Measuring social equity in urban energy use and interventions using fine-scale data

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Cities seek nuanced understanding of intraurban inequality in energy use, addressing both income and race, to inform equitable investment in climate actions. However, nationwide energy consumption surveys are limited (<6,000 samples in the United States), and utility-provided data are highly aggregated. Limited prior analyses suggest disparity in energy use intensity (EUI) by income is ∼25%, while racial disparities are not quantified nor unpacked from income. This paper, using new empirical fine spatial scale data covering all 200,000 households in two US cities, along with separating temperature-sensitive EUI, reveals intraurban EUI disparities up to a factor of five greater than previously known. We find 1) annual EUI disparity ratios of 1.27 and 1.66, comparing lowest- versus highest-income block groups (i.e., 27 and 66% higher), while previous literature indicated only ∼25% difference; 2) a racial effect distinct from income, wherein non-White block groups (highest quintile non-White percentage) in the lowest-income stratum reported up to a further ∼40% higher annual EUI than less diverse block groups, providing an empirical estimate of racial disparities; 3) separating temperature-sensitive EUI unmasked larger disparities, with heating–cooling electricity EUI of lowest-income block groups up to 2.67 times (167% greater) that of highest income, and high racial disparity within lowest-income strata wherein high non-White (>75%) population block groups report EUI up to 2.56 times (156% larger) that of majority White block groups; and 4) spatial scales of data aggregation impact inequality measures. Quadrant analyses are developed to guide spatial prioritization of energy investment for carbon mitigation and equity. These methods are potentially translatable to other cities and utilities.

fine spatial scale data | intraurban analysis | energy use inequality | social inequity in energy intervention investment

Cities have become a key action arena for carbon mitigation, with the US Mayors' Climate Protection Agreement launched in 2005 and the inclusion of cities in the 2011 United Nations Climate Change Conference. More recently, cities have also started to address equity in their carbon mitigation plans (1, 2). For example, in the United States, New York City and Boston have begun to evaluate social inequality in energy use to inform more equitable distribution of energy-related investments (e.g., efficiency rebates) (3–7). To inform equity, cities are seeking methods and metrics that advance a more nuanced and fine-scale understanding of inequality in energy use and in investments, addressing both race and income.

Here, we distinguish between social inequality and inequity. Social inequality metrics quantify differences in any parameter of interest based on social stratification (8). Some inequality metrics, such as those representing income inequality, assess inequality across the whole population (or surveys representing the population), using the Gini coefficient (9–11) and interquantile income ratios (e.g., P80/P20). Other inequality metrics, such as those used in public health, compute health risk disparity ratios by race, gender, or income (12). Social equity goes beyond inequality to evaluate the fairness in allocating resources (e.g., energy assistance or health care investments) among different groups to reduce social inequality with a focus on reducing disparities for the most disadvantaged strata in society (8, 13, 14). Thus, the analysis of inequality guides the distributional aspect of social equity (13, 15), that is, the distribution of burdens and benefits across social strata. Social equity also includes a procedural dimension related to the agency and participation of disadvantaged groups in decisions that impact them (16).

This paper focuses on distributional equity. Cities face four main challenges, described below, in quantifying social inequality in energy use to inform more equitable investments in energy conservation and efficiency.

1. Lack of fine-scale empirical data across a whole city: There have been relatively few analyses of energy use inequality and investments using empirical data (i.e., data provided by utilities) at fine spatial scales within cities to inform equity. A few efforts that explore inequality in intraurban energy use have primarily relied on modeled energy use (17, 18) using the US Energy Information Administration's Residential Energy Consumption Survey (RECS). RECS only surveys some thousands of homes nationwide (e.g., ∼5,700 in 2015 and ∼12,000 in 2012), resulting in scattered coverage within 10 census divisions, each covering five states on average (19). Consequently, modeled intraurban

Significance

Cities seek income and racial equity in residential low-carbon energy efficiency and conservation programs. However, empirical data are limited; prior analyses suggest disparity in energy use intensity (EUI) by income is ∼25% (i.e., 25% greater EUI in low- versus high-income homes), while racial disparities are unquantified. New empirical fine spatial scale energy use data covering all ∼200,000 households in two US cities, along with separation of temperature-sensitive EUI, reveal large EUI disparities by income (27 to 167%) and race (40 to 156%). These disparities are up to a factor of five greater than the 25% income disparity previously reported. New analytics provide key insights on energy use inequality unpacking race and income, informing spatial prioritization for equitable energy efficiency investments.

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energy use derived from RECS reports a goodness of fit of ~60% (17, 18), which can mask social inequality at the fine spatial scale within cities where social stratification by race and income manifests spatially. Thus, empirical data from utilities are much needed, at least at the block group level, which is the finest scale at which sociodemographic data on race and income are reported by the Census Bureau. Furthermore, to inform equity, data on energy conservation and efficiency program participation and investment across the whole city are needed to evaluate the allocation of investments across all neighborhoods in a city. However, only a few cities such as Los Angeles (20) have obtained fine-scale energy use data from utilities to evaluate inequality in energy use covering the whole city. Likewise, only a few studies have explored social inequality in investment in energy conservation and efficiency at the intraurban scale (21, 22). No previous study has evaluated both inequality in energy use and inequity in energy investments at intraurban scales.

2. Lack of analysis of disparities in energy use and intensity by both race and income: No previous studies have explored disparities in energy use and intensity by both race and income using real intraurban consumption data. For example, Los Angeles (20) evaluated energy inequality at a fine spatial scale by income but not by race (23, 24). Only two previous studies addressed intraurban racial disparities in heating energy use intensity (EUI) using modeled data from RECS (17, 18); however, there is high uncertainty in RECS-derived models given the small survey sample sizes noted earlier.
3. The challenge of spatial scale of data aggregation: When utilities provide intraurban energy usage data to cities, these data are aggregated at different spatial scales, with unknown impacts on energy inequality metrics such as disparity ratios and Gini coefficients. Spatial scales of data aggregation range from the most disaggregated premise level to census blocks (~76 person on average in the United States), census tracts (1,200 to 8,000 persons), and ZIP (Zone Improvement Plan) code (with an average of ~8,000 people). For example, several municipal utilities analyze premise-level data for their city policymakers [e.g., Tallahassee (25), Los Angeles (20), and others (26)]; St. Paul, Minnesota has census tract–level data provided by the local utility (27), while California cities have ZIP code–level data (28) complying with state-level regulations on data privacy provided by utilities. The spatial scale of data aggregation can impact the analysis of dispersion, recognized in geography and public health as the modifiable areal unit problem (29, 30). However, this modifiable unit area problem has not been systematically analyzed for energy use inequality due to the lack of both energy use data and sociodemographic data at fine spatial scales. Assessing how the spatial scale of data aggregation impacts energy inequality measures is important, given that different utilities are spatially aggregating data at different scales for subsequent analysis by cities.
4. Suitable energy use metrics and analysis procedures to inform equity: Even when city-wide fine-scale energy use data are available, there are few analysis protocols and metrics to evaluate intraurban equitable distribution of investments in conservation and efficiency. While metrics to assess inequalities in energy access, energy burden (i.e., percentage of income spent on energy services), and energy use are well developed (1, 2, 31–36), energy use metrics that best represent the impact of energy conservation and efficiency investments are still evolving. Energy use metrics, such as household energy use (kilowatt hour/household a year), energy use per capita [kilowatt hour/person a year (36)], and household energy use intensity by floor area [kilowatt hour/square feet a year (17, 18)] have been used, but all have challenges. Studies have shown that high-income households have a higher energy consumption primarily due to having larger homes (37). These high-income households are also found to be more "efficient," showing lower EUI (18, 23). Thus, only tracking total energy use per household will primarily represent floor area effects but not the efficiency of building stock. EUI has more potential to reflect the condition of the building stock and the efficiency of heating and cooling appliances; however, low-income homes may conserve energy by sacrificing thermal comfort, experiencing energy insufficiency (36). Thus, a lower EUI does not necessarily represent more efficient provision of thermal comfort for low-income homes. Housing stock occupancy can also influence EUI, which can be normalized by household size (38), that is, EUI/capita, to capture the impact of occupancy. A better understanding of floor area, along with total household energy use, housing occupancy, and thermal comfort in conjunction with EUI, is needed to develop suitable inequality metrics for energy use. In addition to exploring appropriate energy inequality metrics, there are no analysis protocols to apply those metrics to inform conservation and efficiency investments toward the triple goals of community-wide carbon mitigation, improving energy affordability (reducing burden), and reducing social inequality in energy use and intensity.

To address the above challenges, our paper makes three key contributions. First, we develop a unique intraurban fine-scale dataset, combining sociodemographic data with energy use, occupancy, program participation, and investment data covering all homes/neighborhoods across two cities. Second, using the empirical fine-scale data (suitable to unpack race and income effects), we explore metrics for cities to quantify social inequality in energy use by both income and race and apply those to inform social equity in energy sector investments in conservation and efficiency (ESICE), for example, efficiency rebates, loans, etc. Our study brings together inequality both in energy use and in efficiency investments at the intraurban scale. Third, with the availability of fine-scale data, we provide an assessment on how energy use inequality metrics are impacted by the spatial scale of data aggregation. Overall, this work informs how cities and utilities can gather and analyze information on energy inequality to guide ESICE to advance social equity and carbon mitigation. The analytical tools demonstrated in two cities in this paper are potentially translatable to other cities and utilities.

Fine-scale data (block group or finer) on both residential energy use and ESICE across the entire city for Tallahassee, Florida, and St. Paul, Minnesota, are obtained through partnerships with electric utilities under nondisclosure agreements to preserve data privacy, consistent with state and federal regulations. Data were provided at the premise level for Tallahassee's ~90,000 households with 1 y monthly energy use and 5 y investment data and at the block level for St. Paul's ~110,000 households with 1 y monthly energy use and investment data. The energy investment data include various efficiency programs (e.g., efficiency rebates, home energy use analysis, etc.; *SI Appendix*, Table S1). Investments in household-scale renewable energy programs, for example, rooftop solar panels, are not within the scope of this study, which focuses on ESICE.

The overall method is shown in *SI Appendix*, Fig. S1, wherein the fine-scale database incorporates social, ecological, infrastructural, and urban form variables, consistent with urban systems frameworks (39).

The inequality metrics used in this study include Gini coefficients and disparity ratios. The Gini coefficient provides a general measure of dispersion for a given parameter, without considering social stratification by income or race, with the coefficient ranging from 0 (perfectly equal distribution) to 1 (extremely unequal). We also adapt the concepts of quintile ratios and disparity ratios used in public health (8) to energy use. Energy use disparity ratios by income are computed as the ratio of the average energy attribute (e.g., EUI) reported in the lowest-income quintile block groups

(20% lowest) versus that reported in the highest-income quintile. EUI disparity ratios by race are computed as the ratio of EUI in the top 20% most racially diverse block groups (>80th percentile of non-White population percentage) versus the 20% least racially diverse block groups. Disparity ratios are closely related to differences across social groups, for example, a disparity ratio of 2.5 between the lowest- and highest-income groups indicates a 150% difference with respect to the highest-income group.

Results

Energy Use Disparities by Income and Race. We evaluated inequality considering several energy use metrics, including energy use per household and per capita, as well as EUI and EUI/capita. The results presented focus on EUI rather than energy use per household to avoid floor area effects. EUI/capita showed similar patterns as EUI (*SI Appendix*, Table S2).

Unpacking annual EUI disparities by income and race. We analyzed annual EUI disparities by income and then by race within the lowest-income block groups to further unpack the racial effect from income. The analysis was conducted at the block group level wherein the availability of income and racial structure data for the years 2015 (for Tallahassee) and 2016 (for St. Paul) matches with the companion energy use data obtained from utilities for the same year(s) in these two cities. Fig. 1*A* demonstrates structural income–race inequality patterns, wherein highest-income quintile block groups are majority White (>50% White population), while the lowest-income quintile block groups have racial minorities (non-White) ranging from 16 to ~95% (60% on average) in St. Paul. Fig. 1*A* shows distinct differences across income strata by racial structure. In terms of energy use, lowest-income groups have 24 to 45% lower consumption per household (*SI Appendix*, Table S3), although they have 27% higher EUI (Fig. 1*B*). Furthermore, a statistically significant racial effect is seen in St. Paul within all except the highest-income stratum (Fig. 1*B*), wherein an increase in non-White population percentage is significantly correlated with higher EUI. The impact of race may not be significant at the highest-income stratum because that stratum is majority White (i.e., very little racial diversity).

Fig. 1*B* represents the separation of race and income effects, shown here with annual EUI. This implies that low-income racial minority neighborhoods in St. Paul experience the highest disparities. A race effect was not observed for annual EUI in Tallahassee within any income strata.

Energy use disparity ratios were also computed by race and income for annual electricity and gas use in the two cities (see *Materials and Methods*). Electricity EUI disparity ratio by income in St. Paul is 1.27 (Table 1), indicating block groups with the lowest-income have ~27% higher EUI compared to the highest-income block groups. In Tallahassee, this disparity ratio is 1.66 (Table 1), which corresponds to a difference of 66% between the lowest-income and the highest-income groups, more than double that previously reported in US cities [i.e., ~25% in Los Angeles (23)] and that seen in St. Paul (this paper). Normalizing EUI by

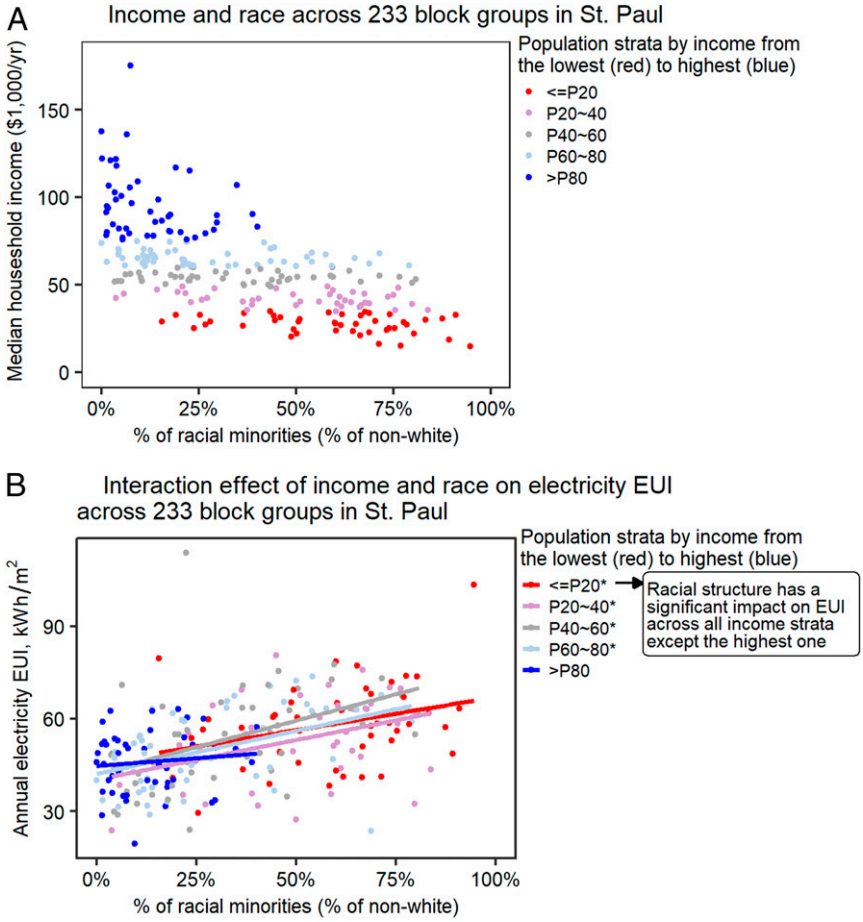


Fig. 1. Unpacking the effect of race on EUI across income strata at the block group level. (*A*) Structural race effects are seen wherein the highest-income block groups are predominantly White (blue dots), while the lowest-income block groups are the most racially diverse (red dots). (*B*) EUI inequality by race is seen across income strata in which the slope of EUI versus the percentage of racial minorities (non-White) is significant and positive, except for the highest-income stratum (>P80).

Table 1. Disparity ratio of EUI by income at the block group level in St. Paul and Tallahassee

City	Energy type	Energy use season	Average in block groups with income <20th percentile* (A)	Average in block groups with income >80th percentile* (B)	Disparity ratio (A/B)
St. Paul	Electricity, kWh/m^2	Not temperature sensitive[†]	40.6	39.3	1.03
		Temperature sensitive (additional energy use in heating and cooling seasons)[‡]	17.7	6.6	2.67[§] [2.79]
		Annual total	58.4	46.0	1.27[§]
	Natural gas, kWh/m^2	Not temperature sensitive[†]	1.4	1.5	0.94
		Temperature sensitive (additional energy use in heating and cooling seasons)[‡]	138.5	159.8	0.87[§]
		Annual total	139.9	161.2	0.87[§]
Tallahassee	Electricity, kWh/m^2	Not temperature sensitive[†]	97.1	54.0	1.80[§] [1.62]
		Temperature sensitive (additional energy use in heating and cooling seasons)[‡]	16.0	14.3	1.12
		Annual total	113.1	68.3	1.66[§] [1.49]

The tan highlights an exceptionally high and statistically different disparity ratio. The disparity ratio in [] is computed using the regression equation approach.

*The income level for 20% population in the lowest-income block groups is $34,750/y and $22,652/y for St. Paul and Tallahassee, respectively. The 80th percentile is $75,722/y and $82,885/y for St. Paul and Tallahassee, respectively.

[†]Not temperature-sensitive EUI is calculated based on the monthly EUI in months when no heating or cooling is needed. We scaled this monthly EUI to annual by multiplying by 12. These months are May, September, and October in St. Paul and March, April, October, and November in Tallahassee.

[‡]Temperature-sensitive EUI is the additional energy use in heating and cooling months.

[§]The difference between two data groups was assessed using a *t* test and found statistically significant at 95% confidence level.

population size (EUI/capita) finds an even higher disparity of 2.09 comparing the lowest versus highest income block groups in Tallahassee (*SI Appendix*, Table S2). Annual EUI disparity ratios by race within the lowest-income stratum, ranging from 1.09 to 1.40 in two cities (Table 2), are similar in magnitude compared to the disparities by income.

Seasonal EUI disparity ratios by income. Annual energy use data can mask disparities. To quantify EUI in a more granular way to address seasonality and account for thermal comfort, we separated EUI for heating/cooling homes (temperature sensitive) from the rest (non-temperature sensitive). We also evaluated the relationship of monthly EUI versus ambient temperature (40) to delineate the apparent "turning point temperature"—that is, the temperature below which homes turn on gas heat (*SI Appendix*, Fig. S4). In St. Paul, the highest-income homes show a temperature for the onset of heating energy use at 13.11 °C versus 11.95 °C for the lowest-income block groups, indicating that low-income homes are indeed sacrificing thermal comfort. This perhaps contributes to the lower EUI for gas use of 0.87 (Table 1). This behavioral phenomenon likely also extends to the cooling seasons; however, it is not as visible because, unlike heating, not all homes in St. Paul have air conditioners. The disparity ratio of temperature-sensitive electricity EUI combining summer and winter is in the range of 2.67 to 2.79 in St. Paul (Table 1). This indicates that despite the thermal comfort effect (*SI Appendix*, Fig. S4), low-income homes use more than twice the electricity per square foot as high-income homes in St. Paul (for heating and cooling). The disparity ratio by income for non-temperature–sensitive EUI is not statistically different from 1 in St. Paul, while it is significant and high (1.62 to 1.80) in Tallahassee.

Seasonal EUI disparity ratios by race among lowest-income quintile block groups. By separating temperature-sensitive energy use, high disparities by race are seen within the lowest-income block groups, comparing top quintile non-White population block groups versus the bottom quintile non-White (i.e., majority White) block groups. These disparity ratios are high and statistically significant as confirmed using two different approaches (see *Materials and Methods*), ranging from 2.05 to 2.56 for temperature-sensitive electricity EUI in Tallahassee (Table 2). This indicates non-White poorer block groups' seasonal electricity EUI is 105 to 156% higher for similar comparisons in Tallahassee. Indeed, a statistically significant race effect separate from income could be discerned in Tallahassee for temperature-sensitive EUI in the lowest-income quintile (*SI Appendix*, Fig. S9), further confirming the disparity ratio.

Overall, these results show that EUI derived from fine spatial scale data and/or with the separation of temperature-sensitive energy use reveal higher disparities by income (up to 2.67 in St. Paul; Table 1) compared to what was reported previously [~1.25 in Los Angeles (23)]. These fine-scale data, for the first time, also enable separating energy use disparities by race from income (Fig. 1*B*) with EUI disparities by race in the lowest-income stratum being as high as 2.56 in Tallahassee for temperature-sensitive energy use (Table 2). EUI/capita revealed similarly high disparities ratios (*SI Appendix*, Table S2).

Multiple social, ecological, infrastructural, and urban form drivers of annual energy use. We conducted regression analysis to better understand built environmental factors that influence annual energy use beyond socioeconomics factors. We found that the median household income of block groups and the percentage of floor area occupied by single-family homes are moderately correlated, and both together explain the 34 and 20% variation in annual gas and annual electricity EUI, respectively (*SI Appendix*, Table S5). Beyond these two factors, the age of housing stock emerges as significant for both gas and electricity EUI, while the level of education and family size are significant for electricity and gas EUI, respectively. The tree canopy effect is significant only for electricity EUI. EUI/capita largely shows similar relationships (*SI Appendix*, Table S7). Future work is needed to address the seasonal impact of tree canopy on seasonal energy use and EUI at fine intraurban scales, which is beyond the scope and focus of this paper. EUI and EUI/capita are more sensitive than energy use per household in revealing relationships with natural environment features (*SI Appendix*, Tables S5–S7).

Impact of Spatial Scale of Data Aggregation on Inequality Metrics. We explored data aggregation effects on inequality metrics (i.e., Gini coefficients and disparity ratios) using annual EUI and

Table 2. Disparity ratio of EUI by race in the lowest-income stratum at the block group level in St. Paul and Tallahassee

City	Energy type	Energy use season	Average in block groups with highest % non-White* (A)	Average in block groups with lowest % of non-White* (B)	Disparity ratio (A/B)
St. Paul	Electricity, kWh/m^2	Not temperature sensitive	40.9	30.0	1.36
		Temperature sensitive (additional energy use in heating and cooling seasons)	25.5	17.4	1.46
		Annual total	66.4	47.5	1.40† [1.22]
	Natural gas, kWh/m^2	Not temperature sensitive	1.49	1.23	1.21
		Temperature sensitive (additional energy use in heating and cooling seasons)	158.1	114.2	1.38
		Annual total	159.6	115.4	1.38
Tallahassee	Electricity, kWh/m2	Not temperature sensitive	93.9	97.2	0.97
		Temperature sensitive (additional energy use in heating and cooling seasons)	20.8	8.1	2.56† [2.05]
		Annual total	114.6	105.3	1.09

The tan highlights an exceptionally high and statistically different disparity ratio. The disparity ratio in [] is computed using the regression equation approach.

*In St. Paul, we used the 80th and 20th percentile of non-White percentage within the lowest-income population quintile, corresponding to 75 and 43.5% non-White population. In Tallahassee, we used the 70th and 30th percentile within the lowest-income population quintile, corresponding to 77 and 38.4% non-White population.

†The difference between two data groups was assessed using a *t* test and found statistically significant at 95% confidence level.

household energy use as example parameters. During aggregation, energy use and population are composited from finer to coarser spatial scales to compute relevant metrics, similar to utility data reports provided to St. Paul. At higher spatial scales of data aggregation, Gini coefficients, representing inequality in EUI across different geographies within the city, decrease by up to ~50%, from 0.24 and 0.12 for electricity EUI in St. Paul and from 0.20 to 0.15 in Tallahassee, when data were aggregated from census block to census tract level (*SI Appendix*, Fig. S2*A*). Such sharp and monotonical decreases in Gini coefficients are also seen for energy use per household in both cities (*SI Appendix*, Fig. S2*A*). Given that a Gini of zero represents a perfectly equal distribution, our results show a substantial apparent reduction in inequality because of data aggregation.

Annual EUI disparity ratios by race also changed substantially (−19 to 22%) when going from census block to block group to census tract levels (*SI Appendix*, Fig. S2*B*), while changes of disparity ratios by income were smaller (−21 to 10%) (*SI Appendix*, Fig. S2*C*). Synthetic experiments using Tallahassee's premise-level data explored aggregation effects on disparity ratios from the premise level to census block level, which were 4% for income and −12 to 26% for racial disparities, respectively (*SI Appendix*, Fig. S3). Unlike the Gini coefficient, disparity ratios are not monotonically decreasing (i.e., both increases and decreases) when data are aggregated from one spatial scale to another. A likely explanation is the divergent shape of the probability density functions for non-White population percentage at the three spatial scales (*SI Appendix*, Figs. S7 and S8).

Quadrant Analysis Assessing Equity in Energy Program Participation and Spatial Aspects of Program Design. A quadrant approach was developed to quantify and prioritize energy program outreach and investments in block groups based on the following goals: 1) community-wide carbon mitigation, 2) reducing energy burden, and 3) reducing social inequality by race and income. The method bins all block groups in a city into four quadrants based on pairs of variables chosen to reflect these three goals, with the quadrant cutoffs established at each variable's average. We applied the quadrant method to household participation in ESICE programs (Fig. 2) and to the share ratio of investment (*SI Appendix*, Fig. S5).

Tallahassee and St. Paul show different patterns in the preferred quadrants to meet these goals. In St. Paul, greater participation rates are seen in the desired quadrant (top right in Fig. 2 *A*, *Left*) for carbon mitigation, that is, block groups with a higher EUI and floor area relative to the city's average (collectively using 29% of total residential energy). Tallahassee's energy use is such that very few block groups exhibit both higher EUI and higher square footage. The priority for carbon mitigation shifts to the next quadrant (top left in Fig. 2 *B*, *Right*) with lower EUI and higher square footage (collectively using 53% of total residential energy) in which participation rates are high, signaling good program outcomes. However, in both cities, participation rates in quadrants that prioritize reducing energy burden (bottom-right quadrant in Fig. 2*B*) and social inequality (top-left quadrant in Fig. 2*C*) focusing on disadvantaged groups are mixed, helping identify areas where programs must be modified to increase participation (*SI Appendix*, Fig. S5).

We also quantified the share of investment dollars alongside the share of energy use as a good marker for allocating resources for carbon mitigation and the share of investment by the percentage of households experiencing energy burden or belonging to disadvantaged groups as a measure of social equity in investment (*SI Appendix*, Fig. S5). These metrics provide multiple dimensions from which to assess equity. During the study period, both St. Paul and Tallahassee allocated resources effectively and proportionally to energy use for carbon mitigation but comparatively less so from a social equity perspective. These results are sensitive to the cutoffs in developing the quadrants; results using 200% of the federal poverty line as the cutoff (often used in social services) are shown in *SI Appendix*, Fig. S6 and are similar to Fig. 2.

We spatially mapped block groups associated with the priority quadrants for each of these three goals to understand whether cities could focus on specific block groups to achieve all three objectives. Fig. 3 spatially illustrates the inherent dichotomy between the goal of community-wide carbon mitigation and addressing social inequality in both cities. This is due to structural income–race

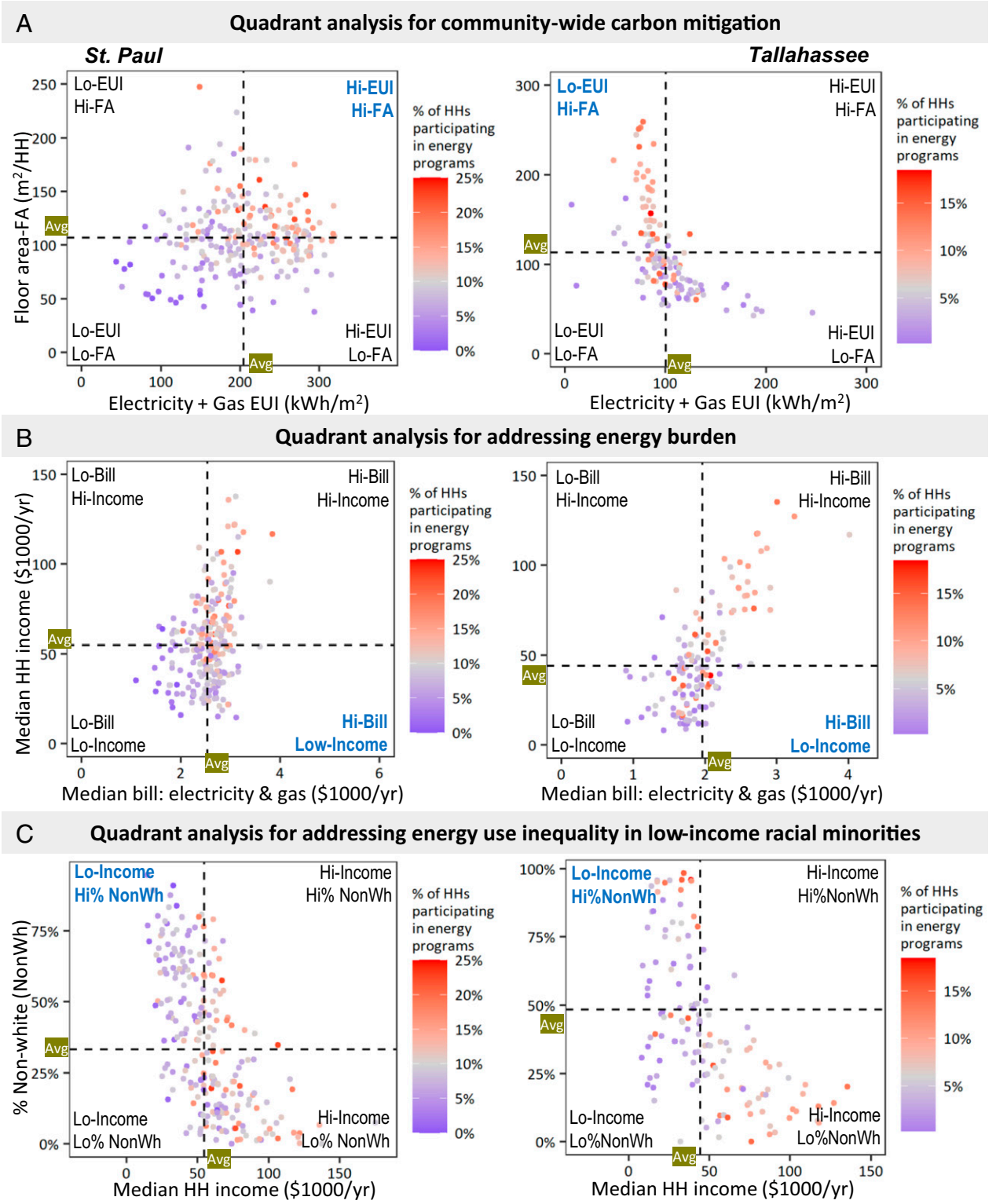


Fig. 2. Quadrant analysis for prioritizing energy sector investments for conservation and efficiency against three goals: 1) community-wide carbon mitigation, 2) reducing energy burden, and 3) addressing social inequality in low-income racial minorities. Household rebate participation rates (color dots) across 233 block groups in St. Paul (left column) and 133 block groups in Tallahassee (right column) are depicted in quadrants representing pairs of attributes. (*A*) Quadrant to prioritize community-wide carbon mitigation based on a higher share of energy use (quadrants shown in blue in panel). (*B*) Quadrant to prioritize reducing energy burden based on household energy cost and income (bottom-right quadrants). (*C*) Quadrant to prioritize equitable allocation of the efficiency investment by race and income (top-left quadrants). Higher rebate participation rates are seen in the preferred quadrants for carbon mitigation and to some extent for reducing energy burden but not for addressing inequality in disadvantaged population by race and income compared to the quadrants with least disadvantaged population.

inequality patterns wherein highest-income areas are majority White with higher consumption, and lowest-income areas have lower consumption, although a higher EUI (Fig. 1 and *SI Appendix*, Table S3). Hence, separate programs with specific quantitative goals (drawn from Fig. 3 and *SI Appendix*, Fig. S5) are indicated for cities to achieve both outcomes.

Discussion

Overall, this paper shows that empirical energy use data with fine spatial and temporal granularity, that is, fine spatial scale and the separation of temperature-sensitive energy use, provide key insights on social inequality in energy use.

Using fine-scale data, we find annual EUI disparity ratios by income of 1.27 and 1.66, comparing lowest- versus highest-income block groups (i.e., 27 and 66% higher), while previous literature indicated an ∼25% difference.

Few previous studies have quantified racial disparities in EUI separated from income. Our results reveal a racial effect distinct from income even with annual energy use in St. Paul, wherein non-White block groups (highest quintile non-White percentage; >75% non-White) in the lowest-income stratum reported up to a further ∼40% higher annual EUI than majority White block groups (>55% White), providing a first empirical estimate of racial disparities.

Furthermore, our results show that separating temperature-sensitive energy use can reveal significantly larger social inequalities. By separating the heating and cooling season's EUI from the rest, we find even higher disparity ratios (Tables 1 and 2). These disparity ratios for temperature-sensitive EUI correspond to maximum differences of 167% by income in St. Paul and 156% for EUI by race in the lowest-income stratum in Tallahassee. These differences are nearly five times the magnitude of energy use disparities previously known [e.g., 25% difference by income reported in Los Angeles (23)]. Given such high temperature-sensitive disparities, low-income racial minorities will be even more vulnerable to the significant anticipated temperature changes due to climate change (26).

Overall, both cities report up to a factor of five larger inequality in certain energy use metrics. However, energy prices and energy burden (∼5% on average and ranging from ∼2 to 20% in both cities) are similar (*SI Appendix*). In St. Paul, the heating season is important wherein racial disparities in temperature-sensitive gas EUI in the lowest-income stratum are seen. In Tallahassee, the cooling season is very long; EUI disparity by income becomes emergent in the non-temperature–sensitive EUI, while the race effect separated from income was observed only for the temperature-sensitive EUI and only in the lowest-income stratum (*SI Appendix*, Fig. S9). These results indicate methods developed in this paper can unpack and make visible important social disparities. Future studies are needed to explore potential causes of intercity differences, which is beyond the scope of this paper. It is likely that accessing finer spatial and temporal-scale data in other cities will reveal similar levels of disparities seen here, given systemic income–race relationships (Fig. 1*A*) are likely widespread across the United States and other countries, where religion, caste, and ethnicity may play a role. Electric utilities by themselves will be unable to address the structural inequality shown in Fig. 1*A*. However, recognizing that income plays a large role and that race appears to play a role even within income groups can stimulate community conversations. Furthermore, utility investment can be realigned to address income effects, while outreach can be customized to reach racial minorities equitably in culturally sensitive ways.

As cities seek to understand inequality in energy use, they must be mindful of the spatial scale at which data are aggregated, which has bearing on the magnitude of inequality computed. Our paper provides an empirical exploration of the impact of the spatial scale of data aggregation on energy inequality metrics. We find both Gini coefficients and disparity ratios are susceptible to data aggregation effects when aggregating energy use data from the block to census tract scale (*SI Appendix*, Fig. S2). While utilities are aggregating data to comply with data privacy regulations, we suggest that cities and utilities report explicitly at what scale they are aggregating data, recognizing that it may impact energy inequality metrics. Alternatively, the census block group could be used as a consistent scale or cities could invest in more granular surveys.

Last, quadrant analysis using energy use and EUI metrics along with income, race, and floor area (Fig. 2) can help cities identify, quantify, and prioritize their investment relative to different goals, that is, carbon mitigation, reducing energy burden, and reducing energy use inequality. If quadrant analysis demonstrates cities underinvest in low-income and racially diverse neighborhoods or that participation rates are low (Fig. 2*C*), it can stimulate redirecting investments and redesigning programs from a procedural equity perspective (15, 16) by engaging those neighborhoods in design and implementation. Thus, our analysis focusing on distributional justice can be combined with procedural equity, contributing to the overarching goal of energy justice (15, 16).

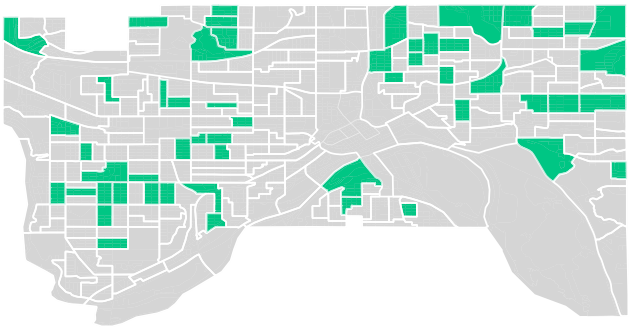
Spatial analysis of quadrants demonstrates that block groups to be prioritized for community-wide carbon mitigation have very little spatial overlap (12% and 7% for St. Paul and Tallahassee, respectively) with those block groups to be prioritized to address social inequality. Therefore, it is difficult to achieve both community-wide carbon mitigation and social equality in one program by focusing on sweet spots of intersection. This finding indicates that cities must design dual programs to achieve both goals, since their focus will necessarily be on different neighborhoods. Programs addressing social equity would focus on reducing disparity in low-income and racially diverse neighborhoods. In contrast, programs addressing carbon mitigation through a focus on high energy users (e.g., higher income with larger floor area) could utilize the concept of sufficiency (36), highlighting the potential of achieving well-being with comparatively lower energy use (41) (e.g., smaller homes, conservation behaviors, and lifestyle changes).

Overall, with fine-scale spatial data on energy use, program participation, and investment becoming increasingly available from utilities and smart grid programs, our paper suggests that cities can directly evaluate these data to determine baseline measures of inequality to track progress. Empirical data, with the separation of temperature-sensitive EUI from the annual total, can reveal important features of inequality at fine urban scales that are not readily captured by current models. Indeed, models themselves will be further refined with more fine-scale energy use data coupled with social–ecological–infrastructural–urban parameters. Furthermore, fine-scale spatial data on energy use must be evaluated together with data on investment, potentially using methods developed in this paper, to chart quantitative goals and track progress for both carbon mitigation and social equity.

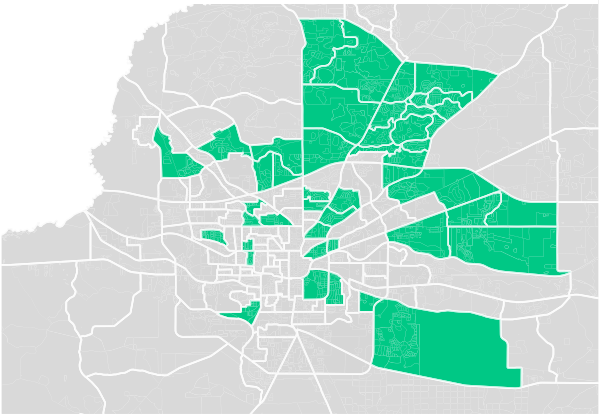
Materials and Methods

Electric utilities provided residential energy use data and ESICE data at the census block level in St. Paul and the premise level in Tallahassee under nondisclosure agreements. Nondisclosure agreements ensured data privacy in compliance with state and federal regulations. Energy use data for St. Paul are anonymized and aggregated by the utility to the census block level and meet the 15/15 criteria (i.e., the aggregated sample must have more than 15 customers and no single customer's data may comprise more than 15% of the total aggregated data). Such aggregated data do not constitute human subject research and do not require institutional review board (IRB) approval. Data for Tallahassee are already gathered by the utilities and are in the public record; therefore, they are exempt from IRB (42). We spatially joined energy use and investment data with available sociodemographic (43), ecological (44, 45), infrastructural (46, 47), and urban form variables (39) at three spatial scales, that is, census block, block group, and census tract, for further analysis (*SI Appendix*). Energy use data years were 2015 (Tallahassee) and 2016 (St. Paul), which matched with years during which

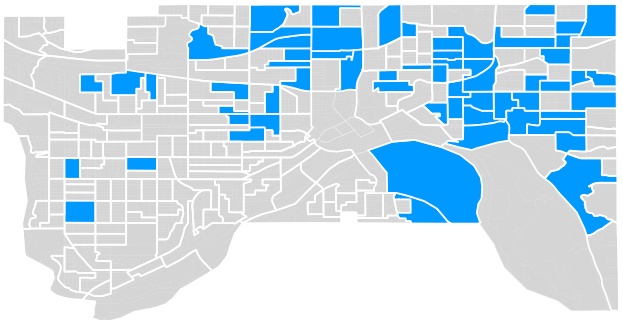
A Prioritizing community-wide carbon mitigation in St. Paul: Block groups in green collectively have higher energy use, i.e. higher EUI and higher sqft (wrt city average).



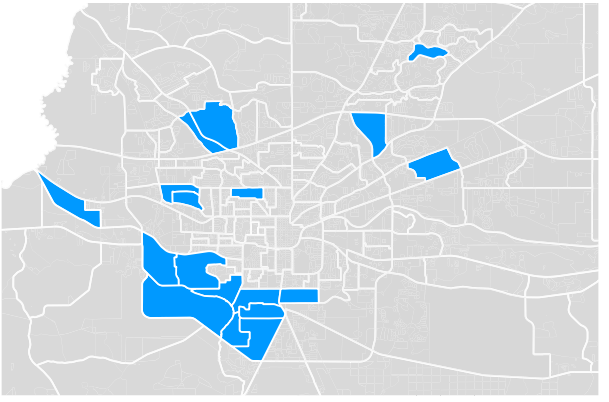
B Prioritizing community-wide carbon mitigation in Tallahassee: Block groups in green collectively have higher energy use, i.e., lower EUI and higher sqft (wrt city average).



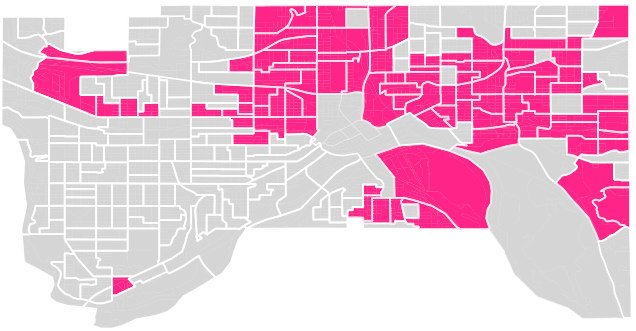
C Prioritizing reducing energy burden in St. Paul: Block groups in blue have higher energy cost per HH and lower income (wrt city average).



D Prioritizing reducing energy burden in Tallahassee: Block groups in blue have higher energy cost per HH and lower income (wrt city average).



E Diadvantaged population by race and income in St. Paul: Block groups in red have higher % of racial minorities (non-white) and lower income (wrt city average).



F Diadvantaged population by race and income in Tallahassee: Block groups in red have higher % of racial minorities (non-white) and lower income (wrt city average).

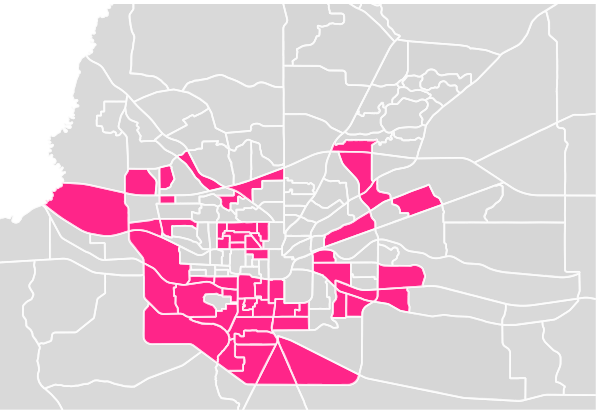


Fig. 3. Little overlap in block groups that would be prioritized for community-wide carbon mitigation (highlighted in green in *A* for St. Paul and *B* for Tallahassee), reducing energy burden (highlighted in blue in *C* for St. Paul and *D* for Tallahassee), and equitable energy sector investment for conservation and efficiency by race and income (highlighted in red in *E* for St. Paul and *F* for Tallahassee).

sociodemographic data (e.g., race and income) were gathered for 233 block groups in St. Paul and 133 in Tallahassee.

We developed innovative methods to unpack the effects of income and race on various energy use metrics (i.e., EUI, EUI/capita, energy use/household, and energy use/capita), with the separation of temperature-sensitive energy use from the annual total. Except for spatial scale exploration, energy use metrics were calculated at the block group level. For example, the EUI of a block group was calculated by dividing the sum of all households' energy use with the sum of these households' floor area in this block group. When separating temperature-sensitive energy use, we first calculated the average

monthly energy use in non-heating/cooling months in a block group as the baseline (not temperature sensitive). The additional energy use during all heating and cooling months was noted to be temperature sensitive. Block groups wherein buildings were served by district energy systems in St. Paul were excluded in the analysis to avoid the impact of different heating/cooling technologies.

EUI disparity ratio by income, DR^{EUI}_{inc}, was calculated by dividing the average EUI reported in block groups with median income lower than the 20th percentile income (P20) (by population) with the average EUI in block groups with median income higher than the 80th percentile (P80) (shown below). The EUI disparity ratio across the two income quintiles are shown in Eq. **1**.

$$DR^{EUI}_{inc} = \frac{Avg.\,EUI_{inc<P20}}{Avg.\,EUI_{inc>P80}}. \quad [1]$$

Student's *t* test was used to assess statistical differences in the two components that constitute the ratio.

EUI disparity ratio by race in the lowest-income stratum (bottom income quintile), $DR^{EUI}_{race,lowest\ income}$, was computed by separating the lowest-income group further into quintiles based on non-White population percentage in St. Paul. Quintiles (80th and 20th percentiles on non-White population) in the lowest-income group in St. Paul enabled comparing 10 block groups each with percentage cutoffs of non-White population at >75% non-White and <43.5% non-White, representing the fifth-most and fifth-least racially diverse block groups, respectively. The EUI disparity ratio by race in the low-income quintile in St. Paul was computed using Eq. **2**:

$$DR^{EUI}_{race,lowest\ income} = \frac{Avg.\,EUI_{Non-white>75\%\&inc<P20}}{Avg.\,EUI_{Non-white<43.5\%\&inc<P20}}. \quad [2]$$

For Tallahassee, the sample size of block groups in the lowest-income stratum was only 27, for which dividing further into quintiles (80 to 20) would yield small numbers of block groups; hence, we used a wider 70th and 30th percentile non-White population as cutoff, corresponding to >77% non-White and <38.4%, respectively.

Because of the relatively small sample sizes by racial quintile within the lowest-income stratum, we also confirmed the disparity ratios by regression analysis, that is, utilizing the relationship between EUI and non-White population percentage across all block groups within the lowest-income group. This can be seen, for example, in the statistically significant regression illustrated in the red line, lowest income in Fig. 1*B* and *SI Appendix*, Fig. S9. This allowed the consideration of racial effect across a larger number of block groups; we computed EUI in the lowest and highest non-White percentage quintiles using the regression equation and computed the disparity ratios using this approach. The results from both approaches were similar in magnitude and shown in tables and affirmed our findings.

Additional method details are in *SI Appendix*.

Data Availability. Data cannot be shared. (The sharing of raw data is restricted by nondisclosure agreements established between the research team and the energy utilities, developed to ensure data privacy and security. The aggregated data at the census block group level used in the analyses can be made available to other researchers upon contacting the corresponding author.)

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