor air is cold. While this study provides a reasonable depiction of the influence of cooling mode switching on water-cooled DC performance and environmental metrics, the values reported here are conservative estimates since (1) the study

excludes the effects of a combined mode containing air mixing, and (2) the system capacitance associated with mode switching is ignored. Nevertheless, the estimates presented here provide key insights into how the environmental benefits of economization are affected by different economization strategies in different locations, suggesting that economization strategies can lead to significant power and water savings and reductions in carbon and water scarcity footprints.

The contributions of this work to the body of scientific research are summarized as (1) providing the first known evaluation of the impact of location on carbon and water scarcity footprints for data centers cooled using chilled water systems, (2) calculating the reduction in carbon and water scarcity footprints when airside and/or water-side economization are employed, and (3) showing how the reduction in carbon and water scarcity footprints is impacted by location and the ASHRAE envelope.

2. DC performance metrics

DC performance can be evaluated from different performance metrics. This study investigates the effects of economization on a total number of four different metrics.

2.1. PUE

First, from an energy efficiency perspective, one of the most important performance metrics is the Power Usage Effectiveness (PUE), which describes how efficiently a DC utilizes their power resources. PUE is defined as the ratio of the total amount of energy used by a DC to the energy delivered to computing equipment:

$$PUE = \frac{\text{Total Facility Energy } (P_{site})}{\text{IT Equipment Energy } (P_{IT})} \quad (1)$$

In this study, the PUE is calculated for the cooling system only as a major contributor to the numerator of Eq. (1), however it should be noted that inefficiencies in the electrical system, such as those in the uninterruptible power supply (UPS), also contribute to PUE (Barroso et al., 2013; Wemhoff and Ahmed, 2022).

2.2. CUE and wue

Two complementary metrics were later proposed by The Green Grid (Belady, 2010; Belady and Pouchet, 2011) to access the DC performance

from a sustainability perspective: Carbon Usage Effectiveness (CUE) and Water Usage Effectiveness (WUE). According to The Green Grid, the CUE is defined as the ratio of total emissions caused by the total DC energy to IT equipment energy since the majority of carbon emissions stem from DC operation instead of in DC materials (Belkhir and Elmeliqi, 2018). The units of the CUE metric are kilograms of carbon dioxide equivalent (kg CO₂e) per kWh. The CUE related to PUE by

$$CUE = EF \cdot PUE \quad (2)$$

where EF is the emission factor that quantifies the total amount of emissions emitted for consumption of 1 kWh electricity. Much research has been done to determine the appropriate regional EF values. Here, Scope 3 U.S. county-level consumption EFs are used that utilize input-output theory (Chen and Wemhoff, 2021a), and state-level EFs are estimated as the average of the state's county-level EFs. It should be noted that while this study examines EFs based on grid-based electricity consumption, the use of on-site renewable energy with ample storage, smart UPS systems, and workload management tools are key to reducing the environmental burden of data centers (Goori et al., 2013; Peng et al., 2022).

WUE is used to address the water consumption associated with DCs and is defined as the amount of water consumed onsite (in Liters) per kWh of IT power. WUE can be further extended to incorporate the water consumption associated with power generation for data center energy consumption (Belady and Pouchet, 2011) and is referred to as WUE_{source}:

$$\begin{aligned} WUE_{\text{source}} &= \frac{W_{\text{site}} + W_{\text{offsite}}}{P_{\text{IT}}} \\ &= EWIF \cdot PUE + WUE \end{aligned} \quad (3)$$

where W_{site} and W_{offsite} represent DC onsite and offsite water consumption, respectively; and EWIF is the energy water intensity factor, which measures the amount of water used to produce the energy consumed by the DC. Although little has been published about DC onsite WUE predictions and measurements, Pegus et al. (2016) analyzed the PUE, CUE and WUE of a university DC that employs many modern techniques to improve its energy efficiency, such as hot aisle containment, renewable energy and free cooling (via an evaporative cooling tower) from outdoor air. They concluded that (1) the water usage is higher in the warmer months and lower in cooler months due to evaporative loss and chiller use, and (2) free cooling in cooler months leads to a lower WUE. Recently Lei and Masanet (Lei and Masanet, 2022) applied a hybrid physical-statistical method to estimate PUE and WUE values for data centers of different sizes in different climate zones with airside and waterside economization. The simplistic physical model includes a range of estimates for power and water consumption based on specified ranges of input variables such as equipment efficiencies, air temperatures and relative humidity values, and climate zone. The results suggest a strong WUE correlation to cooling system type, with a CRAH-based system containing a water-cooled chiller having among the largest WUE values for any climate zone. They also showed that implementing airside economization can reduce PUE and WUE values by approximately 30% each.

2.3. WSUE

This study also considers the recently proposed metric Water Scarcity Usage Effectiveness (WSUE), which is defined as the holistic DC water scarcity footprint (WSF) per IT load. The WSF represents the volume of water consumption that also accounts for water availability at the various points of consumption (onsite and at the power generation source), thereby enabling the comparison of water scarcity in different regions (Boulay et al., 2018). WSUE is important since several regions in the U.S. are experiencing more frequent and longer durations of droughts due to climate change (Jones and van Vliet, 2018), and WSUE

enables the quantification of DC water scarcity impacts, which is lacking in the commonly-used WUE metric. The WSUE is calculated as:

$$WSUE = \frac{WSF}{P_{\text{IT}}} = A_{\text{cf}} \cdot W_{\text{site}} + SWI \cdot P_{\text{site}} \quad (4)$$

where A_{cf} is the regional water scarcity coefficient (Lee et al., 2019). By its definition, A_{cf} is bounded between 0.1 to 100, and high A_{cf} values represent water scarce regions. Thus, large WSUE values, indicating a more intense relationship between water consumption and regional water availability, can either be caused by high water consumption or severe water scarcity. SWI represents the scarce water index, which quantifies the impact of electricity consumption on regional water scarcity (Chen and Wemhoff, 2021b). Values of SWI ranging from 0.53 L/kWh (water-rich Boston, MA) to 890 L/kWh (water-scarce Phoenix, AZ) have been reported (Chen and Wemhoff, 2022b).

3. Modeling

3.1. DC modeling

The simulations in this study are intended to raise awareness of the potential for reducing environmental burden when economization technologies are introduced. Furthermore, the large quantity of simulations requires a rapid, robust modeling strategy to achieve this goal. As a result, the DC models contain the relevant physics but with some simplifications (e.g., fixed parameters) to enable this strategy. In this study, a generic DC with a CRAH-based cooling system is computationally modeled at 925 locations using the National Renewable Energy Laboratory's (NREL's) TMY3 database. The Villanova Thermodynamic Analysis of Systems (VTAS) software is used to perform the computational modeling work in this study. VTAS is a thermal-fluidic flow network modeling tool for DC cooling systems, including contributions by individual servers, the DC airside, and the HVAC components (Wemhoff et al., 2013) through detailed component models. VTAS solves the coupled network and component models using MATLAB. VTAS models of DC cooling systems have previously been validated to experimental measurements (Khalid and Wemhoff, 2019).

Fig. 1 shows the schematic diagram of a DC with a CRAH-based cooling system. The IT load in the DC is designed to be a typical data center value of 400 kW, which falls into ranges attributed to localized internal data centers, mid-tier internal data centers, localized service provider data center, and mid-tier service provider data center using size and power density values provided by Isazadeh et al. (Isazadeh et al., 2023). The CRAH-based cooling system contains four CRAHs, four chillers and four cooling towers in a parallel configuration, and the supply air temperature is set at 19 °C. In the CRAH component model, the cooling load (100 kW), indoor supply air temperature (19 °C), and indoor supply air flowrate (2.0 m³/s) are fixed for an air-water crossflow heat exchanger with airside mixing. The cooling tower here is modeled as an infinite parallel flow heat exchanger with an outlet relative humidity of 100% for the moist air when allowable by entering air and water conditions, which is commonly employed simplification (J. W. Mitchell and J. E. Braun, 2013). The temperature difference of the exiting water temperature of the cooling tower in relation to the air inlet temperature is fixed at 4 °C to ensure that the Second Law of Thermodynamics is achieved in the cooling tower regardless of outdoor air conditions (although the actual temperature difference also depends on wet bulb temperature), and the water mass flow rate is fixed at 4 kg/s. All pumps and fans are assumed to have an efficiency of 80%. Relaxation parameters are 1.0 and 0.01 for the global and flow network algorithms, and convergence tolerances of 10⁻² and 10⁻⁴ for the global and flow network solvers. The figure shows an indoor air loop connecting the airside of redundant CRAH units to the data center whitespace, and a chilled water loop connecting the evaporative side of redundant chillers to the CRAH units. The condenser water loop runs from the condenser

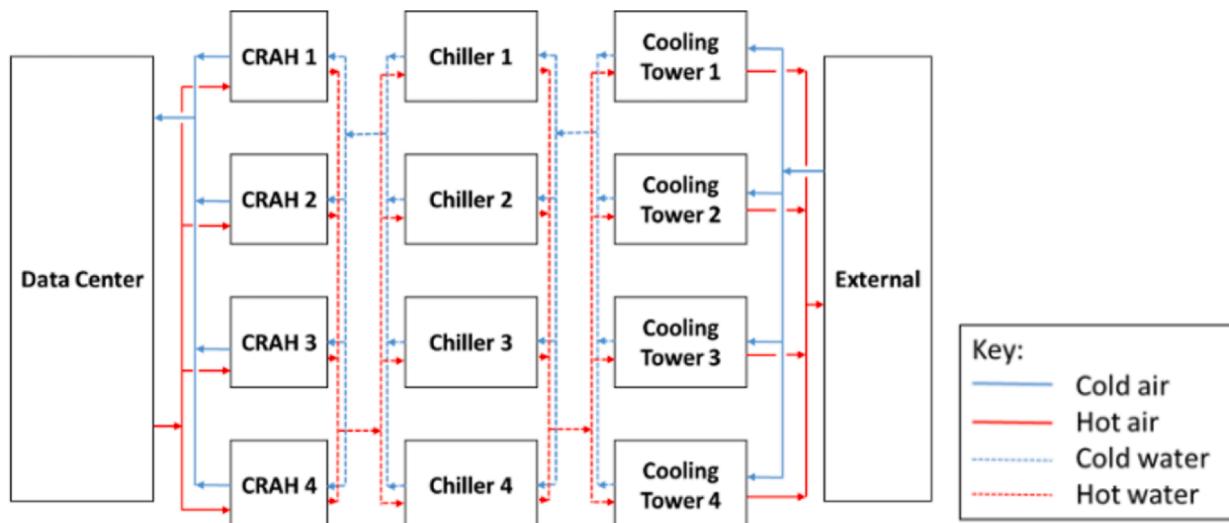


Fig. 1. Schematic diagram of a DC with CRAH-based cooling system (A fan is provided in each airstream, and the make-up water lines for the cooling towers are not shown).

side of redundant chillers to redundant cooling towers, where heat and mass transfer occurs with outdoor air.

Fig. 2(a) shows the schematic diagram of a DC cooled by an evaporative cooler, which is the airside economizer implemented in this study. The evaporative cooling system uses an adiabatic evaporative cooler with a typical efficiency η of 0.9, which is defined as:

$$\eta = \frac{T_{ao} - T_{ai}}{T_{wb} - T_{ai}} \quad (5)$$

where T_{ai} , T_{ao} , and T_{wb} are the inlet air, outlet air, and wet bulb temperatures, respectively. This efficiency is slightly higher than the reported efficiency of 0.85 by Bruno in 2011 (Bruno, 2011) and accounts for anticipated improvements in efficiency since then. The mass flow rate of the external air through the evaporative cooler and into the DC is fixed at $8.0 \text{ m}^3/\text{s}$ for consistency with the CRAH-based cooling system, although this approach allows for an elevated supply air temperature. 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. The water loss for the cooling system is therefore by evaporation in either the cooling towers or the evaporative coolers

and is calculated as the dry air mass flow rate times the change in humidity ratio.

Fig. 2(b) shows the schematic diagram of a DC cooled by a CRAH units with a water-side economizer. The water-side economizer is modeled as a standalone air-water crossflow heat exchanger with mixing on the air side and a fixed thermal conductance ($UA = 10,000 \text{ W/K}$). The water-side economizer is activated when the ambient air temperature drops below the water inlet temperature of 39°C .

3.2. COP modeling

The key to PUE estimation for CRAC and CRAH cooling system configurations in different climate zones is the temperature dependence of the COP of direct expansion units. This dependence was determined through a separate, secondary system model where a single 100 kW chiller component model that includes a detailed refrigeration cycle was adjusted to determine the COP under various conditions. This separate chiller component is modeled via an ideal R134a refrigeration cycle (i.e., refrigerant exits evaporator as saturated vapor, refrigerant exits condenser as saturated liquid, isotropic heat exchange in the evaporator

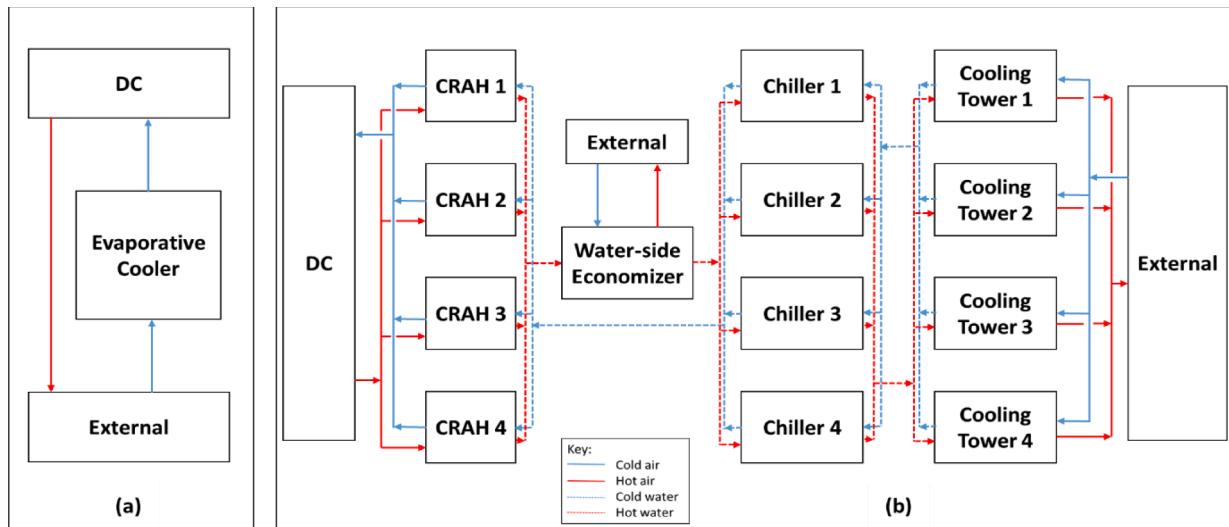


Fig. 2. (a) Schematic diagram of a DC with airside economization (evaporative cooling system) and (b) Schematic diagram of a DC with water-side economization (standalone heat exchanger that bypasses the chiller).

and condenser, isentropic compression in the compressor, and isenthalpic transition in the expansion valve) with a varying condenser water supply temperature by directly connecting the condenser water return line to an external water reservoir with specified temperature. This external temperature is altered between 10 °C and 40 °C, and the condenser saturation temperature is adjusted to achieve a fixed condenser conductance ($UA = 160,000 \text{ W/K}$) that satisfies the Second Law of Thermodynamics in the condenser heat exchange process and provides COP values that are consistent with feedback from manufacturers. The chiller capacity is maintained by connecting a 100 kW CRAH unit and data center on the chilled water side of the chiller per Fig. 3a. The refrigerant evaporator temperature is fixed at -4 °C, and the chilled water supply temperature was adjusted to 20 °C for condenser water supply temperatures of 30 °C and 40 °C, 15 °C for a condenser water supply temperature of 20 °C, and 5 °C for a condenser water supply temperature of 10 °C to satisfy the Second Law of Thermodynamics. The

resultant data are used to approximate the COP variation under the above fixed conditions but with varying condenser water supply temperatures, where linear interpolation is used between points. Fig. 3b provides the resultant predicted variation in chiller COP values under these conditions along with reported values by Squillo (T. Squillo, 2018) demonstrating good agreement.

3.3. DC performance metrics prediction

Conservative estimates of reductions in DC performance metrics were achieved by modeling a series of steady-state simulations in the system of Fig. 1 to TMY3 data at 925 U.S. locations, with each steady-state simulation corresponding to a specific hour in the TMY3 database. The resultant calculated annualized DC metrics are the average of the collection of simulations. Economization technologies (Fig. 2) were employed when the outdoor climate for the specific hour in the TMY3

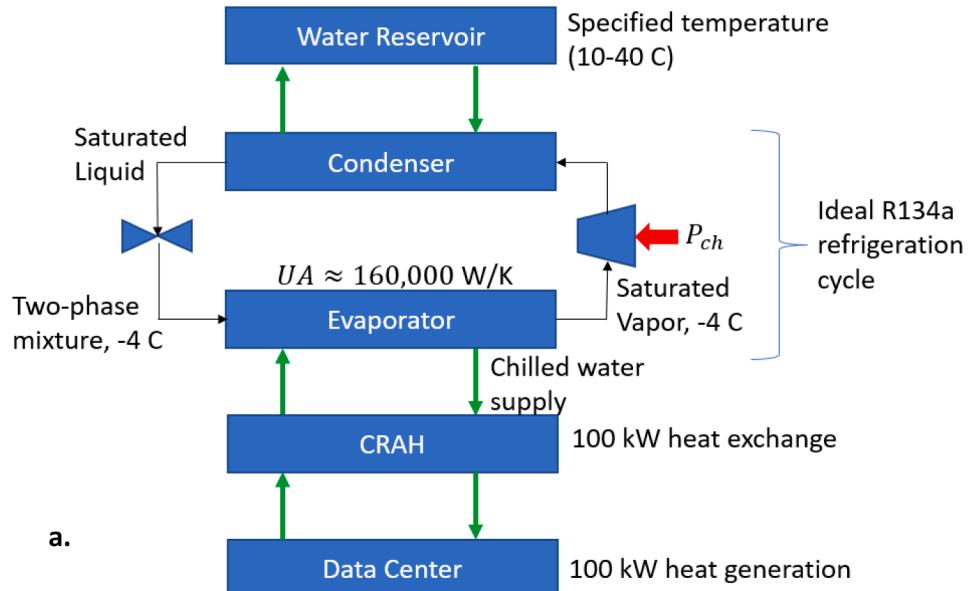


Fig. 3. a. Diagram of chiller COP calculation. b. Chiller COP based on condenser water supply temperature. Also provided are estimates based on data by Squillo (T. Squillo, 2018) for 100% load, 6.7 °C chilled water supply temperature, 5.6 °C chilled water temperature change.

database fell into the ASHRAE Recommended and/or A1 Allowable envelopes, enabling a comparison of the reduction in DC performance metrics when economization is employed. These two envelopes were chosen as the most popular standards for DC operation. Fig. 4 depicts this approach for a simplified five-hour period. State averages are calculated based on the values associated with each TMY3 location. This study applies airside economization, water-side economization, and both economization technologies in this manner to perform the estimated DC metric improvements. The estimates here are conservative since the actual implementation of economization technologies is generally not "either/or" but rather a continuous introduction of outside air into a return airstream (Khalid and Wemhoff, 2019). The approach here was used to ensure stability in the vast ensemble of simulations for different outdoor weather conditions.

PUE calculations for specified external conditions i follow

$$PUE_i = \frac{\sum P_f + \sum P_p + P_{ch} + P_{IT}}{P_{IT}} \quad (6)$$

where the subscripts f , p , ch and IT represent fan, pump, chiller compressor, and IT equipment. Fan power consumption includes the CRAH fans and cooling tower fans, and pump power consumption includes the chilled water, condenser water, and makeup water loops. The WUE for specified external conditions i is calculated as

$$WUE_i = \frac{W_{evap} + W_{ct}}{P_{IT}} \quad (7)$$

where W_{evap} and W_{ct} represent the water loss in the evaporative cooler and cooling tower, respectively. Note that Eqs. (6) and (7) are direct impacted by the psychrometric state of the ambient air via the cooling provided by the evaporative cooler and cooling tower, thereby influencing P_{ch} , as well as the on-site water consumption to achieve an evaporative cooler efficiency of 0.9 and a saturated outlet air stream from the cooling tower.

3.4. Statistical significance determination

Statistical significance testing on DC performance metrics was performed using a COP expanded uncertainty (95% confidence interval) of $\pm 10\%$ based on Fig. 3a, an evaporative cooler efficiency expanded uncertainty of $\pm 10\%$, and a pump/fan efficiency expanded uncertainty of 0.2 per earlier work (Wemhoff and Ahmed, 2022). Therefore, a set of 50

data center simulations were performed for mean external conditions of $22^{\circ}\text{C} \pm 3^{\circ}\text{C}$, $45\% \pm 10\%$ RH to capture a subset of ambient conditions under the ASHRAE recommended envelope. The simplified cooling tower model used in this study was compared to the more detailed, but less robust model (Khan and Zubair, 2004) on a test data center model, indicating that the simplified cooling tower overestimates the evaporative cooling rate by 38%, so the expanded uncertainty was set as $\pm 38\%$ for the cooling tower evaporation rate. The aforementioned 4°C temperature difference seen in the cooling tower was also adjusted with an expanded uncertainty of $\pm 2^{\circ}\text{C}$. Finally, the expanded uncertainty is set as $\pm 10\%$ for local environmental metrics SWI and A_{cf} based on engineering judgement. Baseline values for SWI and A_{cf} are for Philadelphia, PA, USA. Random sampling of external conditions and input variables was used following a normal distribution. The statistical significance testing for 95% confidence follows that in earlier work where a two-sample z -test for comparing means is employed (Wemhoff and Ahmed, 2022).

4. Results and discussion

4.1. DC energy efficiency - PUE

Fig. 5 shows the predicted PUE values of a water-cooled DC built in different continental U.S. states, and Table S.1 in the Supporting Information reveals the PUE percentage decrease achieved by utilizing economization with various operating modes compared to a base case with no economization. The DC PUE associated with the base case is the highest for each state among the various DC operating cases as expected, and base case PUE values vary from 1.51 (ME) to 1.59 (FL). Higher PUE values are seen in southern states due to their warmer climate. In general, incorporating airside economizers achieves a 2.4% to 7.7% state-averaged PUE reduction for AR and AA envelopes, respectively. The AA envelope enables more energy savings compared to the AR envelope due to a longer operation time for airside economization. Further, implementing water-side economizers allows for a state-averaged PUE reduction of 4.5%. The lowest PUE is achieved when both economization technologies are employed (6.5% to 11.2% decrease, per AR and AA envelopes, respectively). The percentage of time that external conditions fall within the AR envelope for all chosen locations, enabling airside economization, ranges from zero to 21.4%, with a mean of 6.6%. The percentage of time that these conditions fall within the AA envelope varies between 0.4% to 50.2%, with a mean of 21.5%.

To seek key insights of how the environmental benefits of economization are affected by different economization strategies in different locations, the chosen cities were also categorized into seven different climate zones according to the International Energy Conservation Code (IECC). Table 1 shows the PUE reduction at various climate zones by implementing different economization strategies. Overall, lower PUE values are seen more often at colder regions. The maximum PUE savings by airside economization is found to be at Zone 3 (up to 10.0%). The water-side economization is also a good strategy to improve data center energy efficiency, which yields up to 5% of PUE reduction in Zone 1. Combining both airside and water-side economization, a total of 13.3% of PUE can be reduced in Zone 3, which is the most PUE saving scenario in this case. This number, albeit smaller than the roughly 30% reduction predicted by Lei and Masanet (Lei and Masanet, 2022), provides a conservative value of reduction due to the "either/or" nature of our model and is consistent with the 3–17% PUE reduction (depending on climate zone) predicted by Gozcu et al. (Gozcu et al., 2017).

4.2. DC carbon emissions – CUE

Fig. 6 shows the aggregated state-level CUE values under various economization operating modes, and Table S.2 in the Supporting Information documents the CUE percentage decrease of each mode as

Day/time	Base ¹	AE-AR	AE-AA
Hour 1	1.34	1.34	1.34
Hour 2	1.22	1.22	1.18
Hour 3	1.43	1.32	1.32
Hour 4	1.50	1.50	1.42
Hour 5	1.30	1.22	1.22
Average:	1.36	1.32	1.30

¹Key: Ambient conditions allow for airside economization within the allowable range only
Ambient conditions allow for airside economization in both the allowable and recommended ranges

Fig. 4. Simplified depiction of the method used to calculate the metrics for a five-hour period at a specific location. Calculated PUE values are shown in each column. The ambient conditions in this case allow for airside economization in both the ASHRAE recommended (AR) and allowable (AA) ranges in Hours 3 and 5, whereas airside economization is used in only the allowable envelope for Hours 2 and 4. The ambient conditions in this case do not allow for airside economization in Hour 1.

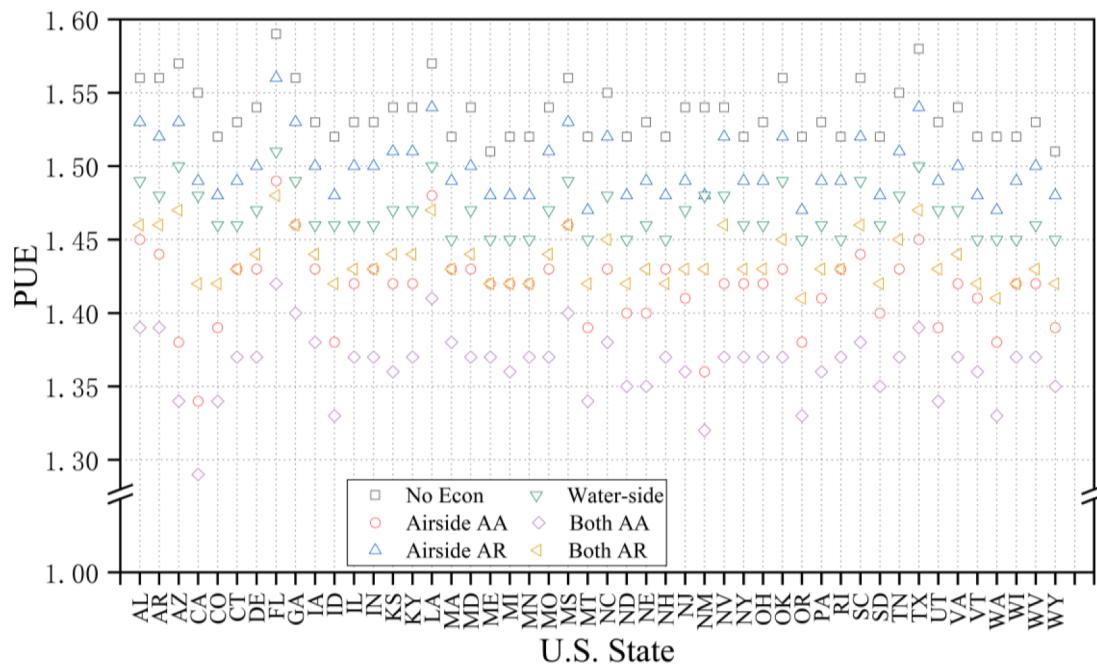


Fig. 5. State-averaged PUE predictions for water-cooled DCs.

Table 1
PUE reduction by IECC climate zone.

IECC Climate Zone	No Econ	Airside AR	Airside AA	Water-side	Both AR	Both AA
1	1.61	1.9%	6.2%	5.0%	6.8%	10.3%
2	1.58	2.0%	7.2%	4.8%	6.6%	11.1%
3	1.56	2.9%	10.0%	4.6%	7.2%	13.3%
4	1.54	2.5%	8.0%	4.5%	6.7%	11.5%
5	1.53	2.6%	7.9%	4.4%	6.6%	11.3%
6	1.52	2.3%	7.1%	4.2%	6.2%	10.4%
7	1.51	2.1%	6.2%	4.2%	6.0%	9.6%

compared with the base case. The base case DC CUE ranges from 0.31 kg/kWh (VT) to 0.97 kg/kWh (WY) due to variations in PUE and the regional power generation portfolio. Specifically, implementing an air-side economizer in the chilled water DC within the AR envelope could save 2.4% nationally and higher for high-emission states (e.g., up to nearly 4% in CA). Using the AA envelope as a basis enables a larger range of ambient conditions for airside economization, leading to carbon emissions savings of 7.7% as a national average, and up to 13.5% in CA.

Another effective way to reduce carbon emissions is through water-side economization, which saves a national average of 4.4% of carbon emissions, with savings as high as 5.0% in some cases. The lowest CUE can be achieved by employing both economization technologies (6.5% and 11.0% decrease as a national average using AR and AA envelopes,

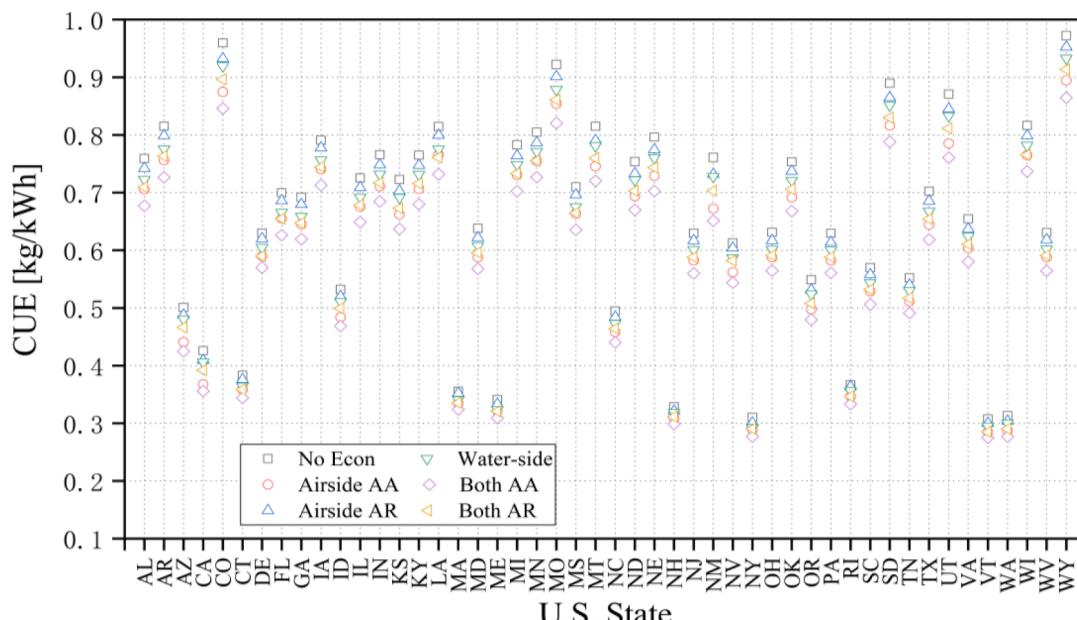


Fig. 6. State-averaged CUE predictions for water-cooled DCs.

respectively). The State of CO is found to be the location with the maximum carbon savings potential, 11.8%, or 0.12 kg CO₂e per kWh of electricity consumption, indicating that economization can be used as a promising carbon emissions reduction strategy.

4.3. DC water consumption – WUE

Fig. 7 shows the aggregated state-level on-site WUE values of the DC with various airside economization operating modes, and Table S.3 in the Supporting Information documents the percentage decrease of each mode, compared with the base case. The base case DC WUE ranges from 1.85 L/kWh (ND) to 2.30 L/kWh (FL), which is the highest among all other cases per state as expected. The waterside economization does not alter the DC WUE since the water loss within the chiller and the economizer are negligible. However, results reveal that the utilization of the airside economization technology reduces the DC water consumption considerably since evaporative coolers involve less water consumption than cooling towers. 7.0% and 22.4% of water consumption on average can be saved using the AR and AA envelopes as a basis, respectively, the latter of which is on par with savings predicted by Lei and Masanet (Lei and Masanet, 2022), and the reduction of WUE by approximately one L/kWh from introducing airside economization is similar to results by Gozcu et al. (Gozcu et al., 2017). Specifically, the State of CA saves up to 37.2% of water, which converts to over 0.8 L of water savings per kWh, indicating that airside economization in chilled water-based DC cooling systems reduces water consumption effectively, especially in areas with severe drought situations.

4.4. DC water scarcity impact – WSUE

Fig. 8 shows the aggregated state-level WSUE under various economization operation conditions, and Table S.4 in the Supporting Information lists the WSUE percentage change at each condition. It is found that the WSUE varies greatly among regions with a median of 2.95 L/kWh with a population standard deviation σ of 168 L/kWh. The base case DC WSUE ranges from 1.20 L/kWh (VT) to 968 L/kWh (AZ). Implementing airside and waterside economizers in all states reduces water scarcity impact. State-averaged WSUE values are reduced by 3.9% and 12.4% based on AR and AA envelopes, respectively, for airside economization. Water-side economization also reduces WSUE by an

average of 3% due to the reduction in PUE.

Our previous research indicates that CRAC-based DCs in CA are attributed with annual average WSUE of 262 L/kWh, while in this study, a chilled water-based DC at the same location has a lower WSUE of 252 L/kWh due to the higher chiller COP compared to the CRAC COP. This result also reveals the limitations of the WUE metric since a water-intensive cooling solution with larger on-site water consumption could potentially result in a lower WSUE than a solution requiring no or less on-site water consumption. This result is due to the higher water scarcity impact associated with the indirect water consumption in some locations (higher SWI per eq. (4)).

4.5. Statistical significance testing

The results of statistical significance testing are provided in Table 2. The table shows that the use of both economization technologies provide a statistically significant reduction in metrics. The expanded uncertainty values for the metrics are small compared to the mean values. The reduction seen in airside economization is more significant than in waterside economization due to the removal of the chiller and cooling tower from the cooling system.

4.6. Discussion

Fig. 9 compares the CUE and WSUE results for four states in different climate zones with different water availability values: CA, CO, FL, and MA. The results reveal that both CUE and WSUE vary significantly by region. Notably, CA possesses the highest WSUE among this group of states due to the state's dry climate. Electricity imports from neighboring water scarce regions (e.g., AZ and NV) also contribute to the higher WSUE value. On the other hand, MA maintains the lowest value due to abundant water resources and a clean energy production portfolio. Similarly, the highest and the lowest CUE values are found in CO and MA, respectively, due to significant power production portfolio differences. Overall, economization technologies have positive impacts on both DC carbon emissions and regional water scarcity impacts. However, CUE and WSUE reductions are more noticeable in regions with greater inherent carbon emissions and water scarcity, respectively.

The approach used here for WSUE estimation requires knowledge of the distribution of SWI metrics, which may be difficult to obtain if grid

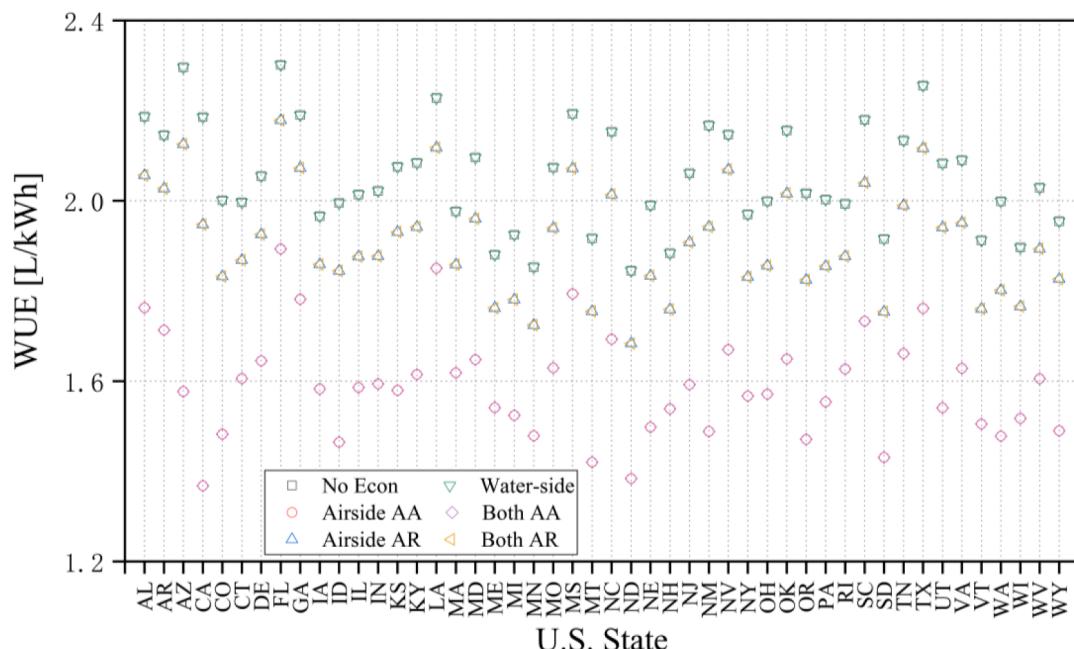


Fig. 7. State-averaged WUE predictions for chilled water-based DC cooling systems.

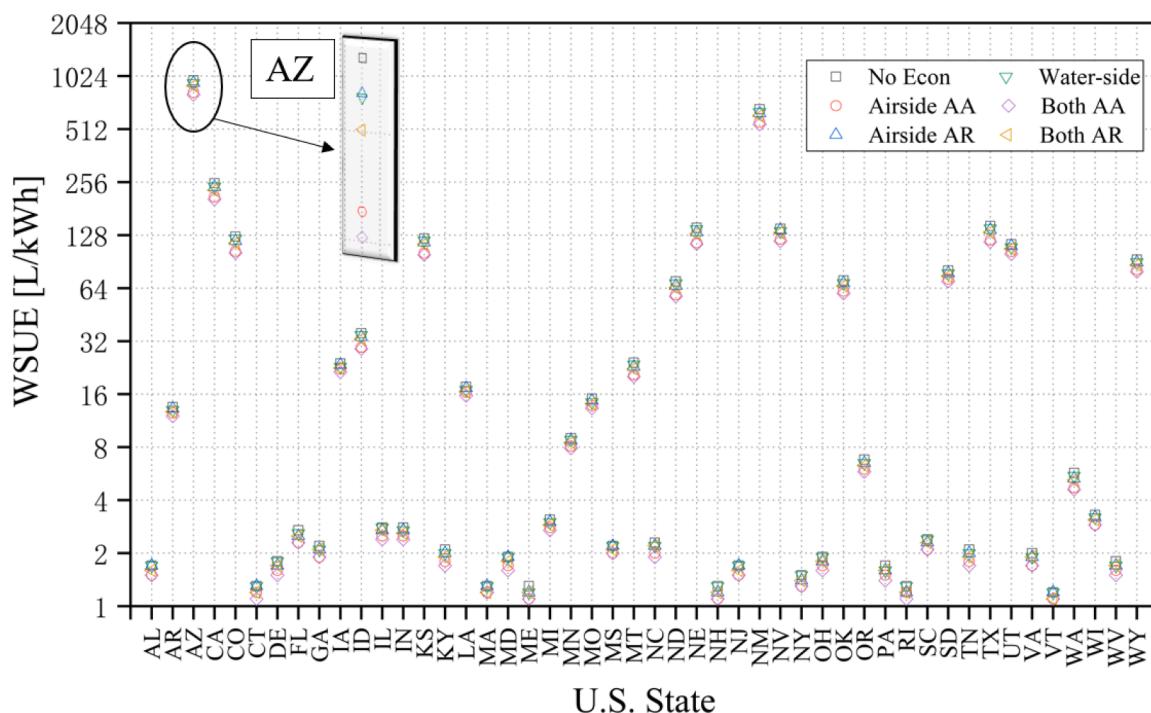


Fig. 8. State-averaged WSUE predictions.

Table 2
Results from statistical significance modeling¹.

Metric	Baseline ²	Airsides Economization ³	Waterside Economization ³
PUE	1.65 ±0.02	1.01±0.00	1.61±0.02
WUE, L/kWh	2.57 ±0.13	0.24±0.01	2.07±0.11
CUE, kg CO ₂ e/ kWh	0.68 ±0.01	0.41±0.00	0.66±0.01
WSUE, L/kWh	1.95 ±0.05	0.76±0.01	1.76±0.04

¹ Intervals shown in table are expanded uncertainties for 95% confidence.

² The baseline case is defined here as the system without economization.

³ The reductions in all metrics in the table are found to be statistically significant.

electricity transfer information is unknown. However, SWI may be approximated as the product of the energy water intensity factor (EWIF) and available water remaining (AWARE) factor, and the accuracy of this approximation is needed. Furthermore, the WSUE does not factor in other contributors to water stress such as water pollution.

The results presented in this article show promising energy (PUE), carbon emissions (CUE), water consumption (WUE) and water scarcity impact (WSUE) savings by applying both airside and water-side economizers to DCs with chilled water-based cooling systems. However, it is important to acknowledge that applying economization to DCs requires other considerations to fulfill DC design criteria such as humidification, particulate contamination, gaseous contamination, cooling tower freezing protection and necessary maintenance. Humidifiers, air filters, gas treatment and monitoring devices and other control schemes are needed to ensure a healthy DC operating environment, which could mitigate potential energy and environmental savings in some regions. Although economizers consume little energy, they still have a long payback period because of the construction cost and relatively short DC facility life cycle (10–15 years) compared to other commercial and institutional buildings (Lui, 2010). More detailed economic analyses are therefore needed to support investment decisions.

5. Conclusion

This paper investigates the potential improvements in sustainability performance of a DC with a chilled water cooling system by implementing both airside and water-side economization at different regions in the continental U.S. Results indicate that airside economization reduces state-averaged PUE values from 2.4% to 7.7%, and water-side economization leads to a nationally-averaged 4.5% PUE reduction. The maximum PUE savings are achieved when both economization technologies are implemented (6.5% and 11.2% of PUE reduction for AR and AA envelopes, respectively). The carbon emissions and water consumption of these DCs are also mitigated significantly due to energy savings. Specifically, when the AA envelope is used as a basis, then up to 11% of carbon emissions and up to 22.4% of water consumption can be recovered using airside economizers only. Results also reveal that the water scarcity impact of a DC can be reduced by up to 14.7% when both economization technologies are in use with the AA envelope as a basis. Results show that a water-intensive cooling solution with large on-site water consumption could result in a lower WSUE than a solution requiring no or less on-site water consumption, which indicates the importance of the WSUE metric when evaluating DC water scarcity. However, these numbers could be higher if the mixing of outside and return air streams is used in airside economizers and the supply air setpoint was allowed to modulate in conjunction with various economization technologies, thus warranting further investigation. Furthermore, the evaporative cooling efficiency may vary with outdoor air conditions, and this effect should be explored further.

CRediT authorship contribution statement

Li Chen: Methodology, Writing – original draft, Investigation, Data curation, Visualization, Software. **Aaron P. Wemhoff:** Conceptualization, Methodology, Software, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial

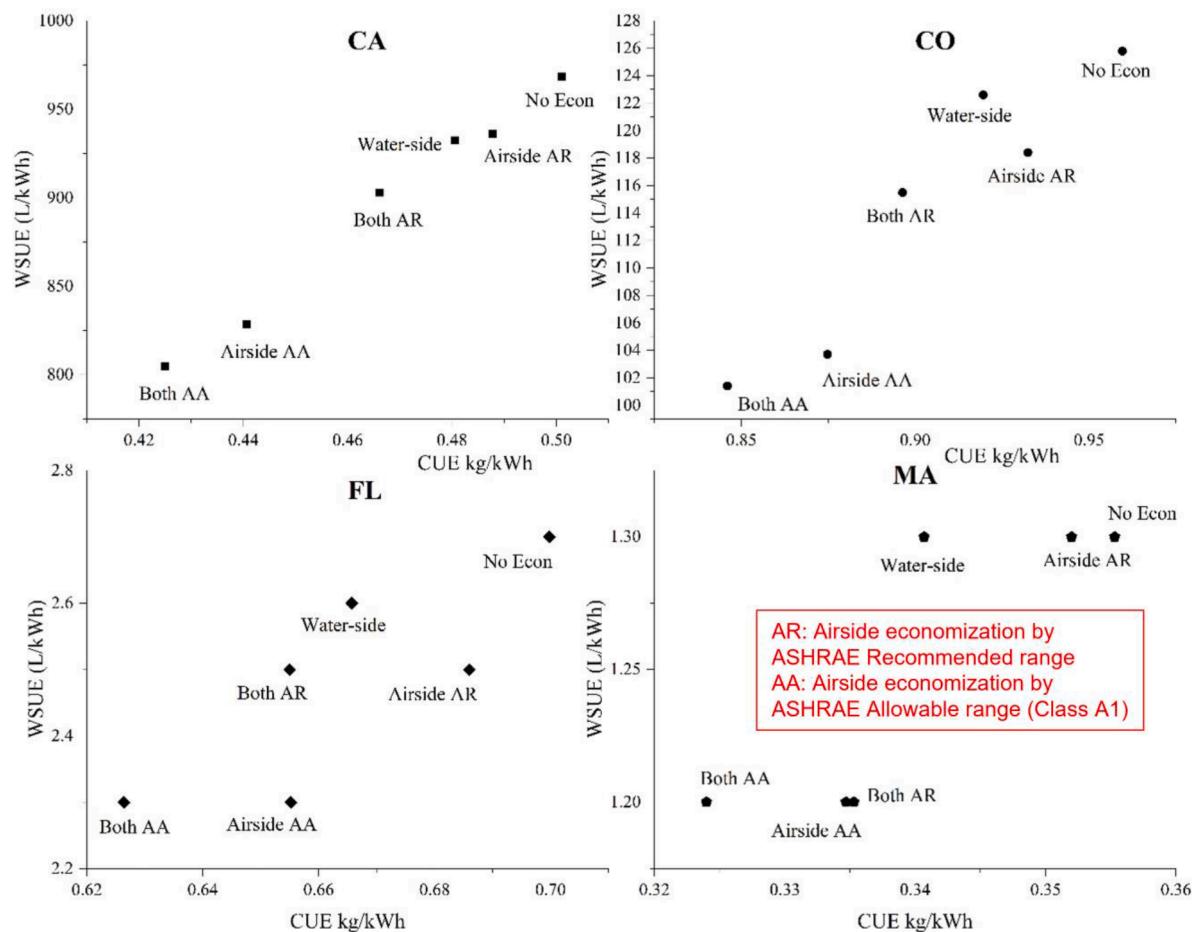


Fig. 9. CUE & WSUE comparison for selected regions.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This material is based upon work supported by the National Science Foundation (NSF) under Grant no. IIP 1738782. 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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.resconrec.2023.107053](https://doi.org/10.1016/j.resconrec.2023.107053).

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