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A spatial analysis of the development potential of rooftop and community solar energy

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ABSTRACT

Solar energy is a technically and economically feasible solution for transitioning to renewable sources for electrification. Physical and socio-economic conditions that are important determinants of solar access and use have been discussed in the literature. However, the relative access of different population groups to surfaces able to accommodate equipment to generate solar energy (both individual and community levels) is rarely investigated. In this study, we use remote sensing (e.g., LiDAR) and land use data (e.g., tax parcels) to identify residential rooftop and community solar potential (SP) in Erie County, New York. Underlying socio-demographic and urbanization context are then examined to show if community solar is a solution for population groups who have limited access to rooftop solar. Results indicate that rooftop and community SP have similar distributions among socio-demographic groups. Low income and minority population have not only relatively low access to rooftop solar (54% compared to affluent households, 60% compared to white households), but also have limited access to potential community solar sites in their neighborhoods (37% compared to affluent households, 16% compared to white households). Nevertheless, our methodology provides a way to identify neighborhoods where community solar can be a solution for population with limited access to rooftop solar. Results show that in selected areas with available space (e.g., brownfields), community solar is an accessible alternative. The results imply the need for policy development to address such access issues so that technological advancements can benefit different communities.

1. Introduction

Adopting solar technology (e.g., photovoltaic or PV) is one sustainable option for mitigating effects of energy burden (Bohr and McCreery, 2019; Byrne et al., 2015; Gooding et al., 2013). Energy burdened households spend more than 10 percent of their income on energy services. Supplying solar energy may reduce household energy expenditures, reduce government subsidy dependence for energy, and provide opportunities for the household to better utilize their resources. However, solar energy adoption is a complex phenomenon reliant on environmental, economic, technological, socio-demographic, as well as household level factors embedded in a multi-scalar policy framework. Residential rooftop solar provides economic benefits to households and reduces the environmental impact of traditional nonrenewable energy (Byrne et al., 2015; Gagnon et al., 2018; Melius et al., 2013; Rodríguez et al., 2017; Rylatt et al., 2003), but access to the technology is uneven. Spatial variations in access to energy, in turn, results in uneven benefits from solar use (Bouzarovski and Simcock, 2017; Forman, 2017; Sovacool and Dworkin, 2015).

However, analyses of access to solar potential (SP) are rare and are mostly inferred from surveys with a limited sample size (e.g., Rai et al., 2016). The spatial distribution of SP and unevenness in access to SP are often overlooked. Studies investigating the relationship between SP and socio-demographic factors are usually at the city or neighborhood level (Gooding et al., 2013; Suomalainen et al., 2017), finding that renters and poor population groups face barriers accessing the technology (Karakaya and Sriwannawit, 2015). Community solar projects are an opportunity for these groups to obtain solar energy. However, questions remain if people without access to traditional solar delivery forms (e.g., rooftop PV) can establish the new technology in their community.

In this paper, we analyze the relationship between access to SP and socio-demographic factors, aiming to answer the following three questions: (1) Is the distribution of community SP different from residential rooftop SP? (2) Which socio-demographic groups are disadvantaged in

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their access to SP? (3) What is the spatial distribution of the disadvantage? To achieve this goal, we quantified rooftop and community SP at the census tract level by measuring suitable area for solar installation. The estimated SP data are linked to census data, to investigate the relative distribution of access to rooftop and community SP among different socio-demographic groups and urbanization contexts. The contribution of individual census tracts to differences in SP distribution is identified and mapped to visualize spatial patterns of SP access.

2. Factors influencing solar adoption

2.1. Rooftop solar

External household environment. The policy framework surrounding rooftop solar adoption is an important determinant of adoption because policies help mitigate the cost of solar adoption, and increase technology competitiveness over other energy sources (Crago and Chernyakhovskiy, 2017; Karakaya and Sriwannawit, 2015; Kwan, 2012; Sigrin et al., 2015). In the United States (US), differences in state-level policies are found to cause regional variation in adoption rates (Crago and Chernyakhovskiy, 2017; Kwan, 2012). In general, the presence/activity of local solar promotion programs (e.g., renewable energy fairs, education programs, and pooled purchase programs) are positively associated with solar adoption – these programs are especially effective if reliant on established social and organizational networks in communities and provide access to financing or discounts (Graziano and Gillingham, 2014; Noll et al., 2014; Schelly, 2014).

Households are sensitive to economic feasibility and amortization period in their decision-making process (Rai and McAndrews, 2012; Rai and Sigrin, 2013; Schelly, 2014). Economic feasibility is a result of price, the relative pricing of solar to other energy sources, environmental conditions, and the policy environment. A relatively lower solar price, compared to other energy sources, promotes adoption (Crago and Chernyakhovskiy, 2017; Graziano and Gillingham, 2014; Kwan, 2012).

Uncertainty, technological and political, deters solar adoption because initial investment cost is high and the risk of changing policy frameworks affects economic feasibility. While immediate or short-term policy incentives like rebates and tax credits increase adoption, long-term regulations and policy support reduce uncertainty and is very useful in promoting solar adoption (Bauner and Crago, 2015). Empirical evidence suggests that the presence of rooftop solar systems in a neighborhood or social network encourages further adoption by making benefits observable and reducing uncertainty (Graziano and Gillingham, 2014; Rai and Robinson, 2013).

Geographic context is a major determinant of rooftop solar adoption. High levels of solar radiation increase the technical and economic feasibility of solar home systems. Energy yield is positively correlated with solar radiation (Crago and Chernyakhovskiy, 2017; Kwan, 2012; Sarzynski et al., 2012). This results in uneven solar adoption across the US, with higher adoption rates found in states with high solar influx like California and Arizona.

Urban morphology influences solar adoption - rural and suburban areas tend to have higher solar adoption rates than urban areas (Crago and Chernyakhovskiy, 2017; Kwan, 2012; Li et al., 2005). This is a result of more available space and homeownership representing control over solar adoption. Urban areas with high population densities, people renting apartments in high-rise buildings, and lacking control over rooftops have low solar adoption rates (Graziano and Gillingham, 2014; Karakaya and Sriwannawit, 2015).

Household factors. In this section, the internal characteristics of households or decision-makers associated with rooftop solar adoption are identified to understand which population groups are likely to adopt solar and who may face barriers. The architecture of a building strongly affects the viability of solar as an energy alternative (Karakaya and Sriwannawit, 2015; Paidipati et al., 2008). Solar panels need a sufficiently sized area for installation and need to be oriented towards the sun to maximize energy output. In that regard, roof size, roof orientation, and roof slope are essential variables determining the energy output of a PV system (Gagnon et al., 2018; Paidipati et al., 2008). Furthermore, roofs need to able to support the weight of a solar installation adding structural requirements and excluding dilapidated structures. Estimates predict that only approximately 25% of residential rooftops in the US can support solar (Paidipati et al., 2008).

Solar adoption is linked to wealth. Income represents spending power and the ability to invest in new technology (Sigrin et al., 2015). The median value of a house is associated with solar adoption, too (Crago and Chernyakhovskiy, 2017; Kwan, 2012). House values represent equity, which may be used as collateral for solar investment loans. A different interpretation assumes that high-value homes can realize the highest financial benefit.

Adopters are usually young, and increasing age has a negative association with adoption (Crago and Chernyakhovskiy, 2017; Kwan, 2012). Younger population may have a higher willingness to use new technologies than older population. This encourages solar adoption among the young population.

Education is assumed to have an impact on solar adoption, but results differ across studies (Kwan, 2012; Zahran et al., 2008). Kwan (2012) and Rai and McAndrews (2012) found that population with bachelor's degree or higher is associated with solar adoption in the US. However, Crago and Chernyakhovskiy (2017) found no significant relationship between educational attainment and solar adoption.

Race/ethnicity is found to be an indicator of solar adoption. High shares of African American population are associated with lower levels of solar adoption (Kwan, 2012). Whittaker et al. (2005) found that Whites are more likely to adopt pro-environment practices than other racial/ethnic groups. Sunter et al. (2019) found that minority-dominated census tracts have lower levels of PV adoption than white-majority census tracts.

Personal values and norms related to green energy affect the household adoption decision (Crago and Chernyakhovskiy, 2017; Schelly, 2014; Wolske et al., 2017). Non-financial factors like altruism, the prestige associated with green energy adoption, and technology affinity were found to promote adoption. Furthermore, political beliefs are influential - the share of Democratic Party votes is positively associated with solar adoption in studies investigating the adoption of solar hot water and PV systems (Crago and Chernyakhovskiy, 2017; Kwan, 2012; Zahran et al., 2008).

2.2. Community solar

For renters and low-income households to benefit from solar technology, new strategies and technology delivery models are needed. Community solar is an option (Funkhouser et al., 2015). Definitions of community solar vary (Creamer et al., 2018), and we focus on community-owned and organized solar installations (e.g., community-owned solar power plants) in this study. Participation in a community solar project is less costly than installing a residential PV system. Although consumers still pay transmission charges and the operation cost of a third party, the electricity bills of households are reduced compared to traditional energy sources. Similar to rooftop solar adoption (Graziano and Gillingham, 2014; Noll et al., 2014), adoption and support of community solar may depend on observability, and proximity between the community and solar installation seems to sustain support, marketing, and engagement (Creamer et al., 2018).

Community solar deployment faces social and physical constraints (Carrión et al., 2008; Gómez et al., 2010; Sánchez-Lozano et al., 2014; Watson and Hudson, 2015). Avoiding competition with recreational, conservational, industrial, and agricultural uses is important, otherwise it will increase cost and lower support for installations. Low infrastructure cost is also preferred which calls for proximity to streets and electricity grid access. To maximize efficiency, solar plants need to be able to generate economies of scale requiring sufficiently sized

Table 1
Data description.

Data	Description	Use	Data Source
LiDAR Data Erie County, NY (2008)	• 3D information of the buildings • Average point density: 1.26 points/m^2	• Rooftop suitability characterization (roof slope, roof aspect, roof shading, building height) • Community suitability characterization (land slope, land surface)	New York State (NYS) Department of Environmental Conservation (NYSDEC)
Microsoft Building Footprint Data	• Building footprints created from Bing images.	• Rooftop identification	Microsoft Bing Maps Team
Google's Project Sunroof data (G-PS)	• SP at roof scale • Covers heavily populated areas in the US	• Validation at roof scale	Google's Project Sunroof
National Hydrography Data (NHD)	• Waterbody boundaries	• Land identification	US Geological Survey (USGS)
OpenStreetMap (OSM)	• Waterboy boundaries	• Land identification	© OpenStreetMap contributors under the Open Database License
NYS Statewide 2016 Parcels for Public Use	• Contains data related to land use and spatial extent of individual tax parcels	• Identification of relevant land uses for solar adoption	NYS Office of Information Technology Services GIS Program Office
American Community Survey 2012-2016 5-year estimates	• Socio-demographic characteristics	• Unevenness assessment	US Census Bureau
NYS Civil Boundaries (City/Town)	• Contains boundaries of Municipalities in NYS	• Assign census tracts to Central City (Buffalo) for unevenness assessment	NYS Office of Information Technology Services GIS Program Office
2016 TIGER/Line Shapefiles: **Urban Areas**	• Boundaries of urban areas across US	• Identify census tracts as suburban/rural for unevenness assessment	US Census Bureau

contiguous land areas. Low slope reduces installation cost. South facing land areas are preferred to maximize solar influx.

Communities face societal challenges in addressing their energy needs via community projects (Catney et al., 2014). Considering urban power distribution, low-income and minority population in the US may have even fewer possibilities than other population groups to address their energy needs proactively and garner political support or obtain control over land (Eckerd et al., 2012). Establishing and supporting community ownership may be a way to reduce inequalities (Forman, 2017). In this paper, we examine if all population groups have similar access to community solar suitable areas. A comparison with rooftop solar suitability is also examined.

3. Study area, data, and methods

The empirical analysis to investigate the distribution of SP is conducted for Erie County, NY, which had in 2016 a population of approximately 922,000. Buffalo is the primary city with a population of approximately 259,000. This region is representative of many deindustrialized metropolitan areas in the US, with distinct concentration of minority population and poor households in certain parts of the city (Zou and Wang, 2019). We assume the natural sunlight exposure and policy framework are similar across our study area (approximately 2701 km^2). Data used are presented and described in Table 1. The data processing flowchart is presented in Fig. 1 and will be described in the following sections.

3.1. LiDAR data processing

Using the LiDAR data, we generate the Digital Terrain Model (DTM), Digital Surface Model (DSM), and normalized Digital Surface Model (nDSM) with three feet (0.91 m) spatial resolution. The DTM, which measures the ground elevation, is generated by the average elevation of all the ground points in each pixel and interpolated for pixels with no ground points. The DSM, which measures the rooftops elevation, is generated by the maximum height of all the points in each pixel. The nDSM, which represents the height of the buildings, is generated by subtracting DTM from DSM (Yin and Wang, 2019). The slope, aspect, and hillshade of the roof surface are then generated from the DSM and combined with nDSM-derived building height for rooftop SP estimation. Shading at peak times in the spring, summer, and fall at 2 p.m. are considered to represent the general shading condition of the roofs (Song et al., 2018).

For community SP which usually involves larger solar panels, we create a DTM with 16 ft (4.88 m) spatial resolution. This coarser resolution DEM is then used to create land slope and land aspect, which serve to estimate community SP.

3.2. Estimating residential rooftop SP

Residential Rooftop solar suitability is determined by the following four factors (Gagnon et al., 2018; Paidipati et al., 2008). (1) Rooftop aspect. South-facing roof planes receive the highest degree of solar exposure and are thus preferable. (2) Rooftop slope. Slopes over 60° incur high installation cost, while slopes under 10° have only a 0.7 module to roof area ratio leading to inefficient use of space (Gagnon et al., 2018). (3) Shading. Only roof area that is not always shaded are suitable for solar energy consumption (Paidipati et al., 2008). (4) Contiguous area. We assume similar to Gagnon et al. (2018) that at least 10 m^2 is necessary for solar adoption. This represents approximately a 1 kw system. A minimum area ensures that fixed cost of installation is spread over sufficient capacity (Barbose et al., 2019).

Highly suitable roof planes are (1) south-facing (aspect between 90° and 270°), (2) medium slope (between 10° and 60°), (3) without considerable shading (relative illumination $>$ 50%), and (4) larger than 10 m^2. To make sure only rooftops are included, we limit the analysis to within the building footprints (2 m buffer is allowed to account for the possible displacement between the footprint data and the LiDAR data) and exclude pixels where nDSM is lower than 1.5 m (probably ground or low vegetation) or higher than 30 m (non-residential buildings or LiDAR data noise). All analyses are conducted only in residential parcels.

To represent rooftop SP, the total area of highly suitable residential roof areas (Santos et al., 2014) are calculated in each census tract. The quality of our estimation is evaluated by comparing the roof area available for solar installation from G-PS with our estimated area for 265 randomly selected buildings in the G-PS covered counties.

3.3. Estimating community SP

Community SP is determined by four factors (Carrión et al., 2008; Gómez et al., 2010; Sánchez-Lozano et al., 2014; Watson and Hudson, 2015). (1) Land use type. Tax parcels with non-competitive use (vacant lands) and connected to the electricity grid reduce the cost of solar installation and delivery (Gómez et al., 2010; Sánchez-Lozano et al., 2014). To make sure only land is included, we further exclude water areas by excluding parcels with land use type "underwater" or "other"

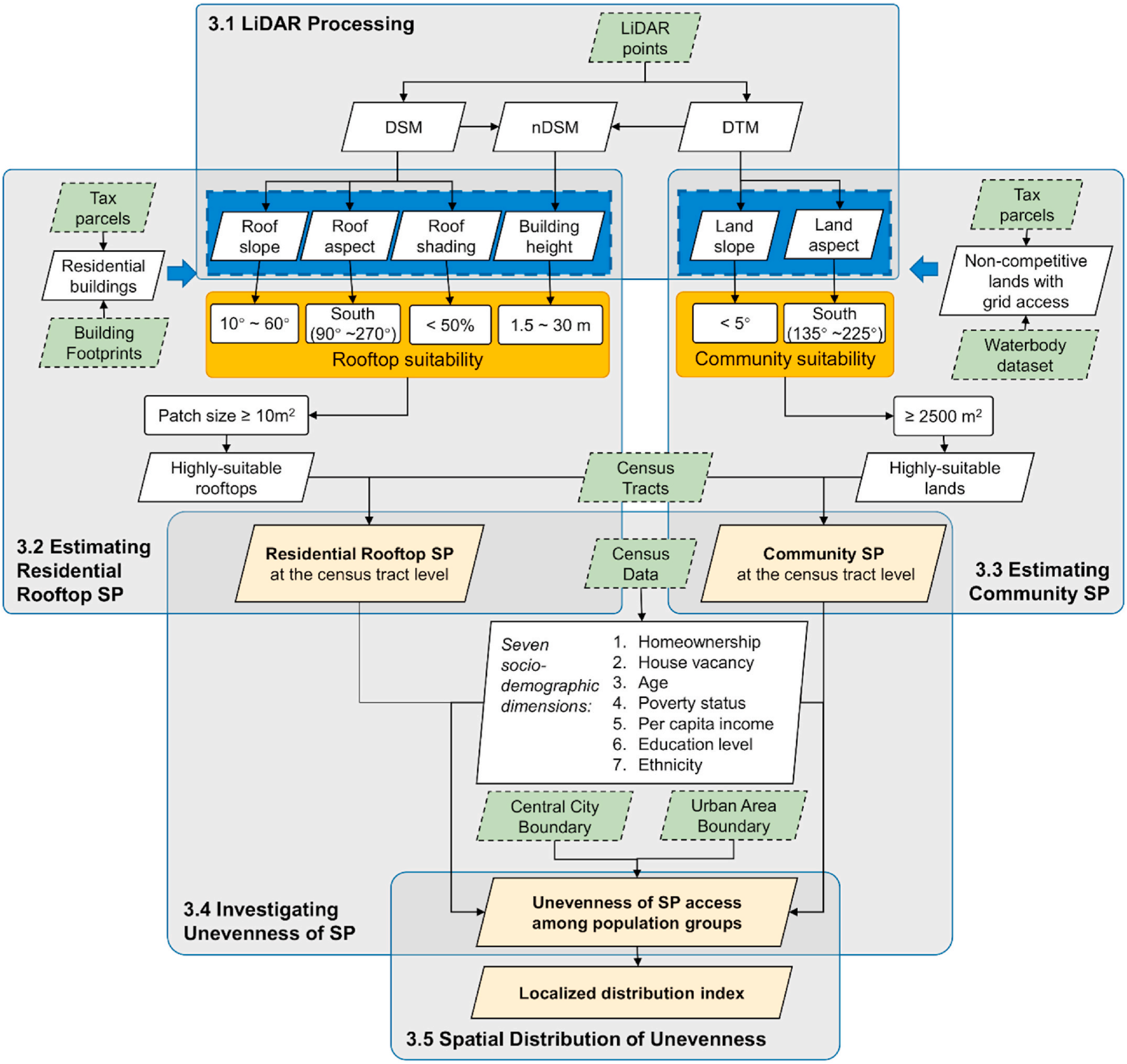

Fig. 1. Flowchart of data processing. The dotted line boxes (green) indicates input datasets, the dashed line boxes (dark blue) indicate intermediate datasets that are used to determine solar suitability, the orange boxes indicate essential criteria that are used to determine SP, and the light yellow boxes (bold texts) indicate the final output of the analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(swamps, etc.) and masking out water body using the NHD and OSM datasets. (2) Land slope. Under 5° slope is used to ensure easy installation (Carrión et al., 2008). (3) Land aspect. South-facing (aspect between 135° and 225°) receives high solar exposure (Watson and Hudson, 2015). (4) Land size. A typical solar farm with 1 MW capacity requires approximately 4–5 acres of land (Ong et al., 2013) – while this is not a linear relationship we assume that a minimum of 2500 m^2 can ensure deployment of systems in the 50–250 kW range. Systems in this range achieve economies of scale represented in substantive cost reductions compared to smaller systems with larger systems achieving better economies of scale (Barbose et al., 2019). Land patches that meet these criteria are considered highly suitable.

To represent community SP, we summarize the area of highly suitable land by census tracts. The quality of our estimation is evaluated by visually comparing the identified land area available for solar installation with high resolution images in Google Maps.

3.4. Uneven access to SP among socio-demographic groups

Based on the discussion in section 2, we use census-tract level data related to seven socio-demographic dimensions relevant in solar adoption: homeownership, housing unit vacancy, age (measured as median age in each census tract), poverty status, per capita income, educational attainment, and ethnicity. These variables determine not only who may adopt solar but also which population groups may face barriers in using rooftop solar and have to rely on alternative forms of solar delivery (e.g., community solar installation). Vacancy is added because high shares of vacant buildings may indicate a lack of maintenance and disinvestment

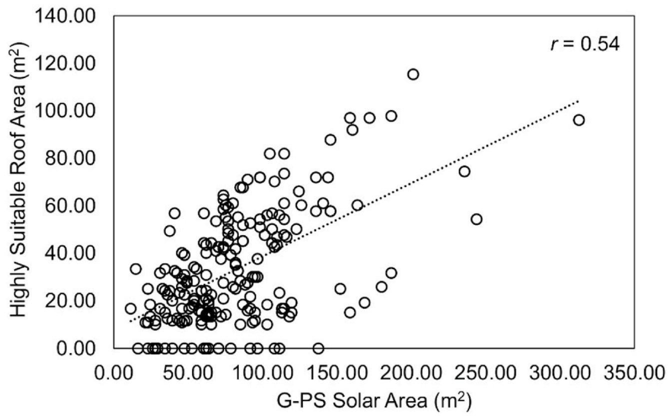

Fig. 2. Comparison of our estimated area suitable for solar installation with G-PS data.

in a neighborhood (Hackworth, 2016). Additionally, we consider the role of location in the distribution of SP by comparing SP of census tracts in the central city with suburban and rural census tracts (derived from urban area and municipality data). We did not consider factors like personal beliefs because such data were not available at the household or census tract level.

Within each dimension, the average SP (ASP) of a population group is calculated as the population (POP) weighted average of SP in each census tract (Equation (1)) (Perlin et al., 1995), where the subscripts *g*, *ct*, and *S* represent the observed population group, the census tract, and the entire study area respectively.

$$\mathrm{ASP}_{g,\,S} = \frac{\sum_{ct}^{S} \mathrm{SP}_{ct} \cdot \mathrm{POP}_{g,ct}}{\mathrm{POP}_{g,S}} \tag{1}$$

To assess the relative distribution of both rooftop SP and community SP, the ASP in each dimension are compared juxtaposing an observed group ($g1$) and a reference group ($g2$) (e.g., renting population vs. owning population), using a distribution index (Equation (2)), which has been commonly used in environmental justice assessments (Perlin et al., 1995).

$$\text{Distribution Index} = \frac{\mathrm{ASP}_{g1}}{\mathrm{ASP}_{g2}} \times 100\% \tag{2}$$

Values around 100% indicate no difference, and values under 100% indicate the comparison group has less SP – a disadvantage compared to the reference group. A value of 20% could be interpreted as $g1$ having only 20% SP of $g2$.

We divided the seven dimensions into the following groups: (1) homeownership: renting vs. owning, (2) housing unit vacancy: vacant/occupied, (3) age: younger vs. older (separated by median age of all census tracts in Erie County), (4) poverty status: households in vs. not in poverty, (5) income: lower vs. higher (separated by median per capita

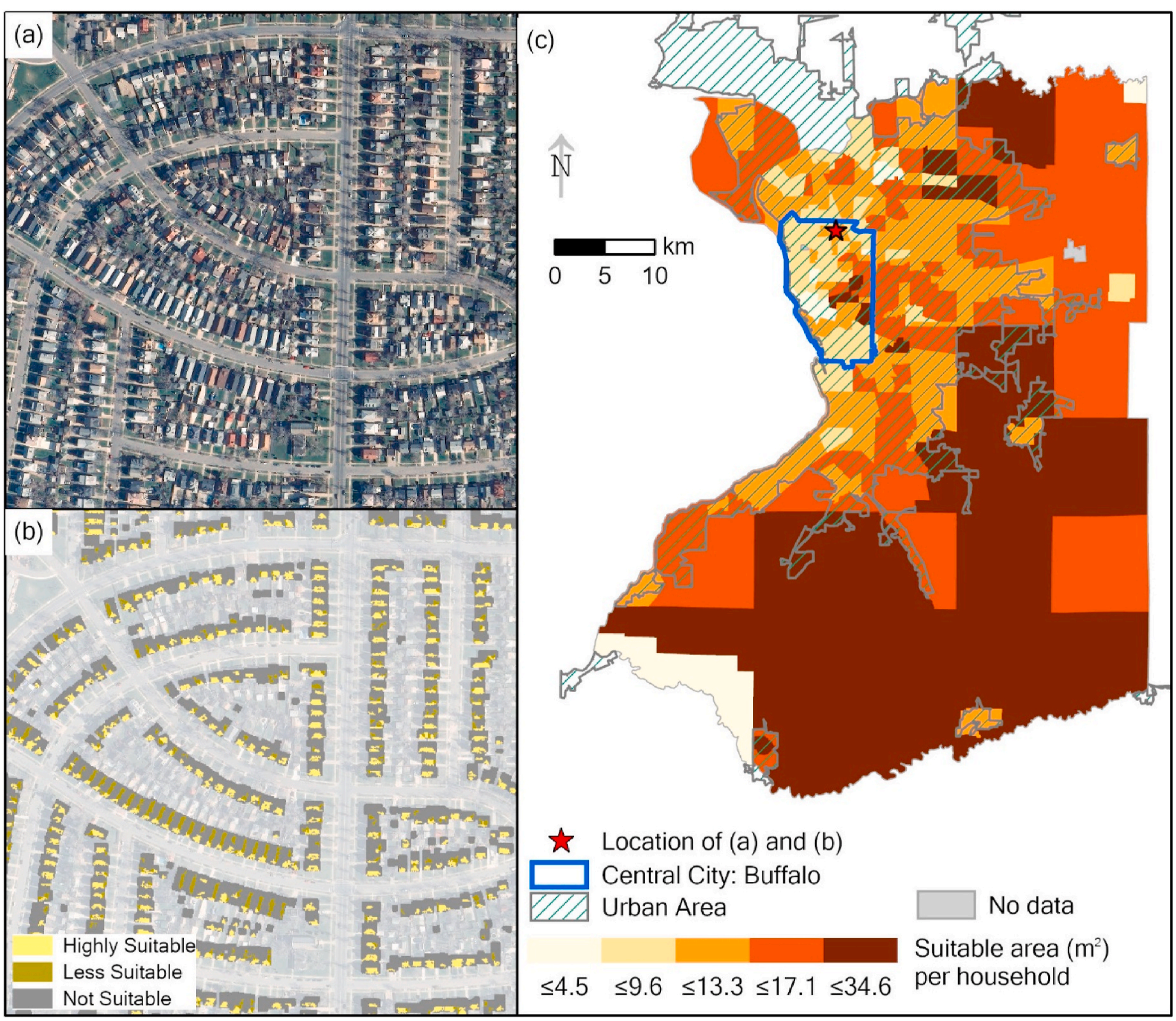

Fig. 3. Rooftop SP. (a) Aerial photo of houses (near 78°50′38″W, 42°57′1″N). (b) Highly suitable roof areas for rooftop solar adoption. (c) Rooftop SP aggregated to census tract scale.

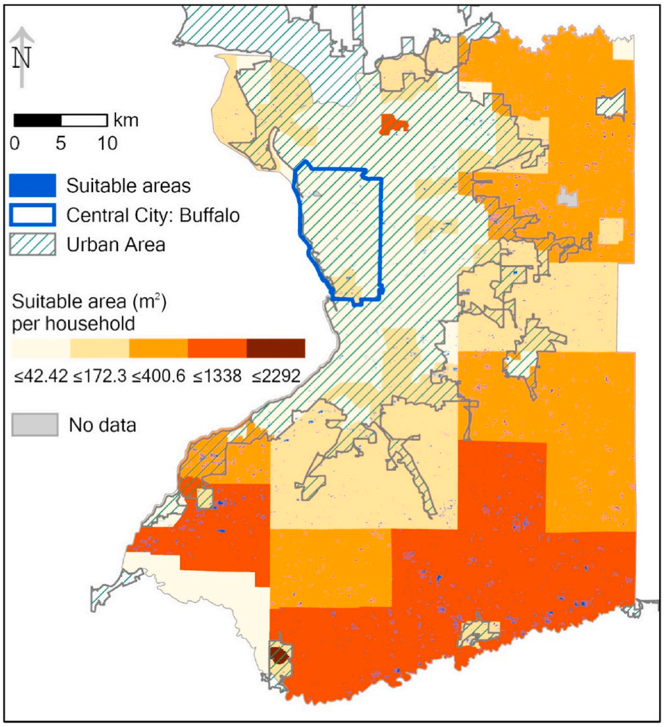

Fig. 4. Community SP at census tract scale and highly suitable parcels for community solar adoption.

income of all census tracts in Erie County), (6) educational attainment: population without high school degree vs. bachelor or higher, and (7) ethnicity: non-white vs. white population. Additional specific disadvantages in education and ethnicity were investigated by taking a further look at African American population and the population with high school or associate degrees.

3.5. Spatial distribution of uneven access to SP

To assess the spatial distribution of the unevenness, the results of section 3.3 were further localized by identifying census tracts with lower than average SP and higher than average shares of the potentially disadvantaged population (Equation (3)). The disadvantage was summed across dimensions to represent the prevalence. A multi-dimensional disadvantage of 7 means that for all seven dimensions higher than average shares of the potentially disadvantaged population are located in a census tract with below than average SP.

$$\text{disadvantage} = \begin{cases} 1, & \text{SP}_{ct} < \dfrac{\sum_{ct}^{S}\text{SP}_{ct}}{n}\ \textit{and}\ \dfrac{\text{POP}_{g1,ct}}{\text{POP}_{g2,ct}} > \dfrac{\text{POP}_{g1,S}}{\text{POP}_{g2,S}} \\ 0, & \textit{Otherwise} \end{cases} \tag{3}$$

4. Results and discussion

4.1. Residential rooftop and community SP

Because there are still areas where G-PS has no data, only 232 of the validation samples are usable. The correlation between our estimation and G-PS data is moderately good ($r = 0.54$, Fig. 2), which confirms that our method is generally valid. We used LiDAR in 2008 and Microsoft building footprints while G-PS uses the latest Google images; we consider only residential rooftops for feasibility while G-PS estimates SP for all rooftops they recognized; we consider 10 m^2 as the minimum area for solar installation while G-PS considers all areas suitable for 4 panels of 1.650m x 0.992m dimensions; We account for shading using three typical time points while G-PS used about 50 timepoints to estimate the annual solar irradiance. To sum up, we have better configuration of residential rooftops and roof shapes than G-PS–G-PS considers more details of actual solar energy productivity, which explains the difference between our results. In other words, our approach can be more beneficial because we can cover more areas than G-PS, especially in rural areas.

We selected a subset of the study area where houses are of different orientations and rooftop shapes to show the result of residential rooftop solar suitability (Fig. 3). Rooftops that are south-facing and with large continuous areas are selected (Fig. 3b), which shows the effectiveness of the method. Although there may still be trees inside the building footprints, tree canopies would show abrupt changes in the nDSM which results in high slopes, high shading, and small patches. Therefore, their impact should be alleviated effectively.

Census tract level results (Fig. 3c) show that rooftop SP increases from downtown (Buffalo) to suburbs to rural, which is consistent with previous findings that urban areas have lower solar adoption rates compared to rural or suburban areas (Crago and Chernyakhovskiy, 2017; Graziano and Gillingham, 2014).

The suitable area selected for community SP is of good quality upon visual inspection. The census tract level community SP is shown in Fig. 4. Community SP is overall higher than rooftop SP (Fig. 3c). Although the urban area still shows generally lower SP than the rural and suburban areas which is similar to rooftop SP, some parts of the urban area with low rooftop SP may be able to benefit from community solar adoption.

4.2. Unevenness of SP access

The results for the relative distribution of residential rooftop and community SP in the context of socio-demographic dimensions indicate uneven distribution of SP between observed and reference groups (Fig. 5, Table 2). For example, in terms of overall area available for rooftop solar and for community solar, respectively, the renting population only have 67% and 36% access compared to homeowners.

Residential Roof SP access: Census tracts with high shares of renters and high shares of vacant housing units have less area (67%, 78%) compared to their corresponding reference groups. Young population compared to older people lives in census tracts with smaller total area (57%) available. Large degrees of disadvantage can be observed for poor population (households in poverty (70%) and low income (54%)). Compared to these dimensions, educational attainment has lower unevenness. While there is no strong difference between people with high school or associate degrees and people with a bachelor degree or higher, population without a high school degree has lower access to SP compared to groups with higher educational attainment. Ethnicity shows disadvantages for minority groups, with non-white population having access to approximately 60% of the SP accessible to the white population. This difference is especially pronounced for African Americans who have even lower access than the overall non-white population. The role of urban morphology in the distribution of SP is confirmed. Areas in the central city (51%) and rural (66%) areas have less area available than suburban areas. These results qualify the lower degree of SP access for low-income population, minorities, and vacancies as they tend to be concentrated in the central city (Weaver et al., 2017).

Community SP access: The results for community solar area and the number of suitable properties available mirror the results for rooftop solar. Census tracts with high shares of renters and high shares of vacant housing units have less area (36%, 72%) compared to their respective reference groups available. Young population compared to older population has access to lower SP (7%). Similarly, low-wealth population (households in poverty: 48%, low income: 37%) has lower access. Compared to these dimensions, educational attainment shows relatively lower unevenness. Again, the population without a high school degree

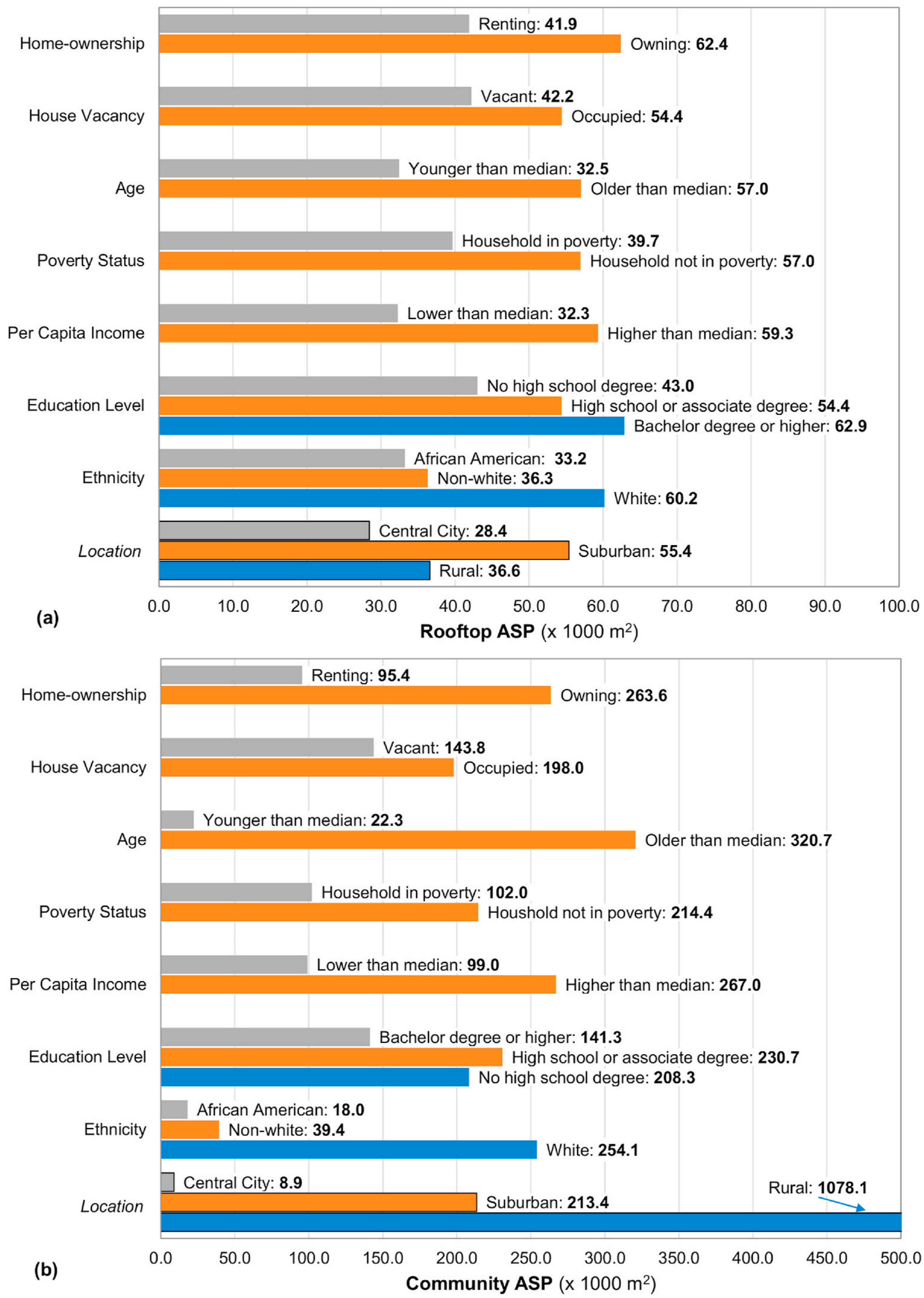

Fig. 5. Uneven access to (a) Rooftop SP and (b) Community SP.

has lower access to SP, while population with a high school degree may have slightly more SP (111%) available than population with a bachelor degree or higher. Ethnicity shows disadvantages for minority groups, with non-white population accessing approximately 16% of the SP accessible to the white population. This difference is especially pronounced for African Americans who have lower access than the overall non-white population. Urban morphology impacts the distribution of community SP. Rural areas have access to large areas suitable while access in the central city is lowest.

Both rooftop SP and community SP analyses indicate overall that low income and minority population have unequal access and opportunity to benefit from solar technology. More severe unevenness is observed for community solar than for rooftop solar. The majority of variable dimensions assessed in regards to SP follow the patterns observed in research related to solar adoption (Li et al., 2005; Rai and McAndrews, 2012; Sunter et al., 2019). Home-owning, wealthy, educated, and white population have access to more SP than comparison groups. High vacancy neighborhoods (a sign of divestment) have lower degrees of SP. However, the conclusion on age deviates from solar adoption studies. While at the individual level associated with high solar adoption (Crago and Chernyakhovskiy, 2017; Kwan, 2012), younger population at the spatial aggregate level has lower access to SP than older people. The observed unevenness in access to SP complements survey-based solar adoption studies. Controlling for uneven access may enhance our understanding of spatial solar adoption patterns and inform spatial policies.

Table 2
Relative distribution of SP among socio-demographic groups and urbanization contexts.

Dimensions	Observed Group ($g1$)	Reference Group ($g2$)	Area Available for Rooftop Solar	Area Available for Community Solar
Home-ownership	Renting	Owning	67%	36%
House Vacancy	Vacant	Occupied	78%	73%
Age	Younger than median	Older than median	57%	7%
Poverty Status	Households in poverty	Households not in poverty	70%	48%
Per Capita Income	Lower than median	Higher than median	54%	37%
Education Level	No high school degree	Bachelor degree or higher	68%	68%
	High school or associate degree	Bachelor degree or higher	87%	111%
	No high school degree	High school or associate degree	79%	61%
Ethnicity	African American	White	55%	7%
	Non-white	White	60%	16%
	African American	Non-white	91%	46%
Location	Central City	Suburban	51%	4%
	Central City	Rural	78%	1%
	Rural	Suburban	66%	505%

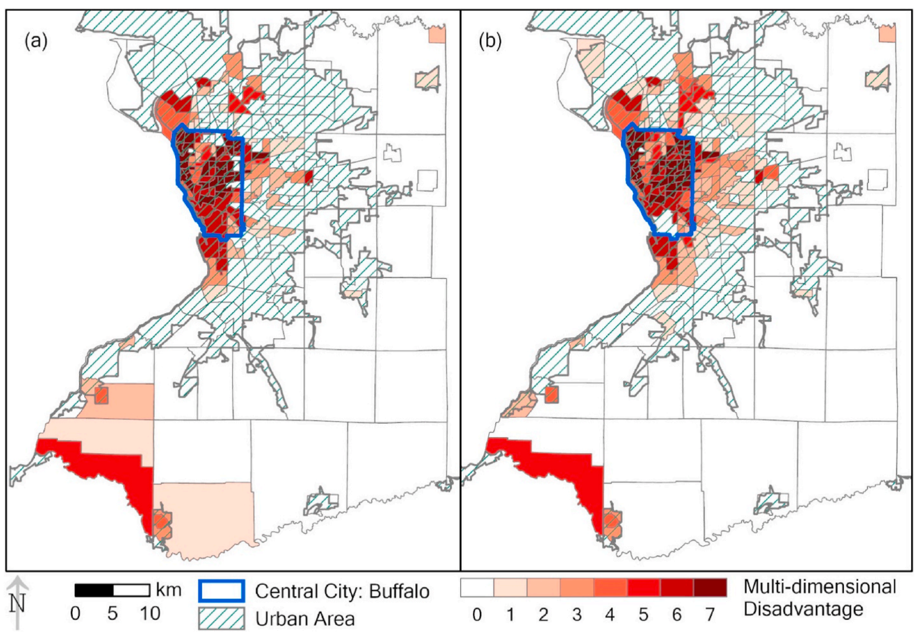

Fig. 6. Spatial distribution of uneven access to (a) rooftop and (b) community SP of population groups in Erie County, NY, across multiple data dimensions.

4.3. *Spatial distribution of unevenness*

Localized results of the Distribution Index for residential rooftop and community solar area show the spatial distribution of multi-dimensional disadvantage (Fig. 6). Disadvantages in access to SP appear to be highly concentrated in the central city of Buffalo. Especially Buffalo's east and west, which is characterized by high shares of minority and low-income population shows concentration. Furthermore, these neighborhoods have high vacancy rates, which is an outcome of urban population decline (Zou and Wang, 2019). These patterns persist for rooftop and community SP, though some areas show differences. For example, in south Buffalo, disadvantage exists for rooftop solar but not for community solar – above average area for community solar deployment is available. This may be a result of the presence of large brownfields - South Buffalo was the location of large heavy industry (steel) and brownfields may provide potential space for solar deployment (NYSDEC, nd). In such areas, community solar may be an alternative solution. Outside the central city, similar patterns for rooftop and community SP persist. In suburban areas in Erie County, both rooftop and community SP show localized and coinciding patterns of disadvantage – again in selected locations, one technology may be more equitable than the other - this may indicate a fractured solar landscape requiring localized approaches to solar adoption rather than a general suburban solar policy. In rural areas, both rooftop and community SP show no signs of disadvantages and both are potential solution. Overall the results indicate that population in the central city, especially minority households, renters, and low income housheolds, have no easy access to solar technology and may require assistance in participating and benefitting from renewable energy transition.

5. Conclusions

Solar energy is a renewable energy source with the potential to reduce household energy cost. However, access to residential rooftop and community SP is unevenly distributed. In general, low-income population and non-white population exhibit low degrees of access to SP – similar patterns exist for renters and population with low educational attainment. The degree of unevenness for these groups is higher for community solar than for residential rooftop solar. While young age is associated with technology adoption, younger population has lower access to rooftop and community SP compared to older population. On the whole, the spatial distribution of unevenness of community SP coincides with that of rooftop SP. Population with disadvantages in accessing solar is concentrated in urban areas while suburban areas have high rooftop and community SP, reinforcing the idea that urban patterns of inequality can affect energy transition to solar. In selected areas, such as south Buffalo, community-led solar initiatives are an alternative – here brownfields may provide the necessary space.

The proposed methodology to measure residential rooftop and community SP is applicable across the US and other geographic context if relevant data (LiDAR, land use data) are obtainable. It could be improved in two aspects: (1) The use of fewer datasets – combining multiple datasets not only limits the application area, but also introduces more uncertainties due to the temporal difference and spatial mismatch. Techniques to better accommodate these discrepancies are worth exploring while advanced methods to accurately estimate the SP using only LiDAR or imagery need to be developed. (2) The use of optimized criteria – e.g. threshold of slope should be adjusted according to the local condition. A sensitivity analysis is a next-step towards optimizing the criteria.

The analysis of the uneven distribution of SP access among population groups relies on public census data, which can be obtained for the US, Canada, European Countries. The method for unevenness assessment (e.g., spatial aggregation for any given unit) can be applied independently from the SP assessment using any solar inventory. It would be interesting to construct a spatial index that summarizes the findings of our method into one number, which will facilitate easier decision making and context adapted solar energy planning.

This paper shows that population data linked to building characteristics improves our understanding of SP in a city. The transition process to renewable energy, without understanding the unevenness in access to technology, may not work out for communities that probably need cheap and sustainable energy. Planning and policy intervention to reduce unevenness may include subsidies for community-led community solar initiatives or policy support in acquiring suitable land. Neighborhoods affected by disadvantages related to rooftop solar and community solar may require third-party projects or redistribution policies to take part in order to benefit from the renewable energy transition. Another venue may be the development of new technology delivery methods to increase productivity of available spaces. Future research in energy transition with a focus on solar technology adoption needs to be aware of the unevenness in the distribution of SP. Erie County and Buffalo are representative of many deindustrialized metropolitan areas in the US, but additional place-specific studies are necessary for implementation.

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.

CRediT authorship contribution statement

Torsten Schunder: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Dameng Yin:** Methodology, Software, Data curation, Visualization, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Sharmistha Bagchi-Sen:** Writing - original draft, Writing - review & editing, Supervision. **Krishna Rajan:** Conceptualization, Supervision, Funding acquisition.

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