Minimizing heatwave risk through an equitable distribution of solar panels

Samuel G. Dotson[1*], Shannon R. Anderson[2], Alankrita Sahay[3], Pranjali Borse[3], Charumeghana Samantula[3]

[1] Department of Nuclear, Plasma, and Radiological Engineering, University of Illinois Urbana-Champaign, Urbana IL, United States
[2] Department of Natural Resources and Environmental Sciences, University of Illinois Urbana-Champaign, Urbana IL, United States
[3] Department of Civil and Environmental Engineering, University of Illinois Urbana-Champaign, Urbana IL, United States
[*] Author to whom correspondence should be addressed

E-mail: `sgd2@illinois.edu`

May 2022

Abstract. Testing abstract. Climate and Energy Justice Screening Tool (CEJST). CEJST

Keywords: solar, heatwave, equity, energy justice, policy

1. Introduction

Climate change will increase the frequency and severity of extreme heat events and, due to the Urban Heat Island (UHI) effect, urban centers are more susceptible to heat waves and heat stress [1, 2]. The Union of Concerned Scientists estimates that the number of days above 32 °C in the Midwest will increase five-fold by midcentury unless action is taken to reduce carbon emissions and slow climate change [2]. The lack of strong federal climate policies leaves individual states and institutions responsible for acting on climate change. Illinois passed the Climate and Equitable Jobs Act (CEJA) in 2021 which established strong climate goals and programs for the state, including subsidies for rooftop solar panels [3]. This case study investigates the optimal distribution of rooftop solar panels that minimizes heat wave risk for the City of Chicago.

We chose Chicago as the focus of this work for two reasons. First, Chicago was the epicenter of a deadly heat wave in 1995; one of the deadliest heat waves in United States history. Over 700 people died in this heat wave [4]. Further, the death toll from this heat wave was exacerbated by a combination of social factors including income, isolation, and crime rates [4]. As a result of this heat wave, Chicago officials recognized the need to prepare for future heat waves. This work proposes rooftop solar panels as a possible mitigation strategy. Second, the State of Illinois has programs such as Solar for All and Illinois Shines that aim to provide greater access to clean energy for low-income populations [5]. Thus, the resources to increase rooftop solar penetration already exist but lack guidance based on heat wave risk.

Illinois Solar for All and Illinois Shines are two programs strengthened by the 2021 CEJA bill [3, 5]. These policies intend to expand the rooftop solar capacity in Illinois by providing incentives or subsidies for solar installation, with specific allocations for low-income communities. Rooftop solar panels help reduce the percentage of household income spent on energy costs, known as the energy burden, through net-metering policies that pay consumers for excess energy generation [6]. This reduction of energy burden improves resilience to heat waves by increasing access to air-conditioning for low-income households during high-demand times when electricity is most expensive. However, a high penetration of intermittent renewables, such as solar panels, increases price volatility and the energy burden for consumers without solar installations [7, 8]. This is called the "paradox of renewable energy policy" and highlights the need for efficient prioritization of at-risk areas [9]. Therefore, the purpose of this study is to identify areas with the highest heat wave risk so they may be prioritized by programs like Solar for All and Illinois Shines.

In order to identify high-priority areas, we curated economic and demographic data for Chicago, along with satellite data from the National Solar Radiation Database (NSRDB) published by the National Renewable Energy Laboratory (NREL). We identified regions of similar risk and suitability for solar panels with a hierarchical clustering algorithm. Section 3 discusses details of the data selection and processing, section 4 presents the results of the clustering algorithm, and section 5 develops a descriptive typology based on the clustered areas.

2. Literature Review

The UHI effect, where urban areas tend to be warmer than their surroundings, is among the most well studied phenomena, often using remote sensing technology and land surface temperature data [10, 11]. Some studies evaluated UHI intensity for particular cities by incorporating data about urban features such as albedo, building height, and vegetation [12, 13] along with urbanization trends [14]. Other work in the literature examined UHI along a socio-economic axis. Chakraborty et al. [15] used satellite and census data for multiple cities and found that UHI disproportionately affects low-income residents in most places, including Chicago, and suggest that UHI mitigation should benefit demographic groups that experience greater UHI intensity. Hsu et al. [16] also found that race and income level were correlated with greater UHI intensity.

Strategies to mitigate UHI typically interrupt the heat storage process that drives UHI, where low albedo surfaces such as pavement and rooftops absorb and trap heat. Green roofs are a popular method to reduce UHI by reducing heat storage and increasing the energy from latent heat rather than sensible heat [17]. Similar to green roofs, several studies determined that increasing the urban tree canopy is an effective way to reduce UHI by reducing heat storage in surfaces, but also by providing shade [18–22]. "Cool" roofs reduce UHI by increasing the albedo of rooftop surfaces and decreasing the amount of radiation that gets absorbed [17, 18, 23]. Lastly, rooftop solar panels are also found to mitigate UHI effects at night due to boundary layer structure and by reducing energy requirements for cooling [23–25]. However, the primary function of solar panels is to improve adaptive capacity by generating energy for cooling [24].

As with UHI intensity, the literature also indicates that UHI mitigation efforts disproportionately benefit wealthier residents. McDonald et al. reported that high-income areas had nearly twice the tree canopy of neighboring low-income regions [20]. Further, efforts to mitigate UHI with vegetation may lead to gentrification, thereby excluding the intended beneficiaries [15]. Solar panel adoption has also developed along socio-economic lines. Vaishnav et al. [26] showed that subsidies for rooftop solar panels favored the affluent. Reames et al. [27] identified that the greatest solar panel penetration was found in areas with the greatest income, although it remained quite low compared with other cities. The researchers also indicate that lack of information contributes to these disparities [26, 27]. Illinois' Solar for All campaign sought to prioritize low-income areas using a tool called the Environmental Justice Screening Tool (EJSCREEN) from the Environmental Protection Agency (EPA) [28]. Another tool that identifies climate justice areas is the Climate and Energy Justice Screening Tool (CEJST) [29]. However, neither of these tools incorporate temperature data nor UHI effects, thereby limiting their effectiveness at targeting areas facing heat wave risk.

In the present work, we use the hazard-exposure-vulnerability framework for risk established by International Panel on Climate Change (IPCC) in 2018 [30]. This framework is useful for understanding the different factors that contribute to risk. Hazards are the climate events that can produce adverse outcomes. Examples include flooding, hurricanes, and heat waves. Our work focuses on the latter. Exposure implies the presence of people. People are not at risk from a hazard if they are not present. Regions with different population densities have different levels of exposure. Further, cities have a higher exposure to heat waves due to UHI. Lastly, vulnerability describes susceptibility and adaptive capacity to particular hazards. This includes socio-economic factors such as race, income, and age. Adaptive capacity reduces exposure or vulnerabilities while mitigation efforts minimize the hazard itself.

Lower income is associated with greater UHI and therefore both a greater exposure to heat waves with less adaptive capacity. However, income is one of many factors that contribute to heat wave risk. Maragno et al. [31] mapped heat stress risk by adapting the hazard-exposure-vulnerability framework and included age as a demographic vulnerability along with landuse for different types of buildings. There are other socioeconomic factors that contribute to heat wave risk, such as crime rate, educational attainment, access to cooling centers, and housing characteristics [4, 32] that Maragno et al. do not include.

Several works mapped regions with the highest UHI [10], identified disparities in UHI [15] and its mitigation [20, 27]. At least one study applied the hazard-exposure-vulnerability framework in a heat wave risk assessment [31]. However, there is no existing literature that prescribes a methodology for efficient allocation of rooftop solar panels. The present work fills that gap by collecting satellite and socio-economic data to identify areas of high heat wave risk that accounts for disparities in exposure and adaptive capacity.

3. Methods and Data

In this section we review the data we collected for the City of Chicago and the methods we used to cluster Chicago's census tracts into priority areas for solar panel distribution. We used the hazard-exposure-vulnerability framework asserted by the IPCC to categorize the datasets used in this work [30,33]. Table 1 summarizes these datasets.

3.1. Hazard

Hazards are the climate-related events the may lead to adverse outcomes for people, such as losses of life, function, property, infrastructure, and resources [30]. In this work, we focus on the risk of heat stress and the potential for heat-related deaths, for which temperature is the primary hazard. We gathered hourly temperature data for each community area in Chicago for the years 2000 to 2020 using the NSRDB [34]. In order to capture the temperature difference among Chicago's community areas during heatwaves, we set a temperature threshold of 32°C and filtered out the data below this threshold. We defined a heatwave temperature anomaly,

$$H_a = T_{ca} - T_{city}, \tag{1}$$

where T_{ca} is the temperature of the community area and T_{city} is the mean temperature of the city (i.e. the mean of all community areas), in celsius. We then took the mean of the hourly H_a to use in our clustering algorithm. Figure 1 shows the variations in temperature during heatwaves in Chicago.

Table 1. Summary of curated data for the city of Chicago

Dataset	Risk Aspect Aspect	Spatial Resolution	Factor	Source
Temperature	Hazard	Community Area	Aggravating	[34]
Population density	Exposure	Census tract	Aggravating	[35]
Percent tree canopy	Vulnerability	Census tract	Mitigating	[36]
Energy burden	Vulnerability	Census tract	Aggravating	[29]
Age	Vulnerability	Census Tract	Aggravating	[35]
Crowded housing	Vulnerability	Community Area	Aggravating	[35]
Cooling centers	Vulnerability	Community Area	Mitigating	[35]
Social network	Vulnerability	Community Area	Mitigating	[35]
Crime rate	Vulnerability	Community Area	Aggravating	[35]
Percent qualified roof area	Vulnerability	Census Tract	Mitigating	[37]

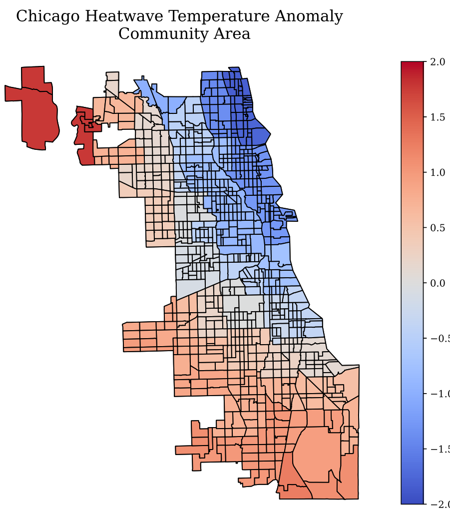

Figure 1. The temperature variations among community areas in Chicago during heatwaves. Higher values indicate warmer temperatures than the city mean temperature and lower values indicate cooler temperatures.

A positive H_a indicates regions that experience higher temperatures during heatwaves and a negative H_a indicates regions with lower heatwave temperatures, with respect to the citywide average temperature. The region near O'Hare International Airport experiences the highest temperatures, nearly 2°C above the citywide average. The temperature anomalies are further adjusted by subtracting the minimum temperature difference such that the coolest area of the city has an $\bar{H}_a$ value of zero and other values indicate the temperature above this minimum value. This is done to ensure good behavior from the clustering process.

3.2. Exposure

Exposure is the presence of people or important assets in places that could be adversely affected by climate hazards [30]. Figure 2 shows the population density throughout Chicago.

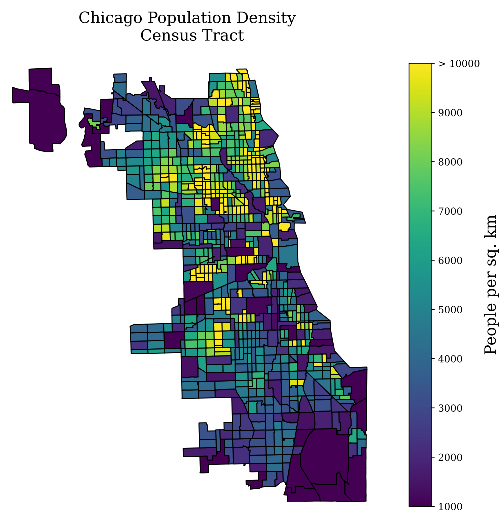

Figure 2. The population density throughout the City of Chicago.

3.3. Vulnerability

Vulnerabilities are the factors that predispose certain groups or areas to adverse outcomes. We consider several physical and social vulnerabilities. Studies that mapped heat stress and heatwave risk tend to focus on weather effects (hazards) alone [2, 11, 38, 39]. One study incorporated a hazard-exposure-vulnerability framework by treating land use and building purpose as proxies for exposure and vulnerability, along with population age [31]. Conversely, studies that map the disparities in solar panel distribution do so along a social axis, without considering the spatial distribution of UHI intensity [27]. We extend the vulnerabilities to include energy burden, crime rates, solar potential, crowding, and social network. We use the number of churches in each community area as a proxy for social network since church attendance is one of main avenues of social interaction for elderly people [4]. Further, strong social networks facilitate wellness checks that may be lifesaving during a heat wave [32].

3.3.1. Energy Burden Energy burden is the ratio of household energy costs to household income. We created a map of energy burden in Chicago using data from CEJST [29]. Energy burden affects access to electricity, especially during heatwaves when demand and cost of electricity are highest. Rooftop solar panels can reduce energy costs and therefore improve access to cooling during heatwaves. Figure 3 shows the distribution of energy burden throughout Chicago.

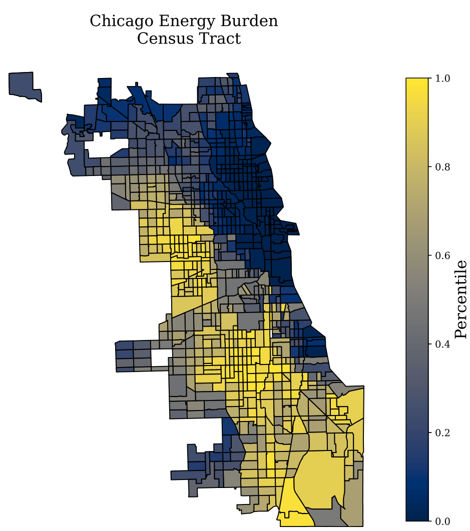

Figure 3. Energy burden throughout Chicago as a percentile. A region in the zeroth percentile has the least energy burden and a region in the 100th percentile has more energy burden than any other region.

3.3.2. Tree Canopy Urban tree cover effectively mitigates land surface temperatures in cities [19, 20, 22]. Tree canopy reduces temperature by preventing ground heat storage through shade and encouraging evapotranspiration [20]. Thus, areas with greater tree cover are less vulnerable heat waves. Figure 4 shows the distribution of trees in Chicago from the Morton Arboretum Tree Census [36].

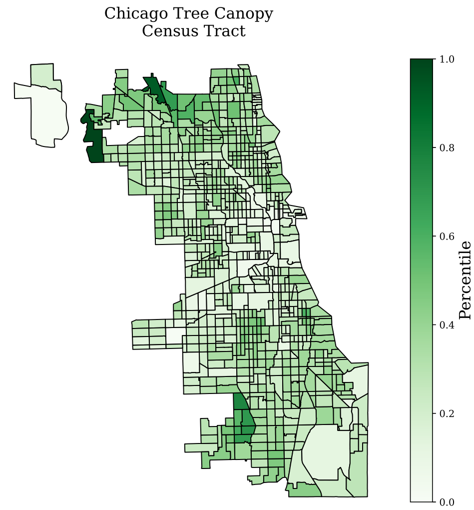

Figure 4. Distribution of trees in Chicago by percentile. A region in the zeroth percentile has the least tree canopy and a region in the 100th percentile has more tree cover than any other region.

3.3.3. Crime Rate An ethnographic study of the 1995 Chicago heat wave found that income level was not the only predictor of heat wave mortalities as communities with similar income levels had different heat wave outcomes. Some of this difference was explained by crime rate as heat wave victims elected to keep their windows and doors shut out of fears of crime [4]. This fear is prevalent among the elderly whose age is an additional vulnerability [32]. We filtered out crimes whose primary descriptions included "gambling," "non-criminal," or "interference with public officer." Otherwise, we did not distinguish between violent crimes and "non-violent" ones. Figure 5 shows a heatmap of the crime locations in Chicago for 2021.

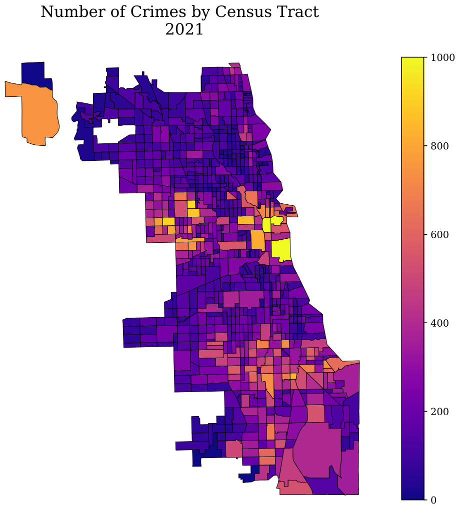

Figure 5. Map of crime locations in Chicago from 2021.

3.4. Data Processing

The data were prepared by first normalizing using the infinity norm,

$$L^{\infty} = \max\left(\mathbf{X}\right), \tag{2}$$

of each dataset to ensure all values are between zero and unity. Then, all mitigating values, as identified in Table 1, are subtracted from unity. For example, this process negates the percentage of area covered by tree canopy into the percentage of community area not covered by tree canopy. Doing this facilitates simple interpretation and identification of high-risk areas without invoking complicated weighting schemes.

3.5. Hierarchical Clustering

In this study, we use hierarchical clustering to identify regions of similar risk. Hierarchical clustering maximizes the similarity among samples within a cluster, while simultaneously maximizing the differences across clusters [40–42]. The fundamental algorithm is

(i) set each sample as its own cluster;
(ii) determine the "mean" sample of each cluster;
(iii) measure the Euclidean distance between each cluster;
(iv) Merge the two clusters with the minimum distance;
(v) check if the number of clusters is greater than the desired number;
(vi) stop if the desired number of clusters is exceeded, otherwise, return to step 2.

This algorithm is implemented in the Python library Scikit-learn [43] which was used throughout this work. Finally, we prioritize the clusters according to the L^1-norm of each cluster's mean sample, where

$$L^1 = \|\mathbf{X}\|_1 = \sum_{i}^{N} x_i. \tag{3}$$

This gives each cluster a "score" between zero and the number of data points used in the analysis.

4. Results

After clustering the data with a hierarchical clustering algorithm, we developed a map of the most similar regions according to their cluster. Figure 6 shows these regions. The colors and numbers in Figure 6 simply identify the cluster and do not correspond to heat wave risk nor priority.

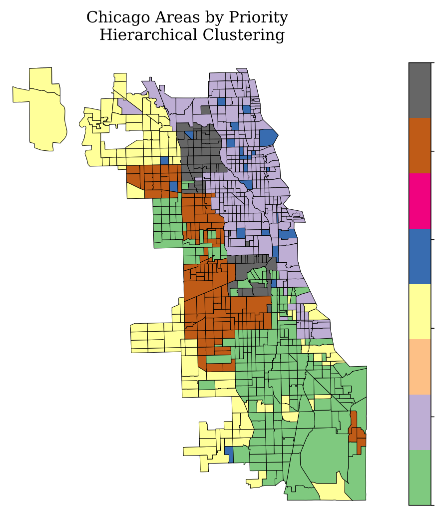

Figure 6. The map of Chicago clusters. The numbers correspond to the order in which the algorithm created the groups and not the heatwave risk.

Figure 7 compares the mean vector of each cluster. The colors and group numbers match the colors and group numbers from Figure 6.

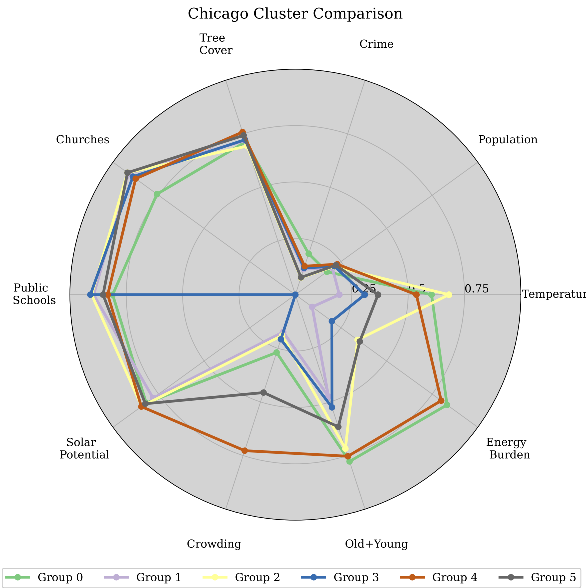

Figure 7. The map of Chicago clusters. The numbers correspond to the order in which the algorithm created the groups and not the heatwave risk.

There are several points of interest in Figure 7. First, the average number of churches, public schools, crime rates, population, and tree cover were similar across each cluster. The similarity in tree cover was unexpected due to the strong effect of tree cover on temperature and UHI noted in the literature [20–22]. Further, there was little difference in average crime rates across clusters. This is likely due to the fact that a few census tracts had a much higher crime rate than all others. With the exception of a single group, group 3, solar potential (i.e. the percent of rooftops that qualify for solar panels [37]) was nearly identical across all clusters.

Second, crowded housing, age, energy burden, and temperature were the most divergent factors across the clusters. The key difference between the highest and second highest priority clusters was crowding. It makes sense that the number of people per household should be used to differentiate priority, *ceteris paribus*.

The "score" that ranks the clusters is incidentally the area drawn by each curve in Figure 7. The rank of each cluster is shown in Figure 8.

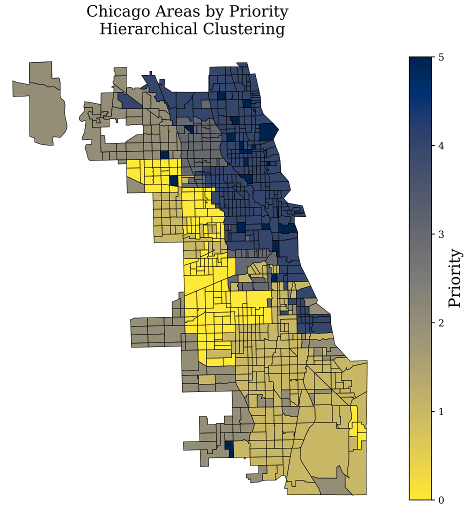

Figure 8. The map of Chicago clusters according to priority. 0 = Highest priority. 5 = Lowest priority.

The highest priority region (priority 0) are on the west side of the city, where it is warmer, crowded, and energy burden is high. The areas closest to Lake Michigan tend to be the coolest part of the city and the most affluent, thus making them the lowest priority (priority 5) for rooftop solar panels.

5. Discussion

The prioritization mapping protocol outlined by this research is better suited for identifying regions for targeted incentive distribution to address specific issues in urban settings than existing general environmental justice community identification tools currently used for funding dissemination.

5.1. Comparison to other Energy Justice Mapping Tools

Other screening tools have been developed to analyze spatial characteristics of environmental justice. The EJSCREEN tool from the EPA [28] and the US Council on Environmental Quality's CEJST tool can both be used to identify disadvantaged or vulnerable populations spatially [29]. However, the map generated by this research identifies a more precise region of the city of Chicago to be prioritized for rooftop solar initiatives, therefore informing more efficient allocation of resources to the most vulnerable communities for this particular issue. Figure 9 and Figure 10 show the at-risk areas in Chicago identified by EJSCREEN and CEJST, respectively.

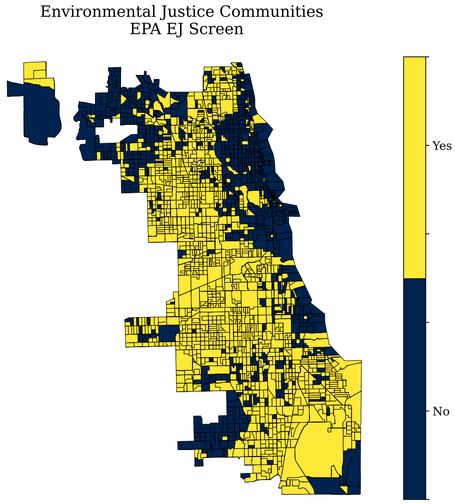

Figure 9. Environmental justice communities identified by EJSCREEN. "Yes" indicates that the community has environmental justice concerns.

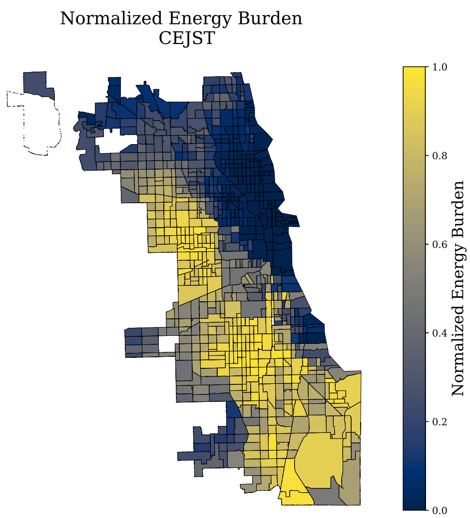

Figure 10. Normalized energy burden from the CEJST tool.

Importantly, neither of these tools incorporate heatwave risk and use a limited set of social features. The prioritization created in this research considers traditional environmental justice factors, including age, income, and race, but also incorporates urban heat island impacts, qualified roof area, access to cooling centers, tree cover, and energy burden to more specifically interrogate spatial distribution of heat impacts that could be mitigated through access to cleaner, cheaper energy for cooling. This is a more holistic approach to understanding environmental justice for the specific issue of access to affordable energy to cool urban homes in a heat wave. While mapping the distribution of spatial attributes of environmental justice can illuminate inequities at a multitude of scales, this more precise issue-specific mapping could be more effective for policy and incentive development.

5.2. Targeted Incentive Distribution

Illinois Solar for All (SFA) is a state-funded program that "promotes equitable access to the solar economy through program incentives that help make solar more affordable for low-income communities" [5]. The program allows low-income communities to benefit from community solar arrays and distributed generation installations, as well as providing low-cost solar installations to non-profit organizations and public facilities. Initial funding for SFA was provided by Illinois' 2017 Future Energy Jobs Act, but when funds were exhausted, talk of a "solar cliff" highlighted the uncertainty of the future of solar incentives in the state (Lydersen, 2020). The popularity of this program and limited funding for solar projects emphasizes the need for targeted distribution of funds to the communities that need it most.

SFA has an explicit commitment to increasing access to solar energy among environmental justice communities. SFA uses EPA's EJSCREEN and a self-designation process to identify environmental justice communities across the state of Illinois. However, this method of identifying communities to target for SFA incentives is based on a more general understanding of environmental justice, and does not necessarily consider the potential impact of solar energy to reduce the energy burden on low-income households through solar installation. Targeted prioritization as outlined in this research could result in allocation of limited solar incentive funds to the communities that would experience the greatest benefit from solar installations by reducing risks associated with heatwaves.

6. Conclusion

References

[1] Zhao, Lei, Lee, Xuhui, Smith, Ronald B., and Oleson, Keith. Strong contributions of local background climate to urban heat islands. *Nature*, 511(7508):216–219, July 2014. Number: 7508 Publisher: Nature Publishing Group.

[2] Dahl, Kristina, Spanger-Siegfried, Erika, Licker, Rachel, Caldas, Astrid, Abatzoglou, John, Mailloux, Nicholas, Cleetus, Rachel, Udvardy, Shana, Declet-Barreto, Juan, and Worth, Pamela. Killer Heat in the United States. Technical report, Union of Concerned Scientists, July 2019.

[3] Harmon, Don, Hastings, Michael, Cunningham, Bill, Castro, Cristina, Joyce, Patrick, Landek, Steven, Sims, Elgie R., Fine, Laura, Gillepsie, Ann, and Peters, Robert.

Climate and Equitable Jobs Act : Illinois SB2408, September 2021.

[4] Klinenberg, Eric. *Heat Wave: A Social Autopsy of Disaster in Chicago*. University of Chicago Press, Chicago, July 2003.

[5] All, Illinois Solar For. Environmental Justice Communities by Calculation, 2022.

[6] Brown, Marilyn A., Soni, Anmol, Lapsa, Melissa V., Southworth, Katie, and Cox, Matt. High energy burden and low-income energy affordability: conclusions from a literature review. 2(4):042003, October 2020. Publisher: IOP Publishing.

[7] Rai, Alan and Nunn, Oliver. On the impact of increasing penetration of variable renewables on electricity spot price extremes in Australia. *Economic Analysis and Policy*, 67:67–86, September 2020.

[8] Johnathon, Chris, Agalgaonkar, Ashish Prakash, Kennedy, Joel, and Planiden, Chayne. Analyzing Electricity Markets with Increasing Penetration of Large-Scale Renewable Power Generation. *Energies*, 14(22):7618, January 2021. Number: 22 Publisher: Multidisciplinary Digital Publishing Institute.

[9] Blazquez, Jorge, Fuentes-Bracamontes, Rolando, Bollino, Carlo Andrea, and Nezamuddin, Nora. The renewable energy policy Paradox. *Renewable and Sustainable Energy Reviews*, 82:1–5, February 2018.

[10] Almeida, Cátia Rodrigues de, Teodoro, Ana Cláudia, and Gonçalves, Artur. Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review. *Environments*, 8(10):105, October 2021. Number: 10 Publisher: Multidisciplinary Digital Publishing Institute.

[11] Cotlier, Gabriel I. and Jimenez, Juan Carlos. The Extreme Heat Wave over Western North America in 2021: An Assessment by Means of Land Surface Temperature. *Remote Sensing*, 14(3):561, January 2022. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

[12] Sangiorgio, Valentino, Fiorito, Francesco, and Santamouris, Mattheos. Development of a holistic urban heat island evaluation methodology. *Scientific Reports*, 10(1):17913, October 2020. Number: 1 Publisher: Nature Publishing Group.

[13] Abulibdeh, Ammar. Analysis of urban heat island characteristics and mitigation strategies for eight arid and semi-arid gulf region cities. *Environmental Earth Sciences*, 80(7):259, March 2021.

[14] Li, Xueqin, Stringer, Lindsay C., Chapman, Sarah, and Dallimer, Martin. How urbanisation alters the intensity of the urban heat island in a tropical African city. *PLOS ONE*, 16(7):e0254371, July 2021. Publisher: Public Library of Science.

[15] Chakraborty, T., Hsu, A., Manya, D., and Sheriff, G. Disproportionately higher exposure to urban heat in lower-income neighborhoods: a multi-city perspective. *Environmental Research Letters*, 14(10):105003, September 2019. Publisher: IOP Publishing.

[16] Hsu, Angel, Sheriff, Glenn, Chakraborty, Tirthankar, and Manya, Diego. Disproportionate exposure to urban heat island intensity across major US cities. *Nature Communications*, 12(1):2721, May 2021. Number: 1 Publisher: Nature Publishing Group.

[17] Zhang, Ning, Chen, Yan, Luo, Ling, and Wang, Yongwei. Effectiveness of Different Urban Heat Island Mitigation Methods and Their Regional Impacts. *Journal of Hydrometeorology*, 18(11):2991–3012, November 2017. Publisher: American Meteorological Society Section: Journal of Hydrometeorology.

[18] Middel, Ariane, Chhetri, Nalini, and Quay, Raymond. Urban forestry and cool roofs: Assessment of heat mitigation strategies in Phoenix residential neighborhoods. *Urban Forestry & Urban Greening*, 14(1):178–186, January 2015.

[19] Loughner, Christopher P., Allen, Dale J., Zhang, Da-Lin, Pickering, Kenneth E., Dickerson, Russell R., and Landry, Laura. Roles of Urban Tree Canopy and Buildings in Urban Heat Island Effects: Parameterization and Preliminary Results. *Journal of Applied Meteorology and Climatology*, 51(10):1775–1793, October 2012. Publisher: American Meteorological Society Section: Journal of Applied Meteorology and Climatology.

[20] McDonald, Robert I., Biswas, Tanushree, Sachar, Cedilla, Housman, Ian, Boucher, Timothy M., Balk, Deborah, Nowak, David, Spotswood, Erica, Stanley, Charlotte K., and Leyk, Stefan. The tree cover and temperature disparity in US urbanized areas: Quantifying the association with income across 5,723 communities. *PLOS ONE*, 16(4):e0249715, April 2021. Publisher: Public Library of Science.

[21] Marando, Federica, Heris, Mehdi P., Zulian, Grazia, Udías, Angel, Mentaschi, Lorenzo, Chrysoulakis, Nektarios, Parastatidis, David, and Maes, Joachim. Urban heat island mitigation by green infrastructure in European Functional Urban Areas. *Sustainable Cities and Society*, 77:103564, February 2022.

[22] Schwaab, Jonas, Meier, Ronny, Mussetti, Gianluca, Seneviratne, Sonia, Bürgi, Christine, and Davin, Edouard L. The role of urban trees in reducing land surface temperatures in European cities. *Nature Communications*, 12(1):6763, November 2021. Number: 1 Publisher: Nature Publishing Group.

[23] Salamanca, F., Georgescu, M., Mahalov, A., Moustaoui, M., and Martilli, A. Citywide Impacts of Cool Roof and Rooftop Solar Photovoltaic Deployment on Near-Surface Air Temperature and Cooling Energy Demand. *Boundary-Layer Meteorology*, 161(1):203–221, October 2016.

[24] Masson, Valéry, Bonhomme, Marion, Salagnac, Jean-Luc, Briottet, Xavier, and Lemonsu, Aude. Solar panels reduce both global warming and urban heat island. *Frontiers in Environmental Science*, 2, 2014.

[25] Sailor, D. J., Anand, J., and King, R. R. Photovoltaics in the built environment: A critical review. *Energy and Buildings*, 253:111479, December 2021.

[26] Vaishnav, Parth, Horner, Nathaniel, and Azevedo, Inês L. Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost? *Environmental Research Letters*, 12(9):094015, September 2017. Publisher: IOP Publishing.

[27] Reames, Tony G. Distributional disparities in residential rooftop solar potential and penetration in four cities in the United States. *Energy Research & Social Science*, 69:101612, November 2020.

[28] EPA, US. EJScreen: Environmental Justice Screening and Mapping Tool, September 2014.

[29] on Environmental Quality, Council. Climate and Economic Justice Screening Tool.

[30] Viner, David, Ekstrom, Marie, Hulbert, Margot, Warner, Nicolle K., Wreford, Anita, and Zommers, Zinta. Understanding the dynamic nature of risk in climate change assessments—A new starting point for discussion. *Atmospheric Science Letters*, 21(4):e958, 2020. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/asl.958.

[31] Maragno, Denis, Dalla Fontana, Michele, and Musco, Francesco. Mapping Heat Stress Vulnerability and Risk Assessment at the Neighborhood Scale to Drive Urban Adaptation Planning. *Sustainability*, 12(3):1056, January 2020. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

[32] Gronlund, Carina J. Racial and socioeconomic disparities

in heat-related health effects and their mechanisms: a review. *Current epidemiology reports*, 1(3):165–173, September 2014.

[33] Cardona, Omar-Dario, van Aalst, Maarten K., Birkmann, Jörn, Fordham, Maureen, McGregor, Glenn, Perez, Rosa, Pulwarty, Roger S., Schipper, E. Lisa F., Sinh, Bach Tan, Décamps, Henri, Keim, Mark, Davis, Ian, Ebi, Kristie L., Lavell, Allan, Mechler, Reinhard, Murray, Virginia, Pelling, Mark, Pohl, Jürgen, Smith, Anthony-Oliver, and Thomalla, Frank. Determinants of Risk: Exposure and Vulnerability. In Field, Christopher B., Barros, Vicente, Stocker, Thomas F., and Dahe, Qin, editors, *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, pages 65–108. Cambridge University Press, Cambridge, 2012.

[34] Sengupta, Manajit, Xie, Yu, Lopez, Anthony, Habte, Aron, Maclaurin, Galen, and Shelby, James. The National Solar Radiation Data Base (NSRDB). *Renewable and Sustainable Energy Reviews*, 89:51–60, June 2018.

[35] City of Chicago. Boundaries - Census Tracts - 2010 | City of Chicago | Data Portal.

[36] Kua, Chai-Shian, Scott, Lydia, Darling, Lindsay, Cannon, Chuck, Turner-Skoff, Jessica B., Bethke, Tricia, Miesbauer, Jake, and Cavender, Nicole. Chicago Region Tree Census Report. Technical report, The Morton Arboretum, Lisle, Illinois, 2020.

[37] Google. Project Sunroof, February 2022.

[38] Kang, Cinoo, Park, Chaerin, Lee, Whanhee, Pehlivan, Nazife, Choi, Munjeong, Jang, Jeongju, and Kim, Ho. Heatwave-Related Mortality Risk and the Risk-Based Definition of Heat Wave in South Korea: A Nationwide Time-Series Study for 2011–2017. *International Journal of Environmental Research and Public Health*, 17(16):5720, August 2020.

[39] Mazdiyasni, Omid, Sadegh, Mojtaba, Chiang, Felicia, and AghaKouchak, Amir. Heat wave Intensity Duration Frequency Curve: A Multivariate Approach for Hazard and Attribution Analysis. *Scientific Reports*, 9(1):1–8, October 2019. Number: 1 Publisher: Nature Publishing Group.

[40] Karypis, G., Han, Eui-Hong, and Kumar, V. Chameleon: hierarchical clustering using dynamic modeling. *Computer*, 32(8):68–75, August 1999. Conference Name: Computer.

[41] Kotzur, Leander, Markewitz, Peter, Robinius, Martin, and Stolten, Detlef. Impact of different time series aggregation methods on optimal energy system design. *Renewable Energy*, 117:474–487, March 2018.

[42] Rodriguez, Mayra Z., Comin, Cesar H., Casanova, Dalcimar, Bruno, Odemir M., Amancio, Diego R., Costa, Luciano da F., and Rodrigues, Francisco A. Clustering algorithms: A comparative approach. *PLOS ONE*, 14(1):e0210236, January 2019. Publisher: Public Library of Science.

[43] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.