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Data Center Environmental Burden Reduction Through On-Site Renewable Power Generation

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The energy demands from data centers contribute greatly to water scarcity footprint and carbon emissions. Understanding the use of on-site renewable power generation is an important step to gain insight into making data centers more sustainable. This novel study examines the impact of on-site solar or wind energy on data center water scarcity usage effectiveness (WSUE) and carbon usage effectiveness (CUE) at a U.S. county scale for a given data center size, water consumption level, and energy efficiency. The analysis uncovers combinations of specific metrics associated with grid-based carbon emissions and water scarcity footprint that enable predictions of the improvements anticipated when implementing on-site solar or wind energy. The implementation of on-site renewables has the most benefit in reducing carbon footprint in areas with high existing grid-based emissions such as the western side of the Appalachian Mountains (e.g., central and eastern Kentucky). The largest benefit in reducing water scarcity footprint is generally seen in counties with low water scarcity compared to adjacent areas (e.g., northern California). [DOI: 10.1115/1.4065053]

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1 Introduction

The growth in the size and quantity of data centers has increased concern about the sector's energy consumption. In 2018, it was reported that data centers consume up to 200 TW h of electricity annually, accounting for 1% of the global energy demand [1]. More recent estimates have suggested that data centers consume up to 500 TW h of electricity annually [2].

The large demand for electricity coming from data centers has raised concerns about the environmental impacts of consuming large quantities of energy. The utilization of renewable energy resources, such as wind and solar power, has been proposed as a potential solution to reduce a data center's carbon footprint [3]. While most of these approaches involve using power purchase agreements with renewable energy providers [4], some have used on-site renewables such as installing solar panels on the roofs of hyperscale facilities [5]. The significance of on-site renewables' impact on carbon emissions can be quantified by tracking flows through the electric grid [6–9], generally through economic input–output theory. The resultant emission factors for electricity consumption are based on accepted life cycle values for various approaches to power generation [10,11].

While reducing carbon emissions is essential for a more sustainable data center, carbon emissions are just one factor that contributes to the sustainability of data centers. Hadian and Madani suggested that to consider an energy system "green," water and land footprints should also be considered [12]. Therefore, it is important to determine the total scope 1 and 2 water footprint associated with data center operation, as indicated by The Green Grid [13]. Furthermore, the amount of water consumption relative to water availability should also be considered, so a scope 1 and 2 water scarcity footprint is an important quantity when considering the holistic environmental burden of data center operation, even though public pressure tends to focus on scope 1 (on-site) water consumption [14].

The use of renewable energy for data centers has been proposed by several investigators, with an emphasis on the power distribution network in conjunction with workload allocation. Kumar et al. [15] investigated the use of renewable energy in conjunction with server virtualization and showed potential energy savings of 10–28%, depending on the virtualization scheme. Li et al. [16] suggested that the tuning of intermittent load fluctuations and available intermittent renewable energy sources reduces the capability to utilize renewable energy with increasing energy capacity, indicating a utilization of 54% and 5% for low and high energy capacity systems, respectively. Wang and Ye [17] proposed that using renewable energy in a microgrid works best with a cluster of data centers, utilizing the advantages of cluster-wide workload allocation. Their optimized model for a test case with three data centers indicates that renewable energy consumption exceeded grid energy consumption most of the time among the three data centers. Wan et al. [18] extend this concept to internet data centers with the goal of minimizing carbon footprint, demonstrating a reduction in emissions exceeding 80% for their test case. This approach may be more

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viable since it is difficult to manage the load variations and power availability for a single data center with on-site renewable energy production [19].

The aforementioned studies are important in determining the challenges posed by implementing on-site renewables, yet no known study exists that shows the potential reductions in carbon and water scarcity footprints at the U.S. county level when implementing on-site solar and wind power for data centers. The current study therefore provides the best-case values of combined carbon and water scarcity footprint reductions based on geographic location, with the guidance that the actual environmental benefits will depend on workload variation and renewable power availability.

A comprehensive study evaluating the impact of on-site renewable energy on the pairing of carbon and water scarcity footprints that include indirect contributions from power generation sources and grid electricity transfers is lacking in the literature. This is particularly true for water scarcity footprint in the data center industry, where existing research is lacking in identifying mitigating strategies. Therefore, this study fills an important research gap by calculating the reductions in these footprints at the U.S. county scale when on-site solar or wind energy is implemented. The study specifically examines how changes in these footprints are affected by geographic location, indicating, for the first time, specific metrics to provide guidance on the anticipated environmental benefits from an on-site power generation strategy.

2 Materials and Methods

Metrics have been widely used to measure the water consumption and energy efficiency of data centers, namely power usage effectiveness (PUE) and water usage effectiveness (WUE):

$$\mathrm{PUE} = \frac{P_{\mathrm{tot}}}{P_{\mathrm{IT}}} \tag{1}$$

$$\mathrm{WUE} = \frac{W_{\mathrm{site}}}{P_{\mathrm{IT}}} \tag{2}$$

where P_{tot}, P_{IT}, and W_{site} represent total power draw, IT load, and on-site water consumption, respectively. However, the holistic data center water footprint includes the water consumed at the power generation source and is represented by the metric

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

where the energy water intensity factor (EWIF) quantifies the amount of water required to produce the electric power consumed by the data center [13]. PUE is dimensionless, and the units of EWIF, WUE, and $\mathrm{WUE}_{\mathrm{source}}$ are L/kW h. The values of EWIF depend on both electricity generation method and geographic location [20].

The above performance metrics are commonly used to indicate environmental impact by data centers, but they do not provide a direct indication of neither carbon footprint nor water scarcity footprint. However, the metrics water scarcity usage effectiveness (WSUE) and carbon usage effectiveness (CUE) are direct indicators of the water scarcity and carbon footprints associated with data center operation:

$$\mathrm{WSUE} = \frac{\mathrm{WSF}}{P_{\mathrm{IT}}} \tag{4}$$

$$\mathrm{CUE} = \frac{C_{\mathrm{tot}}}{P_{\mathrm{IT}}} \tag{5}$$

where WSF is the water scarcity footprint, and C_{tot} is the total facility carbon footprint. The above metrics in Eqs. (4) and (5) include both direct and indirect sources. All metrics in Eqs. (1)–(5) are calculated on an annual basis.

The most accurate approach to assessing WSUE and CUE is to incorporate electricity transfers within the grid [21]. Carbon emissions and water scarcity footprint are embedded in electricity generation through both fuel combustion and also in the materials used to generate electricity, so it is important to use lifecycle calculations of emissions and water footprint. Furthermore, electricity transfers in the grid should be incorporated to accurately estimate the energy portfolio feeding a particular geographic location [22–24]. The equations to calculate these metrics are

$$\mathrm{WSUE} = A_{\mathrm{CF}}\mathrm{WUE} + \mathrm{SWI} \cdot \mathrm{PUE} \tag{6}$$

$$\mathrm{CUE} = \mathrm{CEF} \cdot \mathrm{PUE} \tag{7}$$

where A_{CF} is the available water remaining (AWARE)-characterization factor (CF) factor (a measure of water scarcity), SWI is the scarce water index, and CEF is the carbon emissions factor. Values of A_{CF}, SWI, and CEF are based on geographic location and may be estimated down to the U.S. county level. Equations (6) and (7) indicate that knowledge of the geographical distribution of these three factors enables location-dependent predictions of grid-based water scarcity footprint and carbon emissions for a data center with known PUE and WUE.

One can see from comparing Eqs. (1) and (2) to Eqs. (6) and (7) that while PUE and WUE are related to data center environmental burden (i.e., reducing PUE and WUE reduce WSUE and CUE), the true measure of environmental impact also requires examination of A_{CF}, SWI, and CEF. The use of on-site renewable energy effectively adjusts SWI and CEF by replacing a portion of upstream grid-based scarce water and carbon flows by their corresponding lifecycle values associated with on-site solar or wind energy.

2.1 Assessing Water Consumption From Power Generation.

To first assess the water scarcity and carbon footprints of a data center, it is helpful to examine the water flows within the grid to see which geographic areas are most impacted by water consumption in electricity generation. The U.S. Energy Information Administration's (EIA) annual report includes every power generation source in the US that produces over 1 MW h of electricity annually, as well as the geographic coordinates of these power plants [25]. Using geolocation software, each power generation plant is first assigned its home U.S. county. A power generation mix is then calculated for each county. In this study, emissions generation resource integrated database (eGRID) subregion boundaries and county boundary regions are taken from the U.S. Environmental Protection Agency (EPA) [26]. Counties are assigned to one of the 26 eGRID subregion boundaries in the contiguous U.S. using the geographic centroids of each county.

Peer et al. [20] provide EWIF values based on power generation technology and location (eGRID subregion). Combining a county's power generation mix with the associated power generation EWIF value yields a county-level EWIF value:

$$\mathrm{EWIF} = \frac{\sum_i P_i \mathrm{EWIF}_i}{\sum_i P_i} \tag{8}$$

where all recorded power generation sources i within the county are used.

Figure 1 shows the EWIF values for each county based solely on county power generation sources using data from Ref. [20], the EIA [25], and Eq. (8). EWIF values contain a median value of 1.61 L/kW h. The figure shows that the highest EWIF values are seen in the southwestern U.S., indicating large water loss in power generation technologies in this region, which is likely due to the high evaporation rate of water due to a dry climate. This conclusion indicates a larger contribution to indirect water consumption by a data center compared to other parts of the country. The large EWIF values in the southwestern U.S. are specifically due to the prevalence of hydropower-based generation, which has an

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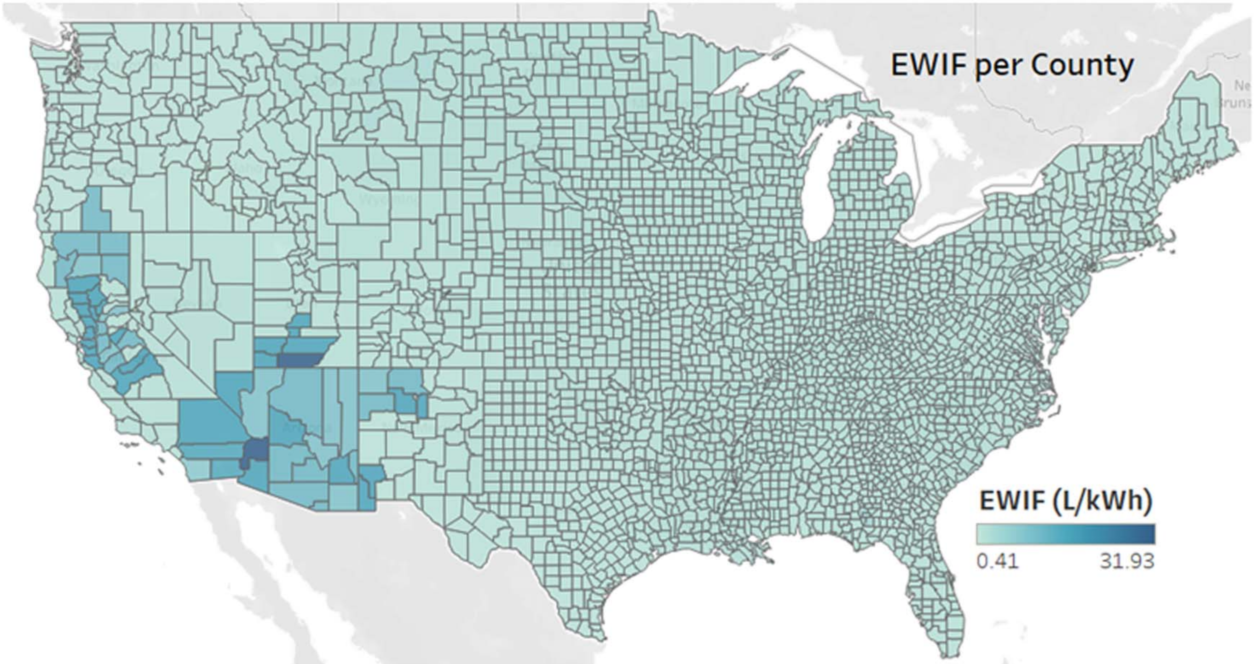

Fig. 1 EWIF values for every contiguous U.S. county

exceptionally large value (126 L/kW h in the Arizona-New Mexico eGRID subregion) compared to values ranging from 0 to 13 L/kW h for other generation technologies and/or eGRID subregions [20]. Since power can be transported across county borders and eGRID subregion borders, the EWIF can be defined here as only a rough approximation, but general trends at broader geographic scales (i.e., relatively large EWIF values in the southwestern U.S.) are independent of the inclusion of electricity transfers.

2.2 Assessing Water Scarcity. The amount of water available for human use after environmental needs are met varies across each U.S. county. Several areas across the country are experiencing longer and more harsh droughts due to climate change, and it is important to quantify the scarcity of water in our results [27]. Lee et al. [28] created a U.S. model that quantifies water scarcity and the impact of water consumption in different U.S. counties. The AWARE-US CF, as the metric is named, compares regional water availability to a reference value of $0.0093\ \mathrm{m^3/m^2 \cdot month}$ and is bounded between 0.1 and 100 [29]. The factor is defined as

$$A_{\mathrm{CF}} = \frac{\mathrm{AMD_{REF}}}{\mathrm{AMD}} \tag{9}$$

where A_{CF} is the county's AWARE-US CF factor, AMD is water availability minus demand, and the subscript REF denotes a universal constant reference value. The factor is geographic-specific and applied within the calculations of WSUE (Eq. (6)). A high AWARE-US CF value represents areas of high-water scarcity. Figure 2 depicts the AWARE-US CF values for each county in the U.S., showing the largest water scarcity in the south-central and southwestern U.S., demonstrating a consistent trend with the EWIF values in Fig. 1.

2.3 Assessing Carbon Emissions From Power Generation. Embodied carbon in electricity flows is captured via the carbon emission factor (CEF) and is used in the CUE calculation of Eq. (7). CEF quantifies the amount of carbon emissions embodied in unitary electricity consumption by the percentage of each category of power production per county. The units for CEF are kg/kW h. Values of CEF for each power generation source are based on lifecycle emissions data by the Intergovernmental Panel on Climate Change and the World Nuclear Association [30] and incorporate electricity transfers within the grid, culminating in scope 1 and 2 emissions due to data center operation [31].

Figure 3 shows the CEF values for each county. CEF scores range from 0.007 kg/kW h to 0.902 kg/kW h, with a median CEF score of 0.17 kg/kW h, and a standard deviation of 0.452 kg/kW h. The largest values appear in the mountain regions (e.g., WY, UT, MT, SD, and ND) and near the western side of the Appalachian Mountains (e.g., WV, KY, and TN). The highest CEF values appear in the LGEE (Louisville Gas and Electric Company and Kentucky Utilities Company) balancing authority, which contains 83% coal power generation [32], where coal contains the highest life cycle emission rates of all power generation sources [30].

2.4 WSUE and Carbon Usage Effectiveness Metrics With On-Site Power Generation. The proposed solution to reduce data center environmental impacts is the introduction of on-site solar or wind power generation. Depending on the size, workload distribution, and electricity demand, each data center would be capable of producing a different quantity of electricity on-site. For this study, it is approximated that the hypothetical data center studied can produce 25% of their electricity demand on-site, on average. This percentage is a reasonable approximation and is based off conservative estimates from discussions with industry executives. Baseline values of PUE and WUE are taken as 1.85 and 1.80, respectively, as typical for many data centers. In this study, PUE and WUE are constant, although for computer room air conditioner (CRAC) cooling systems they are generally higher in the southern U.S. due to the effects of external air temperature on CRAC coefficient of performance [33] or the external wet-bulb temperature on the performance of evaporative cooling towers [34]. The nonzero WUE values largely stem from the use of evaporative cooling towers to reject heat from a condenser water loop connected to a chilled water system. Knowledge of PUE and WUE enable predictions of scope 1 and 2 carbon and water scarcity footprints due to data center operations since other factors are location dependent.

Calculations of WSUE and CUE via Eqs. (6) and (7), respectively, are modified to enable evaluation of the effects of on-site solar or wind power generation. Since PUE and WUE are taken

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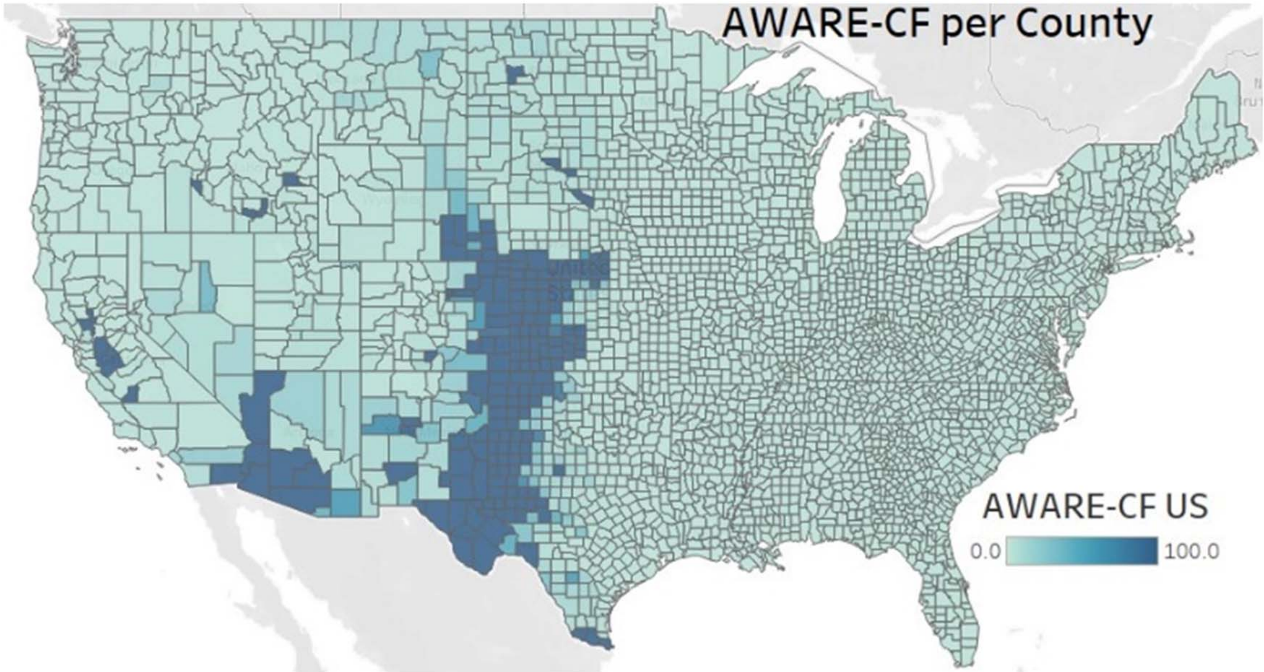

Fig. 2 AWARE-US CF values for every contiguous U.S. county (adapted using Ref. [28] supplementary information dataset, plotted via Tableau software)

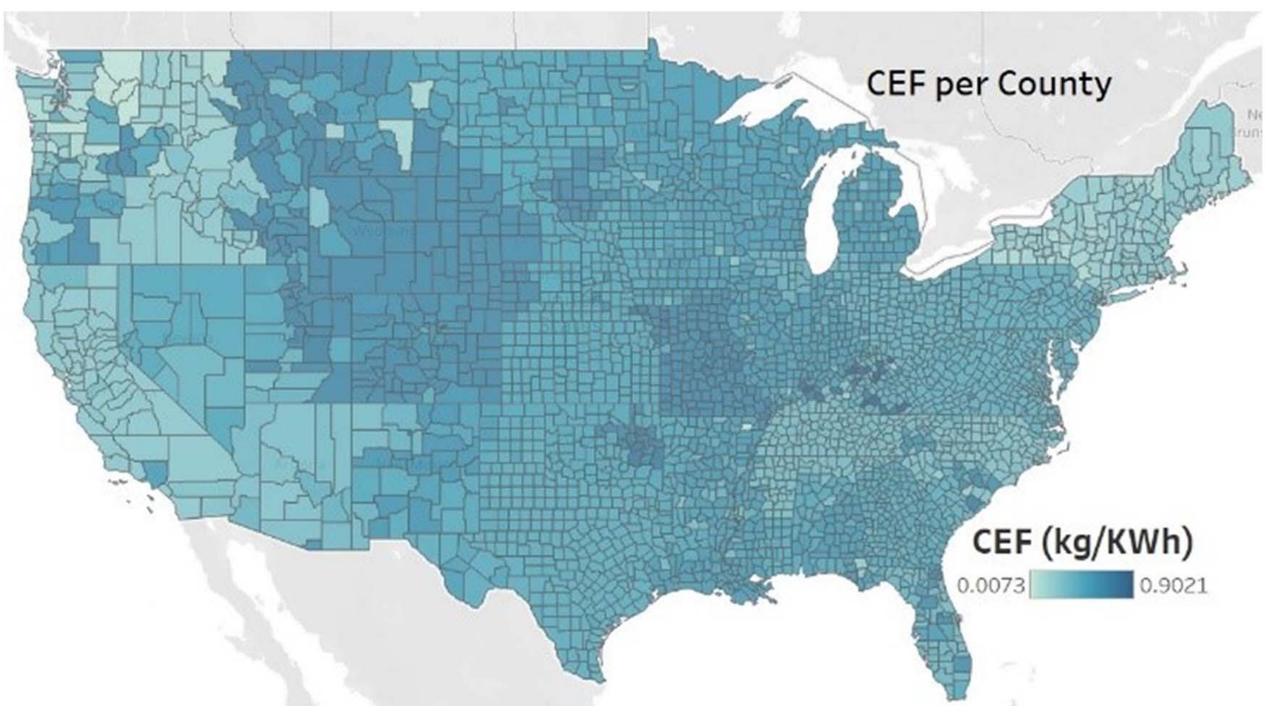

Fig. 3 CEF values for every contiguous U.S. county

to be constant, then only the factors related to electricity generation source are altered. Equation (6) may therefore be modified as

$$\mathrm{WSUE} = A_{\mathrm{CF}}\mathrm{WUE} + \mathrm{SWI}_{\mathrm{EFF}} \cdot \mathrm{PUE} \tag{10}$$

where $\mathrm{SWI}_{\mathrm{EFF}} = \{\mathrm{SWI}_{\mathrm{GS}}, \mathrm{SWI}_{\mathrm{GW}}\}$ is the effective scarce water index that incorporates the influence of on-site renewable energy. The subscripts GS and GW represent the combination of grid power with solar and wind power, respectively. The presence of on-site renewable energy sources only impacts the quantity of scarce water within electricity flows, thereby only altering SWI. The scarce water index is therefore modified by adding the contributions by the grid power sources as well as the on-site renewable energy sources:

$$\mathrm{SWI}_{\mathrm{GS}} = \mathrm{SWI}_{\mathrm{G}} x_{\mathrm{G}} + \mathrm{EWIF}_{\mathrm{S}} \cdot A_{\mathrm{CF}} \cdot (1 - x_{\mathrm{G}}) \tag{11}$$

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$$\mathrm{SWI_{GW}} = \mathrm{SWI_G} x_G + \mathrm{EWIF_W} \cdot A_{CF} \cdot (1 - x_G) \tag{12}$$

where x_G is the fraction of energy consumed by the data center that originates from the electric grid (off-site), and $\mathrm{EWIF_S}$ and $\mathrm{EWIF_W}$ are the EWIF values associated with solar and wind energy, respectively. The first term in Eqs. (11) and (12) therefore indicates the contribution of scarce water flows from power generation by the grid, whereas the second term incorporates the embodied water in the on-site renewables (captured as EWIF) times the water scarcity metric (A_{CF}).

CUE can similarly be defined as

$$\mathrm{CUE} = \mathrm{CEF_{EFF}} \cdot \mathrm{PUE} \tag{13}$$

where $\mathrm{CEF_{EFF}} = \{\mathrm{CEF_{GS}}, \mathrm{CEF_{GW}}\}$ is the effective CEF which incorporates contributions by the grid and on-site renewable sources:

$$\mathrm{CEF_{GS}} = \mathrm{CEF_G} x_G + \mathrm{CEF_S}(1 - x_G) \tag{14}$$

$$\mathrm{CEF_{GW}} = \mathrm{CEF_G} x_G + \mathrm{CEF_W}(1 - x_G) \tag{15}$$

where $\mathrm{CEF_S}$ and $\mathrm{CEF_W}$ are the emission factors associated with solar and wind energy sources, respectively.

One can view Eqs. (11), (12) and (14), (15) as weighted contributions of virtual scarce water and carbon flows from two sources: the grid with known effective flow parameters of $\mathrm{SWI_G}$ and $\mathrm{CEF_G}$, and on-site solar or wind with effective flow parameters $\mathrm{SWI_S}$ or $\mathrm{SWI_W}$ and $\mathrm{CEF_S}$ or $\mathrm{CEF_W}$. The $\mathrm{SWI_S}$ or $\mathrm{SWI_W}$ parameter represents the scarce water flow between on-site solar panels/wind turbines and the data center, but since no grid electricity transfers occur, then $\mathrm{SWI_S}$ or $\mathrm{SWI_W}$ reduces to the on-site scarce water flow, captured as the water requirement for solar/wind power generation ($\mathrm{EWIF_S}$ or $\mathrm{EWIF_W}$) times the local water scarcity factor (A_{CF}). The values of $\mathrm{EWIF_S}$ and $\mathrm{EWIF_W}$ are taken from Ref. [35] as 0.338 L/kW h and 0.0547 L/kW h, respectively, and are location-independent.

3 Results and Discussion

3.1 Improvement in WSUE. The improvement in WSUE when implementing on-site solar power is defined as

$$I_{\mathrm{WSUE,S}} = (100\%)\left(\frac{\mathrm{WSUE_G} - \mathrm{WSUE_{GS}}}{\mathrm{WSUE_G}}\right) \tag{16}$$

where the subscript GS indicates a value featuring a combination of grid power (75%) and on-site solar (25%). The improvement is therefore equal to the negative percentage change in WSUE. Figure 4 depicts the distribution of $I_{\mathrm{WSUE,S}}$ predictions. Green counties see a reduction in WSUE due to the addition of on-site renewable energy production, while red counties see higher WSUE values. Many counties experience considerable improvements, whereas others have larger WSUE values because of on-site power generation.

Combining Eqs. (6), (10), (11), and (16) shows that the value of $I_{\mathrm{WSUE,S}}$ can be rewritten as

$$I_{\mathrm{WSUE,S}} = (100\%)\left(\frac{(1 - x_G)(\mathrm{PUE}/\mathrm{WUE})((\mathrm{SWI_G}/A_{CF}) - \mathrm{EWIF_S})}{1 + (\mathrm{PUE}/\mathrm{WUE})(\mathrm{SWI_G}/A_{CF})}\right) \tag{17}$$

Relations for wind energy can be derived by modifying Eqs. (16) and (17) by replacing the subscript S with the subscript W, and similar results are seen in the county distribution of $I_{\mathrm{WSUE,W}}$ (Fig. 5) as for $I_{\mathrm{WSUE,S}}$ (Fig. 4). Since $\mathrm{EWIF_S}$ and $\mathrm{EWIF_W}$ are constant, then the largest benefit is seen in areas where the ratio $\mathrm{SWI_G}/A_{CF}$ is largest, or areas with a relatively large $\mathrm{SWI_G}$ and relatively low A_{CF}. Figure 6 depicts this relationship for varying ratios of $\mathrm{SWI_G}/A_{CF}$, pinpointing the possibility of increased WSUE when the ratio falls below $\mathrm{EWIF_S}$. This ratio is therefore the key metric to gauging the viability of reducing water scarcity footprint for a given location. The figure also shows that more improvement is seen for on-site wind power due to the lower EWIF of wind energy compared to solar energy. Figure 7 provides the distribution of $\mathrm{SWI_G}/A_{CF}$, showing similar patterns as seen in Figs. 4 and 5, providing confidence in this conclusion. This ratio is physically defined as being proportional to the scarce water draw from grid-based power generation versus on-site scarce water generation, since the

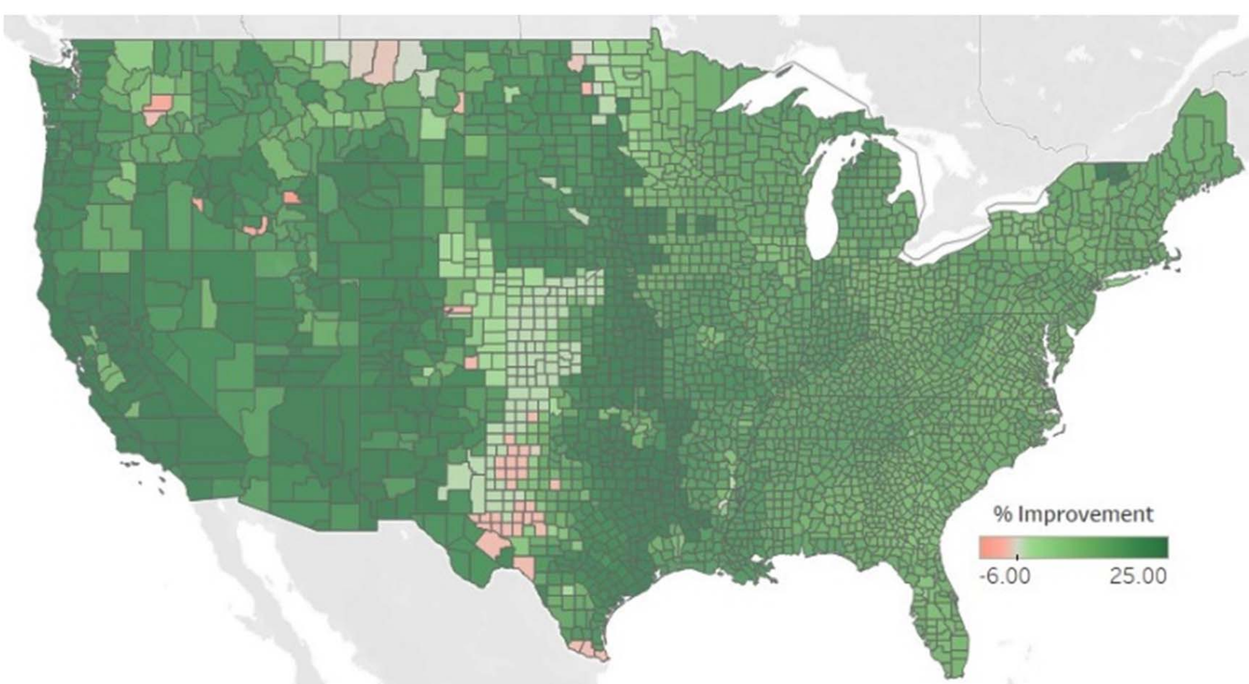

Fig. 4 Percent improvement in WSUE after implementing 25% on-site solar energy production

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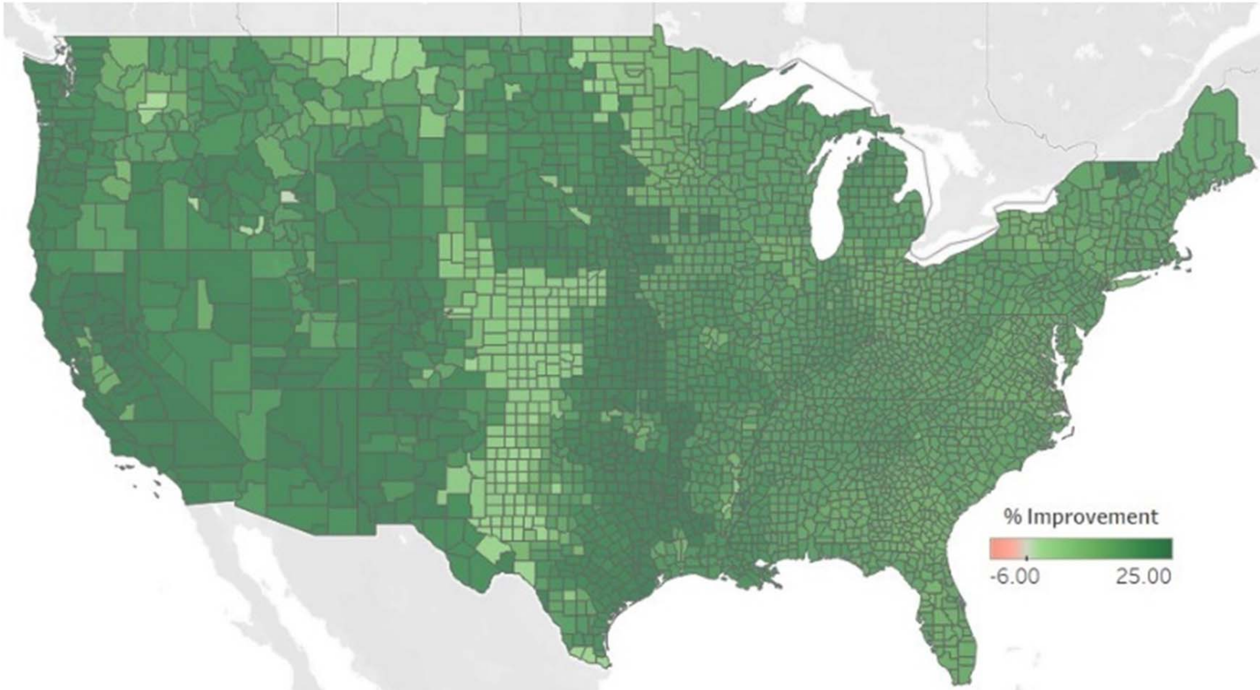

Fig. 5 Percent improvement in WSUE after implementing 25% on-site wind energy production

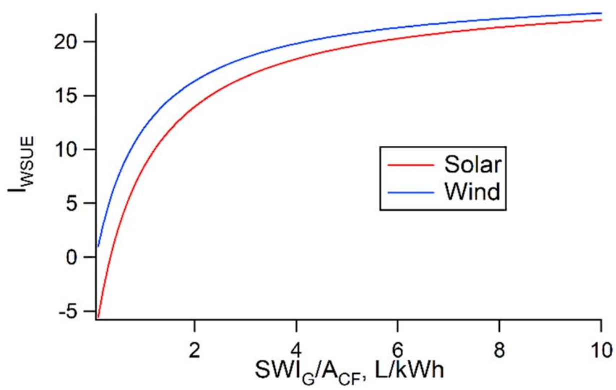

Fig. 6 Percent improvement in WSUE after implementing 25% on-site solar or wind energy production for the system in this study based on ratio SWI_G/A_{CF}

latter is defined as $EWIF_S \cdot A_{CF}$ (solar) or $EWIF_W \cdot A_{CF}$ (wind). Figures 4 and 5, when compared to Fig. 2, show that counties with low A_{CF} and low SWI_G have little benefit, which agrees with Eq. (17), but counties with low A_{CF} that border counties with large A_{CF} have maximum benefit since they have large SWI_G values due to some power draw from their adjacent water-scarce counties. This is most readily seen in Humboldt County, CA, which has a low A_{CF} (0.178, first percentile of all contiguous U.S. counties) but a high SWI_G (124 L/kW h, 96th percentile) due to its assignment to a balancing authority containing power generation with high-water consumption.

3.2 Improvement in Carbon Usage Effectiveness.

The definition of improvement in CUE values using on-site solar energy follows the same approach as that for WSUE:

$$I_{CUE,S} = (100\%)\left(\frac{CUE_G - CUE_{GS}}{CUE_G}\right) \tag{18}$$

where again the subscript S can be replaced with W to represent wind energy. Here, Eq. (18) is combined with Eqs. (13) and (14) to yield

$$I_{CUE,S} = (100\%)\left((1 - x_G)\left(1 - \frac{CEF_S}{CEF_G}\right)\right) \tag{19}$$

It follows that the improvement in carbon footprint follows

$$I_{CUE,S} \propto \left(1 - \frac{CEF_S}{CEF_G}\right) \tag{20}$$

Therefore, the largest improvement is seen where CEF_G is large as expected.

Figure 8 shows the CUE percent improvement values of each U.S. county from 0% on-site to 25% on-site solar power generation for data centers. As expected, almost every county saw significant improvement in their CUE value when using on-site solar energy as expected. Those counties seeing an increase in CUE may be attributed to the fact that these counties produce power through existing wind and hydropower energy, which both have lower CEF values than solar energy. One can see that the amount of improvement follows trends seen in Fig. 3 for CEF_G distribution. The benefits of on-site solar are nearly universal in nature except for a few counties fed by large existing renewable energy sources from the grid.

A Pareto front was generated based on the combined values of CEF_G and SWI/A_{CF} for all contiguous U.S. counties. The front was generated by finding the minimum combinations of $1/CEF_G$ and A_{CF}/SWI as shown in Fig. 9. The list of optimal counties on the front is provided in Table 1, which indicates that on-site renewable power should be incorporated into Sierra, Yuba, and Humboldt counties in California to maximize the reduction in WSUE, whereas incorporation into Mason, Russell, and Pulaski counties in Kentucky will provide the largest reduction in carbon footprint. These results are consistent with Figs. 7 and 8.

3.3 Case Study.

A case study was performed on the publicized implementation of 7.2 MW solar energy on an Iron Mountain data center in Edison, NJ [5]. The array is reported to address

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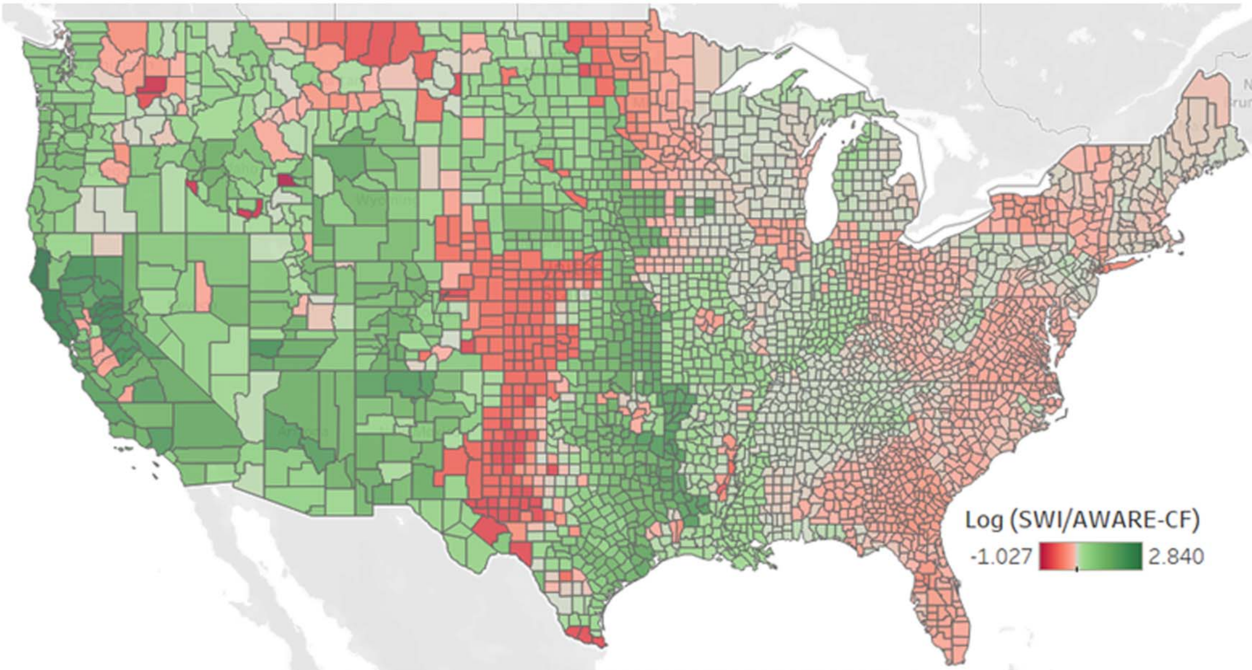

Fig. 7 Geographic distribution of SWI_G/A_{CF}

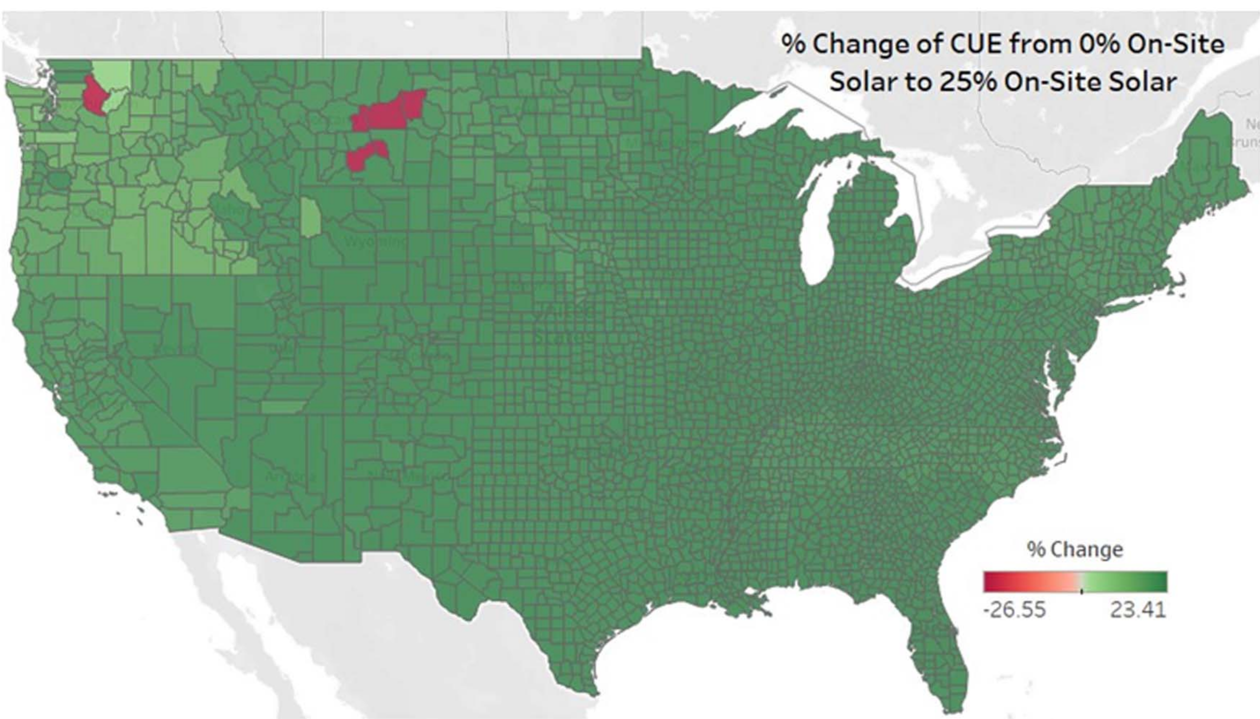

Fig. 8 Percent improvement in CUE after implementing 25% on-site solar energy production. The implementation of wind energy production produces similar results.

"approximately 15 percent of the data center's current energy load." The grid-based EWIF, CEF, A_{CF}, and SWI associated with Middlesex County, NJ, are 1.65 L/kW h, 0.412 kg CO_2e/kW h, 0.315, and 0.686 L/kW h, respectively, using methods outlined in Refs. [8,31]. The combined PUE and WUE values are generally not reported [36], so typical values of 1.85 and 1.80 for PUE and WUE, respectively, are used. Values of CEF_S and $EWIF_S$ are taken as 0.0441 kg CO_2e/kW h [30] and 0.338 L/kW h [35], respectively. The resultant predicted reductions in WSUE and CUE are 9% and 13% after employing Eqs. (17) and (19), respectively.

3.4 Sensitivity Analysis. A sensitivity analysis was performed to verify the assumption of fixed PUE and WUE in this study. Lei and Masanet [37] provide estimated ranges of PUE and WUE for various cooling system configurations and American Society for

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Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) climate zones. The average values of PUE and WUE were found based on the statistical ranges provided for a cooling system containing airside economization with adiabatic cooling and a water-cooled chiller, typical of large data centers (case 1). The average and standard deviation of this set of PUE and WUE values (one for each of 15 ASHRAE climate zones) are used, along with the mean and standard deviation of CEF, AWARE-CF, EWIF, and SWI for all counties in the contiguous U.S. (Table 2). Uncertainty quantification employed on Eqs. (6) and (7), respectively, yield

$$s_{\mathrm{WSUE}}=\sqrt{(\overline{\mathrm{WUE}}\cdot s_{A_{\mathrm{CF}}})^2+(\overline{A_{\mathrm{CF}}}\cdot s_{\mathrm{WUE}})^2+(\overline{\mathrm{PUE}}\cdot s_{\mathrm{SWI}})^2+(\overline{\mathrm{SWI}}\cdot s_{\mathrm{PUE}})^2} \tag{21}$$

$$s_{\mathrm{CUE}}=\sqrt{(\overline{\mathrm{PUE}}\cdot s_{\mathrm{CEF}})^2+(\overline{\mathrm{CEF}}\cdot s_{\mathrm{PUE}})^2} \tag{22}$$

where s represents the standard deviation, and the bar accent indicates a mean value. The contributions to overall uncertainties in WSUE and CUE are represented by the individual terms inside the parentheses in Eqs. (21) and (22) and are shown in Table 3. The table indicates that variations in A_{CF} and SWI are dominant contributors to the uncertainty in WSUE, and the variation in CEF is the dominant contributor to the uncertainty in CUE. The assumption of a fixed PUE and WUE are therefore justified for this study since the geographic variations in A_{CF}, SWI, and CEF dominate over variations in PUE and WUE.

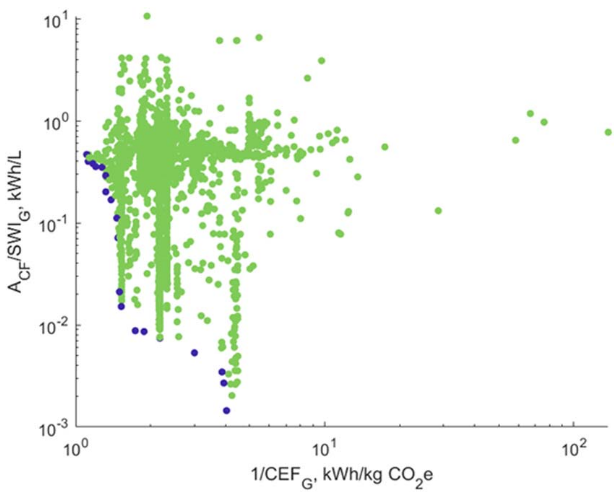

Fig. 9 Pareto analysis of grid-based environmental carbon and water scarcity characteristics for contiguous U.S. counties. The optimal counties are indicated by the darker markers.

3.5 Discussion. This analysis provides a simple means to predict the environmental benefits of incorporating on-site renewable energy, but other factors must also be considered. A full STEEP (social, technological, environmental, economic, and political) analysis [38] should be undertaken to identify all the pros and cons of incorporating on-site renewables, where this study provides calculations focused on the environmental category only. Further work is required to examine the remaining STEEP aspects, in

Table 2 Mean and standard deviation of parameters used in sensitivity analysis

Parameter	Mean	Standard deviation
PUE	1.18	0.0361
WUE (L/kW h)	0.760	0.164
CEF (kg CO_2e/kW h)	0.452	0.123
EWIF (L/kW h)	2.01	1.63
AWARE-CF	7.83	23.7
SWI (L/klW h)	21.3	65.4

Table 3 Contributions of parameter uncertainty to WSUE and CUE

Parameter	Metric	Contribution
A_{CF}	WSUE (L/kW h)	18.0
WUE	WSUE (L/kW h)	1.28
SWI	WSUE (L/kW h)	77.2
PUE	WSUE (L/kW h)	0.769
CEF	CUE (kg CO_2e/kW h)	0.145
PUE	CUE (kg CO_2e/kW h)	0.0163

Table 1 Predicted optimal counties for on-site power generation

County	FIPS	SWI_G/A_{CF} (L/kW h)	CEF_G (kg CO_2e/kW h)
Mason County, KY	21,161	2.14	0.902 (most CF reduction benefit)
Russell County, KY	21,207	2.49	0.890
Pulaski County, KY	21,199	2.62	0.853
Harlan County, KY	21,095	2.81	0.830
Whitley County, KY	21,235	2.85	0.783
Randolph County, MO	29,175	3.43	0.757
New Madrid County, MO	29,143	4.96	0.756
Le Flore County, OK	40,079	5.92	0.720
Cache County, UT	49,005	8.97	0.683
Madison County, ID	16,065	14.0	0.676
Lincoln County, WY	56,023	47.4	0.666
Park County, WY	56,029	66.0	0.655
Taos County, NM	35,055	114	0.576
Los Angeles County, CA	6037	116	0.531
Polk County, AR	5113	135	0.459
Iron County, UT	49,021	188	0.333
Sierra County, CA	6091	289	0.258
Yuba County, CA	6115	371	0.254
Humboldt County, CA	6023	691 (most WSF reduction benefit)	0.248

FIPS: Federal Information Processing Standards.

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particular a through engineering economic analysis featuring return on investment and payback period.

An additional extension of work can be to predict future changes in water scarcity footprint and carbon footprint trends using historical data, but with assumptions required for missing data. The EIA [25], for example, provides power generation data back to 2012, and the Uptime Institute tracks changes in PUE [39]. Assumptions will need to be made, however, regarding WUE due to a lack of reporting data, and AWARE-CF factors have only been recently reported.

4 Conclusions

This study uncovered the key parameters associated with the existing grid-based environmental metrics as a first-order guide to implementing on-site power generation. The study found that the ratio of SWI_G/A_{CF} is a good indicator as to the anticipated improvement in water scarcity footprint from implementing on-site renewable energy in a given location, with wind energy providing a larger benefit than solar energy because of the former's lower EWIF. The study also found that the reduction in carbon footprint roughly corresponds to the magnitude of existing grid-based carbon emission factor, as expected. The largest potential areas for improvements in carbon footprint are in mountain regions, specifically WY, UT, MT, SD, ND, WV, KY, and TN. The areas that can most benefit from on-site renewables for decreasing their water scarcity footprint are more scattered by generally fall in the western portions of the U.S. or are low-A_{CF} counties adjacent to high-A_{CF} counties. The information provided therein can aid data center owners and operators in site selection for new data centers and electrical system retrofits for legacy data centers as part of a broader STEEP analysis.

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Author Contribution Statement

Matthew McMullen: model development, data analysis, manuscript drafting; Aaron Wemhoff: funding, data analysis, manuscript drafting, and revision.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

Nomenclature

s = standard deviation
x = fraction of flow
C = carbon emissions, kg CO_2e
I = improvement
P = electric power consumption, kW h
W = water consumption, L
A_{CF} = AWARE-CF factor
AMD = availability minus demand, L
CEF = carbon emission factor, kg CO_2e/kW h
CRAC = computer room air conditioner
CUE = carbon usage effectiveness, kg CO_2e/kW h
EIA = U.S. Energy Information Administration
eGRID = emissions generation resource integrated database
EPA = U.S. Environmental Protection Agency
EWIF = energy water intensity factor, L/kW h
PUE = power usage effectiveness
SWI = scarce water index, L/kW h
WSF = water scarcity footprint, L
WSUE = water scarcity usage effectiveness, L/kW h
WUE = water usage effectiveness, L/kW h
WUE_{source} = modified water usage effectiveness that includes source water flows, L/kW h

Subscripts

G = grid
S = solar
W = wind
site = on-site component
tot = total
EFF = effective values
GS = combined grid and on-site solar power
GW = combined grid and on-site wind power
IT = information technology equipment
REF = reference

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