Intersections of disadvantaged communities and renewable energy potential: Data set and analysis to inform equitable investment prioritization in the United States

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Renewable energy development can bolster local economies through job creation, local tax revenues, and reduced energy costs; however, communities most in need of economic development and employment opportunities often see lower levels of renewable energy deployment. We sought to identify areas where disadvantaged community indicators and high generation potential from cost-effective renewable energy opportunities intersect and deployment could lead to economic development and job creation. Through a geospatial intersection of energy burden, environmental hazard, and sociodemographic data with technical generation potential and the levelized cost of energy for multiple renewable energy technologies, we calculated county-level correlations and identified trends across disadvantaged community indicators and renewable energy deployment potential. Data sources and tools included the Low-Income Energy Affordability Data (LEAD) tool, the Environmental Justice Screening and Mapping (EJSCREEN) tool, the State and Local Planning for Energy (SLOPE) platform, and the Renewable Energy Integration and Optimization (REopt®) model. Metrics include levelized costs and generation potential for utility-scale photovoltaics (PV), rooftop PV (residential and commercial), distributed PV plus storage, land-based wind, geothermal, and hydropower development. This research and the associated county-level data set are intended to inform national- and state-level energy-related assistance programs, economic development efforts, and infrastructure programs seeking to prioritize investments in disadvantaged communities.

Introduction

The U.S. clean energy transition is at an inflection point. Declining costs and technological breakthroughs in renewable energy are driving the market toward a future in which energy generation and consumption are completely transformed. At the same time, climate change is accelerating, prompting urgency in scaling up clean energy transitions. Moreover, significant rural-urban and racial disparities persist, reflected in indicators of wealth, environmental hazard exposure, and renewable energy adoption [1-8]. Providing disadvantaged communities (DACs) with data on the most cost competitive and highest generation potential renewable energy technologies in their county can enable more strategic energy planning and local development efforts. Similarly, prioritizing renewable energy investments in communities with a high prevalence of environmental hazard exposure and other DAC indicators can enhance equity in the transition to a clean energy economy and broaden access to renewable energy benefits.

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1755-0084/ https://doi.org/10.1016/j.ref.2022.02.002

The U.S. has ambitious climate goals, including a "carbon pollution-free power sector by 2035, a net-zero economy by 2050," and a 50% reduction in greenhouse gas emissions by 2030 [9,10]. In addition, the Biden administration's Justice40 initiative aims to "deliver 40% of the overall benefits of climate investments to disadvantaged communities and inform equitable research, development, and deployment" [11]. In response, the U.S. Department of Energy (DOE) created a beta Energy Justice Dashboard and dedicated $15.5 million to increasing solar development in underserved areas [12,13]. To generate data that can inform decision making and investment prioritization in working toward these directives, we sought to use energy justice concepts to identify where DAC indicators overlap with high-potential, cost-effective renewable energy development opportunities.

The concept of energy justice arose from both the environmental justice and climate justice movements, which emerged in the 1980s and early 21st century respectively [14]. Energy justice is a framework in which energy resources are readily available, affordable, and environmentally sustainable [15]. Incorporated into the framework are the environmental justice concepts of intragenerational and intergenerational distributive justice (the equitable distribution of environmental burdens and benefits across current and future generations) and procedural justice (transparency in decision making and the meaningful participation of all stakeholders, especially those who have historically been marginalized and excluded from the decision-making process) [15,16]. Energy justice is rarely a priority in energy development, as local communities in general, and non-white communities in particular, are often marginalized in energy-siting decision making [16,17]. Further, investment prioritizations, such as subsidies, are currently accessed predominantly by higher-income individuals, who are less likely to experience environmental hazard exposures and other DAC indicators, than lower-income individuals [18,19].

There is evidence of distributive and procedural injustices in the distribution of wealth and environmental hazard exposure in the United States across the rural-urban continuum and between racial groups. For example, the Great Recession of 2007 to 2009 exacerbated the persistent racial wealth gap [7,8]. Rural areas have also yet to recover from the Great Recession and have seen income and employment increase more slowly than in urban areas [20]. Poverty rates in metropolitan counties in the United States are increasing at a faster pace than rural and micropolitan counties, though rural counties still experience the country's highest rates of poverty [6]. These income disparities are compounded because low-income households generally have higher energy burdens than more affluent households, meaning that a higher proportion of their income is spent on household energy [2,4,21]. Racial disparities in energy burden, even when controlling for income, also exist, with Black and Hispanic households having higher energy burdens than non-Hispanic, white households in some parts of the country [2,4,22]. Similarly, rural areas have higher energy burdens than urban areas across the United States [4,23]. Further, not only do households with a higher energy burden experience increased financial strain, high energy burden is also associated with adverse health impacts. Outdated building infrastructure that often leads to a higher energy burden can also lead to or exacerbate existing health problems, such as respiratory illness. Moreover, high energy burdens can result in low-income households foregoing medical treatment to pay for energy expenses, which can lead to poorer overall health and premature mortality [21,24].

Disparities in environmental hazard exposure, which is associated with adverse human health impacts, also exist [19,25,26]. Individuals living in urbanized areas are at higher risk of exposure to fine particulate matter ($PM_{2.5}$), a major environmental health risk, than those living in rural areas [27]. In addition, not only do Black and Hispanic individuals and low-income individuals have greater residence-based exposure to $PM_{2.5}$, but they are also at increased risk of $PM_{2.5}$-related mortality than non-Hispanic, white individuals and higher-income individuals respectively, even across similar exposure levels [5,26,27,28,29]. There are also disparities in non-air-based pollution, such as lead exposure. Although there is evidence that disparities in lead exposure are declining, Black and Hispanic children and low-income children have been found to have higher blood lead levels than white children and higher-income children [30-34]. Given these distributional and procedural inequities, disadvantaged communities are thus defined herein as communities with high prevalence of the socioeconomic factors and/or high exposure to the environmental hazards described in Table 1.

The current transition to renewable energy technologies can provide cleaner energy and bolster local economies through job creation and local tax revenues. Communities with higher rates of poverty, unemployment, and pollution exposure, however, often see lower levels of renewable energy deployment. Residential photovoltaic (PV) adopters are more likely to have higher incomes, be more educated, and live in white-majority census geographies than non-adopters [1,35,36]. Communities defined as DACs using CalEnviroScreen [37] tend to have lower levels of residential PV adoption than non-DACs [38]. Additionally, low-income households in the United States receive far fewer clean energy tax credits than higher-income households [18]. Reames [3] intersected residential PV deployment potential, defined as the "proportion of solar-suitable, single-family rooftops," and actual residential PV deployment with several socioeconomic and demographic characteristics—including low-income community status, percentage of the population with less than a high school education, and percentage of nonwhite individuals—in four cities across the United States [p. 3]. Reames [3] found lower residential PV adoption among low-income individuals and among racial/ethnic minorities. He also found that, although certain low-income communities have greater potential to deploy residential PV than higher-income communities, PV adoption disparities still exist. In addition, Sigrin and Mooney [39] found that low-to-moderate income (LMI) residential buildings in the United States make up 43% of the U.S. population and contain 42% of the residential rooftop PV technical potential (i.e., the maximum generation and capacity if PV was installed on all suitable rooftops), further illustrating the gap in deployment.

As the deployment of renewable energy technologies increases, there is an opportunity to create a more equitable energy system. Although previous work has examined select

TABLE 1

Data Sets Used to Intersect DACs with Renewable Energy Deployment Potential.

Data set	Data resolution	Metric	Year
EJSCREEN	Census block group	Less than high school (HS) education	2013–2017
		Low-income	2013–2017
		Minority	2013–2017
		Air toxics cancer risk	2014
		Air toxics respiratory hazard index	2014
		Diesel particulate matter (PM)	2014
		$PM_{2.5}$ concentration	2016
		Ozone concentration	2016
		Traffic proximity and volume	2017
		Lead paint indicator	2013–2017
		Proximity to risk management plan (RMP) facilities	2019
		Proximity to treatment, storage, and disposal facilities (TSDF)	2019
		Proximity to national priorities list (NPL) sites	2019
		Wastewater discharge indicator	2017
LEAD	Census tract	Energy burden	2018
Rural Atlas	County	Employment in mining, quarrying, and O&G extraction	2015–2019
		Farming-dependent counties	2015
		Persistent-poverty counties	2015
		Rural-urban continuum code	2013
		Unemployment	2020
SLOPE	County	Technical generation potential for PV and wind	2020
		Levelized cost of energy for PV, wind, geothermal, and hydropower	2020
		Capital cost for geothermal and hydropower	2020
REopt	Utility service area	Cost savings estimates for solar-plus-storage	2019

Note. The metrics with 5-year ranges are single-value estimates generated by the American Community Survey that provide more statistical reliability to representations of small populations [46].

sociodemographic factors across renewable energy deployment and potential metrics, to the authors' knowledge, our work is the first to establish a data set that incorporates the potential of multiple renewable energy technologies and both sociodemographic information and environmental hazard exposures, allowing for easier and more accessible analysis across these metrics. Thus, recognizing the disproportionate access to renewable energy benefits from disadvantaged communities, we sought to map DAC indicators and other community characterization metrics in the contiguous United States to corresponding favorable renewable energy opportunities to enable prioritization of DACs in federal and state clean energy investments and programs. The resulting data set of comparative generation potential and cost metrics by county can also inform community-level energy planning and prioritization.

Method

Disadvantaged community indicators, including rural-urban classifications, race, income, unemployment, and employment in mining, quarrying, and oil and gas (O&G) extraction, were geospatially intersected with deployment opportunity metrics for utility-scale PV, residential rooftop PV, commercial rooftop PV, distributed PV plus storage (solar-plus-storage), land-based wind, geothermal, and hydropower. Using exploratory correlational analyses, we identified patterns in renewable energy technical potential and cost for these seven renewable technologies across the DAC metrics (see Section 3.1). We also conducted two case studies to highlight the ways in which our data set can be used to prioritize renewable energy technology deployment for any given DAC and identify the DACs with the highest opportunity for specific renewable energy technologies (see Section 3.2).

Materials

To intersect DACs with renewable energy potential, we used the U.S. Environmental Protection Agency's (EPA) Environmental Justice Screening and Mapping (EJSCREEN) tool [40], the DOE's Low-Income Energy Affordability Data (LEAD) tool [41], the U. S. Department of Agriculture's (USDA) Atlas of Rural and Small-Town America (the Rural Atlas) [42], the State and Local Planning for Energy (SLOPE) platform [43], and the Renewable Energy Integration and Optimization (REopt®) platform [44]. Each of these data sets were incorporated into one master data set using RStudio. See Table 1 for an overview of each data set and their associated metrics.

The Rural Atlas, SLOPE, and REopt data sets were originally resolved at the county level, whereas the EJSCREEN and LEAD data sets were originally resolved at the census block group and census tract levels respectively. Thus, to create the master data set, the EJSCREEN and LEAD data sets were aggregated to the county level. We avoided mean aggregation for the EJSCREEN and LEAD data because highly impacted communities could be missed using this method. For example, a highly energy-burdened census tract, if surrounded by census tracts in the same county with low energy burdens, would be hidden; thus, we aggregated using national quintiles by the processes described in the next several sections. Data sets were then merged by matching the five-digit county Federal Information Processing Series (FIPS) codes, which are unique county identifiers maintained by the American National Standards Institute [45].

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TABLE 2

EJSCREEN Metric Descriptions.

Type	Metric	Definition
Sociodemographic	Less than high school education	Percentage of individuals who have less than a high school education in each census block group
	Low-income	Percentage of households in each census block group that make less than or equal to twice the federal poverty level
	Minority	Percentage of Hispanic or nonwhite individuals within each census block group
Environmental hazard*	Cancer risk (air toxics)	Lifetime cancer risk due to inhalation of outdoor air toxics
	Diesel particulate matter concentration	Hazardous air pollutants, measured in $\mu g/m^3$
	Lead paint indicator	Percentage of occupied housing units in each census block group that were built before 1960
	National priorities list sites proximity	Superfund sites where remediation is needed; number of sites "within five km of the average block group resident, divided by distance" in kilometers (p. 56)
	Ozone concentration	Summer average daily maximum 8-hour concentration in parts per billion (ppb)
	$PM_{2.5}$ concentration	Average annual concentrations of fine particles in the air, measured in $\mu g/m^3$
	Respiratory hazard index (air toxics)	Ratio of exposure concentration to health-based reference concentration
	Risk management plan proximity	Facilities that house hazardous materials for which a risk management plan must be established; number of sites "within five km of the average block group resident, divided by distance" in kilometers (p. 56)
	Treatment, storage, and disposal facilities proximity	Hazardous waste disposal sites; number of sites "within five km, divided by distance" in kilometers (p. 59)
	Traffic proximity	Average annual daily vehicle counts divided by the distance in meters
	Wastewater discharge	Water pollutant concentrations divided by the distance in meters

Source [47].
*Each environmental hazard metric is associated with adverse human and environmental health impacts. A higher score for each metric indicates an increased presence of the hazard within each census block group.

EJSCREEN xxx

This analysis used 14 EJSCREEN sociodemographic and environmental hazard metrics, each of which are resolved at the census block group level and described in Table 2 [47,48]. To aggregate the EJSREEN metrics to the county level, we created indicators for each of the metrics. Although a single environmental indicator combining each of the 11 environmental hazard metrics might help identify communities most in need (i.e., those that are most exposed to environmental hazards), the EPA advises against this because viewing the metrics separately provides a more complete picture of hazard exposure across the country [47,p. 25]. In addition, indicator creation requires making determinations about weighting the metrics, and determining the importance of the various weighting criteria (e.g., public health or financial implications) is subjective and should be established by local communities; thus, we investigated each metric independently and created 14 distinct indicators through the following process (see Figure 1).

First, to aggregate EJSCREEN to the county level, we used the *ntile* function from the *tidyverse* in RStudio to assign a quintile score to each block group. Quintiles were created for each of the 14 metrics across all block groups to describe how well the block group compares to the nation as a whole. For example, if a census block group scored within the fifth quintile (80^{th}–100^{th} percentile) for a given metric, it was given a score of 5. If the block group scored within the fourth quintile (60^{th}–80^{th} percentile) for a given metric, it was given a score of 4, and so forth (see Appendix A for the descriptive statistics for each metric within each quintile). Lastly, we calculated the proportion of census block groups within each county that fell within each of the five quintiles, creating county-level proportion scores.

We then created the sociodemographic indicators using the fourth- and fifth-quintile proportion scores to create a weighted sum for each county. We used the fourth and fifth quintiles to highlight the counties most representative of the sociodemographic metrics. We began with the proportion score from the fourth and fifth quintiles for each metric (i.e., the proportion of block groups in each county that fell within the fourth and fifth quintiles). Counties with quintile bins greater than .20 have a disproportionately high number of census block groups in those bins; thus, we subtracted .20 from the fourth-quintile proportion and from the fifth-quintile proportion to determine how much the values exceed the national distribution. We then summed the fourth and fifth quintile values and weighted the fifth quintile value more heavily.[1] The final indicator score for each sociodemographic metric was thus a weighted sum of the proportion of census block groups in the fourth and fifth quintiles in excess of .20 by county.

We created the environmental hazard indicators using the fifth-quintile proportion score for each county. The fifth quintile alone was used because that quintile is associated with a sharp increase in risk score assigned by EJSCREEN for most of the environmental metrics (see Appendix A). The maximum air toxics cancer risk scores, for example, in the first through fourth quintiles are 24, 29, 33, and 38, respectively, and the maximum score in the fifth quintile is 1505. Further, scores within the fifth quintile for two of the metrics mark the point at which the EPA has

[1] The weights applied to the fifth quintile were calculated by dividing the national mean score for the fifth quintile by the national mean score for the fourth quintile. For example, for the low-income EJSCREEN metric, the mean fourth quintile score was .44 and the mean fifth quintile score was .66 (see Appendix A). Thus, we weighted the fifth quintile by 1.5 for the low-income indicator. Using the same process, we weighted the fifth quintile for the minority indicator by 1.7 and the fifth quintile for the less than high school education indicator by 2.1.

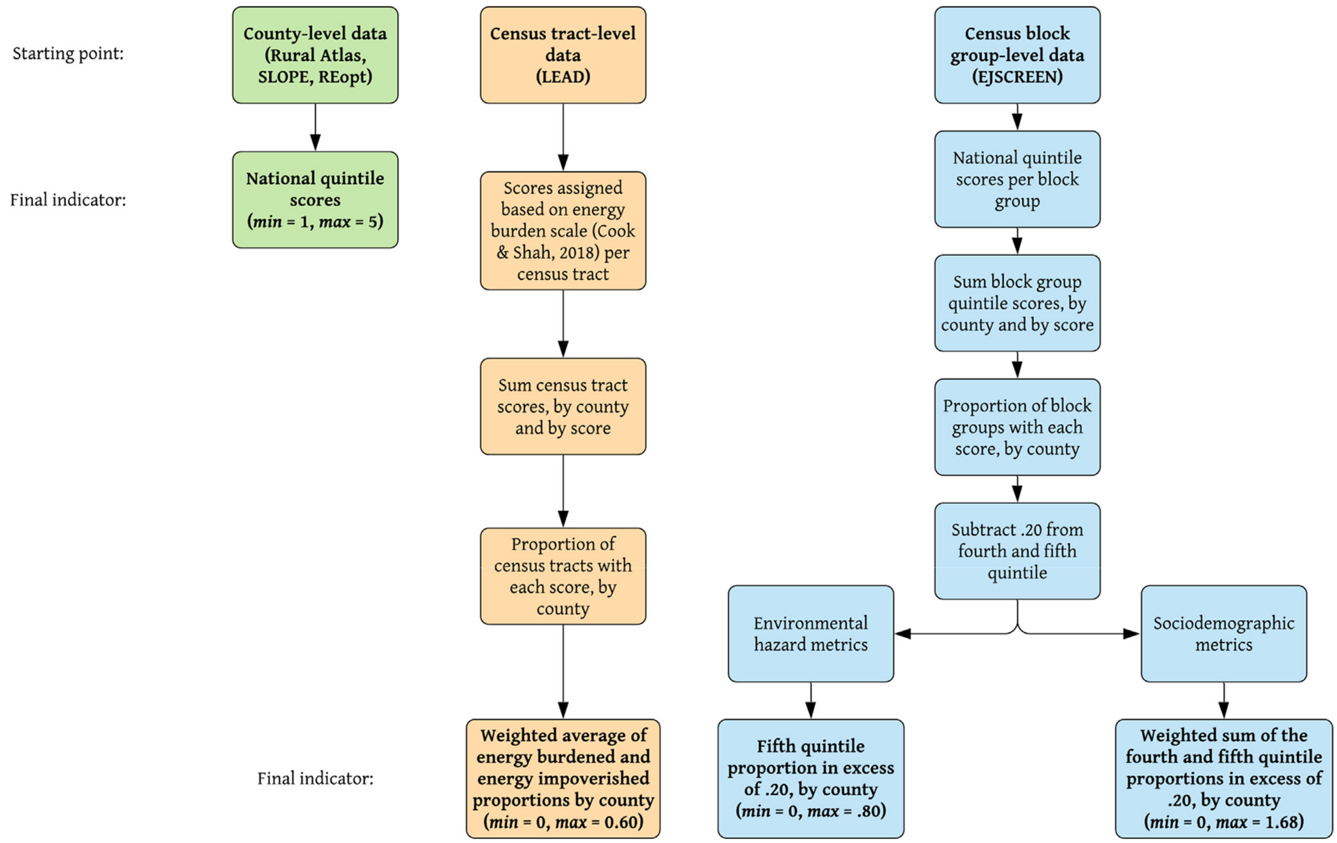

FIGURE 1

Flowchart Describing the Indicator Creation Process.

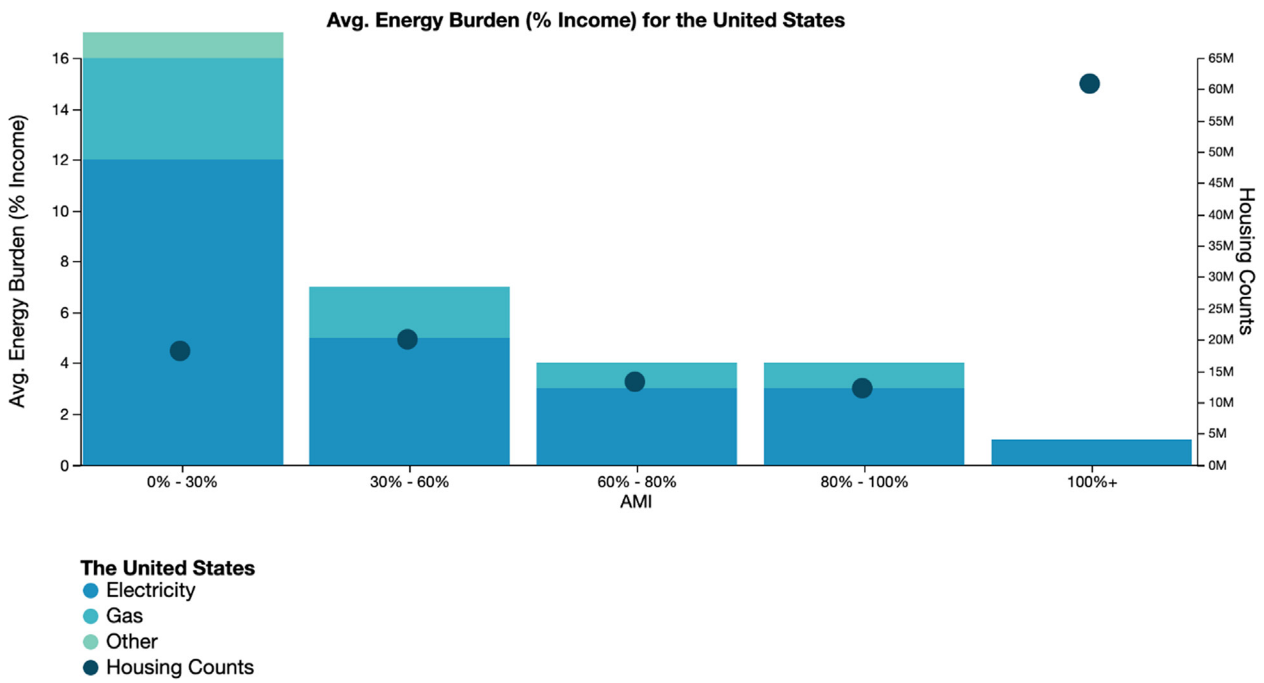

FIGURE 2

Average Energy Burden in the United States by Area Median Income Level, Used to Calculate Weights for County Energy Burden Indicator Scores. Source [41].

set a break point for public health risk; the EPA public health limits for $PM_{2.5}$ and ozone are 2.0 μg/m^3 and 70 ppb, respectively, both of which fall within the fifth quintile range for their given metric [49,50]. This indicates that all counties that fall within the fourth quintile or lower do not exceed the annual public health limit for these metrics. The final indicator score for each environ-

TABLE 3

Rural Atlas Metric Descriptions.

Metric	Definition
Farming-dependent counties	Yes/no binary of farming dependence, defined as a county in which farms account for at least 25% of a county's earnings or at least 15% of total county jobs
Mining, quarrying, and O&G jobs	Percentage of labor force employed in mining, quarrying, and oil and gas extraction
Persistent-poverty counties	Yes/no binary of persistent poverty, defined as a county in which the poverty level was consistently at or greater than 20% in the 1980 census, the 1990 census, the 2000 census, and the 2007–2011 American Community Survey
Rural-urban continuum code	Ranges from 1 (most urban and metropolitan) to 9 (most rural and non-metropolitan); includes measures of population sizes and, for non-metropolitan areas, adjacency to metropolitan areas*
Unemployment	Percentage of unemployed individuals, defined as those over age 16 who are unemployed and actively seeking employment

Sources. Rural-urban continuum code [57]; all others [42].

*For example, a score of one indicates a county with a population of at least 1 million people, and a score of nine indicates a rural county not adjacent to a metropolitan area with a population of less than 2500.

mental hazard metric was thus the proportion of census block groups in the fifth quintile in excess of .20 by county.

LEAD xxx

The LEAD tool provides data on energy expenditures and income level for counts of housing unit types [41] (see Figure 2). We used the LEAD tool's census tract-level calculations for energy burden and aggregated the data to the county level. Energy burden is defined as the proportion of household income spent on housing energy costs [41,p. 1]. To aggregate energy burden to the county level, national quintiles were not used because the LEAD data have a skewed distribution (*skewness* = 6.3) and the national quintile calculation produced 20th, 40th, 60th, and 80th energy burden percentiles of 2%, 3%, 3%, and 4% respectively, which fails to provide meaningful energy burden cut-off points. Previous research identifies energy burden exceeding 6% as a high energy burden [51], and Cook and Shah [52,p. 3] reported a scale of energy burden describing households that spend less than 4% of annual income on energy as "*not burdened*," those that spend between 4% and 7% on energy as "*energy stressed*," those that spend between 7% and 10% as "*energy burdened*," and those that spend greater than 10% as "*energy impoverished*." To go beyond an energy burden binary, we use the Cook and Shah [52] scale to create the energy burden indicator through the following process.

We first applied the Cook and Shah [52] scale to each census tract. Energy burdens less than 4% received a score of one, energy burdens greater than or equal to 4% and less than 7% received a score of two, energy burdens greater than or equal to 7% and less than or equal to 10% received a score of three, and energy burdens greater than 10% received a score of four. We then calculated the percentage of census tracts within each county in each category: *not burdened, energy stressed, energy burdened,* and *energy impoverished*. According to previous research [51], we focused on energy burdens exceeding 6%; thus, we took an average of the *energy-burdened* and *energy-impoverished* proportions from each county and weighted the averages to account for higher burdens among energy-impoverished households. The resulting energy burden indicator is thus a weighted average of the percentage of census tracts labeled as *energy burdened* and *energy impoverished* by county.[2]

Rural Atlas

This analysis uses five metrics from the USDA Rural Atlas [56] (see Table 3). Two of the metrics—unemployment and percentage employed in mining, quarrying, and O&G extraction—are raw scores taken from the Rural Atlas' Jobs data set. Quintiles were calculated to provide an indication of how county scores compared across the nation. To assign quintile scores for these two metrics, we used the *ntile* function in RStudio's *tidyverse*. If a county's raw value was within the first quintile, it was assigned a score of one. If a county's raw value was within the second quintile, it was assigned a score of two, and so forth. Quintile scores were used to identify specific DAC targets but were not used in the correlation analyses. The other three Rural Atlas metrics used in this analysis—the rural-urban continuum code, farming dependence, and persistent poverty—originated from the Rural Atlas County Classifications data set, which assigned scores to each county based on certain criteria (see Table 3). This analysis uses the last three metrics unmanipulated.

SLOPE xxx

The DOE and National Renewable Energy Laboratory's SLOPE platform provides modeled energy efficiency, renewable energy, and sustainable transportation data at city, county, and state levels [43]. From SLOPE, we used estimates for technical generation potential, levelized cost of energy (LCOE), and capital costs. Technical generation potential, or simply technical potential, is the modeled maximum generation in megawatt hours (MWh) per year that could be produced by a given technology if all suitable land or rooftop area were used. Technical potential considers resource availability and quality but not market conditions, transmission capacity, or integration into the electricity grid [58][3]. LCOE is the cost to generate electricity ($/MWh), assumes new construction, and considers the technology's capital costs, operation and maintenance costs, performance costs, capacity fac-

[2] We arrived at the weights through the following process. Using LEAD data, we determined that energy burden increases as income decreases. Households earning less than 30% of the median income, or approximately $20,000 in the U.S. [53], have an average energy burden of 16%, and households earning between 30%–60% of the median income, or between approximately $20,000–$40,000, have an average energy burden of 6% (see Figure 2) [41]. In addition, energy consumption increases with income. Households in the lowest two income brackets consume an annual average of 57.0 and 68.9 million Btu respectively, including electricity, natural gas, fuel oil/kerosene, and propane, whereas households earning $140,000 or more per year consume an average of 111.2 million Btu [54], [55]. This means that although those at the lowest income bracket consume the least amount of energy, they have the highest energy burden. To account for this lower consumption, census tracts with a score of four (i.e., those that are energy impoverished with energy burdens exceeding 10%) were assigned a weight of 1.2 because they would need to consume 1.2 times more energy to consume as many Btus as the next largest income bracket. Census tracts with a score of three (i.e., those that are energy burdened with energy burdens between 7%–10%) were assigned a mid-point weight of 1.1 because their energy burdens fall between the lowest two income brackets.

[3] Modeled annual technical generation potential for commercial PV includes buildout on rooftops of both commercial and industrial buildings.

TABLE 4

Technology Definitions, Metrics, and Assumptions

Technology	Source	Definition	Metrics and Assumptions
Utility PV	SLOPE	Uses ground-mounted, tracking, large-capacity systems to convert solar energy into electricity	**Technical potential**: Single-axis tracking, 20 MW capacity systems [58] **LCOE**: 100 MW capacity facility and several cost inputs (see [59])
Residential PV	SLOPE	Uses residential building roof-mounted, fixed tilt, small-capacity systems to convert solar energy into electricity	**Technical potential**; **LCOE**: Site-specific; calculated for representative census blocks and aggregated to the county level [58,59]
Commercial PV	SLOPE	Uses commercial and industrial building roof-mounted, fixed tilt, medium-capacity systems to convert solar energy into electricity	**Technical potential**; **LCOE**: Site-specific; calculated for representative census blocks and aggregated to the county level [58,59]
Land-based wind	SLOPE	Uses utility-scale, large-capacity onshore wind turbines to convert wind energy into electricity	**Technical potential**: 2.6-MW nameplate capacity turbine, 121 m rotor diameter, and 90 m hub height [58] **LCOE**: 200 MW facility capacity and several cost inputs (see [59])
Geothermal	SLOPE	Converts energy from naturally occurring underground reservoirs of hot water into electricity	**Capital cost**; **LCOE**: Site-specific and considers the hydrothermal resource temperature and well productivity and depth [59]
Hydropower	SLOPE	Converts potential energy from flowing water into electricity	**Capital cost**; **LCOE**: Site-specific and considers new stream reach and non-powered dam development but not upgrades to existing facilities [59]
Solar-plus-storage	REopt	Behind-the-meter battery energy storage systems (BESS) coupled with rooftop solar for commercial buildings	**Cost savings**: Medium office building loads, varied by climate zone; fixed PV array costs of $1,600/kW, BESS power costs of $840/kW, and BESS energy costs of $420/kWh (among other inputs; see [60,61])

tors, labor markets, and interconnection costs [59]. For utility PV, residential PV, commercial PV, and land-based wind, we used the technical potential data set and the 2020 data from the LCOE data set [58,59]. For geothermal and hydropower, we used the 2020 LCOE and capital cost data from the LCOE data set [59]. For all technologies, we used the median technical potential, LCOE, and capital cost estimates. Technical definitions and assumptions for all technologies can be found in Table 4.

We grouped SLOPE county-level data for each technology into quintiles using the *ntile* function in RStudio's *tidyverse* to indicate how county scores compared across the nation. Quintile scores were used to identify specific DAC targets but were not used in the correlation analyses. If a county's raw value was within the first quintile, it was assigned a score of one. If a county's raw value was within the second quintile, it was assigned a score of two, and so forth. For the technical potential metrics, a higher score indicates that more potential exists for energy generation development of a given technology in that county. For LCOE and capital cost metrics, a higher score indicates relatively higher costs for a given technology in that county.

REopt

We used cost-savings estimates for solar-plus-storage from the REopt model to assess the geographic locations for which commercial solar-plus-storage is most economically viable. The REopt model, developed by the National Renewable Energy Laboratory, is a techno-economic, mixed-integer linear program that determines the technology type, sizing, and dispatch strategy for a cost-optimal renewable energy system [62,p. 1,2]. REopt cost-savings estimates were derived from a recent nationwide assessment of the economic viability of commercial solar-plus-storage systems conducted by Kwasnik and others [60][4], assumptions for which can be found in Table 4.

The data were reaggregated from utility subdivisions to the county-level using county geometries from the U.S. Census Bureau, intersecting the REopt data with the U.S. county shapefile, calculating the percentage of overlap between reference sites and counties, and scaling the cost savings for each site within the county by percentage overlap. These scaled savings were then summed for each county. REopt county-level data were then grouped into quintiles using the *ntile* function in RStudio's *tidyverse*. The 53% percent of counties with cost-savings estimates of $0 ($N = 1649$) were removed from the quintile calculation so that the quintiles were based only on counties with cost savings greater than $0. If a county's raw value was within the first quintile, it was assigned a score of one. If a county's raw value was within the second quintile, it was assigned a score of two, and so forth. The quintile scores were used to identify specific DAC targets; however, for the correlation analyses, we used the raw cost-savings estimates and included counties with cost savings estimates of $0.

[4] The assessment [60] modeled potential savings for 2,541 scenarios generated by varying common utility rates at reference sites partitioned by climate zone, state, and solar resource intensity. The assessment included service territories for all investor-owned-utilities (IOUs) and non-IOUs with more than 400,000 customers in 2010, as well as the 45 biggest non-IOUs by area.

TABLE 5

Correlations Between Renewable Energy Potential and Cost Metrics and Environmental and Sociodemographic Indicators.

	Technology													
	Commercial PV		Residential PV		Utility PV		Land-based wind		Geothermal		Hydro		Solar + storage
Indicator	Technical potential	LCOE	Technical potential	LCOE	Technical potential	LCOE	Technical potential	LCOE	Capital costs	LCOE	Capital costs	LCOE	Cost savings
Energy burden	-.07***	.02	-.08***	.02	.02	.04*	.04*	-.01	.08	.07	.07***	.07***	-.04*
Less than HS	-.08***	-.24***	-.12***	-.22***	.06***	-.32***	-.01	.22***	-.11^{+}	-.10^{+}	-.18***	-.09***	.01
Low-income	-.12***	-.17***	-.15***	-.16***	.04*	-.26***	-.01	.20***	.10^{+}	.11^{+}	-.13***	-.05*	-.04*
Minority	.15***	-.37***	.13***	-.35***	.23***	-.25***	.12***	.10***	-.09	-.10^{+}	-.08***	-.06**	.14***
Mining, quarrying, and O&G employment	-.07***	-.25***	-.09***	-.25***	.29***	-.25***	.31***	-.15***	-.09	-.10^{+}	-.07***	-.02	-.03^{+}
Rural	-.29***	-.10***	-.35***	-.11***	.14***	-.12***	.22***	-.24***	.11^{+}	.11^{+}	.11***	.10***	-.11***
Unemployment	.18***	.21***	.17***	.23***	-.11***	.16***	-.19***	.24***	-.23***	-.23***	-.10***	-.04*	.17***
Cancer risk	.07***	-.07***	.07***	-.06***	-.07***	-.12***	-.15***	.39***	-.18**	-.18**	.01	.07***	.04*
Diesel PM	.33***	.02	.29***	.02	-.06**	.09***	-.07***	.12***	.09	.08	-.06**	-.06***	.01
Lead paint	.14***	.12***	.10***	.12***	-.05**	.15***	-.02	-.15***	.00	.00	.04*	.01	-.02
NPL proximity	.16***	.08***	.16***	.07***	-.06***	.12***	-.08***	.03^{+}	.05	.04	.00	-.03^{+}	.04*
Ozone	.06***	-.42***	.07***	-.45***	.39***	-.22***	.37***	.01	.23***	.23***	.08***	.04*	.14***
$PM_{2.5}$	.22***	.00	.22***	.00	-.06**	.12***	-.08***	.25***	-.19***	-.18**	-.02	-.05***	.14***
Respiratory hazard	.08***	-.09***	.06***	-.09***	-.07***	-.09***	-.16***	.43***	-.33***	-.33***	.03	.08***	.12***
RMP proximity	.04*	-.10***	.03	-.10***	.08***	-.08***	.10***	-.22***	-.11*	-.12*	.17***	.15***	-.01
TSDF proximity	.43***	.04*	.32***	.04*	-.08***	.15***	-.08***	.08***	-.24***	-.24***	-.04*	-.06***	.15***
Traffic proximity	.49***	-.02	.37***	-.02	-.08***	.12***	-.08***	.09***	-.24***	-.24***	-.03	-.04*	.21***
Wastewater discharge	.08***	-.02	.08***	-.03^{+}	.04^{+}	.02	.02	.04*	.00	-.01	.04^{+}	.03	.03

Note: Blue shades indicate positive correlations, with darker blue indicating a stronger positive correlation. Pink shades indicate negative correlations, with darker pink indicating a stronger negative correlation. The lightest shade indicates a correlation between ±.10 and ±.30, and the darkest shade indicates a correlation greater than ±.30. White indicates either a negligible correlation ($r < .10$) or a correlation with $p > .10$. A p-value less than .05 indicates a significant relationship, and a p-value greater than or equal to .10 indicates a nonsignificant relationship. A p-value greater than or equal to .05 and less than .10 is considered marginally significant.

*** $p < .001$, ** $p < .01$, * $p < .05$, $^{+}$ $p < .10$.

Results and discussion

Identifying intersections of DAC indicators and renewable energy development potential

To identify areas of overlap between the DAC indicators and renewable energy development potential, we identified correlations between the sociodemographic and environmental hazard indicators and the raw renewable energy technical potential and cost estimates using RStudio (see Table 5 for the correlation). These correlations indicate possible avenues for renewable energy development, given the metrics considered in this analysis. The data sources supported analysis within the 48 contiguous states and Washington, D.C., creating a data set with 3,108 counties (see Appendix B for the number of counties with data for each metric). A higher score on the rural classification indicates a more rural county. Higher scores on the other indicators represent a greater presence of the metric in each county. For example, a higher score on the unemployment metric indicates a higher proportion of unemployed individuals in each county [41,47,56,58] (see section 2.1). Thus, for the technical potential[5] metrics, positive correlations mean that as the environmental hazard or sociodemographic indicator score increases, potential tends to increase, indicating that those communities might have opportunities for technology development with high generation potential. For the capital cost and LCOE metrics, negative correlations mean that as the environmental hazard or sociodemographic indicator score increases, costs for a technology tend to decrease, indicating that those communities might have opportunities for development of that technology at lower costs relative to the costs in other communities. For solar-plus-storage, positive correlations mean that as the environmental or sociodemographic indicator score increases, cost savings tend to increase, indicating that those communities might have opportunities for cost savings from solar-plus-storage. The strongest correlations for each technology are described in the following sections.

Commercial and residential PV

Commercial and residential PV share similar relationships at similar strengths across each sociodemographic and environmental hazard indicator. Technical potential is generally higher in urban areas due to higher concentrations of commercial and residential buildings. LCOE for commercial and residential PV tends to be lower in areas with higher concentrations of minority individuals, higher percentages of mining, quarrying, and O&G extraction jobs, and higher concentrations of individuals with less than a high school education. As technical potential is generally higher in areas in closer proximity to traffic and TSDFs and higher concentrations of diesel PM and $PM_{2.5}$, residential and commercial PV may also present a targeted investment opportunity in certain environmental justice communities.

Utility PV

Utility PV correlations indicate relatively high development potential in many areas with higher concentrations of minority individuals and in many areas with greater ozone exposure. Low LCOE for utility PV in areas with concentrations of individuals with less than a high school education and low-income individuals and high technical potential in areas with high mining, quarrying, and O&G jobs indicate that there could be an opportunity for utility PV in communities in need of workforce development who may be transitioning away from fossil fuel production.

Land-based wind

LCOE for land-based wind tends to be lower in rural areas and in areas with closer proximity to RMP facilities. Greater technical potential for land-based wind correlates relatively strongly with higher levels of employment in mining, quarrying, and O&G extraction, with rural status, and with greater ozone exposure, indicating that wind development might present an economic development opportunity in communities transitioning away from fossil fuel production, while potentially drawing on skilled workers from these industries.

Geothermal

Hydrothermal utility-scale generation from geothermal resource is not feasible in most counties. As a result, only 304 counties had geothermal data points. Areas with relatively lower-cost geothermal generation are associated with higher air toxics respiratory hazard, closer proximity to traffic and TSDFs, and higher rates of unemployment.

Hydropower—non-powered dams and new stream reach development

For hydropower capital costs and LCOE, the strongest relationship is between capital costs and proximity to RMP facilities; however, none of the correlations with hydropower are relatively strong.

Solar-plus-storage

Cost savings for solar-plus-storage had relatively weak correlations with the DAC indicators but did tend to be higher in areas closer to traffic, indicating that the technology might have the potential to be broadly developed in these areas.

Case studies

While correlations between DAC and renewable energy metrics can identify trends across counties, perhaps the highest value of this new data set is in the array of county-level metrics it provides. The data set created for this analysis could help identify which renewable energy technologies have comparatively high potential and low costs for any given DAC and, similarly, to identify the DACs with high opportunity for specific renewable energy technologies. In the next two sections, we provide example analyses of these types.

Identifying a county with high need and high potential

Costilla County in southern Colorado scores relatively highly on several DAC indicators (see Table 6). The county is categorized as completely rural and a persistent poverty county by the USDA's Rural Atlas. It is also categorized as a farming-dependent community and exceeds the 60th percentile for unemployment and for employment in mining, quarrying, and O&G extraction. More than 80% of its census block groups are in the highest quintile for percentage of low-income individuals, and its two census

[5] Technical potential is the amount of generation per year that could be produced by a given technology if all suitable land or rooftop area is used. LCOE is the cost to generate electricity per MWh (see Section 2.1.4).

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TABLE 6

DAC and Renewable Energy Deployment Potential Indicators in Costilla County, CO.

Metric	Raw value	Indicator score
Utility PV		
Technical potential	91,650,546 MWh	4th quintile
LCOE	$45/MWh	1st quintile
Land-based wind		
Technical potential	10,961,518 MWh	4th quintile
LCOE	$38/MWh	2nd quintile
Solar-plus-storage		
Cost savings	$3,363	4th quintile
Unemployment rate	7.2%	4th quintile
Mining, quarrying, and O&G employment	.86%	4th quintile
Low-income[a]	59%	0.88
Energy burden[b]	8%	0.55
Less than high school education[a]	22%	0.93
Hispanic or nonwhite individuals[a]	69%	0.81
Ozone concentration[a]	49 ppb	0.80

[a] Unweighted average taken across Costilla County's four census block groups.
[b] Unweighted average taken across Costilla County's two census tracts.

tracts are considered *energy burdened*, as defined by Cook and Shah [52]. Half its census block groups are in the highest quintile for percentage of the population with less than a high school education. Additionally, 80% of its census block groups fall in the highest quintile for percentage of Hispanic or nonwhite individuals. All the county's census block groups score in the highest quintile for the ozone indicator.

The renewable energy metrics for Costilla County indicate substantial opportunity for job creation and investment from renewable energy development. Utility PV technical potential is in the fourth quintile and LCOE is in the first quintile, indicating higher technical potential and lower cost than the average U. S. county. The county has similarly high potential and relatively low LCOE compared to other counties for land-based wind. Solar-plus-storage also presents an opportunity, as the cost savings associated with solar-plus-storage are in the fourth quintile. In sum, our analysis found that Costilla County may have high need and high renewable potential. Utility PV, land-based wind, and solar-plus-storage deployment have relatively favorable conditions to create jobs and increase local tax revenues for Costilla County community members.

Identifying top DAC opportunities for utility PV development

As discussed, utility PV has relatively high potential in areas with higher ozone concentrations and higher employment in mining, quarrying, and O&G extraction. To demonstrate the usefulness of the data set in increasing equity in investment decision making, we identified the top ten DACs with potential for development of utility PV, considering the DAC metrics of ozone and mining, quarrying, and O&G employment. To generate this list, we filtered the data set to include only counties that fall in the highest quintile for utility PV technical potential and the lowest quintile for utility PV LCOE. We also filtered the data set to include only counties with the highest score for the ozone indicator that fall in the highest quintile for mining, quarrying, and O&G jobs. We then sorted the data set first by highest percentage employed in mining, quarrying, and O&G extraction; then by highest utility PV technical potential; and finally, by lowest utility PV LCOE. Table 7 identifies the top ten counties resulting from this process.

Counties in Table 7 have strong potential for utility PV development relative to national averages. Additionally, between 16.3% and 27.3% of these counties' labor forces are employed in mining, quarrying, and O&G extraction, and each county is considered non-metropolitan. Finally, each of the counties' census block groups falls within the fifth quintile for ozone. This indicates that utility PV development could present an economic development opportunity in these communities if they are to transition away from fossil fuel production. Queries assessing the top DAC opportunities for additional combinations of technologies and DAC metrics can also be performed with our data set.

General discussion, limitations, and future directions

Our data set can contribute to energy justice by enabling consideration of distributive justice in relation to renewable energy development. For example, decision-makers can use the data set to prioritize marginalized communities with renewable

TABLE 7

Top Ten DACs for Utility PV Development Considering Ozone Concentrations and Employment in Mining, Quarrying, and O&G Extraction.

County	Technical Potential (MWh)	LCOE ($/MWh)	Employed in mining, quarrying, and O&G (%)	Ozone Indicator Score	Rural-Urban Continuum Code
Loving, TX	117,310,996	39	27.3	.80	9
Andrews, TX	260,067,236	39	24.0	.80	6
Campbell, WY	316,499,376	44	23.0	.80	5
Yoakum, TX	131,520,286	41	21.6	.80	7
Winkler, TX	147,923,745	39	21.2	.80	6
Weston, WY	213,349,257	44	18.8	.80	7
Ward, TX	145,515,427	39	18.7	.80	6
Hemphill, TX	109,192,439	41	18.1	.80	7
Lea, NM	771,322,461	41	17.8	.80	5
Uintah, UT	182,290,073	47	16.3	.80	7

energy investments without sacrificing generation potential. Further steps can ensure the benefits of renewable energy development are absorbed by the community, for example by establishing local hire provisions to set aside jobs for community members. Communities can use the data set to investigate the DAC indicators in their area and prioritize renewable energy technology development based on comparative potential. Researchers outside the U.S. can also use our work as a template for their own investigations into energy, incorporating tools relevant to their regions. For example, the Environmental Justice Atlas (EJAtlas) is a tool that documents environmental justice conflicts around the world and could be used to examine distributive justice in other regions by intersecting environmental concerns with renewable energy development potential [63].

The energy justice principle of procedural justice, however, is missing from our analysis; our work was conducted without input from community members. Thus, decision-makers will need to incorporate and rely on community guidance to ensure community agency. Mobilizing local knowledge [14,p. 178] increases equity in renewable energy investment decision making, and thus, involving community members meaningfully in the decision-making process is a key component of energy justice and can increase local acceptance of renewable energy projects [64]. We have provided a starting point, but communities must determine the factors and strategies that are most important and relevant for them.

For this reason, community, decision-, and policymakers need to rely on the correlations reported in this work in addition to other important factors. The correlations highlighted in this analysis describe the tendency for any two given metrics to be related, and many counties do not follow these patterns. Future research at a more granular geospatial level is needed, especially in counties with large populations, to inform county-specific or regional investment decisions and to determine the renewable energy technologies with the highest potential for a given area or DAC. Further, although many of the correlations found in this analysis are strong relative to the correlations found across all technologies and metrics considered, they generally do not explain a large portion of variance. More exploration into the correlates of renewable energy development potential is needed to determine whether the correlations found in this research are strong in the context of renewable energy development potential. The correlations found in this research also do not imply causation; thus, the relationships might not replicate beyond the geographies considered here, and renewable energy deployment might not directly mitigate the challenges faced by DACs. Finally, although our analysis found that some DAC metrics (e.g., energy burden) are not correlated with the renewable energy metrics, renewable energy development could still be highly beneficial to such communities (e.g., by reducing energy burden). A lack of correlation might indicate a greater need for enacting policies that make renewable energy technologies more financially viable, and our data set can help to support those types of analyses. Additionally, the expansion of distributed energy resources (DERs; e.g., rooftop PV) has both energy justice benefits and drawbacks [65]. For instance, regardless of whether DERs have relative financial viability in a community, DERs that are unaffordable to DACs will exacerbate existing inequalities, and thus, program and policy interventions are required to expand access to the benefits of DERs for DACs. Our analysis can help policymakers establish criteria for program participation by aiding in DAC definition and identification. Policymakers prioritizing DACs and targeting renewable energy development in specific counties or regions can also use our data set to match DAC status with technical potential and LCOE. In this way, the appropriate technology, based on technical potential and LCOE, can be prioritized in the appropriate areas, maximizing the benefits of the technology.

Our analysis highlighted opportunities for renewable energy development in DACs considering three broad categories of metrics: socioeconomic, environmental hazard, and renewable energy deployment potential metrics. The benefits and drawbacks, however, of renewable energy deployment for DACs cannot be assessed by these metrics alone, and there are other important factors to consider when developing new technologies. Certain renewable energy technologies might generate more jobs than others, and some might reduce energy burden more than others. Environmental impacts also vary across technologies and geographies, and in some cases, renewable energy technologies are themselves associated with environmental justice concerns [66]. Additionally, the development of renewable energy technologies does not necessarily equate to net economic benefit where fossil-based jobs and local revenues may decrease. Finally, and importantly, support for renewable energy development varies across communities. Our analyses do not quantify these effects, and optimal renewable energy development intersections with DACs might change if these additional factors are considered. Future research can thus expand on the metrics included in this analysis to make these additional considerations. For example, the National Renewable Energy Laboratory's Jobs and Economic Development Impact (JEDI) models can be applied to examine the number of local jobs that could be generated from maximum deployment of each renewable technology. DER adoption rates could also be incorporated into the data set to examine adoption patterns across DACs and renewable energy development potential. Additionally, a metric to estimate community support and policy readiness for renewable energy development can further illustrate feasibility. For instance, a policy metric could be used that assesses the level of renewable energy-supportive policy that exists in a jurisdiction. Our data set can provide a pathway into these investigations.

Conclusion

Data presented in this research can inform renewable energy development strategies for disadvantaged communities. We first looked at the correlations between DAC metrics and renewable energy deployment potential metrics. The strongest correlations indicate that mining, quarrying, and O&G extraction counties tend to have higher wind resources, which represents an opportunity for developing new sources of stable income and employment in energy transitions. Counties with larger populations of minority individuals tend to have good opportunity for commercial and residential rooftop PV development, and counties with higher proportions of individuals with less than a high school education tend to have good opportunity for utility PV develop-

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ment. Counties in closer proximity to traffic and TSDFs and those with higher diesel pollutant concentrations tend to have higher potential for the development of commercial and residential rooftop PV. Counties with higher ozone concentrations tend to have higher potential to develop utility PV and land-based wind, in addition to having relatively lower-cost commercial and residential PV opportunities. Finally, counties with higher respiratory hazard due to air toxics tend to have relatively lower-cost geothermal opportunities.

We also identified how individual communities can use our data set to better understand their comparative renewable energy development opportunities and to inform more strategic economic development and energy planning. The Costilla County, Colorado example showed relatively high potential for utility PV, land-based wind, and solar-plus-storage development. In addition, we identified several rural counties in Texas, Wyoming, New Mexico, and Utah that have high employment in mining, quarrying, and O&G extraction, are exposed to high concentrations of ozone, and have good potential to develop utility PV.

Transitioning to a low-carbon energy economy is inevitable if we are to limit future climate change [67]; transitioning equitably, however, is not. We risk exacerbating existing inequalities if we fail to prioritize energy justice and expand access to the benefits of renewable energies to DACs. Our analysis and resulting data set can enable prioritization of renewable energy investments in DACs, help to bring the benefits of renewable energy to frontline communities, and ultimately help make the transition to low-carbon energies more equitable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Weatherization and Intergovernmental Program Office and the Joint Institute for Strategic Energy Analysis (JISEA). The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes. This material is also based upon training supported by the National Science Foundation under Grant No. 1828902.

Appendix A

See Table A1.

TABLE A1

Descriptive Statistics for the Metrics from EJSCREEN.

Metrics	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	Min–max	Mean	Min–max	Mean	Min–max	Mean	Min–max	Mean	Min–max	Mean
Less than high school education (%)	0–.03	.01	.03–.07	.05	.07–.12	.10	.12–.21	.16	.21–1.0	.33
Low-income (%)	0–.14	.08	.14–.25	.19	.25–.36	.30	.36–.52	.44	.52–1.0	.66
Minority (%)	0–.07	.03	.07–.19	.13	.19–.38	.27	.38–.70	.52	.70–1.0	.88
Cancer risk from air toxics (see [47])	8.8–23.8	20.1	23.8–28.6	26.3	28.6–33.1	30.8	33.1–38.4	35.6	38.4–1,505	44.8
Diesel particulate matter concentration (μg/m^3)	0.01–0.19	0.13	0.19–0.32	0.25	0.32–0.47	0.39	0.47–0.69	0.57	0.69–6.08	1.08
Lead paint indicator (%)	0–.05	.01	.05–.18	.11	.18–.38	.28	.38–.65	.51	.65–1.0	.80
National priorities list sites proximity (# of sites/km)	0–0.02	0.01	0.02–0.05	0.03	0.05–0.08	0.06	0.08–0.16	0.11	0.16–9.0	0.46
Ozone concentration (ppb)	25.0–38.2	34.2	38.2–41.6	40.1	41.6–43.8	42.8	43.8–46.3	44.9	46.3–75.9	52.1
$PM_{2.5}$ concentration (μg/m^3)	4.01–7.40	6.43	7.40–8.22	7.83	8.22–8.78	8.51	8.78–9.41	9.10	9.41–16.5	10.48
Respiratory hazard index from air toxics (see [47])	0.09–0.31	0.25	0.31–0.38	0.34	0.38–0.46	0.42	0.46–0.55	0.50	0.55–4.10	0.65
Risk management plan proximity (# of sites/km)	0–0.12	0.07	0.12–0.21	0.16	0.21–0.53	0.35	0.53–1.2	0.84	1.2–18	2.5
Treatment, storage, and disposal facilities proximity (# of sites/km)	0–0.13	0.06	0.13–0.59	0.29	0.59–1.7	1.10	1.7–4.2	2.7	4.2–442	22.4
Traffic proximity (vehicle count/m)	0–43.7	16.1	43.7–161	95.4	161–409	270	409–1,027	658	1027–37,576	3145
Wastewater discharge (see [47])	0–0.00002	0.000003	0.00002–0.0004	0.0001	0.0004–0.003	0.001	0.003–0.05	0.01	0.04–429,574	76.5

Appendix B

See Table B1.

TABLE B1

Number of Counties with Data for Each Metric.

Source	Metric	N (counties)
EJSCREEN	Less than HS education	3108
	Low-income	3108
	Minority	3108
	Cancer risk	3108
	Diesel PM	3108
	Lead paint	3108
	NPL proximity	3108
	Ozone	3108
	$PM_{2.5}$	3108
	Respiratory hazard	3108
	RMP proximity	3108
	TSDF proximity	3108
	Traffic proximity	2970
	Wastewater discharge	2889
LEAD	Energy burden	3107
Rural Atlas	All metrics	3108
SLOPE	Technical potential	
	Commercial PV	3107
	Residential PV	3107
	Utility PV	3108
	Land-based wind	3108
	LCOE	
	Commercial PV	3107
	Residential PV	3107
	Utility PV	3102
	Land-based wind	3102
	Geothermal	304
	Hydropower	3060
	Capital costs	
	Geothermal	304
	Hydropower	3060
REopt	Cost savings	
	Solar-plus-storage	3108

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