Article

Population-Based Disparities in U.S. Urban Heat Exposure from 2003 – 2018

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Abstract: Previous studies have shown, in the United States (U.S.), that non-White communities are exposed to significantly higher temperatures in urban environments than complementary White populations. Studies highlighting this disparity have usually been cross-sectional and are therefore "snapshots" in time. Using surface urban heat island (SUHI) intensity data, U.S. Census 2020 population counts, and a measure of residential segregation, this study performs a comparative analysis between census tracts identified as prevalent for White, Black, Hispanic and Asian populations and their thermal exposure from 2003 – 2018. The analysis concentrates on the top 200 most populous U.S. cities. SUHI intensity is shown to be increasing through time for all examined tracts. However, the increase is only statistically significant for White and Black prevalent zones. There is a 1.25K to ~2.00K higher degree of thermal exposure on average for non-White relative to White prevalent areas. When examined on an inter-city basis, White and Black prevalent tracts had the largest disparity, as measured by SUHI intensity, in New Orleans, LA, USA by < 6.00K. Hispanic (>7.00K) and Asian (<6.75K) prevalent tracts were greatest in intensity in San Jose, CA, USA. To further explore temporal patterns, two models were developed using a Bayesian hierarchical spatial temporal framework. One models the effect of varying the percentages of each population group relative to SUHI intensity within all examined tracts. Increases in percentages of Black, Hispanic, and Asian populations contributed to statistically significant increases in SUHI intensity. White increases in population percentage lowered SUHI temperature intensity. Throughout all modeled tracts, there is a statistically significant 0.01K per year average increase in SUHI intensity. A second model tests the effect of residential segregation on thermal inequity across all examined cities. Residential segregation, indeed, has a statistically significant positive association with SUHI intensity from this portion of the analysis. Similarly, there is a statistically significant 0.01K increase in average SUHI intensity per year for all cities. Results from this study can be used to guide and prioritize intervention strategies and furthers urgency related to social, climatic, and environmental justice concerns.

Keywords: surface urban heat island; racial disparity; thermal exposure; environmental justice; social justice; climate justice; Bayesian spatial temporal modelling

Introduction

Significant disparities in community-level heat exposure have been identified in many urban locations in the United States (1–5). Due to variations in the surface urban heat island (SUHI) effect, minority (non-White) communities are exposed to significantly higher SUHI temperatures than predominantly White communities within the same city. However, we lack a clear understanding of the temporal and spatial trends in heat exposure within these communities and cities. For example, are SUHI temperatures in predominantly Black communities increasing or decreasing through time? A strong contributor to these disparities are the effects of residential segregation and its influence on disparate thermal exposure. These effects needs further quantification; especially longitudinally.

This study examines the spatial-temporal aspects of urban heat exposure within the top 200 most populous cities in the US. The analysis is performed at the census tract –

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level across all cities and for each city as a whole. Utilizing measurements of the SUHI from 2003 to 2018 and applying a Bayesian hierarchical spatial temporal modelling approach, enables the examination of SUHI measurements relative to US Decadal Census data quantifying the racial composition of census tracts and the level of segregation in the respective city. Tracts are stratified into prevalence of the population-based groups of White, Black, Hispanic, and Asian. This methodology allows for the determination of the temporal trends in heat exposure in affected areas based on racial prevalence. Moreover, it will foster a more complete understanding of the disparity in thermal exposure through time and hopefully, catalyze efforts to improve local environments in affected areas and promote social, climatic and environmental justice. This study should add further weight and urgency to similarly inclined environmental justice pursuits especially related to heat health risk and the inequitable distribution of environmental health hazards.

Disparities in Urban Heat Exposure in the U.S.

Numerous studies have shown there is a significant disparity in heat exposure within U.S. cities between White and non-White communities (1–5). Harlan et al, observed in 2007 that affluent predominantly White communities were more likely to live in vegetated and less climatically stressed neighborhoods than those in poor Latino communities within Phoenix, AZ, U.S. (1). In a study focusing on Richmond VA, U.S., Saverino et al, found census block level areas occupied by people of lower SES and/or non-White minorities disproportionately experienced higher temperatures and higher impacts on health (5). Mitchell and Chakraborty observed that census tracts with higher percentages of non-White minorities and higher percentages of those in poverty had significantly higher temperatures than predominantly White census tracts in Pinellas County, FL, U.S. (3). In a separate study focusing on the three largest U.S. cites (New York City, Los Angeles, and Chicago) they also found significant bivariate statistical associations between lower SES, non-White minority status and urban heat risk (6).

Expanding on their 2015 study and including 20 of the largest US cities along with a measure of residential segregation, Mitchell and Chakraborty, found variables representative of lower SES to be consistently statistically associated with higher heat exposure. However, non-White minority status and residential dissimilarity (a measure of segregation) has a varied but significant relationship using a multilevel modeling approach (7). In a national-level study using block group-level data across 304 metropolitan areas in the U.S., Jesdale, Morello-Frosh, and Cushing found that non-Hispanic Blacks were 52%, non-Hispanic Asians 32% and Hispanics 21% more likely to live in areas with higher concentrations of "heat risk related land cover" (8). These conditions increased with increasing degrees of residential segregation. This was determined using the 2001 National Land Cover Dataset to identify 'heat risk related land cover" and 2000 US Decadal Census data. Hsu et al. (2021), utilizing the same SUHI dataset used in the present study and 2017 ACS 5-year data, found that on average persons of color live in census tracts with higher SUHI intensity than non-Hispanic Whites in all but 6 of the 175 largest urbanized areas in the continental US (2).

The aforementioned studies are very important and shed light on the significant disparity in urban temperature exposure in the U.S. However, a major limitation is they are cross-sectional and are therefore a "snapshot" in time. As of summer 2022, there are no readily available studies examining these thermal/social relationships through time and quantifying trends in inequitable exposure.

Methods

Data Collection and Descriptive Comparison

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The top 200 most populous cities in the US were selected for this study from the US Decadal 2020 Census (Walker, 2022; U.S. Census Bureau, 2021). The counts for total populations of White, Black, Hispanic, and Asian were retrieved for the respective census tracts of each city. These counts were used to create a percentage of each population group for each census tract.

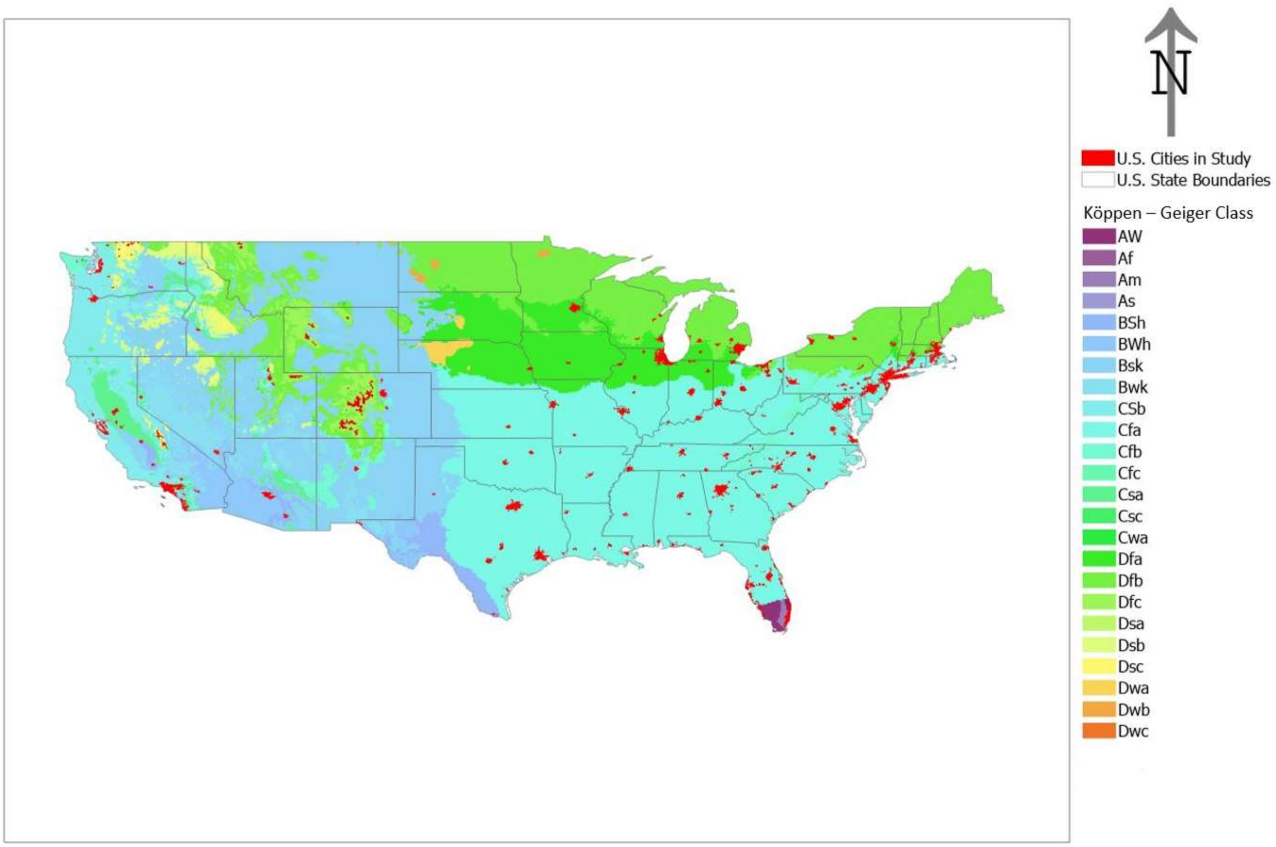

Figure 1 Urban areas in the study (n = 191) and their respective Köppen - Geiger climate classification.

Data for SUHI intensities were collected from the "Yale Center for Earth Observation (YCEO) Surface Urban Heat Islands: Pixel-Level Composites of Yearly Summertime Daytime and Nighttime Intensity" dataset on Google Earth Engine™ (Gorelick et al., 2017; *YCEO Surface Urban Heat Islands*, 2022). These data are pixel level composites of average daytime and nighttime SUHI temperature differential (intensity) within the urban areas. The differential is calculated by comparing the pixels in the urban spaces to those that are in the rural adjacent or background landscape. These data are developed using MODIS 8-day land surface temperature products, the Landscan urban extent, terrain elevation data, and land cover derived from the European Space Agency (13–17). The data utilized in this study cover the summer daytime SUHI intensity temperature for the years 2003 to 2018; data are downscaled to a 300M spatial resolution. Each city was assigned to its respective Köppen - Geiger climate zone to account for climatic variations in modeling. Figure 1 shows the selected urban areas in the study and the respective Köppen - Geiger climate zones.

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The SUHI dataset only contained data for 191 of the 200 selected cities. Of those 191 identified, not all census tracts were congruent with the SUHI boundary for each city; some of the tracts lie outside the boundary and no temperature data were available for them (cf: Figure 2). If a tract contained any portion of the SUHI dataset it was included in the study. Overall, 44,622 census tracts were initially extracted but after accounting for spatial overlay with the SUHI dataset, 44,476 tracts remained. The tracts selected include 48.11% of the total US population; 70.05% of Black; 66.31% of Hispanic; 78.80% of Asian; and 44.03% of White (as of 2020). A zonal mean function calculated the average SUHI intensity temperature of each census tract for each year. Census tracts were then categorized by their percentile ranking of SUHI intensity. This was used to examine the percentages from each group living in the different thermal categorizations. For example, the number of non-White persons living in the 95th percentile of SUHI intensity.

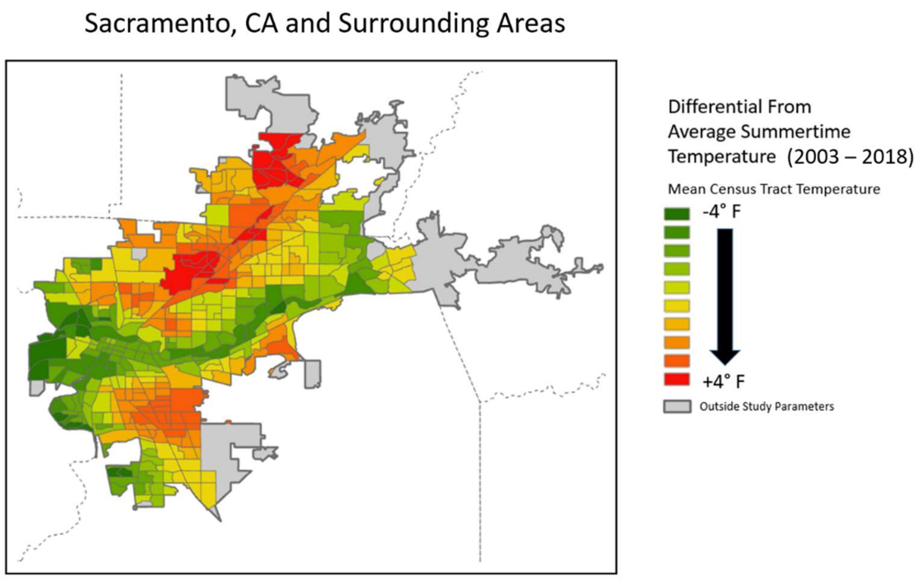

Figure 2. Example city used in the study demonstrating the overlay, or lack thereof, between SUHI intensity dataset (classed) and census designated urban areas.

In order to further compare heat exposure among the different population groups, prevalence was used to categorize census tracts. For example, if there were more Hispanic people in a census tract than any other population group, it was categorized as a "Hispanic Prevalent" tract. There are a total of 27,338 White, 6,597 Black, 7,917 Hispanic, and 2,624 Asian prevalent tracts in the study. Categorization in this way enables descriptive comparisons between population groups, tracts, and cities.

A second dataset was created to perform inter-city analysis. Prevalent tracts were grouped by city. All 191 cities contained White prevalent tracts. This was not the case for non-White populations with only 132 cities containing Black prevalent tracts; 118 Hispanic and 46 Asian. A segregation index using a multi-group version of the Duncan Dissimilarity (*D*) metric was then calculated using the counts of each population group (18,19). This index relates the amount of each group's population that would have to move between tracts for each census tract to have the same percentages of population distribution as the respective city. Values range between zero and one; zero being perfect integration and one being absolute segregation. The index was calculated using the R statistical platform and the OasisR package (20). The SUHI intensity of the city was calculated by averaging the SUHI temperature differential for all respective tracts for each year.

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Modeling

Two models were created using a Bayesian spatial temporal ecological regression methodology. The first utilized daytime SUHI intensity averages for each census tract in the study (44,476 in number), from 2003 – 2018 with the z-scores of the population percentage of each group as fixed effects; these variables were assigned $\beta_{1:4} \sim Normal(\mu, \sigma)$ prior distributions (n = 711,616; 44,476 tracts * 16 years). SUHI intensity was modeled with a Gaussian distribution specification. An improved Besag, York, Mollie (BYM) model (BYM2) was used to account for spatially structured and unstructured random effects with the assignment of a penalized complexity prior (Simpson et al., 2017; Simpson et al., 2015). This scaled specification has been shown to be superior to the often-employed unscaled BYM model and as its name suggests penalizes complexity (Riebler et al., 2016; Simpson et al., 2017). To account for temporal structure the conditional autoregressive random walk of order one (RW1) was utilized. The temporally unstructured effect was assigned an IID specification. The spatial temporal component, a parameter that varies through space and time, allowing for deviations from the space-time structure and expressing patterns between areas temporally, was also specified as IID. The spatial temporal interaction utilized was Knorr-Held Type 1; thereby allowing no restraints on spatial variations locally and globally through time (24). Variations in Köppen - Geiger climate zones and population density were accounted for in the models as fixed effects (IID). Independent variables were standardized to aid in interpretation and due to the presence of interaction terms in the models. Model calculations were performed in the Indiana University High Performance Computing environment using the R statistical platform and the R – INLA package (*Research and High Performance Computing*, 2022; *R-INLA Project*, 2022)

The second model utilized the inter-city dataset. Daytime SUHI intensities averaged across each city were modeled with D (n=3,056; 191 cities * 16 years) as a fixed effect. SUHI intensity was specified as a Gaussian (normal) distribution and D was assigned $\beta_D \sim Normal(\mu, \sigma)$ prior. The random effect specifications for the first model were also utilized here only on an inter-city basis. This model similarly accounted for population density and variations in Köppen - Geiger climate zones between cities.

Limitations and Caveats

Before presenting the results several limitations of the methodology should be considered. The primary limitation is the use of 2020 census data to determine the prevalence of each tract from 2003 – 2018. Potentially, the use of ACS data throughout the timeframe would give a better indication of population prevalence within tracts through time. One would take the ACS releases between 2003 and 2018 and correspond them to the years from the SUHI dataset. However, the number of census tracts or their spatial arrangement for a city can change through time (at each decennial census) and this could potentially add a level of complexity to the models that could affect the comparative ability of the results. This study uses only 2020 data so that trends in the current tracts identified for each representative prevalent population group could be examined. Therefore, these results show SUHI intensity trends in areas that currently (as of 2020) are prevalent with each population group and not necessarily demonstrative of the comprehensive degree of disparate exposure throughout the timeframe. Future spatial temporal studies might look to incorporate five year ACS data (which data availability begins in 2009) – with consideration of these and other inherent limitations - and compare to results from this analysis.

A further limitation is the spatial resolution of the SUHI dataset; the development of which uses MODIS land surface temperature (MOD11A2, MYD11A2). These SUHI intensity data have a downscaled 300M resolution and this level likely results in much of the spatial variation at the census tract – level being lost; especially in urban areas. Landsat or a finer resolution Earth observation sensor is superior to MODIS for intra-city SUHI intensity studies but lacks the temporal resolution and spatial coverage necessary for a

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large-scale spatiotemporal study. Utilizing a finer resolution dataset, one could relatively easily incorporate a series of images for a specific city and examine local disparities through time. Results from the current study could be used to identify such cities.

Results

Census Tract – Level Comparisons

Table 1. Table 1: Descriptive statistics for census tract and city – level variables.

Census Tract-Level Descriptive Statistics

	Percentage White	Percentage Black	Percentage Hispanic	Percentage Asian	SUHI Intensity
Minimum	0.00	0.00	0.00	0.00	-13.63
Maximum	100.00	97.64	100.00	100.00	11.06
Range	100.00	97.64	100.00	100.00	24.68
Mean	51.16	17.87	21.99	8.10	2.05
Standard Deviation	26.69	23.44	23.02	11.60	2.44
Variance	7.12	5.50	5.30	1.35	5.96
	n = 44,476	n = 44,476	n = 44,476	n = 44,476	n = 711,616

City-Level Descriptive Statistics

	Percentage White	Percentage Black	Percentage Hispanic	Percentage Asian	*D*	SUHI Intensity
Minimum	0.00	0.00	0.00	0.00	0.08	-2.61
Maximum	90.53	60.40	81.89	49.27	0.63	7.31
Range	90.53	60.40	81.89	49.27	0.55	9.92
Mean	59.16	15.38	16.56	4.75	0.38	1.50
Standard Deviation	17.02	12.74	13.89	5.86	0.11	1.09
Variance	2.90	1.62	1.93	0.34	0.01	1.19
	n=191	n=191	n=191	n=191	n=191	n = 3,056

Table 1 presents the descriptive statistics of the SUHI intensity for all census tracts and cities in the study from 2003 - 2018. The maximum average temperature differential observed in any tract was 11.06K with a -13.63K minimum. The mean SUHI intensity of all included tracts was 2.05. When averaged and grouped by city, SUHI intensity was 1.50K with a 7.31K maximum and -2.61K minimum. For the population groups included in the study the descriptive statistics for all tracts are also shown in Table 1. The mean percentage of White persons living in all tracts was 51.16%, with 17.87% Black, 21.99% Hispanic, and 8.10% Asian. When grouped by city the means were 59.16%, 15.38%, 16.56% and 4.7% for White, Black, Hispanic and Asian populations respectively. The mean *D* value across all cities was 0.38 with a maximum of 0.63 and a minimum of 0.08.

Table 2. Descriptive statistics of SUHI intensity within group-based prevalent tracts.

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SUHI Intensity Descriptive Statistics for Prevalent Tracts of Each Group

	White	Black	Hispanic	Asian
Mean	1.46	3.08	3.15	2.73
Maximum	11.04	11.06	10.26	10.18
Minimum	-13.63	-7.64	-7.90	-10.06
Standard Deviation	2.29	2.14	2.35	3.12
Variance	5.23	4.58	5.50	9.73
		(K-S ρ = 0.0001)	(K-S ρ = 0.0001)	(K-S ρ = 0.234)
	n = 410,070	n = 98,955	n = 118,755	n = 39,360

Table 2 shows the descriptive statistics of SUHI intensity within the group-based prevalent tracts. The mean for White is 1.46K with Black and Hispanic statistically significantly higher at 3.08K and 3.15K respectively. SUHI intensity in Asian prevalent tracts (2.73K) was also higher than White tracts but is not statistically significant based on the Kolmogorov – Smirnov test. The maximums for all groups were within 1K of each other but White has a lower minimum value than the non-White groups. Figure 3 presents SUHI intensity data through time for the prevalent census tracts of each population group. All four groups show a slight trend of increasing average SUHI intensity through time. Based on their lines of best fit, White $(y = 1.36 + 0.011x)$, Black $(y = 3.03 + 0.006x)$, Hispanic $(y = 3.05 + 0.011x)$, and Asian $(y = 2.72 + 0.001x)$, and the associated 95% confidence intervals (shown in shading), these increases are only statistically significant for the White and Black groupings. More striking, is the difference in SUHI intensity exposure between each group. Asian, Hispanic, and Black prevalent tracts are exposed to significantly higher SUHI intensitys than White prevalent tracts, which are on average more than 1.36K – 1.69K cooler than their counterparts from year to year.

A further comparison of each population group and the exposed SUHI intensity is in Table 3. It is organized by the percentage of each group's population living within the differing percentiles of SUHI intensity. Consistently, lower percentages of White population reside in hotter tracts. The three non-White groups show predominantly similar percentages of persons living in the percentile categorizations.

Table 3. Percentage of population (in the study) residing in percentile breakdown of SUHI intensity by census tract.

SUHI Intensity Percentiles

		White	Black	Hispanic	Asian
↑	5th	6.32	2.09	3.1	7.17
	10th	13.08	5.37	6.39	11.91
	25th	32.4	17.33	18.33	25.22
Less Than	50th	60.73	41.22	40.9	47.13
Greater Than	75th	15.96	31.7	33.43	29.03
	90th	5.43	12.91	14.81	12.72
	95th	2.37	7.06	8.16	6.47
↓	99th	0.45	1.07	2.24	1.35

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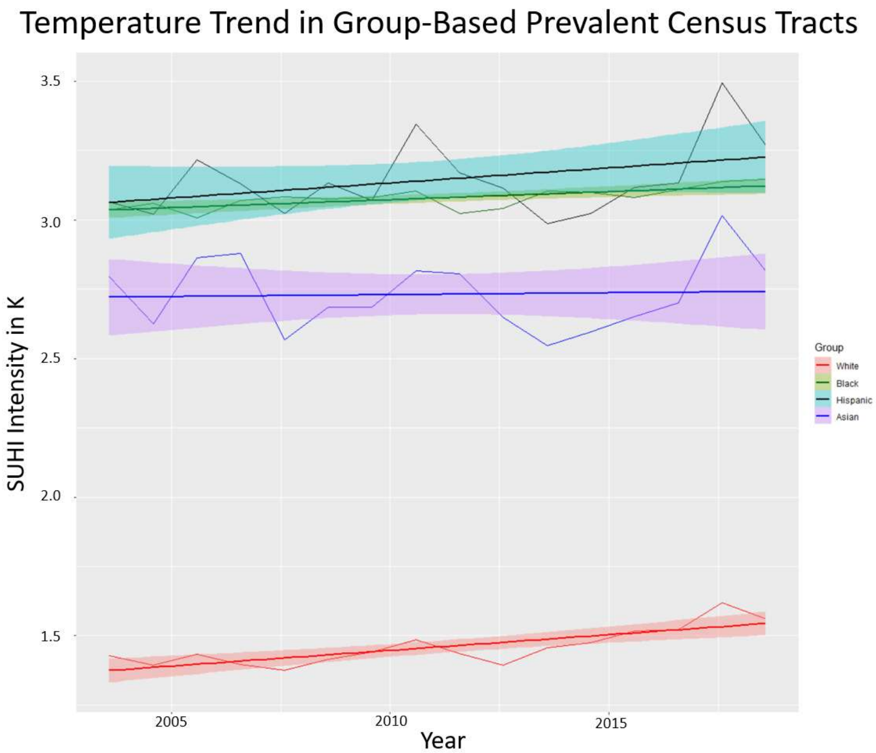

Figure 3. Daytime SUHI intensity for prevalent tracts of each racial group averaged by year. These values are absolute (non-modeled) differences.

City-Level Comparisons

Between city differences are in Figures 4 and 5 stratified by each population group with the daytime average SUHI intensity over the duration of the study. The vertical red line in each plot represents the average SUHI intensity temperature for the respective population group. Averages are significantly higher for Black (K-S ρ = 0.0001) and Hispanic (K-S ρ = 0.0001) groupings compared to White; percentage Asian was not statistically different from White (K-S ρ = 0.43); likely due to the lower number of observed cities with Asian prevalent tracts. New Orleans, LA, USA has the greatest disparity in temperature for Black prevalent tracts with a near 6K differential. San Jose, CA, USA is highest for Hispanic prevalent tracts (>7K) and Asian (<7K). New Orleans also has the greatest SUHI intensity for White prevalent tracts with an approximate difference of ~5.5K. As a further example and using 4K as an arbitrary SUHI intensity threshold, three cities exceed this intensity on average for White prevalent tracts; 12 cities for Black; 22 for Hispanic; nine for Asian.

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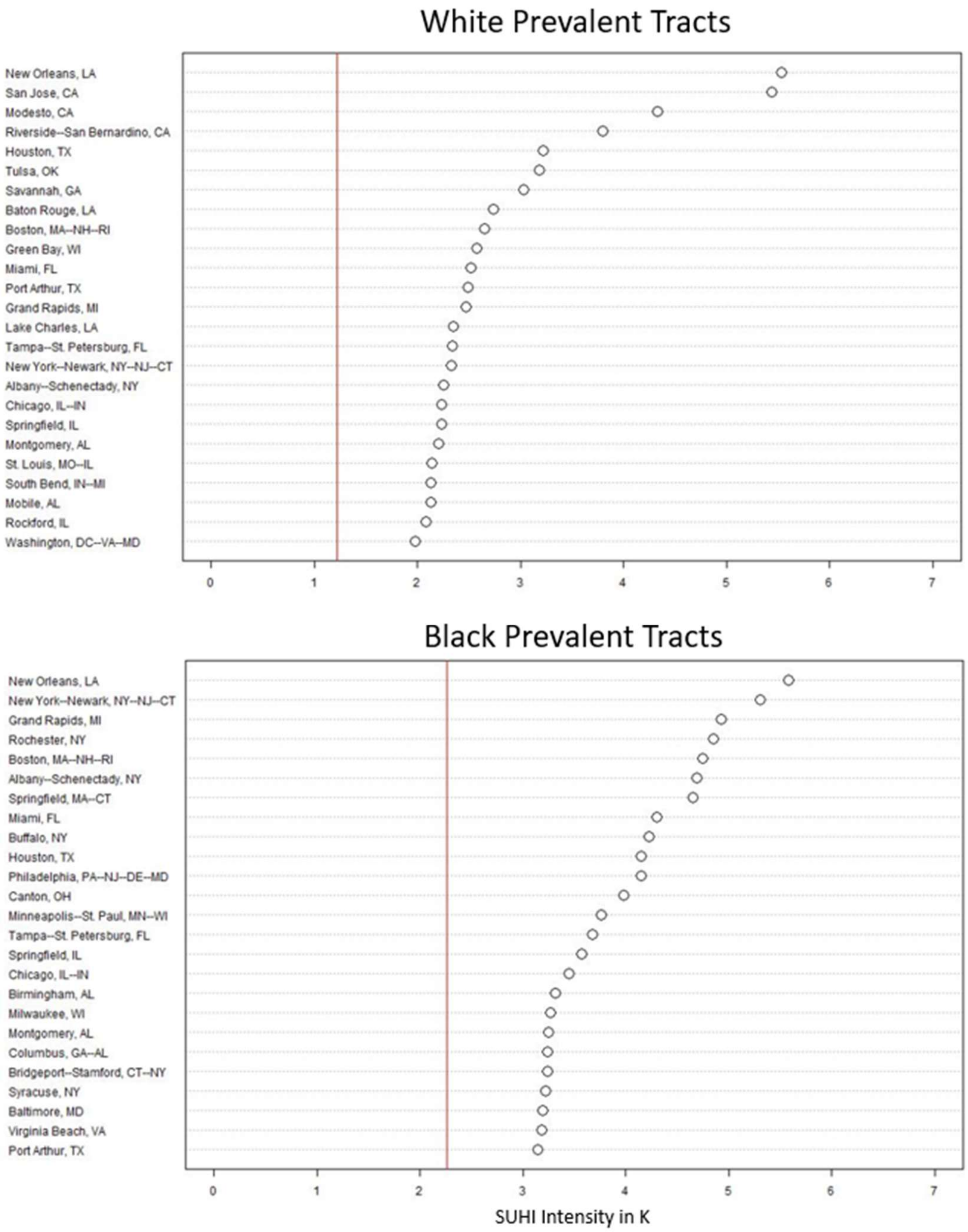

Figure 4. Top 25 cities ranked by highest SUHI intensity for census tracts identified for White and Black population groups. (note: Only white prevalent census tracts were in all cities examined).

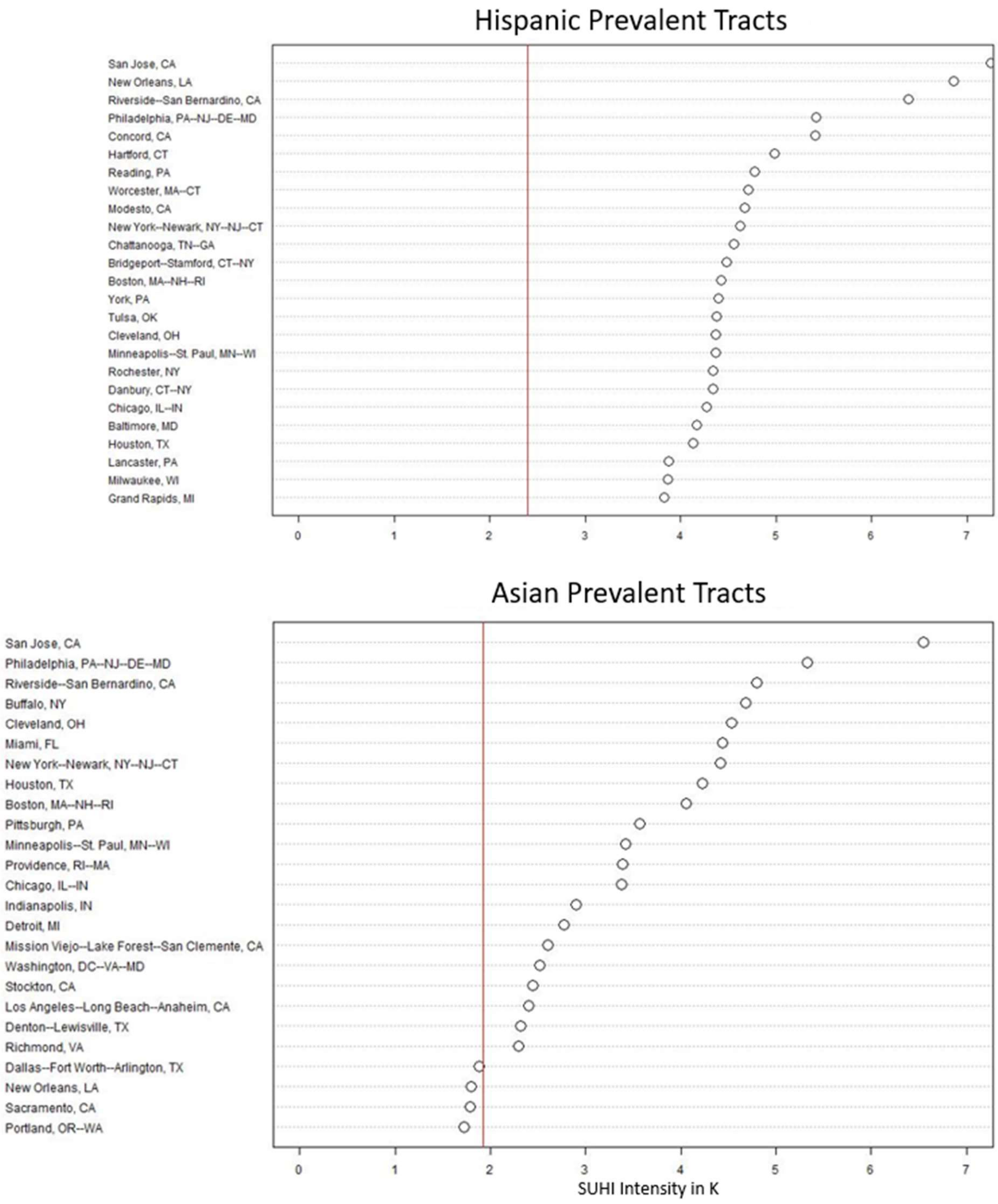

Figure 5. Top 25 cities ranked by highest SUHI intensity for census tracts identified for Hispanic and Asian population groups.

Ecological Regression Models

Results of the ecological regression models are shown in Table 4. All four population groups had a statistically significant association with average daytime SUHI intensity. Of the independent variables Black percentage had the highest posterior estimated β of 0.42. Hispanic and Asian percentage had a mean β of 0.23 and 0.14 respectively. Percentage White had a negative association with average daytime SUHI intensity with

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a mean posterior β of -0.25. The temporally structured effect, γ_t, modeled as a random walk order one, exhibited a statistically significant increase in SUHI intensity through time of approximately 0.01K per year on average (Figure 6).

The model using the *D* index as an independent variable with SUHI intensity averaged across each city throughout the study time-period as the response is shown at the bottom of Table 4. This model demonstrates a statistically significant association between *D* and average daytime SUHI intensity with a mean posterior β of 0.42. γ_t, the temporally structured effect, displayed a similar pattern to the census tract-level analysis with an approximated increase of 0.01K per year increase on average (Figure 7).

Table 4. Bayesian hierarchical spatial temporal ecological regression posterior β's for each model developed in the study.

Posterior β for Each Model

	Independent Variable	Mean β	Credibility Intervals	DIC	Intercept
Model #1	Percentage White	-0.25	(-0.34 - -0.17)	-	-
	Percentage Black	0.42	(0.35 - 0.50)	-	-
	Percentage Hispanic	0.23	(0.17 - 0.28)	-	-
	Percentage Asian	0.14	(0.10 - 0.19)	-	-
				766349400.40	2.05
Model #2	*D* Multi-Group Dissimilarity Index	0.42	(.276 - .558)	-11110.03	0.59

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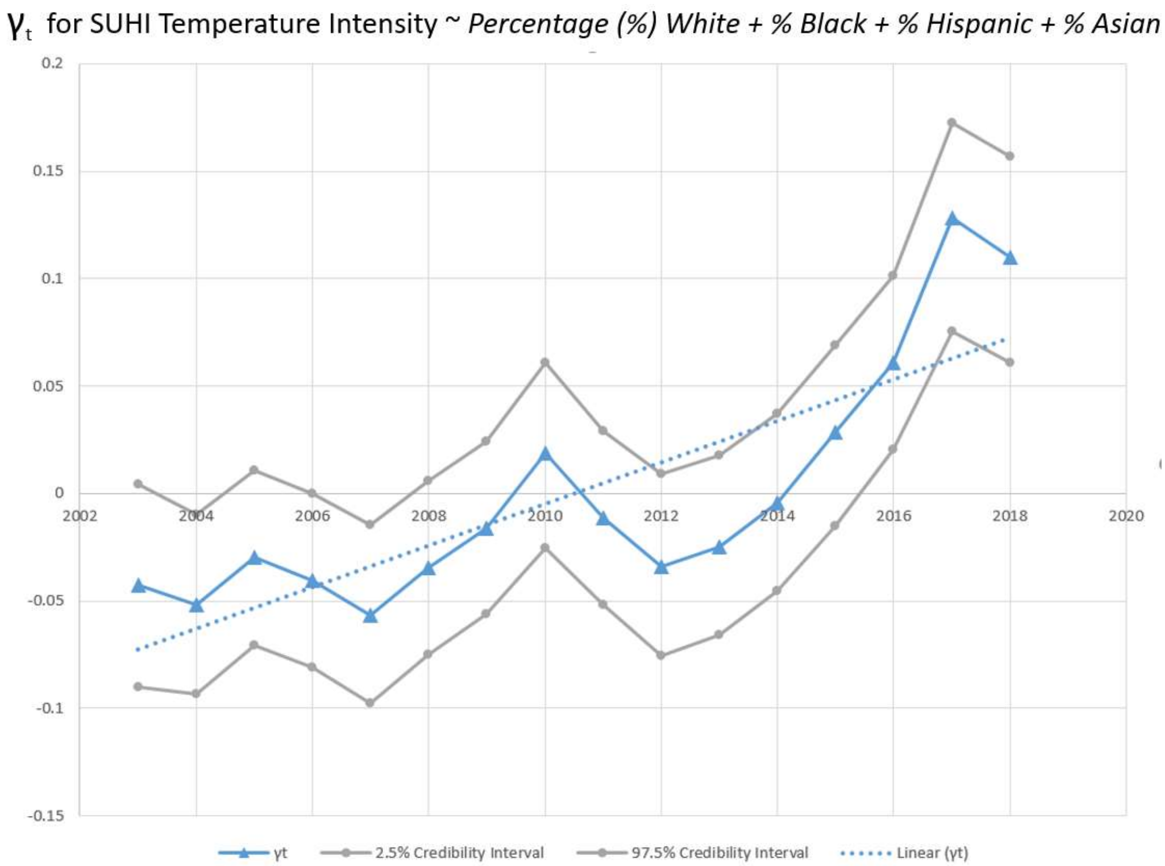

Figure 6. Temporal structure of Bayesian hierarchical spatial temporal model for census tract-level SUHI intensity with percentage of each population group. γt is the temporally structured effect modeled as a random walk of order 1 (RW1).

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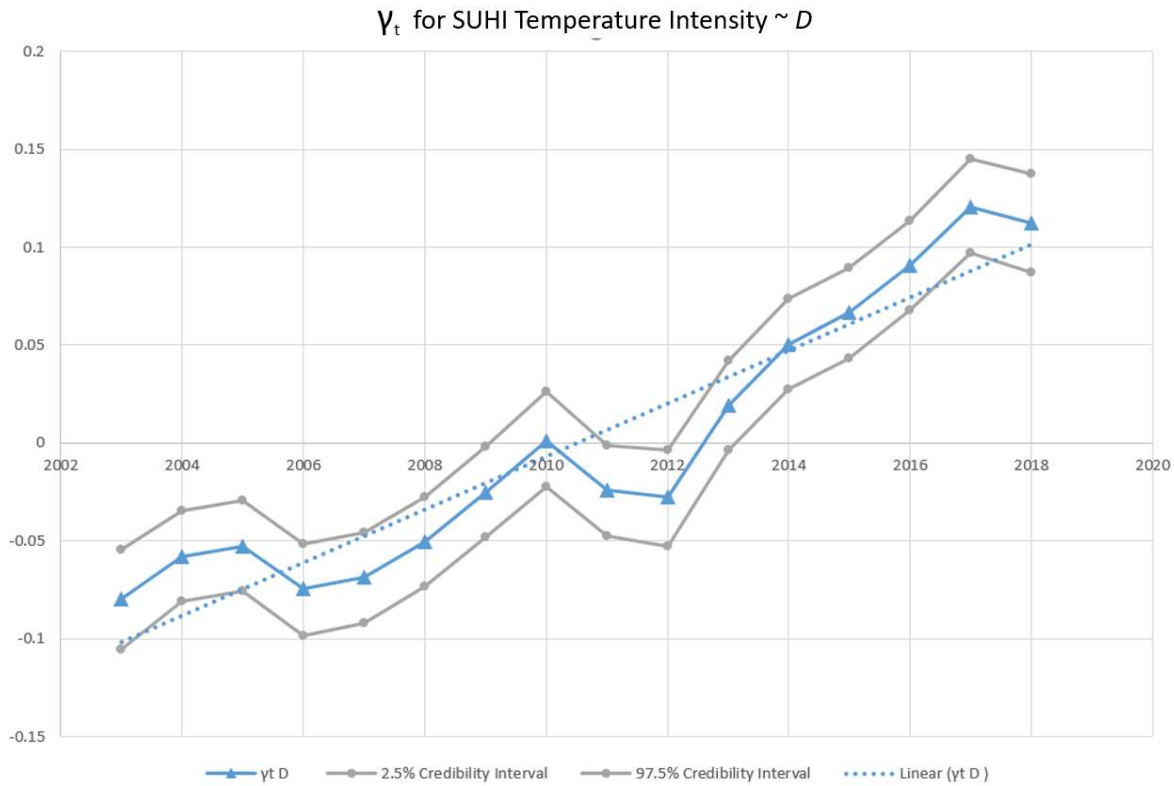

Figure 7. Temporal structure of Bayesian hierarchical spatial temporal model for city-level SUHI intensity and D Multi-Group Dissimilarity Index. γtD is the temporally structured effect modeled as a random walk of order 1 (RW1). .

Discussion

Census Tract-Level Comparisons

The results of the census tract-level analysis support previous work demonstrating disparities in temperature exposure between White communities and those of color (1–3,5,6,8). When SUHI intensity for all tracts is averaged and categorized by population group, temperature differential for each group increases through time (See Figure 3). However, the increase is only statistically significant in White and Black prevalent tracts. There is a high degree of variability from year to year among the Hispanic and Asian prevalent tracts, which is responsible for the lack of statistical significance. Reasons for this degree of variability are hard to isolate but may be due to the overall residential mobility of these populations in urban areas relative to Black and White groups (27,28). Additionally, there may be spatial intricacies within the census tracts of these groups that contain more variability in land cover types, thereby adding to the higher variance.

Equally remarkable is the SUHI intensity difference between the non-White and White groups. On average across all 191 cities examined, there is a greater than 1.25K – 2.0K difference between them. These observations add further support to Hsu et al. (2021) demonstrating that non-White population groups are exposed to higher SUHI intensities; in the present case approaching >2K in some cases on average. However, Hsu finds that Blacks on average have the highest degree of inequitable thermal exposure followed by Hispanics. The findings presented here, which in this case are un-modeled calculations of average temperature across all prevalent tracts (where population density and Köppen –

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Geiger climate zones are not yet accounted for; likely explaining the discrepancy) shows Hispanics to have the highest thermal exposure followed by Black and Asian, with White exposure negligible by comparison.

To illustrate the significance and scale of difference in thermal exposure, by utilizing the trend (slope of interpreted line of best fit) in SUHI intensity exposed to each racial group through time, it is possible to calculate the time it would take White prevalent tracts to reach temperature parity with their non-White counterparts. Based on this analysis and given the temperature average in 2018 and assuming the trend remains stable through time, it would take until the year 2363 for White tracts to reach thermal parity with Black prevalent tracts and 2154 for Asian. White prevalent tracts would never reach thermal parity with Hispanic since they are on average warming the same amount 0.011K per year. It should again be strongly emphasized, these dates are useful only for comparative/illustrative purposes but do underscore the inequitable distribution in thermal exposure through time within different communities. Perhaps such an analysis would be useful for policymakers as a "talking-point" to exemplify the significant thermal disparity between groups.

Examining the breakdown of percentages of different population groups living within various percentile rankings of thermal exposure, significantly more non-White residents, by percentage, live in hotter census tracts; again supporting many of the previous studies. In the 90th percentile of SUHI intensity, 12.91%, 14.81%, and 12.72% of Black, Hispanic, and Asian residents respectively reside. By comparison, only 5.43% of the White population in the study inhabit areas equal to or in excess of the 90th percentile in SUHI intensity. These numbers fundamentally triple when examining the 75th percentile. The coolest, 5th, percentile examined, includes 6.32% of White persons in the study. Compared to 2.09% Black, 3.1% Hispanic, and 7.17% Asian. The fact that Asian percentage is higher in this percentile conceivably illustrates some of the complexities in Asian socioeconomic status in the U.S. (29). If the Asian variable were more stratified ,(i.e. split into countries or regions of origin such as East Asia, South Asia, as is sure to come in future census data releases) examining this outcome in more depth would be possible.

City-Level Comparisons

The city-level analysis continues to further validate prior studies (1–3,5,6,8). The temperature differential for White prevalent tracts averaged and grouped by city is over 1K cooler than Black and Hispanic groupings (Figure 4). New Orleans, LA, USA has the highest temperature differential for both White and Black prevalent tracts categorized in this fashion. New Orleans is the second ranked city for Hispanic communities, which are nearly 1K hotter than their White or Black counterparts. However, as the city-averaged temperature for White groupings rapidly decreases, Black ones do not. Seven cities are more than 3K hotter than their surroundings for associated White communities but there are more than 30 cities for Black, 50 for Hispanic, and 16 for Asian communities surpassing the 3K threshold.

San Jose, CA, USA has the highest temperature differential for both Hispanic and Asian communities; third for White. Based on the 2020 census tract-level data, San Jose, has an Asian plurality population of approximately 38% and is also the location with the largest temperature differential for Asian-Americans. Many of these residents live in "Japantown" or "J town" an area with little vegetation and a high density of impervious surfaces which contribute to the thermal environment (30).

Notable among the Hispanic rankings is there are only five cities west of the Mississippi River; 4 in California, 1 in Texas in the top 25. Most of the remaining cities are within the Midwest and east coast of the US. This suggests that Hispanic populations east of the Mississippi River have a higher degree of unequal thermal exposure; at least within the top 25 cities. Notably missing in the rankings for Hispanic exposure is Phoenix, AZ, USA,

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which has a high degree of heat-related issues every year and a large Hispanic community. The likely reason for the absence of Phoenix among this ranking is the listing not based on absolute SUHI temperature but SUHI temperature differential (intensity) relative to the surrounding environment. The UHI in Phoenix does not show the same degree of intensity during the daytime, compared to the background temperature, as heat islands in the Midwest or US east coast and south; due to the paucity of significant surrounding vegetation (31). This could also help explain the number of cities east of the Mississippi River in the rankings since these are likely to have more significant amounts of vegetation in the background environment. This noted intensity may not hold during the evening hours. Perhaps a future study could examine differences between daytime and nighttime thermal exposure in a manner similar to that employed here.

Models

Each ecological regression model created in this study provided statistically significant results. The first model revealing the relationship between SUHI intensity and the percentage of each population group by census tract suggests the temperature differential in areas of a city with no population (zero for all groups) would on average equal 2.05K hotter than the background temperature; based on the intercept of the model. For each one standard deviation increase in White population (26.69%) SUHI intensity decreases by 0.25K on average. An urban census tract with 100% White population would on average be ~1K hotter than the background rural areas. Standard deviation increases in Black population (23.44%) result in SUHI intensity increases of 0.42K on average. A tract with 100% Black residents would be ~ 4K hotter than the adjacent rural areas. Hispanic increases in percentage by 23.02% amplify SUHI Intensity by 0.23K and on average, an 11.50% increase in Asian population increases SUHI intensity by 0.14K. Tracts with 100% Hispanics would be on average 3K hotter than surroundings and Asian tracts defined the same ~2.5K hotter. Variations in Black population percentage has the strongest effect on the model suggesting a higher degree of inequitable thermal exposure. These results unequivocally support Hsu et al. (2021) and suggest their findings hold through time. Specifically that Black residents had the highest average SUHI exposure, Hispanics the second highest and non-Hispanic Whites with the lowest degree of exposure (2). The observation for Asian populations also supports findings of Jesdale et al., where Asian populations were more likely than Whites to live in more stressful thermal environments but less likely than Blacks (2013). However, Jesdale et al., (2013) found a lower probability for Hispanics to be in stressed thermal environments. Findings here contradict this observation and finds Hispanics to be highly likely to reside in thermally extreme environments.

SUHI intensity is increasing throughout the study period as evidenced by the temporally structured effect in the model (Figure 4) and is statistically significant as measured by the 95% credibility envelope. On average, 2003 – 2018 witnessed a 0.01K per year increase in SUHI intensity within the census tracts examined. This aligns with the earlier finding where absolute SUHI intensity was shown to be increasing. The earlier finding showed a statistically significant increase for Black and White prevalent tracts, but here is shown to be statistically significant across all examined tracts. Moreover, the earlier observation did not take into account population density or Köppen – Geiger climate zone; variables the ecological regression modeling do account for. Demonstrating that SUHI Intensity is increasing through time for all population-based groups, with a robust model, is an important observation and should provide added urgency to mitigation activities directed toward disparities in urban heat exposure.

There is also a statistically significant relationship between the degree of segregation and its effect on SUHI Intensity in the inter-city analysis. For every standard deviation increase (0.11) in the D index there is a corresponding 0.42K increase in SUHI Intensity . The intercept implies that areas with zero degrees of segregation – complete integration –

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would have a SUHI intensity of 0.59K. These findings support Mitchell and Chakraborty (2018) where the D index was shown to indicate increases in urban heat risk for Black and Hispanic communities (7). Residential segregation tends to compact racial and ethnic groups into densely populated smaller communities, evidenced by the varying number of prevalent census tracts in the study for each group (27,338 White, 6,597 Black, 7,917 Hispanic, and 2,624 Asian prevalent tracts). Furthermore such locations tend to have a higher degree of impervious surface land cover and less tree canopy (32,33). Numerous studies have identified "Redlining" or the Home Owners' Loan Corporation practice beginning in the 1930's of grading neighborhoods as being a significant driver in the persistence of the observed spatially variable disparities in thermal exposure (33–36).

Conclusion

This study has contributed to the documentation already present outlining inequitable thermal exposure between different racial groups (1–3,5,6,8). Evidenced by the SUHI intensity measurements within prevalent census tracts of each group the temperature is shown to be increasing through time. This increase is statistically significant for both Black and White prevalent census tracts. Overall, within the Bayesian spatial temporal models, temperature is shown to be increasing by 0.01K per year on average. Granted 0 .01K per year may not seem like an alarming temperature increase but this is on average and there are many tracts examined. Further studies should look to examine or grade the tracts that have the highest level of increase or decrease to determine differences between them. Such a study would advance our understanding of drivers of thermal exposure at a local scale and what constitutes a "good" tract vs. a "bad" tract.

This study has also further demonstrated the degree of difference in heat exposure between the identified population groups. The percentage of Black population in a census tract is the strongest indicator of increased SUHI intensity. A standard deviation increase in Black population (23.44%) increases the average temperature of a census tract by 0.42K. Conversely, increases in White population decrease the SUHI intensity (26.69% increase lowers intensity by 0.25K). Hispanic and Asian population percentages, similar to Black percentages, increase SUHI intensity. Future studies should look to separate these groups by socioeconomic status (these data were not yet available for the 2020 census in this study) to identify the effect of higher/lower degrees thereof. Furthermore, this study could be used to identify the most inequitable cities and perform a more local-scale analysis using higher resolution satellite imagery and possibly a finer level of aggregation such as census block group.

Residential segregation was shown to be a statistically significant factor in city-level SUHI intensity. Higher levels of segregation corresponded to higher SUHI Intensity . A 0.11 increase in the *D* index corresponds with an increase in average SUHI intensity by 0.42K. Future studies could examine other ways of measuring residential segregation or could look at finer-scale segregation in cities such as census tract – level measurements. One could use the block group – level variables identified here to calculate *D* by census tract. Analysis could then determine if this relationship between D and SUHI intensity sustains at this scale.

Most important, is combating the inequitable distribution in thermal exposure and its roll in environmental injustice. This research underscores potential processes within the social – physical environment that create extremely hazardous conditions. As global temperatures continue to rise, and as evidenced by the warming quantified in this study, some locations in cities will become "unlivable" during the summer months in the near future. In fact, it may be too late to alter this outcome and the necessity to prepare to mitigate effects from warming is becoming increasingly evident. The primary way for research (such as this) to have the most impact is through affecting policy and therefore it must be brought before policymakers where objective action can be taken; especially for

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our most vulnerable communities. In this way research not only elucidates the degrees of injustice and the expectations for the future, but can be used to guide necessary intervention strategies that will make environmental and social inequities less pronounced. To have the most effect, these actions will not only require increased funding, resource allocation in affected communities, and involvement from the scientific community, but will necessitate local participation of the populations that are most inequitably exposed.

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