Utilizing smart-meter data to project impacts of urban warming on residential electricity use for vulnerable populations in Southern California

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Abstract
Extreme heat events are increasing in frequency and intensity, challenging electricity infrastructure due to growing cooling demand and posing public health risks to urbanites. In order to minimize risks from increasing extreme heat, it is critical to (a) project increases in electricity use with urban warming, and (b) identify neighborhoods that are most vulnerable due in part to a lack of air conditioning (AC) and inability to afford increased energy. Here, we utilize smart meter data from 180 476 households in Southern California to quantify increases in residential electricity use per degree warming for each census tract. We also compute AC penetration rates, finding that air conditioners are less prevalent in poorer census tracts. Utilizing climate change projections for end of century, we show that 55% and 30% of the census tracts identified as most vulnerable are expected to experience more than 16 and 32 extreme heat days per year, respectively.

1. Introduction

Today over half of the global population lives in urban areas, and by 2050, this fraction is expected to grow to nearly 70% (United Nations 2018). Accordingly, increases in urban warming, influenced by urbanization, population densification, and the local impacts of global climate change, represent key drivers for future changes in energy usage in the United States (US) due to increased cooling needs (Ang et al 1992, Isaac and van Vuuren 2009, Santamouris et al 2015). This warming is likely to have disproportionate effects on poor communities that might be sensitive to increasing electricity bills or lack access to air conditioning (AC) altogether (Hallegatte and Rozenberg 2017, Byers et al 2018). As heat currently kills more people each year in the US than storms, floods, and lightning combined (National Weather Services 2018), identifying those communities most vulnerable to rising residential energy costs is critical (Jones et al 2015).

Similarly, while exploding global demand for cooling is expected to bring AC to billions of people in the coming decades (Davis and Gertler 2015, Kendra Pierre-Louis 2018), the spatio-temporal distributions of these future energy needs for space cooling in the US and abroad are not well understood, and analytical techniques to anticipate these trends with available data are limited.

The residential sector is the biggest electricity consumer in the US, accounting for 37% of total US electricity consumption (US Energy Information Administration 2015a). Space cooling accounts for 15% of electricity consumption within US homes, ranking as the highest single energy-consuming end use activity in the residential sector (US Energy Information Administration 2018). Cities are currently warming due to the local impacts of global climate change and the urbanization-induced intensification of the urban heat island effect. Urban warming is expected to increase residential sector energy usage in the US due to growing cooling and comfort needs (Ang et al 1992, Santamouris et al 2015, Janetos 2016), both in terms of increased AC usage in homes with existing AC and new AC installations in homes without existing AC. Intensifying AC usage will lead to additional greenhouse gas emissions, and its impact
on energy demand is expected to pose challenges to current electricity infrastructure and peak electricity management (Allen et al. 2016, Auffhammer et al. 2017, Larcom et al. 2019, Martinich and Crimmins 2019). In order to anticipate challenges associated with future cooling needs, it is important to quantify how urban warming is expected to increase cooling energy use with high spatial fidelity. However, this task is difficult given spatially heterogeneous distributions in future warming (Knutti et al. 2016) and building characteristics across the built environment (Santamouris et al. 2015), both of which affect the sensitivity of cooling energy use to temperature increases.

Developing a quantitative understanding of how residential electricity use by disparate populations will be impacted in the future by factors such as climate change and urban heat islands requires high resolution energy and climate data to (a) identify the geospatial distribution of warming and (b) quantify how electricity consumption changes according to those temperature and climatic variations (Chen et al. 2018). To the authors’ knowledge, few empirical studies have been performed to understand the functional relationships between electricity usage and ambient temperature at fine spatiotemporal scales. This research gap is largely due to a lack of publicly available, high-resolution (e.g. household level and hourly) residential electricity data (Chen et al. 2018). However, the recent availability of highly resolved electricity use data, collected by smart meters at the household level, enable such analysis. Additionally, few studies have directly investigated the correlation between socioeconomic factors and how a household’s residential electricity consumption varies as a function of ambient temperature (hereafter referred to as the ‘electricity-temperature relationship’).

Based on these knowledge gaps, this study addresses the following research questions:

1. How does residential electricity consumption across Southern California respond to changes in ambient temperature?
2. To what extent is residential electricity behavior influenced by spatial variations in baseline climate and socioeconomic factors?
3. Can we better understand vulnerability to future increases in temperature by considering geospatial distributions of poverty level, AC penetration rates (i.e. the fraction of homes with AC), and extreme heat events?

To answer these questions, we utilize two years (i.e. 2015–2016) of hourly electricity consumption records for 180 476 households in Southern California, as well as local site weather data, to compute household-level relationships between electricity consumption and ambient temperature, using the segmented linear regression model detailed in our previous study (Chen et al. 2018). We also assess the prevalence of AC usage across the investigated area at the household level, in the context of climate characteristics, as well as socio-economic demographics, using a methodology presented in our previous study (Chen et al. 2019). In this study, the investigated area within Southern California is defined as the territory serviced by Southern California Edison, which includes Los Angeles County, Orange County, Riverside County, and San Bernardino County. (However, the City of Los Angeles, within Los Angeles County, is excluded since it is serviced by Los Angeles Department of Water and Power.)

Southern California was selected as a study region because it has widely varying microclimates across relatively small spatial extents, spanning coastal, mountainous, and desert climates. It is also comprised of densely urban through sparsely populated rural communities. Southern California is projected to have uneven spatial distributions of warming due to the combined signatures of urban heat islands and climate change (Hall et al. 2012, Vahmani et al. 2016). Moreover, Southern California has a diverse housing stock ranging from tiny apartments to huge villas, reflecting wide variations in socioeconomic status and housing preferences. This analysis was enabled by the abundance of Advanced Metering Infrastructure smart-meter data across Southern California, which facilitated results to be generated with unprecedented spatio-temporal resolution.

In this study, we characterize the relationship between residential electricity consumption and ambient temperature using two indicators, including:

1. Electricity-temperature sensitivity (referred to as ‘E–T sensitivity’, in kW °C⁻¹), defined as the change in instantaneous electricity consumption of a household corresponding to a unit change in ambient temperature, i.e. one degree Celsius.
2. Stationary point temperature (referred to as ‘SPT’, in °C), defined as the ambient temperature threshold beyond which households are likely to turn on AC if equipped.

For example, a household having an electricity-temperature sensitivity of 0.25 kW °C⁻¹ and a stationary point temperature (SPT) of 20 °C indicates that the household’s electricity consumption is observed to increase at a rate of 0.25 kW per degree C of temperature increase (or 6 kWh °C⁻¹ day⁻¹) on days with daily mean ambient temperatures higher than 20 °C.

2. Methods

2.1. Datasets

2.1.1. Electricity dataset
Hourly residential electricity data records for more than 200 000 randomly chosen households in
Southern California were acquired. The spatial distribution of households at the census tract level can be found in section S4 in supplementary information (available online at stacks.iop.org/EnRL/15/064001/mmedia). These data were provided by the Investor Owned Utility (IOU), Southern California Edison, for the year 2015 and 2016. The sample size of 200 000 was calculated such that it would be representative of the region’s 4.5 million residential households (all equipped with smart meters) at a 99% confidence level using equation (1), allowing for additional degrees of freedom for analysis

\[
n = \frac{Z^2 \rho(1 - \rho)}{e^2} N \left(\frac{1}{N - 1} + \frac{Z^2 \rho(1 - \rho)}{N e^2}\right).
\]

In equation (1), \(n\) is the required sample size; \(Z\) is the Z-score, determined as 2.576 by the confidence level chosen (99%); \(\rho\) is the expected prevalence, chosen as 50%; and \(e\) is the margin of error, set as 0.5% in this study; \(N\) is the total number of residential customers in the studied area (4.5 million). (See section S6 in supplementary information for detail on how we determined these parameters.) To fully capture seasonal variations in the relationship between electricity consumption and ambient temperature, we screened out customers with less than 365 days of electricity records. The data provider did not give information about onsite generation installations (e.g. solar panels). In addition zero values, rather than negative values, were recorded in the dataset when generation exceeded consumption, further complicating the identification of these self-generation. Accordingly, we used a heuristic filtering approach to remove homes with potential solar generation since their electricity-temperature relationships were likely to be distorted. Homes that had at least one hour of zero consumption between 10:00 and 16:00 and positive consumption between 17:00 and 23:00 for more than 36 days (i.e. 5% of the 2-year period of study) were deemed to have solar generation. Once all filtering was complete, 180 476 households were analyzed from the original dataset. Data included hourly household-level electricity consumption and street address. Storage and processing of all data were performed using a highly secure HPC Secure Data Account (HSDA) on USC’s Center for High-Performance Computing (HPC). This was to fulfill the data security and privacy protection requirements of the IOU.

2.1.2. Site weather datasets
Two weather data sources were used to retrieve daily ambient near-surface air temperatures for 2015 and 2016: the California Irrigation Management Information System (CIMIS) (California Department of Water Resources 2017) and National Oceanic and Atmospheric Administration (NOAA)’s National Centers for Environmental Information (NCEI) (NCEI 2016). The two networks are comprised of land-based weather stations that are automated, quality-controlled, and covering most population centers in the investigated area. We utilized 36 CIMIS and 43 NCEI stations in total, which were selected by measuring the shortest distance between a weather station and each household with an electricity data record. Figure S2 shows the number of households per census tract and location of weather stations utilized in this dataset.

2.2. Model
This study applies a model that has been utilized in our previous study (Chen et al 2018). Briefly, to model the nonlinear relationship between residential electricity consumption and ambient temperature, a segmented linear regression model is used (Muggeo 2015). In this model, a stationary point is calculated through iteration to achieve an overall highest coefficient of determination (\(r^2\)). Two variables can be retrieved from such segmented linear regression: (1) the SPT, which is the temperature corresponding to the ‘stationary point’ captured by the regression model, and physically represents the threshold ambient temperature beyond which a household starts to use an air conditioner; (2) E-T sensitivity, the slope of the linear segment to the right of SPT, which represents the change in electricity consumption of a household corresponding to a unit increase in ambient temperature, i.e., one degree Celsius. The segmented linear regression was chosen in this study because space cooling is mainly supported by electricity while the majority of households in California utilize natural gas as a heating energy source (US Energy Information Administration 2009). Hence, there is not a significant rise in electricity use as temperature drops below the SPT. Applicability and limitations of the segmented linear regression model are discussed in our previous study (Chen et al 2019).

In this study, we chose daily accumulated electricity consumption (in kWh) and daily average temperature at the household level as the indicators of electricity consumption and weather to be regressed against each other (i.e. for computing E–T sensitivity). This is motivated by the findings of our previous study (Chen et al 2018), which indicates that for the same household or region, regression between daily accumulated electricity consumption and daily average temperature shows the highest coefficient of determination (\(r^2\)) values compared to other indicators (e.g. hourly electricity consumption, daily maximum/minimum temperature). Note that in this study we also use other weather indicators (e.g. daily maximum temperature, diurnal temperature range) in multivariable regression analysis while investigating relationships between E–T sensitivity and baseline climate.
2.3. Spatial and socioeconomic analysis

To answer research question 2, we developed maps to visualize the spatial distribution of E-T sensitivities and SPTs in Southern California (see figures 1(a), (b)). For the purposes of protecting the privacy of data at the household level, we calculated the mean value of sensitivities and SPTs at the census tract level to create the resulting choropleth maps. We acquired census tract boundary shapefiles from the US Census Bureau (US Census Bureau 2016). For characterizing climate zones in the investigated region, we used boundaries established by California Energy Commission (CEC) (California Energy Commission 2015).

Socioeconomic data were retrieved from CalEnviroScreen 3.0, which is a mapping tool provided by the Office of Environmental Health Hazard Assessment (OEHHA) within California’s Environmental Protection Agency (CalEPA) to help identify vulnerable communities most at risk of being exposed to pollution (OEHHA CalEPA 2018). These data were resolved at the census tract level. CalEnviroScreen reports multiple socioeconomic metrics. We used the poverty percentile index, defined as the percentile rank of each census tract in California according to the percent of population living below two times the federal poverty level within each tract, to represent affluence level. Thus, each household is assigned a poverty percentile index corresponding to its census tract, regardless of its individual household-level income.

2.4. Identifying households with AC

We utilized a method developed and detailed in our previous study (Chen et al 2019) to identify whether a household has AC using household electricity and ambient temperature data. Air conditioner penetration rates at the census tract level were computed as the ratio of homes with AC to total homes in our dataset. We determined whether a home has AC by comparing the slopes to the left and right of the SPT. For simplicity, hereafter we refer slope_left as the slope of the linear segment to the left of the SPT, and slope_right as the slope to the right of the stationary point. We treat households with (1) \( \text{slope_right} > 0 \) and (2) \( \text{slope_left} + \text{slope_right} > 0 \) as households that have air conditioners. In California, space heating is mainly supported by natural gas (Lutzenhiser et al 2016). Hence, slope_left is typically near-zero and has an absolute value much less than slope_right. Using this method, we calculated the overall AC penetration rate of Southern California as 69%, which matches well with previously reported survey-based data in the same or similar geographical area (60%–75%) (Palmgren et al 2010, Borgeson 2013, US Energy Information Administration 2015b, Lutzenhiser et al 2016).

2.5. Projections of future climate change

Historical observations and projections of the number of extreme heat days per year in Southern California were derived from data provided by Cal-Adapt, a
Historical observations were from a gridded dataset at NOAA Cooperative Observer daily temperature observations from about 20,000 stations. In this study, we calculated the mean value of the annual number of extreme heat days from 1961 through 1990 to represent the historical average of observed events for each census tract analyzed. Projections of future extreme heat days were calculated based on data statistically downscaled using the LOCA technique. Four climate models under the RCP8.5 scenario from 2017 to 2099 were used to project extreme heat events at the end of century. We choose RCP8.5 because it is the RCP scenario with the largest temperature increase to bound the analysis.

3. Results and discussion

3.1. Spatial trends in the electricity use response to increases in ambient temperature

Figure 1(a) illustrates spatial variability in E–T sensitivities across Southern California. The mean and median value of E–T sensitivity is 0.068 and 0.054 kW °C⁻¹, respectively. Details about E–T sensitivities and SPTs can be found in section S1 in supplementary information. In general, E–T sensitivities are larger for census tracts within climate zones with higher summer mean temperatures. Similarly, the electricity consumption of homes in coastal census tracts is less sensitive to ambient temperature change relative to those in inland areas. The mean SPT for all households in this study is 18.8 °C ± 3.7 °C (65.8 ± 6.7 °F), which is similar to the widely used base temperature 18 °C (65 °F) for calculating Cooling/Heating Degree Days. The majority of households have SPTs around 18 °C (65 °F). There are some areas, mainly located in Climate Zone 16, showing abnormally low SPT values. We discuss these results in further detail in sections S1 and S3 in supplementary information. Climate characteristics across Southern California are captured by California Building Climate Zones (hereafter referred to as Climate Zones) established by the California Energy Commission (California Energy Commission 2015). Homes contained within Climate Zone 6 (i.e. the only coastal zone) have a mean E–T sensitivity of 0.04 kW °C⁻¹, which falls below the average sensitivities observed for inland climate zones (0.06 to 0.11 kW °C⁻¹). This coastal climate zone also has the lowest summer mean temperature (20 °C), resulting in a low demand for cooling compared to other places in the investigated region. Accordingly, the average AC penetration rate computed for the coastal census tracts within Climate Zone 6 is 46%, which is lower than other climate zones (59%–80%) (see figure 1(c)).

Within inland regions, hotter climate zones (i.e. with higher summer mean temperature) generally have larger mean E–T sensitivities, compared to other regions. Quantitatively, Climate Zones 8, 9, 10, 14, and 15 have summer mean temperatures of 22 °C, 23 °C, 25 °C, 28 °C, and 32 °C, and mean E–T sensitivities of 0.06, 0.08, 0.07, 0.08, and 0.11 kW °C⁻¹, respectively. This trend can be partially explained by higher AC penetration rates in hotter areas since the aforementioned average E–T sensitivities include all households (i.e. those with and without AC). For example, Climate Zone 8 has a mean AC penetration rate of 64%, while low-desert-like Climate Zone 15 has a mean AC penetration rate of 80%. We hypothesize that another contributing factor is that inland regions generally contain larger homes, compared to areas closer to coast, which would require more energy for cooling.

3.2. Impact of affluence on the electricity use response to increases in ambient temperature

With the exception of Climate Zone 16 (i.e. mountainous areas), households in more affluent census tracts generally have higher E–T sensitivities than those in less affluent census tracts (see figures 1(a) and (d)), indicating that electricity usage for more affluent households is typically more sensitive to ambient temperature changes. This trend is confirmed in figure 2, which presents box-and-whisker plots of household-level E–T sensitivity, for all households identified as having AC, differentiated by census tract poverty percentile and Climate Zone. AC penetration rates also reflect this trend, as illustrated in figure 3, which shows that more affluent census tracts have higher AC penetration rates in almost all climate zones, except for the coastal and mountainous climate zones, i.e. Climate Zone 6 and 16, respectively. (Coastal regions had the lowest overall AC penetration rates in the investigated region, due to the relatively mild climate. More discussion regarding the mountainous regions contained within Climate Zone 16, which contains relatively large stocks of seasonal vacation homes, can be found in section S3 of supplementary information.)

Although figure 2 only includes homes identified with ACs, we still observe a decline in E–T sensitivity as fractions of poverty increase within climate zones, indicating that affluence level affects E–T sensitivities, even across homes with space cooling. Thus, affluent populations tend to use AC more intensely, on average, presumably due to: (1) more luxurious lifestyle; and/or (2) larger house sizes. For example, the affluent...
census populations of Malibu, Rancho Palos Verdes, and Laguna Beach, are comprised of larger homes and their energy use is more sensitive to changes in temperature compared to other communities along the coast. (Note: since census tracts are defined to represent similar population (from 1200 to 8000, with an average of 4000), larger land areas indicate less population density and larger homes. However, no data about lifestyle and home sizes were utilized in this study and should be considered in future research.)

3.3. Response of electricity use to increases in ambient temperature in Southern California: combined effects of climate and affluence levels

In this section, we investigate the combined effects of climate and affluence levels on E–T sensitivities and

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**Figure 2.** Box-and-whisker plots of household level electricity-temperature sensitivities for households identified with AC, grouped by climate zone. In each subplot, the distribution of electricity-temperature sensitivities is displayed across 10 bins, each representing a different poverty classification. Integer values inside each box represents the number of households per bin. See methods for details on the calculation of poverty percentile index. Each home plotted in the figure is assigned the poverty percentile index for its respective census tract as reported by CalEnviroScreen3.0.

**Figure 3.** Bar chart of air conditioning penetration rate versus poverty percentile index, grouped by climate zone, in Southern California. AC penetration rate is computed as the number of households identified as having AC divided by the total number of households in our dataset. The total number of households and summer mean temperature per climate zone are shown above each group of bars.
AC penetration. Hotter regions tend to have larger E–T sensitivities than cooler regions, on average, while richer communities tend to have larger E–T sensitivities than poorer populations within similar climate zones. The differences in E–T sensitivities and AC penetration rates between the most affluent and least affluent communities are generally smaller in hotter climate zones. For example, in the hottest Climate Zone 15, differences observed among socioeconomic groups are smaller than other climate zones. Since cooling demand is higher in hotter climate zones, there appears to be a threshold above which AC is used similarly across populations for comfort.

We conducted single and multiple variable linear regressions at the census tract level among a variety of variables to assess the relative importance of climate and socioeconomic factors on E–T sensitivities and AC penetration rates. Explanatory variables associated with larger coefficients of determination ($r^2$) perform better in explaining variance in response variables. The values of slopes cannot be directly compared to assess the relative importance across variables because they have different units, so we compare the sign of the slopes to indicate the direction of correlation between the response and explanatory variables. Statistics are presented in table S1 in supplementary information.

Daily mean temperature, daily minimum temperature, daily maximum temperature, and diurnal temperature range (i.e. the difference between daily maximum and minimum temperature) averaged over summertime (July, August, September) were selected to represent the climate characteristics of each census tract in the regression analysis. Among all climatic variables, the diurnal temperature range best explained the variations in single variable regression in both census tract mean E–T sensitivity ($r^2 = 0.18$) and AC penetration rate ($r^2 = 0.42$), both with positive slopes. In other words, census tracts located in places with large diurnal temperature ranges tend to have higher AC penetration rates and E–T sensitivities. In Southern California, inland regions typically had larger diurnal temperature ranges and daily mean temperatures compared to coastal areas. The positive slopes of E–T sensitivity versus diurnal temperature range and daily mean temperature are consistent with observations presented in figures 1(a) and 2, illustrating that electricity use for homes in hotter (inland) climate zones tends to be more sensitive to temperature than cooler (coastal) climate zones.

Single variable regressions reveal that, compared to climate variables, affluence level was stronger (weaker) in explaining E–T sensitivities (AC penetration rates). Affluence level alone can explain 12% of variations in E–T sensitivities while it can only explain 6% of that in AC penetration rates. Climate variables, particularly diurnal temperature range, can explain 18% of variations in E–T sensitivities but 42% of that in AC penetration rates. Multivariable regressions show that variability in summertime daily maximum temperature, affluence level, and summertime diurnal temperature range together explain 60% of the variability in AC penetration rates but only 38% of that in E–T sensitivities. When summertime average diurnal temperature range and affluence level are used in multivariable regressions, 58% of the variability in AC penetration rates can be explained, compared to 42% when only summertime diurnal temperature is used and 6% when only affluence level is used. This result indicates that a community’s AC penetration rate is associated with both its climate characteristics and affluence level. Other factors likely affect variability in E–T sensitivities such as occupant behavior, home size, and building characteristics, but these factors were not considered in this study due to data limitations. Future research should focus on these variables.

3.4. Locating the most temperature-sensitive hotspots and most heat-vulnerable communities

Although the entire region is likely to experience the impacts of increasing extreme heat events, there are two categories of hotspots that will be particularly important to watch for future grid planning. The first category includes census tracts across the studied region that currently have relatively low AC penetration rates, and thus their overall electricity consumption is not currently very sensitive to changes in temperature. Many places in this category are located in coastal (Climate Zone 6) and mountainous areas (Climate Zone 16). The majority of census tracts in these two climate zones are not in extreme poverty, so as temperatures warm, populations are likely to install AC units and/or intensify their usage (see figure 1(d)). Given projections of anticipated future warming, these might be the regions that experience the largest magnitude of change in residential cooling energy use due to the need for more cooling. Thus, from a grid management perspective, these are the regions that are critical to identify in order to ensure adequate energy services in the future. The second category includes census tracts with populations that currently have high E–T sensitivity values because their electricity consumption could increase more than others given the same temperature rise. (These census tracts are shown in figure 1(a) as census tracts with the highest E–T sensitivities, >0.25 kW °C$^{-1}$.) Some of these census tracts are located in low desert, generally within rich communities (e.g. Palm Springs, Temecula), while others are simply very affluent communities with large houses (e.g. Beverly Hills). The high E–T sensitivities in these places are driven by hot climate, large housing square footages, and/or lifestyle factors (e.g. lack of energy saving behaviors), all of which require more cooling loads. It is important to note that these are regions that currently have high AC loads, so while these loads might intensify, larger growth in cooling-related energy usage might occur in areas with lower AC penetration rates today. However, these highly
E–T sensitive places can potentially serve as reference hotspots for future grid planning as well as targets for heat mitigation plans.

3.5. Identifying communities that may be most vulnerable to ambient temperature increases

Using the aforementioned insights, census tract-level AC penetration estimates along with socioeconomic data were used to identify communities that might be most vulnerable to future warming and increases in extreme heat events. Vulnerable census tracts were defined as those that currently have both low AC penetration rates and high poverty rates (i.e. are more sensitive to future energy cost increases); more specifically, vulnerable census tracts were defined as those falling into the top 10% of the studied region when the (1) percentage of population living in poverty and (2) percentage of households not having AC were summed for each respective census tract and ranked across all tracts in the region. A full list of identified top 10% most vulnerable census tracts can be found in section S7 in supplementary information. Some of the census tracts identified as potentially vulnerable using these criteria are already experiencing large numbers of extreme heat days (e.g. > 16 d per year), as illustrated in figure 4(a).

However, by the end of the century, 100% of the census tracts identified as most vulnerable to future extreme heat events are expected to have more than four extreme heat days per year based on the latest climate change projections for California (Thomas et al 2018). Moreover, 80%, 55%, and 30% of these potentially vulnerable communities are expected to experience over 8, 16, and 32 extreme heat days per year, respectively. These extreme events can pose dire health-related impacts on those populations that cannot afford access to sufficient cooling in the future. Accordingly, this map can serve as a reference point to develop targeted climate change adaptation and energy management policies to help vulnerable populations prepare for a future with more extreme heat events.

3.6. Further considerations

It should be noted that the results in this study are based on present day data and climate change projections for the year 2100 based on the RCP 8.5 scenario. There are several factors other than climate that may change in the future, adding additional complexity to how electricity consumption patterns and vulnerability to extreme heat may evolve in the future. For example, buildings are expected to be more energy efficient as a result of more stringent building energy codes (Reyna and Chester 2017), which will change residents’ electricity-temperature relationships. The increasing utilization of onsite generation (e.g. solar photovoltaic panels) and storage technologies might also markedly affect net energy consumption profiles. While this study investigates factors influencing electricity consumption patterns in the context of future climate change, another important consideration is whether or not existing infrastructure can meet projected increases in electricity demand in general. Similar to other regions, Southern California is expected to experience increases in cooling capacities as well as AC penetration (Fraser et al 2017). However, if targeted policies are not put in place properly, such increases in AC penetration could add additional financial burden to vulnerable populations. Furthermore, increasing AC penetration does not relieve constraints associated with operating AC units.

More research needs to be done to quantify these uncertainties. Though assessing heat exposure based on home address is usually used for practical reasons, negative health effects can involve many more factors (e.g. the time people spend commuting within the region, the time people spend in an air-conditioned environment, and more) (Hoehne et al 2018). These broader activities should be considered in future studies on the topic of heat-related vulnerability assessment.

4. Conclusion and future work

In this research we find large spatial variability in sensitivity of electricity to ambient temperature for...
residential homes across Southern California. Variabilities in these E–T sensitivities are associated with spatial patterns of climate characteristics, as well as socio-economic distributions. Specifically, homes in coastal (cooler) climate zones show electricity consumption that is generally less sensitive to ambient temperature change relative to inland (hotter) communities. Coastal communities also have lower AC penetration rates (i.e. the fraction of homes with AC) relative to inland communities. In addition, more affluent communities generally have E–T sensitivities that are higher than their less affluent counterparts and have higher AC penetration rates in most climate zones. We find that, compared to climate, affluence level was stronger in explaining spatial variability in E–T sensitivities but weaker in explaining AC penetration rates. We identified communities that are likely to be most vulnerable to increases in extreme heat events as those that have the lowest levels of both AC penetration and affluence. 55% and 30% of the census tracts identified as most vulnerable are expected to have more than 16 and 32 extreme heat days per year by the end of the century, respectively. Future work should focus on assessing the impact of housing stock characteristics (e.g. square footage, year of built, insulation levels), as well as behavior related factors, on the relationships between residential electricity consumption and climate.

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