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DATA CENTER ENVIRONMENTAL BURDEN REDUCTION THROUGH ON-SITE RENEWABLE POWER GENERATION

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ABSTRACT

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 gaining insight into making data centers more sustainable. This study examines the impact of on-site solar or wind energy on 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 the 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 on reducing carbon footprint in areas with high existing grid-based emissions such as the mountain regions and the western side of the Appalachian Mountains. The largest benefit in reducing water scarcity footprint is generally seen in the western U.S.

Keywords: renewable energy, water scarcity footprint (WSF), carbon usage effectiveness (CUE), water scarcity usage effectiveness (WSUE)

NOMENCLATURE

A_{CF}	AWARE-CF factor
AMD	Availability minus demand, L
C	Carbon emissions, kg CO_2e
CEF	Carbon emission factor
CRAC	Computer room air conditioner
CUE	Carbon usage effectiveness, kg CO_2e/kWh
EIA	US Energy Information Administration
eGRID	Emissions Generation Resource Integrated Database
EPA	U.S. Environmental Protection Agency
EWIF	Energy water intensity factor, L/kWh
I	Improvement
P	Electric power consumption, kWh
PUE	Power usage effectiveness
SWI	Scarce water index, L/kWh
W	Water consumption, L
WSUE	Water scarcity usage effectiveness, L/kWh
WUE	Water usage effectiveness, L/kWh
WUE_{source}	Modified water usage effectiveness that includes source water flows, L/kWh
x	Fraction of flow

Subscripts

EFF	Effective value
G	Grid
GS	Combined grid and on-site solar power
IT	IT equipment
$site$	On-site component
NT	Non-thermal
REF	Reference
S	Solar
T	Thermal
tot	Total
W	Wind

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 TWh of electricity annually, accounting for 1% of the global energy demand [1]. More recent estimates have suggested that data centers consume up to 500 TWh of electricity annually [2].

The large demand for electricity coming from data centers has raised concerns raised about the environmental impacts of

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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 the environmental impacts that data centers and their electricity consumption may have, resulting in the reduction of a data center's carbon footprint [3]–[6]. 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 [7].

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. [8] investigated the use of renewable energy in conjunction with server virtualization and showed potential energy savings. Li et al. [9] suggested that the tuning of intermittent load fluctuations and available intermittent renewable energy sources degrades the renewable energy system efficiency. Wang and Ye [10] proposed that using renewable energy in a microgrid works best with a cluster of data centers, utilizing the advantages of cluster-wide workload allocation. Wan et al. [11] extend this concept to internet data centers with the goal of minimizing carbon footprint. This approach may be more viable since it is difficult to manage the load variations and power availability for a single data center with on-site renewable energy production [12].

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. The current study therefore provides the best-case values of footprint reductions, with the guidance that the actual environmental benefits will be reduced due to workload variation and renewable power availability.

A comprehensive study evaluating the impact of on-site renewable energy on carbon and water scarcity footprints that include indirect contributions from power generation sources and grid electricity transfers is lacking in the literature. Therefore, this study fills an important research gap by calculating the reductions in these footprints at the U.S. county scale by implementing on-site solar or wind energy. The study specifically examines how changes in these footprints are affected by geographic location. Conclusions are provided regarding the accuracy of predictions based on available data and the relative impact of implementing on-site renewable power generation for different locations.

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):

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

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

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

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

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

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:

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

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

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 are to incorporate electricity transfers within the grid [13]. Carbon emissions and water scarcity footprint are embedded in electricity generation through both fuel combustion but 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 [14], [15], [16]. The methods to calculate these metrics are

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

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

where A_{CF} is the AWARE-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

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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 US Energy Information Administration's (EIA) annual report includes every power generation source in the United States that produces over 1 MWh of electricity annually, as well as the geographic coordinates of these power plants [17]. 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, eGRID subregion boundaries and county boundary regions are taken from the US Environmental Protection Agency (EPA) [18]. Counties are assigned to one of 26 eGRID subregion boundaries in the contiguous U.S. using the geographic centroids of each county.

Peer et al. classified power generation technologies into two categories, non-thermal and thermal power generation sources [19]. Thermal power generation sources include coal, oil, natural gas, nuclear, biomass, and geothermal. Non thermal power generation sources include hydropower, wind, and solar. Each eGRID subregion has a thermal and a non-thermal EWIF value. Using the power generation mix for each county, and assuming counties within the same eGRID subregions have the same EWIF for a given power generation type, an estimate of EWIF for each county is

$$EWIF = (EWIF_T \cdot x_T) + \left(EWIF_{NT} \cdot (1 - x_T)\right) \qquad (8)$$

where $EWIF_T$ is the thermal EWIF value for the EGRID subregion the county lies in, $EWIF_{NT}$ is the non-thermal EWIF value for the EGRID subregion the county lies in, and x_T is the fraction of power generated in the county by thermal sources. The value of x_T is calculated as

$$x_T = \frac{\sum_T P}{\sum_T P + \sum_{NT} P} \qquad (9)$$

where P is power generation by individual sources, and the subscripts T and NT represent summations over thermal and non-thermal individual sources, respectively.

Figure 1 shows the EWIF values for each county based solely on county power generation sources. EWIF values range from 0.4 L/KWh to 21.3 L/KWh, with a median EWIF score of 2.99 L/KWh and a standard deviation of 4.60 L/KWh. 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. 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.

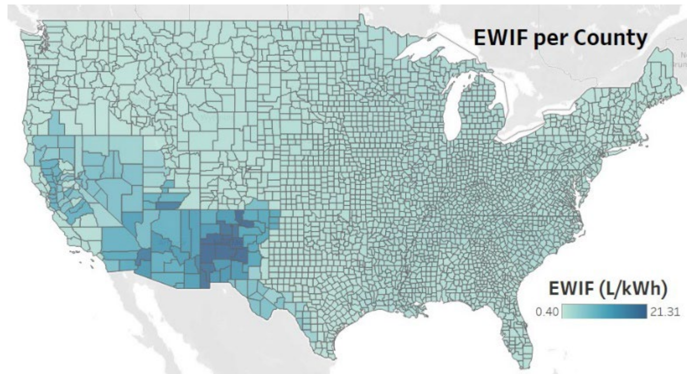

FIGURE 1. EWIF values for every contiguous U.S. county

2.1. Measuring 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 [20]. Lee et al. created a US model that quantifies water scarcity and the impact of water consumption in different US counties [21]. The AWARE characterization factor (AWARE-US CF), as the metric is named, compares regional water availability to a reference value that is bounded between 0.1 and 100 [21]. The factor is defined as

$$A_{CF} = \frac{AMD_{REF}}{AMD} \qquad (10)$$

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.

2.2. 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/KWh. 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 [22] and incorporate electricity transfers within the grid, culminating in Scope 3 emissions due to data center operation [23].

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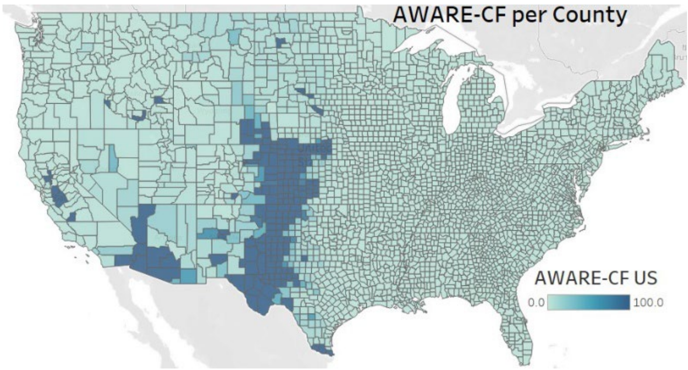

FIGURE 2. AWARE-US CF values for every contiguous U.S. county (adapted from [21])

Figure 3 shows the CEF values for each county. CEF scores range from 0.007 kg/KWh to 0.902 kg/KWh, with a median CEF score of 0.17 kg/KWh, and a standard deviation of 0.452 kg/KWh. The largest values appear in the mountain regions (e.g., WY, UT, MT, SD, ND) and near the western side of the Appalachian Mountains (e.g., WV, KY, TN).

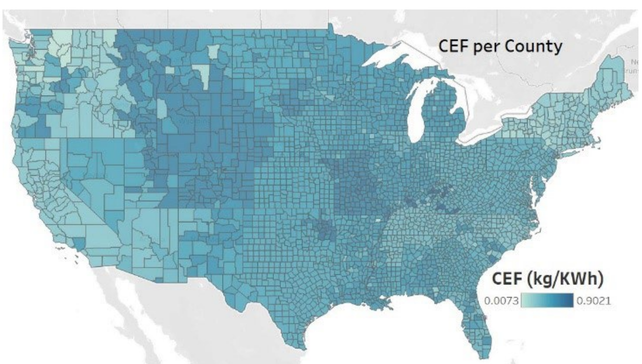

FIGURE 3. CEF values for every contiguous U.S. county

2.3. WSUE and CUE 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 [24].

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

$$WSUE = A_{CF}WUE + SWI_{EFF} \cdot PUE \tag{11}$$

where SWI_{EFF} is the effective scarce water index that incorporates the influence of on-site renewable energy. 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 onsite renewable energy sources:

$$SWI_{EFF} = SWI_G x_G + EWIF_S \cdot A_{CF} \cdot (1 - x_G) \tag{12a}$$

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

where x_G is the fraction of energy consumed by the data center that originates from the electric grid (off-site), and $EWIF_S$ and $EWIF_W$ are the EWIF values associated with solar and wind energy, respectively. The first term in Eqs. (12a) and (12b) 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

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

where the effective CEF incorporates contributions by the grid and on-site renewable sources:

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

$$CEF_{EFF} = CEF_G x_G + CEF_W(1 - x_G) \tag{14b}$$

where CEF_S and CEF_W are the emission factors associated with solar and wind energy sources, respectively.

One can view Eqs. (12) and (14) as weighted contributions of virtual scarce water and carbon flows from two sources: the grid with known effective flow parameters of SWI_G and CEF_G, and on-site solar/wind with effective flow parameters SWI_S/SWI_W and CEF_S/CEF_W, respectively. The SWI_S/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 SWI_S/SWI_W reduces to the on-site scarce water flow, captured as the water requirement for solar/wind power generation ($EWIF_S/EWIF_W$) times the local water scarcity factor (A_{CF}). The values of $EWIF_S$ and $EWIF_W$ are taken from Vengosh and Weinthal [25] as 0.338 L/kWh and 0.0547 L/kWh, 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

$$I_{WSUE,S} = (100\%)\left(\frac{WSUE_G - WSUE_{GS}}{WSUE_G}\right) \tag{15}$$

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. Figures 4 depicts the distribution of $I_{WSUE,S}$ 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

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improvements, whereas others have larger WSUE values because of on-site power generation.

Combining Eqs. (6), (11), (12a), and (15) shows that the value of $I_{WSUE,S}$ can be rewritten as

$$I_{WSUE,S} = (100\%)\left(\frac{(1-x_G)\frac{PUE}{WUE}\left(\frac{SWI_G}{A_{CF}} - EWIF_S\right)}{1+\frac{PUE}{WUE}\left(\frac{SWI_G}{A_{CF}}\right)}\right) \quad (16)$$

Relations for wind energy can be derived by modifying Eqs. (15) and (16) by replacing the subscript S with the subscript W, and similar results are seen in the county distribution of $I_{WSUE,W}$ (Fig. 5) as for $I_{WSUE,S}$ (Fig. 4). Since $EWIF_S$ and $EWIF_W$ are constant, then the largest benefit is seen in areas where the ratio $\frac{SWI_G}{A_{CF}}$ is largest, or areas with a relatively large SWI_G and relatively low A_{CF}. Figure 6 depicts this relationship for varying ratios of SWI_G/A_{CF}, pinpointing the possibility of increased WSUE when the ratio falls below $EWIF_S$. 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 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 latter is defined as $EWIF_S \cdot A_{CF}$ (solar) or $EWIF_W \cdot A_{CF}$ (wind) per Eq. (12). Figures 4 and 5, when compared to Fig. 2, show that counties with low A_{CF} have little benefit, which agrees with Eq. (16), 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.

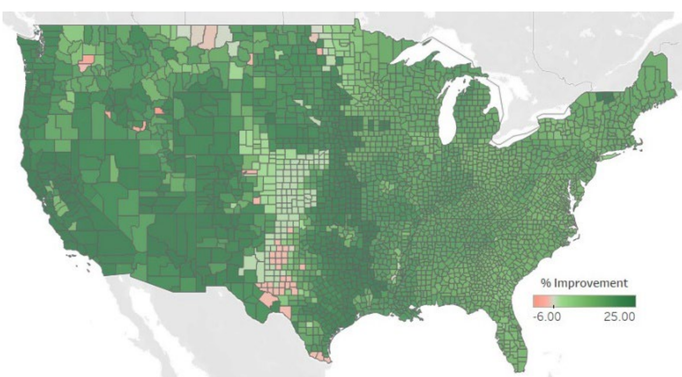

FIGURE 4. Percent improvement in WSUE after implementing 25% on-site solar energy production.

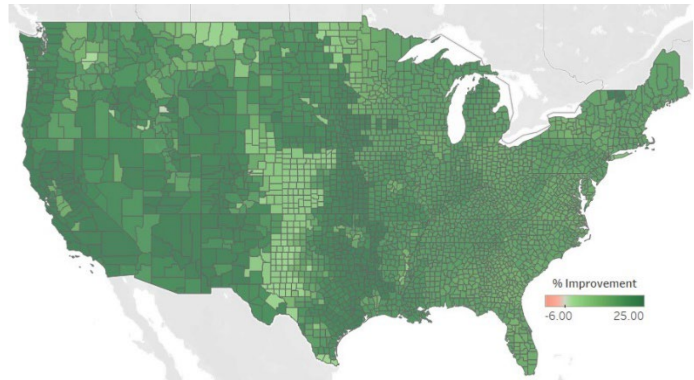

FIGURE 5. Percent improvement in WSUE after implementing 25% on-site wind energy production.

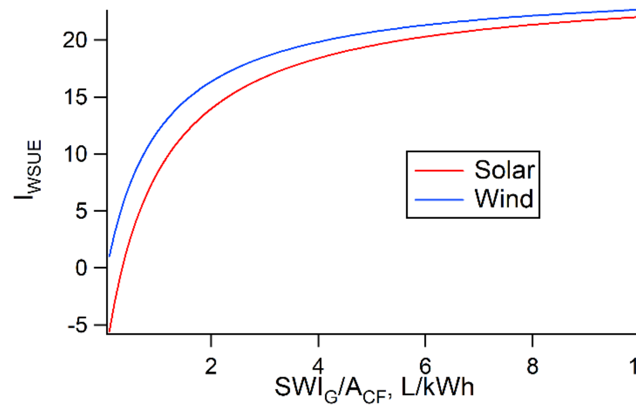

FIGURE 6. Percent improvement in WSUE after implementing 25% on-site solar or wind energy production for the system in this study based on ratio SWI_G/A_{CF}.

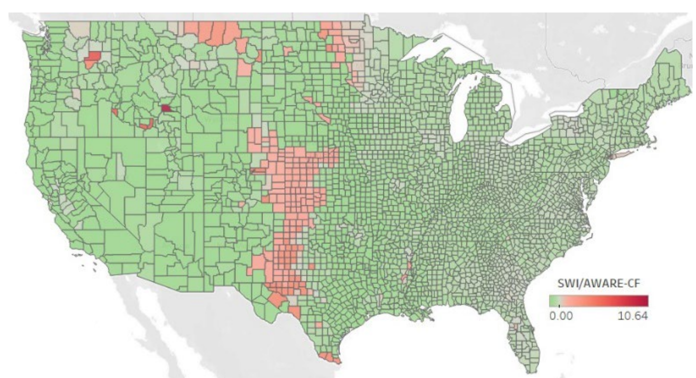

FIGURE 7. Geographic distribution of SWI_G/A_{CF}.

3.2. Improvement in CUE

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

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

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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

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

It follows that the improvement in carbon footprint follows

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

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

Figure 8 shows the CUE percent improvement values of each US 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.

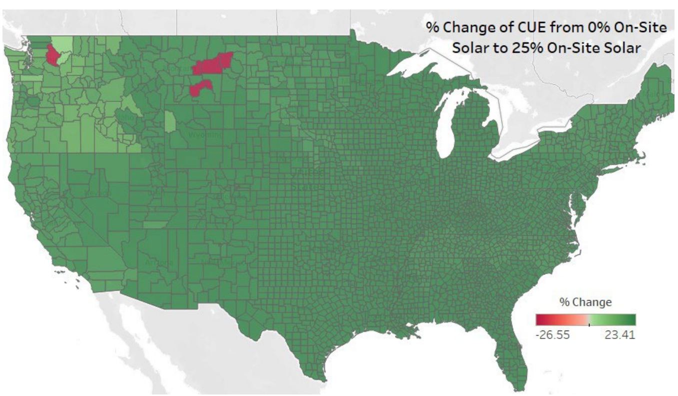

FIGURE 8: Percent improvement in CUE after implementing 25% on site solar energy production. The implementation of wind energy production produces similar results.

4. CONCLUSION

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.

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