Title

The health benefits of reducing micro-heat islands: A 22-year analysis of the impact of urban temperature reduction on heat-related illnesses in California's major cities

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Introduction. By 2050 nearly 70% of the world's population will live in urban areas, suggesting a future surge in the density and sprawl of cities[1,2]. In tandem with an urban expansion, there will be more frequent and severe heat events as a result of anthropogenically accelerated climate change, thus putting individuals at added risk of experiencing heat-related health issues[3,4]. Cities encounter a phenomenon known as urban heat islands (UHI) which occur when natural landscapes are replaced with pavement and buildings that absorb and retain solar radiation, consequently heating up these surfaces[5]. UHIs and within-city variations referred to as micro-heat islands can exacerbate the severity of heatwaves and place individuals within socioeconomically vulnerable urban communities at greater risk of developing heat-related illnesses (HRI) such as hyperthermia, heat exhaustion, and dehydration[6].

In the United States, the incidence rate of HRIs increases by an average of 6% each year, with most cases being seen during summer months when climate-change induced extreme heat events (EHEs) generally occur[7]. For example, in 2006 and 2017, California was struck by a series of exceptionally severe EHE events that lead to substantial increases in HRIs[8,9]. In 2006, most of California experienced numerous record breaking daily maximum temperatures and a similar series of record breaking temperatures occurred in 2017[9]. EHEs can be amplified by an absence of structural adaptations such as green or blue spaces, which cities rely on to reduce ambient temperatures[7,10,11]. Urban infrastructural climate adaptive strategies can play a significant role in reducing the temperature of an urban environment on a fine spatial scale[12]. When looking at microclimate indicators such as land surface temperature within cities, there is evidence that differences in these microclimate indicators influence the risk of morbidity/mortality during heat waves[13,14].

The geography of California is diverse and heterogeneous trends in temperature have been previously recorded between different regions of California[15]. However, to our knowledge, these differences in temperature responses to climate change have been observed at the regional, city, or county resolution but not yet at a ZCTA level within cities in California[9]. In this study, we narrowed the focus to seven of California's most populous cities to infer how different urban landscapes affect temperature changes over a 22-year period. The seven Californian cities assessed in this study were Sacramento, San Francisco, Oakland, San Jose, Fresno, Los Angeles, and San Diego and are in seven different counties across several regions (Figure 1). By measuring trends in temperature by comparing ZCTAs within all seven cities over the past 22 years, we identified significant changes in urban landscape temperatures in the same city.

Generally, surface temperatures are higher in urban settings than in nearby rural settings and a similar trend can occur when looking at different areas within an intracity scale; therefore individuals living in certain ZCTAs may be especially vulnerable to experiencing HRIs during extreme heat events[16]. In this study, we define UHIs as ZCTAs within cities that have either unchanged or increased land surface temperature (LST) from 2000 to 2022. LST is the radiative skin temperature of the land surface recorded by NASA's MODIS Terra Land Surface Temperature and Emissivity Daily Global 1km imagery at night and can be used as a proxy to infer changes in local UHI distribution over time[17]. We created a 22-year time-series analysis and categorized LST trends at the ZCTA level in California as decreased, unchanged, or increased over our study period[18]. We categorize trends over time based on the assumption that temperatures will be increasing across the study area as the result of climate change, however in some ZCTAs the temperature will be increasing at a significantly slower rate or possibly decreasing and therefore were described as "decreased". If the ZCTA's temperature appears to

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be increasing at a significantly higher rate than the other ZCTAs, we defined those as "increased". Once these categorizations were made, we then analyzed the difference in monthly HRIs from two major EHE years in California (2006 and 2017) to quantify the potential difference in HRIs due to UHI changes between comparable ZCTAs.

Our first objective in this study was to identify monthly ZCTA temperature trends between 2000 and 2022 within seven major cities in California and categorize them as decreased, unchanged, or increased. The second objective was to determine if there was a decrease in HRIs in 2017 when compared to 2006 for ZCTAs that we classified as decreased versus unchanged using propensity scoring and inverse probability weighting. We hypothesize that ZCTAs with decreased temperature trends would be associated with decreased rates of HRIs between 2006 and 2017 when compared with their unchanged or increased counterparts, which are areas considered to be UHIs in this study.

Methods.

Study areas. We focused on seven of the eight most populous cities in California. We omitted Long Beach, the seventh most populous city, because of its proximity and geographic similarities to Los Angeles. The seven cities we studied were Sacramento, Oakland, San Francisco, San Jose, Fresno, Los Angeles, and San Diego which, in this analysis, had 29, 14, 28, 28, 18, 64, and 35 ZCTAs of interest per city, respectively (Table 1). We chose to include three San Francisco Bay Area cities because of the geographic and temperature heterogeneities between Oakland, San Francisco, and San Jose[19]. All seven cities had a population sum of 7,507,023 individuals, with Los Angeles, San Diego, and San Jose being the top three most populous cities, in that order.

Data acquisition. We utilized Google Earth Engine (earthengine.google.com) to download MODIS Terra Land Surface Temperature and Emissivity Daily Global 1km (MOD11A1 V6.1) imagery with temperature value derived from MOD11_L2 swath product for the entirety of California. We extracted monthly land surface temperature values for each ZCTA population-weighted centroid, which is a single point coordinate versus an area that makes up the ZCTA boundary, within the state from March of 2000 to the end of October of 2022. Because the effects of UHI are most noticeable at night, we focused on the nighttime LST imagery from MODIS[20].

For ZCTA level data, we relied on TIGER US Census 5-digit Zip Code Tabulation Areas 2010 data from the US Census Bureau (census.gov). The centroid coordinates found in this dataset allowed us to weight our mean LST to the most populated areas within each zip code, which is a common interpolation technique[21]. Demographic data was collected from the American Community Survey's 2017 5-year estimates and were used to develop propensity scores in our model.

To illustrate the potential impacts of different trajectories of UHI on hospital admissions, we conducted a case study in which we focused on the difference between two major summertime extreme heat events taking place in 2006 and 2017. We obtained HRI data through the California Health and Human Services Agency. The data contains ZCTA level mortality and morbidity emergency department (ED) and patient discharge data (PDD) for all of California. In Supplemental Table 1, we included the complete list of heat-related illnesses ICD codes considered to characterize heat-related illnesses (HRI) for our study. To ensure we had enough cases within each ZCTA to maintain sufficient statistical power, we compared ZCTA-level monthly HRI count for both years 2006 and 2017 during the EHE of interest.

Identifying urban heat islands (UHIs). To classify ZCTAs as urban versus rural we relied on the CalEPA Urban Heat Island Interactive Maps urban and rural ZCTA classifications[22]. Using the "urban" and "rural" classifications, we completed sensitivity analyses to determine the most statistically meaningful approach to identify urban heat islands which can be found in our GitHub repository (https://github.com/emlasky/TemperatureTrendsAcrossCA.git). We determined that, because this study focuses solely on ZCTAs that fall within urban areas, ZCTAs that were considered "rural" by CalEPA were filtered out of the dataset and excluded from this study. Using only "urban" classified ZCTAs, we calculated temperatures within the 95th percentile of monthly temperatures within a given year, which primarily occurred during the summer months between June and September and created indices of monthly mean land surface temperature estimates for each ZCTA over the 22-year period to identify micro heat islands in the seven cities (Figure 2). We then compared each ZCTA to the ZCTA with the lowest LST at the start of the study (LST_{min}¿in the same city's boundaries (ex: comparing all target ZCTAs in Los Angeles to the ZCTA with the lowest LST in Los Angeles). Instead of defining an absolute temperature change threshold for all ZCTAs regardless of city, we defined relative thresholds of temperature change between ZCTAs in the same city which resulted in differences of amplitude of temperature change as dependent on the city. We used the LST_{min} to find the difference in temperature per ZCTA within that city by pairing the target ZCTA with the LST_{min} for the same month and year using the following equation:

$$\Delta T_i = LST_i - (LST_{min})$$

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Linear regression comparison of ZCTAs. We categorized our ZCTAs into decreased, unchanged, or increased LST trends. We performed linear regression analyses to identify which ZCTAs experienced statistically significant positive or negative, or non-significant positive or negative trends and mapped their locations (Figure 3) To create our three categories, we calculated the slope and *p*-values of the change in ZCTA's with LST measurements in the 95th percentile from 2000-2022. We used a threshold of $p = 0.10$ for our main analyses. We mapped our ZCTA categorizations using ArcGIS Pro (Version 2.9.3) to identify the locations of our ZCTAs. All syntax to reproduce our results in California or elsewhere can be found at the following link: https://github.com/emlasky/TemperatureTrendsAcrossCA.git.

Determining difference of HRI between decreased and unchanged ZCTAs. We calculated the difference in HRIs between the 2006 and 2017 EHEs. We aggregated monthly PDD/ED HRI data to the annual level and found the difference by subtracting the sum of HRIs for the year 2017 by the sum of HRIs for 2006 for each individual ZCTA(x) in the study using the following equation:

$$\Delta HRI_{i=x} = \sum HRI\,2017_{i=x} - \sum HRI\,2006_{i=x}$$

Inverse probability of treatment weighting (IPTW) estimation. We identified ZCTA propensity scores using a logistic regression model conditional upon ten covariates: total population, total number of males, percent of population under eighteen, percent of population over 65, percent of population that is white, total housing units, total commuters over sixteen, number of individuals with an income below 10,000, total number of individuals with a college degree, and population without health insurance. We chose these ten covariates based on prior

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literature, which intends to control for a holistic range of sociodemographic variables that may directly influence the likelihood of living in a ZCTA with certain temperature trends[23]. Quantifying the conditional probability of a ZCTA falling into the decreased temperature trend based on specific covariates allows for us to create a pseudo-randomized study using observational data by balancing ZCTAs independently of the outcome thus limiting confounding from variables we are uninterested in observing[24,25]. Additionally, we incorporated each city as the random effect in our model to preserve the number of observations while accounting for unobserved heterogeneity among the ZCTAs in the study.

Based on the estimated propensity scores, we used the inverse probability of treatment weighting (IPTW) to balance the ZCTA characteristics (i.e. confounders) between decreased and unchanged ZCTAs[26]. We then performed logistic regression analyses using ZCTA temperature trend status as the predictor, the difference in HRI between the two EHE years as the dependent variable and weighted the model with the IPTW values that we calculated using the propensity scores (Figure 2).

All analyses were conducted with RStudio (Version 2021.09.2) using *dplyr* and *tidyverse*.

Results. When observing 216 ZCTAs throughout California during months that fell within the 95th percentile for LST, 43 ZCTAs decreased, 161 were unchanged, and 12 got worse over the 22-year study period (Table 1). Most ZCTAs in each city remain unchanged over 22 years (161 out of 216 or ~75% of the total number of ZCTAs). We potentially observed spatial clustering of decreased and increased ZCTAs in Oakland, Los Angeles, and San Jose, however an investigation of this clustering goes beyond the scope of this paper (Figure 3) Los Angeles had the greatest number of decreased ZCTAs (26), the largest proportion of ZCTAs (32.7%), and the greatest population observed in the study (2,456,601) (Table 1). San Diego and Sacramento had only one decreased ZCTA each. San Diego and San Jose, the second and third most populated cities in the study, had four increased ZCTAs each, which was the most of all seven cities (Figure 4). Los Angeles had the greatest proportion of individuals living in decreased ZCTAs while San Diego and San Jose had the greatest proportion of individuals living in increased ZCTAs (Figure 4)

In Supplemental Table 2 and Figure 1, we show the descriptive statistics for the ten covariates we controlled for and the estimated propensity scores and IPTW. Of the 216 observed ZCTAs, 150 had HRI data for both 2006 and 2017. The largest difference and increase in HRI between these two EHE years was a ZCTA in Los Angeles that saw an increase of 41 HRIs over the study period. The greatest reduction in HRI was a ZCTA in Sacramento that had twelve fewer HRIs over the study period. The mean ΔHRI for all 150 ZCTAs was 4.5. The mean ΔHRI for decreased and unchanged ZCTAs was 3.5 and 4.9, respectively (Table 2). When comparing the ΔHRI between decreased and unchanged ZCTAs during the 2006 and 2017 EHEs, it was found that ZCTAs classified as decreased observed a reduction of 3.2 HRIs (Table 3).

Discussion. In this study, we proposed an approach to categorize the micro-heat islands temporal trends of neighborhoods within the most populated California as decreased, unchanged, or increased. We found that some cities had greater proportions of decreased ZCTAs than others which had no significant improvement or significantly worsening temperatures over the study period (Figure 3). Based on preexisting knowledge of cooling methods in urban settings, it may be inferred that ZCTAs that have decreased temperature trends over time have undergone heat adaptation strategies such as greening, increasing shade, and other heat reducing infrastructure choices. The opposite may be said for ZCTAs that have experienced no improvement or increased in temperature over time. As an example of the potential correlation between increased greening and reduced temperatures, an increased change in NDVI in Los Angeles between the years of 2000 and 2020 was observed for the downtown portion of the city[27]. In our analysis, the downtown portion of the city was observed to have decreased temperature trends (Figure 3). Though this provides some evidence of the influence increasing greenness may have on temperature trends, investigating the correlation between NDVI and decreased temperature trends is beyond the scope of this study, and we recommend further research be conducted to investigate if there is indeed a correlation between heat adaptation strategies and our findings. Additionally, we have included newspaper articles and planning presentations for some of the cities researched in this study in our GitHub.

We then analyzed to which extent such being categorized as decreased, unchanged, or increased was associated with a differential change in heat-related illnesses between two major extreme heat events across the last two decades. We showed that ZCTAs categorized as decreased experienced 3.2 fewer heat-related illnesses over the summertime study period than unchanged ZCTAs in 2017 when comparing the number of HRIs during the 2006 and 2017 heat wave years (Table 3). The average number of summertime HRIs by ZCTA in 2006 was 4.3 and 8.8 in 2017, therefore a decrease of 3.2 HRIs is not a trivial reduction (Error: Reference source not foundTable 2). This study illustrates that ZCTAs with lower summertime temperatures reduce the number of HRIs, especially during extreme heat events.

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The first limitation of this study was the spatial resolution at which the temperature data (LST) is available. The MODIS satellite records data at a spatial resolution of 1km that may not be precise enough to identify temperature differences in smaller ZCTAs that are adjacent to one another, and this may be why we perceived clustering in Los Angeles (Figure 3). Other alternative remote sensing products may provide more spatially granular data, however these satellites do not provide data at the temporal granularity that was essential to this study. Though not a limitation, we chose to identify UHIs by finding the difference of the ZCTA with the minimum monthly LST to all other ZCTA monthly LSTs in the same city over the study period, which we considered to be an effective way of identifying UHIs for the purposes of this study. There are different methods to identify UHIs that are equally valid, and our results may have differed to an extent had we used a different UHI categorization method[28]. Finally, we only focused on HRI as the primary cause of hospital admission of interest to ensure that these events were directly related to heat exposure and to highlight the potential variation in heat burden that can be attributable to changes in microclimate environments within a city over time. This approach is an underestimation of the total burden attributable of heat exposures but restricting our health data to only HRI codes limited ambiguity about how to directly attribute an individual's illness[29].

Temperatures are generally increasing in California and prior studies looking at long-term meteorological station data have shown regional differences in the rate at which temperatures are increasing, which may be attributed to geographic phenomena such as coastal cooling, fog, and wind-related effects[30]. These studies have indicated differences in the magnitude of change of temperature across different regions of California, therefore the effect of urban climate adaptation strategies will be dependent on the region each city is situated in and

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even the distinct microclimates within each city[15,31]. We attempted to limit the effect geographic variation may have on temperature shifts by finding the slope of temperature trends by ZCTA using the LST_{min} from the ZCTA's respective city, however we recommend investigating these geographic differences and their effect on temperature trends further.

This study demonstrates the importance of analyzing UHIs within major cities. We found differing proportions of decreased, unchanged, increased UHIs in each city that may have resulted from some cities undergoing climate adaptive strategies to a greater extent than others[32–35]. The implications of this study would indicate that significantly reducing temperature in ZCTAs decreases the number of HRIs for those ZCTAs, thus suggesting the protective effect climate adaptive strategies may have on human health during EHEs. Though California has a reputation for being an ambitious environmental leader and has committed to climate related policies, these commitments are not mandated on finer geographic scales and adoption and implementation of climate adaptation plans at the city-level varies across the state. Poorly designed policies and variance in urgency to invest in climate adaptation strategies may be based on the political culture of the city and proximity to other cities that are adopting these strategies[33,34]. Further, regional differences and sensitivity to the impacts of climate change may play a significant role in determining the urgency of adopting climate adaptive policies.

Overall, most of the populations in all seven cities fell within the unchanged temperature trend, indicating a public health need for greater adoption of climate adaptation strategies (Table 1). The 2022 IPCC report on Impacts, Adaptation and Vulnerability (working group II), emphasized the necessity of implementing proactive adaptation strategies, since they can reduce by more than half the health burden attributable to climate sensitive exposure such as extreme heat by the end of the century. Though our investigation looks at change in temperature in cities

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and not necessarily in response to cooling strategies, as cities in the United States and beyond invest heavily in developing their resilience against increasing temperatures, the methodological approach we proposed can be used, adapted, and expanded to guide investments to minimize the health impacts of extreme heat.

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GitHub Link: Temperature Trends Across CA
https://github.com/emlasky/TemperatureTrendsAcrossCA

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