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Source: *Geographical Review*, Vol. 104, No. 4 (October 2014), pp. 459-480
Published by: Taylor & Francis, Ltd.
Stable URL: https://www.jstor.org/stable/43916079

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ABSTRACT. The combined effects of two global trends, urbanization and climate change, have generated considerable concern regarding their adverse and disproportionate impacts on the health of urban populations. This study contributes to climate-justice research by determining whether elevated levels of urban heat, indicated by land surface temperature (LST), are distributed inequitably with respect to race/ethnicity, age, and socioeconomic status in Pinellas County, Florida. Our study utilizes 2010 MODIS and Landsat medium-resolution, remotely sensed thermal data, census socio-demographic information, and both conventional and spatial statistical methods. Results indicate that LST is significantly greater in census tracts characterized by higher percentages of certain racial/ethnic minorities and higher poverty rates, even after controlling for contextual factors and the effects of spatial autocorrelation. This reveals the presence of a landscape of thermal inequity: uneven distribution of heat within the built urban environment and a community structure with varying vulnerability. *Keywords: environmental justice, urban heat island, climate justice, thermal remote sensing, land surface temperature, social vulnerability.*

The combined effects of two global trends, urbanization and climate change, have generated considerable concern regarding their adverse and disproportionate impacts on the health of urban populations (Grimmond 2007; Luber and McGeehin 2008; McCarthy and others 2010). Urbanization increases population density and leads to the spatial expansion of cities, replacing vegetation with built structures of generally lower albedo, greater impervious surface area, and higher thermal mass (Golden 2004). This pattern of urban development alters the thermal exchange between the land surface and lower atmosphere at a local scale, resulting in higher urban heat levels, a phenomenon referred to as the urban heat island (UHI) effect. In addition to the UHI, global climate change (GCC) is predicted to continue to raise the global temperature baseline and cause greater climate variability (IPCC 2007), increasing the intensity and duration of heat waves (Gaffen and Ross 1998; Meehl and Tebaldi 2004). The predicted increase in heat waves has prompted public health concern regarding rising levels of heat-related illness and mortality, especially in densely populated urban areas where heat is amplified by the UHI (Kalkstein and Greene 1997; McGeehin and Mirabelli 2001; Sheridan, Kalkstein, and Kalkstein 2008). The analysis of elevated levels of urban heat is an emerging research area in which human-environmental interactions occurring at a global scale, such as GCC, are linked with regional-scale hazards and disasters such as extreme weather events and heat waves.

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Geographical Review 104 (4): 459–480, October 2014

Mortality rates during heat waves have been studied at least since the 1930s, but attracted increased attention after several high-mortality events in the U.S. (1980, 1988, 1995, and 1999) and Europe (2003, 2010) disproportionately impacted socially vulnerable groups. Social vulnerability is a well-established concept within natural hazards research, which emphasizes demographic, socioeconomic, and housing characteristics that make people more susceptible to the adverse impacts of hazards. In the context of this study, social vulnerability refers to the increased sensitivity to heat waves by specific subgroups—for example, racial/ethnic minorities and low-income residents in urban areas. Socioeconomic status is an important determinant in the ability to access or afford to operate amenities like air-conditioning (Basu and Samet 2002), or increased landscaping that moderates temperature extremes (Jenerette and others 2011). Studies of past heat waves suggest that populations with diminished adaptive capacity to heat are particularly affected, including older people (Ellis 1978; Whitman and others1997), African-Americans (Kalkstein and Davis 1989; Whitman and others 1997; O'Neill 2003; CDC 2012), individuals living alone (Klinenberg 2002), and people lacking the economic resources to mitigate and adapt to elevated urban heat (Semenza and others 1996). The disproportionate health effects on socially vulnerable populations raises the question whether elevated urban heat is an environmental injustice concern.

Environmental justice (EJ) scholarship in the U.S. has traditionally focused on the inequitable distribution of disamenities—air pollution, hazardous waste, undesirable land uses—with respect to racial/ethnic minorities and economically disadvantaged groups. EJ advocates and scholars have emphasized the role of race, ethnicity, and socioeconomic status as powerful determinants of the spatial layout of urban areas, influencing the siting of industry, commercial development, transportation, and housing (Bullard 2000; Pulido 2000). Recent studies have extended the traditional EJ framework by examining social inequities in the distribution of environmental amenities such as parks (Heynen and others 2006; Boone and others 2009), playgrounds (Talen and Anselin 1998), and street trees (Landry and Chakraborty 2009) that provide direct and indirect health benefits to local residents. Climate justice is an emerging subfield of EJ, concerned with the inequitable distribution of the impacts of GCC. While climate justice recognizes that the spatial scale of GCC impacts range widely, it has tended to operationalize these concerns at an international level (Walker 2012). The adverse and disproportionate impacts of urban heat on socially vulnerable groups represent a hazard that integrates the effects of GCC with the UHI, thus combining the global with the local. Since social inequities associated with these impacts stem from the varying spatial distribution of heat across different communities in urban areas, they require an examination of the urban built structure with its varying thermal capacity. The two factors of physical infrastructure and the spatial clustering of population subgroups are entwined in the disproportionate distribution of heat across urban areas creating a landscape of thermal inequity within our cities.

Recent empirical studies have examined social disparities in exposure to elevated levels of urban heat in several metropolitan areas such as Chicago, Phoenix, and Philadelphia (Harlan and others 2006; Uejio and others 2011; Chow and others 2012). Although these studies have made important strides in identifying specific inequities with respect to urban heat, certain limitations have not been consistently addressed. Specifically, much of the previous research has not comprehensively assessed the spatial pattern of urban heat within study areas. Additionally, only a few recent studies have used geostatistical techniques to account for spatial dependence in the data (Grineski and others 2012, 2013; Collins and others 2013). Our study addresses the methodological limitations of previous work and extends climate justice research through a case study that examines social and spatial inequities in the distribution of urban heat in Pinellas County, Florida. We use high spatial-resolution and remotely sensed thermal data to systematically analyze the geographic distribution of land surface temperature (LST), a key parameter used in urban climate studies (Voogt and Oke 2003), with respect to socially vulnerable populations. The analysis also incorporates current geostatistical techniques that account for spatial autocorrelation. These research enhancements should enable improved identification of the hazard's spatial pattern with respect to neighborhoods with greater social vulnerability. Identifying areas of greater thermal potential and their overlap with vulnerable communities is critical to mitigation efforts for this growing problem, allowing more efficient and equitable allocation of resources when restructuring the urban environment. This capability of resolving temperature at the neighborhood scale combined with geostatistical analysis of socio-demographic variables can be used to establish the presence of a landscape of thermal inequity in urban areas, and determine its geographic variation and extent.

Urban Heat and Thermal Inequity

A review of the literature pertaining to heat waves and urban heat indicates a growing emphasis on social disparities in the spatial distribution of this hazard. While studies of heat waves and mortality have a long history, links between urban land use, the UHI, and mortality came later in the work of Robert Buechley and his coauthors (1972) and John F. Clark (1972). Exposure to excessive heat, regardless of the causal factor, is considered to be, on average, the greatest cause of weather-related fatalities in the U.S. (CDC [Center for Disease Control and Prevention], 2012). High mortality rates from heat waves during the summer of 1980, and especially as a result of a 1995 Chicago, Illinois, heat wave, increased public health awareness of the issue. The shocking death toll in Chicago, which by official count resulted in 536 deaths (ILDPH 1997), compelled public officials to recognize social disparities in the impact of urban heat on vulnerable groups. In his book *Heat Wave: A Social Autopsy of Disaster in*

Chicago, Eric Klinenberg (2002) argued that socially vulnerable groups including African-Americans, people living on annual incomes below the poverty level, older people living alone, and people with medical conditions were particularly exposed to the risk of urban heat. The inability to recognize this vulnerability represented a massive public policy failure, in which the most helpless members of society were invisible to the municipal emergency-planning structure of the time.

Since 1995, greater attention has been devoted to the topic of urban heat and social disparities in its adverse health effects. Several studies have taken a quantitative approach to examine the spatial pattern of urban heat and its differential impact on communities in various metropolitan areas. A study by Sharon Harlan and others (2006) was the first to emphasize disproportionate exposure to urban heat as an EJ issue. Comparing the patterns of urban heat in the city of Phoenix and the socio-demographic composition of the city, this research found significant associations between increased temperature and neighborhoods with weaker social networks, lower median income, and higher proportions of Hispanic residents. The study also noted that structural and historical forces had left "poor and minority populations" in "deteriorated urban spaces," which were not amenable to environmental improvement (Harlan and others 2006, 2861). A subsequent study by Darrel Jenerette and his colleagues (2011) suggested that lack of environmental amenities and cooling vegetation in warmer urban areas of Phoenix amounted to an "urban heat riskscape" with varying risk exposure and human vulnerability in the urban environment. Winston Chow and his coauthors (2012) extended Harlan and company's methodological approach in their Phoenix study, calculating summer maximum and minimum temperatures and an index of vegetation abundance for two periods:1990 and 2000. Their findings supported the previous evidence that higher temperatures and lower amounts of vegetation were associated with higher numbers of Hispanic and elderly residents, as well as lower socioeconomic status. Chow's group concluded that economically affluent Phoenicians were better able to manipulate their environment through lower structural density, increased landscaping, and the use of air-conditioning (2012). All of these studies have moved toward a more comprehensive framing of urban heat and the factors associated with social vulnerability as EJ concerns.

The studies conducted in the city of Phoenix have relied on the development of an extensive atmospheric temperature, data-collection system. While atmospheric temperature is the most direct way of assessing exposure to elevated heat, there are other environmental factors that indicate areas of elevated temperature due to the UHI, including the amount and density of vegetation and built structures, the sky-view factor of areas, and the geometry of the urban environment (Voogt and Oke 2003). Areas of elevated LST are also an indicator of the spatial boundaries of the surface urban heat island (SUHI). Other studies have used land surface temperature to assess areas of elevated urban heat. Christopher Uejio and his colleagues (2011) analyzed the health impacts of urban heat in both Phoenix and Philadelphia by utilizing LST and impervious-surface data in conjunction with a generalized linear mixed-model approach to correct for temporal autocorrelation in the data. Additionally, recent studies in the U.S.–Mexico border cities of El Paso, Texas, and Juárez, Mexico, have examined the spatial and social distribution of urban heat exposure at the neighborhood level (Grineski and others 2012, 2013; Collins and others 2013). These studies used LST measures derived from Landsat imagery and spatial regression modeling to correct for spatial autocorrelation, in their analysis of exposure and vulnerability to extreme heat and other climate change related risks.

Several studies in the city of Philadelphia have noted significant and positive correlations between elevated LST and higher rates of heat-related mortality or health risk in urban areas (Johnson and others 2009; Johnson and Wilson 2009;Hondula and others 2012), establishing a precedent for the use of this indicator to measure urban heat exposure. By directly examining biophysical factors of the SUHI and UHI such as LST and its statistical relationship with socially vulnerable population groups, it may be possible to discern whether a landscape of thermal inequity exists in urban areas.

Study Area

As shown in Figure 1, Pinellas County is located on the west-central coast of Florida and is part of the Tampa–St. Petersburg–Clearwater Metropolitan Statistical Area (MSA), commonly referred to as the Tampa Bay MSA. This county has a humid subtropical climate, typified by hot, wet summers and cool, drier winters. Its peninsular geography, bounded by the Gulf of Mexico to the west and Tampa Bay to the east, has constricted growth and development, and it is now considered "built-out" with the last commercially available green space having been developed in the last decade. Pinellas is the most densely populated county in Florida, with 1,264 persons per square kilometer and a total population of 916,542 (U.S. Census 2010). About 76 percent of its land area is urbanized, while the remainder consists mostly of publicly held parks and preserves.

In addition to its relatively high level of urban density in a state characterized by suburban sprawl, Pinellas County has several distinctive socio-demographic characteristics that make it suitable for EJ research, in general, and climate justice, in particular. It exhibits high residential segregation between white and African-American residents, relative to surrounding counties. The white/African-American index of dissimilarity for Pinellas is 0.625, compared to 0.437 for neighboring Hillsborough County (USDHHS 2010). Historically, Pinellas County developed as a winter resort and haven for retirees. In 2010, residents aged sixty-five and older comprised 21 percent of the population compared to 17 percent statewide (U.S. Census Bureau; Census, 2010). The poverty

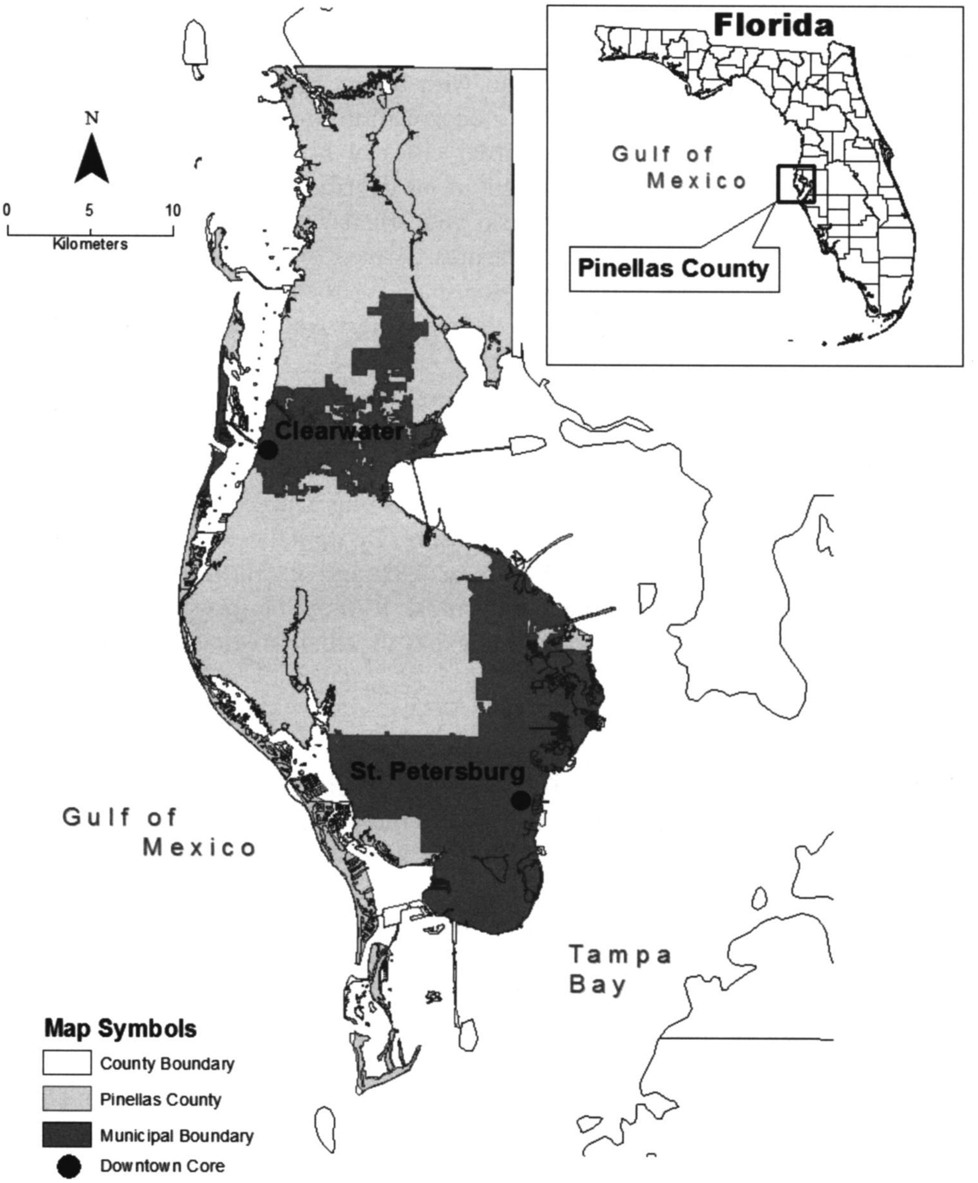

FIG. 1—Pinellas County, Florida.

rate was slightly below the state average of 13.8 percent, at 12.1 percent (U.S. Census). In addition, Pinellas County has the second-largest community of Southeast Asian residents in the state of Florida (U.S. Census Bureau; Census, 2010). Vietnamese and "Other Asians," including Cambodian, Hmong, and Laotian people, comprise almost 45 percent of the Asian population of the county, and are concentrated in the areas of East Lealman, West Lealman, and Pinellas Park in the south-central portion of the peninsula. In the 2000 U.S.

Census, educational attainment levels were lower and poverty rates higher for the Vietnamese, Cambodian, Hmong, and Laotian groups. Pinellas County's history of rapid growth and development from 1960 to 2000, its recent built-out status, its population loss between 2000 and 2010, and a diversifying population make its demographic patterns similar to those of many mature cities of the Sunbelt (Hollander 2011). Both the size of the elderly population and diversity of minority groups make Pinellas County a suitable study area for this research.

Pinellas County's pattern of development has been centered on a few small urban cores consisting mainly of low-rise buildings. These urban areas are linked by a grid-like pattern of commercial thoroughfares and surrounded by sprawling residential suburbs. Because of its peninsular shape, the urban-core areas are generally near the waterfront, creating high-density areas near the coast, sometimes buffered from the water by narrow strips of beach or parkland. Waterfront areas are considered an amenity and are preferred sites of residence for the region's economically affluent residents, as demonstrated by higher median household income and median housing values in cooler coastal census tracts. Commercial districts stretch inland, toward the center of the peninsula, where less-affluent residential areas are located. This creates a general spatial pattern with residences of higher-income population groups located in the cooler waterfront areas, while commercial sites and housing for lower-income residents tend to be located toward the interior of the peninsula where the UHI effect is most pronounced. This is a historical pattern of settlement that can be traced back to the early 1900s in the two principal cities of Clearwater and St. Petersburg. Desirable waterfront locations of urban areas were sites of income-producing tourist housing and were also purchased by affluent residents. Areas inland became sites of commercial or light-industrial activity and housed the economically disadvantaged residents, among them the African-American community who served as domestic servants and laborers for the burgeoning tourist trade and construction industry. This established a spatial pattern of settlement that largely holds true to the present.

It is difficult to accurately gauge the adverse health effects of urban heat on the population of Pinellas County. The climate is humid subtropical and air-conditioning use is widespread, two factors that may indicate greater acclimatization and adaptation to heat by the population (Medina-Ramón and Schwartz 2007; Zanobetti and Schwartz 2008). Although Florida is ranked seventh out of all U.S. states in the overall number of fatalities from excessive heat with 170 deaths from 1999 to 2009 (CDC [Center for Disease Control and Prevention], 2012), these numbers are questionable due to different practices used by physicians and medical examiners in diagnosing heat as a primary or contributing factor in cause of death (Dixon and others 2005). In terms of hospitalization and illness, the Florida Department of Health reports that between 2005 and 2009, there were 16,523 hospital admissions in the state (rate of 18.3/100,000) for heat-related illness (HRI) for residents age sixteen or older, and an additional 2,198 admissions for occupational HRI (Florida Department of Health 2011). Pinellas County ranks lower in terms of occupational HRI admissons than counties located in rural parts of the state where agriculture is still a major economic activity. Despite its lower occupational risks for heat-related illness or injury, Pinellas is a densly populated county with a large number of elderly residents in a state that is ranked high nationally for heat-related fatalities.

Data and Methods

This study uses remote sensing techniques, U.S. Census data, and both conventional and spatial regression analysis to evaluate socio-demographic inequities in the geographic distribution of urban heat in Pinellas County, Florida. A workflow summary is presented in Figure 2, as a schematic of the methods used in this study. The following sections provide a detailed description of specific data sources and methods utilized for this analysis.

DEPENDENT VARIABLE

Land surface temperature (LST) was chosen as the dependent variable in this study because of its status as a key parameter in urban climate studies, and its positive statistical association with rates of heat-related morbidity and mortality (Johnson and Wilson 2009; Johnson and others 2009; Hondula and others 2012), and utilization in EJ studies that have considered disparities in the exposure to environmental hazards, including urban heat (Grineski and others 2012, 2013). LST from two types of remote sensing data were first examined in order to determine whether a UHI pattern was present in the study area. MODIS and Landsat satellite imagery provided indications of the UHI pattern at different spatial and temporal scales. One-kilometer spatial resolution MODIS satellite imagery was acquired to assess whether a diurnal SUHI pattern existed in the study area (NASA LPDAAC 2001). Several MODIS eight-day LST composite images were processed and examined, but due to seasonal weather patterns few cloud-free images were available during the summer months. An image from the period of September 14–21, 2010, which had high average temperatures and the fewest missing pixels, was selected. Figure 3 depicts a pronounced diurnal thermal cycle in this study area. The afternoon image, in particular, shows differences between lower coastal and higher inland temperatures, with the greatest contrast in the south-central portions of the Pinellas peninsula. This pattern reverses at night as land with its lower thermal inertia cools more rapidly than wetlands and water, causing the coastal areas to have higher relative temperatures by 1:30 a.m. (Price 1977).

Although the MODIS imagery allows clear visualization of the diurnal UHI pattern throughout the area, its coarse spatial resolution is poorly suited for finer-scale analysis of urban heat. Higher spatial resolution(120 meter)

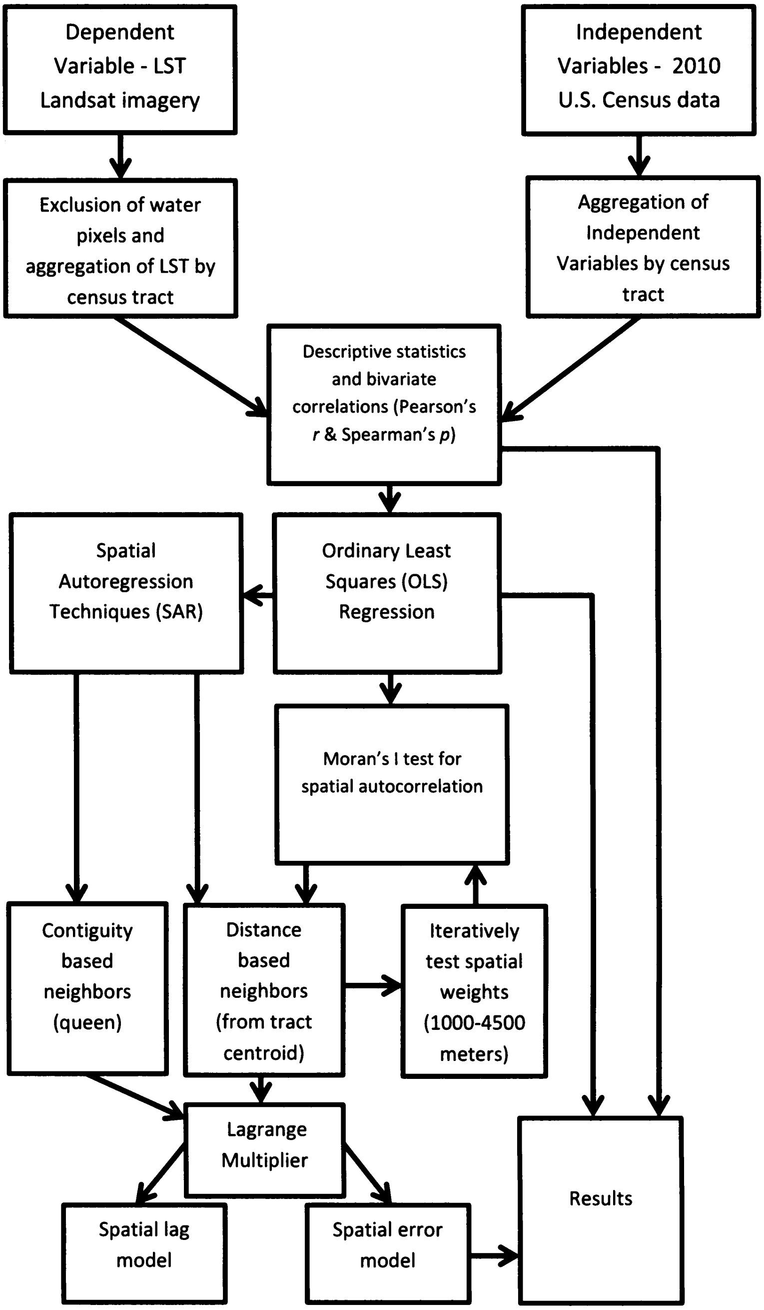

FIG. 2—Workflow and statistical methods.

Landsat 5 Thematic Mapper (TM) satellite imagery was selected to analyze the dependent variable, LST. This level of spatial resolution allows clear determination of neighborhood differences in LST. An image acquired on 16 July 2010 at

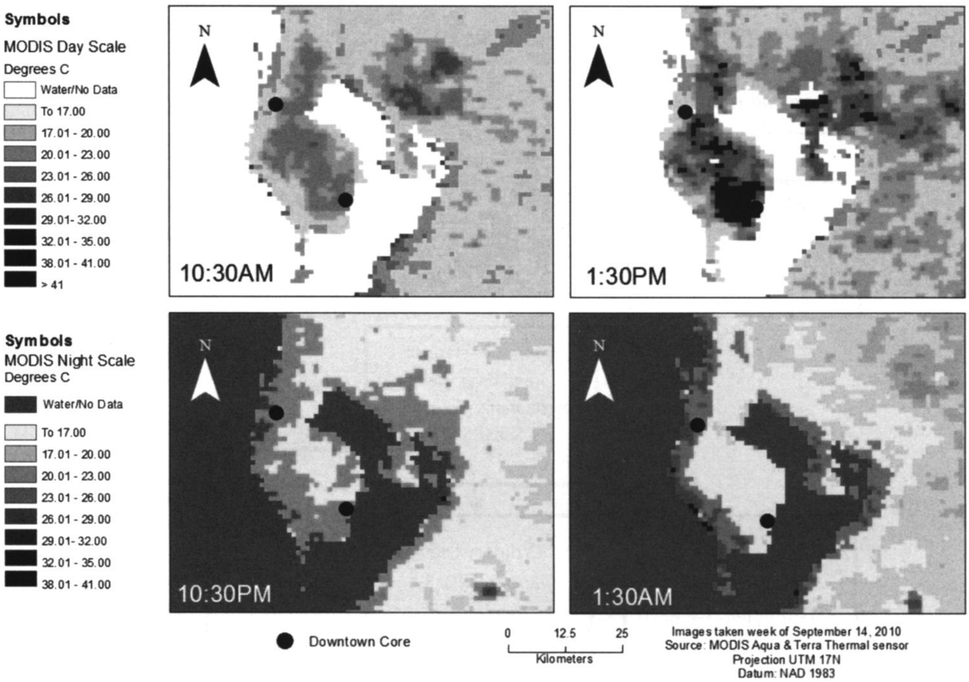

FIG. 3—MODIS Aqua and Terra satellite 8-day composite land surface temperature (LST) image with 1-km spatial resolution for September 14–21, 2010.

11:53 EDT, a day of high daily average atmospheric temperature (31.7°C) with no precipitation and minimal cloud cover was selected.

Several steps were involved in processing the LST image. The USGS *Earthexplorer* portal was used to export the tagged image file format (TIFF) image, which had been processed to level 1 standard, including radiometric correction and georectification. Landsat 5 TM captures spectral data in seven bands, and three of these were used to process an image: bands 3 (red) and 4 (near-infrared), and the thermal band, 6. Moderate spatial resolution images like those from Landsat 5 TM are suitable for general urban studies and have been used to identify neighborhood level effects, like micro-urban heat islands (Aniello and others 1995). LST was calculated using the mono-window algorithm as described by Zhihao Qin and colleagues (2001) and Ruiliang Pu and colleagues (2006). Processing involved deriving two images: the thermal image and an emissivity image. The surface emissivity image was produced using bands 3 and 4 to calculate the Normalized Difference Vegetation Index (NDVI) value for each pixel. Using the NDVI, the pixels were then categorized by predominant land cover into water, vegetated, and impervious types. Atmospheric data from the time, including near-surface temperature and precipitable water acquired at the National Weather Service station in Ruskin, Florida, were used for MODTRAN 4 atmospheric correction. The emissivity and atmospheric data were then used with the Landsat TM thermal data to produce an LST image of the area. Several pixels in the northern part of the peninsula were obscured by clouds and therefore excluded from mean temperature calculations. Their exclusion created minimal differences in temperature (2.32 percent) from the same areas of a July 2011 LST image. Calibration of the LST image was achieved by using in-situ surface-water temperature measurements from National Ocean Service, Clearwater Beach station (CWBF1) (NOAA 2010). Water pixels were subsequently eliminated from the aggregated census tract level value of LST.

The Landsat TM processed image displayed thermal patterns that were generally consistent with the MODIS image of higher daytime temperatures in the south and central regions of the peninsula. Figure 4 shows the distribution of LST in this region. Higher temperature urban-core areas and transportation corridors are clearly evident on this map. The generally cooler temperatures of parks and preserved areas close to lakes, Tampa Bay, and the Gulf of Mexico are also discernible.

The mean LST for all pixels within each census tract was calculated based on Census 2010–tract boundaries and used to represent the dependent variable for the statistical analysis. The spatial distribution of mean LST values at the census-tract level is depicted in Figure 5.

The map shows a similar geographic pattern of LST to that in Figures 3 and 4: generally warmer temperatures for the inland areas and for the densest coastal tracts, with other coastal and wetland areas being cooler.

INDEPENDENT VARIABLES

Inequities in the distribution of LST were analyzed using a set of demographic and socioeconomic variables from U.S. Census Bureau; Census, 2010 and 2006–2010 American Community Survey (ACS) five-year estimates for Pinellas County, Florida, at the census-tract level. Our selection of variables was guided, in part, by previous studies of urban heat mortality (Kalkstein and Davis 1989; McGeehin and Mirabelli 2001; O'Neill 2003; Harlan and others 2006; Basu and others 2008). In this literature, individuals of lower socioeconomic status, the very young or old, and racial/ethnic minorities have been identified as being particularly vulnerable to the health effects of urban heating. Consequently, the percentage of families at or below the federal poverty level (income in past twelve months below poverty level) and the percentage of all housing that is owner-occupied (homeownership), based on the 2006–2010 ACS estimates, were chosen to evaluate socioeconomic status. Although the U.S. Census provides no reliable measures of family wealth at the tract level, homeownership has been used as a general indicator of wealth and assets in previous EJ research (Cutter and others 2009; Chakraborty 2011). Demographic variables were obtained from the 2010 U.S. Census, Summary File 1. We included both the percentage of population aged five years and under, as well as those aged sixty-five or more years. For race and ethnicity, we focused on the three largest

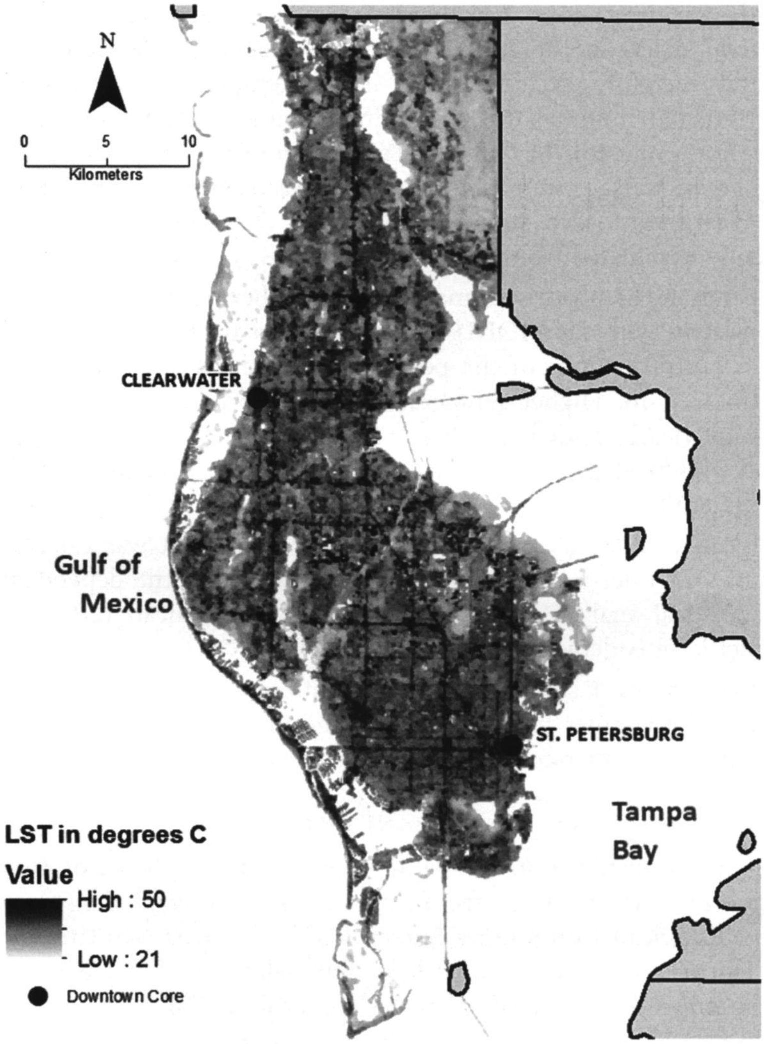

FIG. 4—Land surface temperature (LST) remotely sensed by Landsat 5 TM sensor satellite, Pinellas County, 16 July 2010.

minority groups in this county: the percentage of the tract population identifying themselves as non-Hispanic Black, Hispanic or Latino of any race, and Asian. Additionally, population density was considered as a control variable, and calculated as the number of people per square kilometer of the land area of census tracts. Finally, all variables were standardized before inclusion in the correlation and regression analysis.

STATISTICAL METHODS

To explore basic statistical associations between the dependent variable and each of the independent variables, we began by conducting parametric and

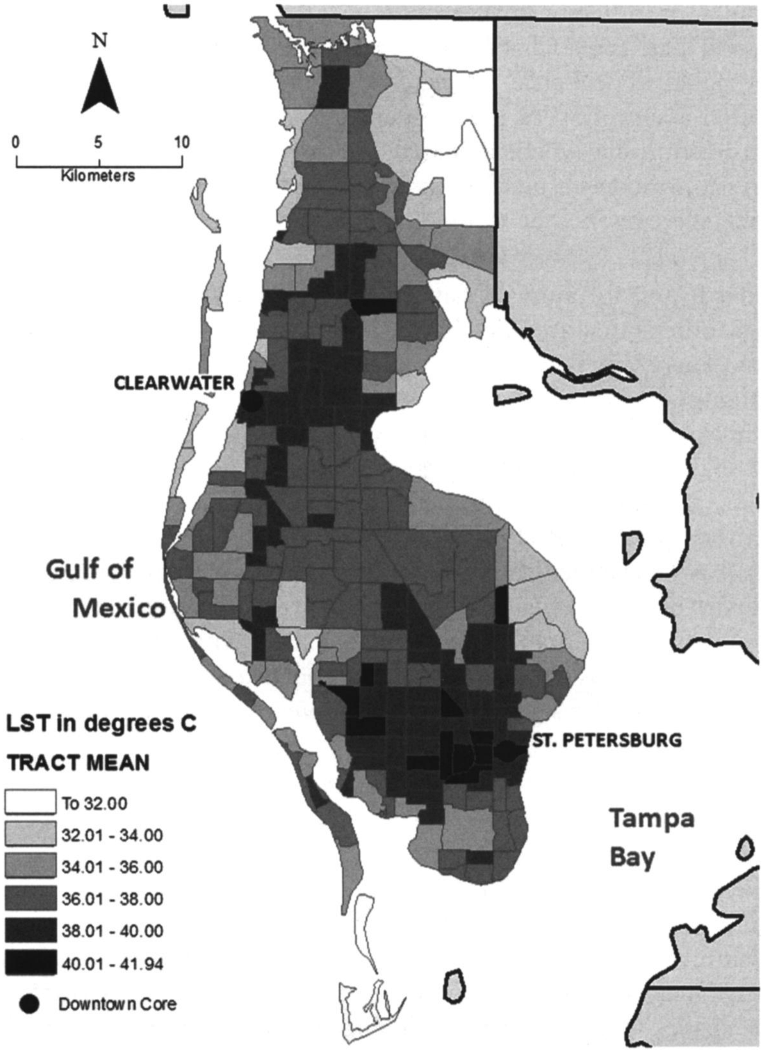

FIG. 5—Mean land surface temperature (LST) by census tracts, Pinellas County, 16 July 2010.

nonparametric tests for bivariate correlation, based on Pearson's and Spearman's correlation coefficients, respectively. We then used multivariate regression analysis to evaluate the relationship between urban heat and all independent variables in a single model, based on a three-step process. First, we constructed a multiple regression model based on the ordinary least-squares (OLS) method, using LST as the dependent variable. This method is typical of conventional statistics and assumes that observations and regression errors are independent. This assumption, however, is unlikely to be valid if there is clustering of similar values in space or spatial autocorrelation in the data. Spatial autocorrelation is typically caused when observations at proximate locations are more similar or different than would be expected of a random distribution (Kissling and Carl 2008; Chakraborty 2011). This phenomenon has the potential to cause spatial dependence of regression-model residuals, thus violating the classical OLS assumption of independence. The second research step thus consisted of determining whether spatial dependence in the data influenced the OLS regression-model results. We used the global univariate Moran's *I*-statistic to examine the presence of residual spatial autocorrelation (Anselin and Bera 1998).

In order to test for autocorrelation, it is necessary to specify for each spatial unit which other units are "neighbors" and may influence its values (Cliff and Ord 1981). There are two approaches for defining the neighbors of a spatial unit: contiguity-based or distance-based. For the contiguity-based approach, we utilized first-order "queen-based" contiguity. All adjacent census tracts, including those sharing vertices with the tract of interest, were included as neighbors. In contrast, the distance-based method relies on Euclidean distance between tract centroids for the selection of neighbors. The distance for selecting spatial neighbors was determined through an iterative process, involving calculation of weights matrices for a series of distances between centroids, ranging from 1,000 to 4,500 meters. The Moran's *I*-statistic associated with regression-model residuals for the various distances was assessed and the distance at which this value ceased to be statistically significant (2,400 meters) at the $p<.10$ level was chosen as the reference value.

Finally, when we detected spatial dependence in the residuals of the OLS model, appropriate spatial regression models were specified to extend the standard regression equation and account for residual spatial autocorrelation. Simultaneous autoregressive (SAR) models are statistical models that consider spatial autocorrelation as an additional variable in the regression and estimate its effect simultaneously with the effects of other independent variables (Chakraborty 2011). This additional is implemented with a (distance-based or contiguity-based) spatial-weights matrix, which accounts for patterns in the dependent variable that are not predicted by independent variables, but are instead related to values of proximate observations. We used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to determine whether the spatial-lag or spatial-error model specification should be used (Anselin 2005). Spatial-lag models assume that spatial autocorrelation is present in the dependent variable; spatial-error models assume that regression errors exhibit spatial dependence. For our case study, the LM tests indicated that the spatial-error specification was appropriate for both contiguity-based and distance-based models.

Results

A pattern of generally warmer LST inland, with cooler areas along the water, is evident in both Figures 3 and 4. This visually detected pattern represents the distribution of LST levels throughout the county on the observation date and is indicative of clear-sky, summer daytime temperatures. Table 1 provides summary statistics for the entire set of variables, with data for the dependent variable calculated from the tract-level values represented in Figure 5. Average LST varies considerably across census tracts within the study area, ranging from 29.55° to 41.94°C, with a mean of 36.92°C. Independent variables such as percent below poverty level, percent owner-occupied, percent age five and younger, and percent age sixty-five and older show substantial range across tracts. This is especially true for the percentage of non-Hispanic Black residents, which ranges from only 0.3 to 95.7 percent, corroborating the high index of dissimilarity between this racial group and the white population, suggesting a high level of residential segregation. Tract-level values of percent below poverty range from 0.70 to 58.0 percent, indicating wide economic disparity. Rates of homeownership also vary greatly, from 11 to almost 96 percent.

BIVARIATE CORRELATION ANALYSIS

Our analysis begins with an examination of bivariate parametric and nonparametric correlations to analyze the strength and direction of the statistical relationship between mean LST and each independent variable at the census-tract level. Pearson's (r-values) and Spearman's (ρ) correlation coefficients for each variable are presented in Table 2.

The Pearson's correlation coefficient indicates statistically significant and positive linear associations between LST and population density, the percent below poverty level, percent age five or younger, as well as the non-Hispanic Black, Hispanic, and Asian percentages, with population density showing the strongest positive correlation. The percentage of owner-occupied homes is the only variable that shows a significantly negative linear correlation with LST. These results suggest that areas of higher LST in this county are associated with significantly higher population density, poverty rates, and racial/ethnic minority proportions, as well as lower levels of homeownership. Spearman's correlation

TABLE 1—DESCRIPTIVE STATISTICS FOR MEAN LAND SURFACE TEMPERATURE (LST) AND EXPLANATORY VARIABLES

VARIABLE	MIN	MAX	MEAN	STD. DEV.
Mean LST	29.55	41.94	36.92	2.15
Population per sq. km	944.00	8,922.00	3,697.30	1,432.01
% African-American	0.30	95.70	10.34	18.71
% Hispanic	1.40	32.30	7.48	4.69
% Asian	0.00	17.50	2.84	2.55
% Age: ≤ 5 years	0.30	12.60	4.48	1.89
% Age: ≥ 65 years	2.10	74.20	22.31	12.69
% Below Poverty	0.70	58.00	12.11	8.67
% Owner-Occupied	11.40	95.60	67.44	17.05

N = 244 census tracts.

TABLE 2—BIVARIATE CORRELATION OF MEAN LAND SURFACE TEMPERATURE (LST) WITH EXPLANATORY VARIABLES

VARIABLE	PEARSON'S r	SPEARMAN'S ρ
Population per sq. km	.414***	.398***
% African-American	.133***	.244***
% Hispanic	.159***	.187***
% Asian	.083**	-.020
% Age: ≤ 5 years	.148***	.145***
% Age: ≥ 65 years	-.002	-.024
% Below poverty	.322***	.300***
% Owner-Occupied	-.288***	-.300***

N = 244 census tracts; *p < 0.10; **p < 0.05, ***p < 0.01

coefficients were also calculated as a nonparametric measure to reduce the effect of outliers. With the exception of the Asian percentage, the values and significance of the Spearman's ρ were similar to those observed for Pearson's r. Densely populated tracts that contain a higher proportion of non-Hispanic Blacks, Hispanics, and individuals of lower socioeconomic status were found to have significantly greater exposure to elevated LST.

CONVENTIONAL REGRESSION ANALYSIS: ORDINARY LEAST SQUARE MODEL

The next step of the analysis uses a traditional ordinary least-squares (OLS) regression model to investigate the simultaneous effects of the eight independent variables on mean LST in Pinellas County. The regression results are summarized in Table 3.

The ANOVA F-test indicates overall significance (p<0.01) and the adjusted R-squared (0.229) suggesting a reasonable goodness-of-fit for this multiple regression model. The multicollinearity condition index is 4.775, confirming low levels of multicollinearity among the standardized independent variables. Variable coefficients for both non-Hispanic Black and Hispanic percentages do not remain significant (p>.10) after controlling for age and socioeconomic status in a multivariate model. However, population density, percent Asian, and percent below poverty level are significantly positive, while percent owner-occupied is significantly negative. The next step was to determine if the regression residuals (errors) from this OLS model satisfy the classical linear regression assumption of independence, or if they exhibit significant spatial autocorrelation. The residual Moran's I statistic associated with the contiguity-based and distance-based approaches for selecting spatial neighbors were 0.362 and 0.367, respectively. Both these positive values are statistically significant (p<.01), confirming that the residuals are spatially dependent with respect to their values in neighboring tracts. Since this is a serious violation of the assumption of independence, the OLS regression model is inadequate for analyzing the association between the dependent and independent variables.

TABLE 3—ORDINARY LEAST SQUARES (OLS) AND SPATIAL ERROR REGRESSION OF MEAN LAND SURFACE TEMPERATURE (LST)

VARIABLE	OLS	SPATIAL ERROR: CONTIGUITY-BASED (1^{ST} ORDER QUEEN)	SPATIAL ERROR: DISTANCE-BASED (2400M)
Constant	0.000	0.007	- 0.194
Population per sq. km	0.334***	0.255***	0.283***
% African-American	-0.049	-0.027	0.010
% Hispanic	0.033	0.016	0.052
% Asian	0.126*	0.193***	0.183**
% Age ≤ 5 years	-0.012	-0.081	-0.100
% Age ≥ 65 years	0.086	0.094	0.096
% Below Poverty	0.227***	0.175**	0.132*
% Owner-Occupied	-0.126*	-0.199***	-0.271***
Spatial error parameter (λ)	N/A	0.540***	0.621***
F - Statistic	10.054***	N/A	N/A
Moran's *I* (queen)	0.362***	-0.018	N/A
Moran's *I* (2400 meters)	0.367***	N/A	0.008
Adjusted/Pseudo *R-squared*	0.229	0.473	0.467
Akaike Information Criterion (AIC)	637.615	575.689	580.799

N = 244 census tracts;*p < 0.10; **p < 0.05; ***p < 0.01.

SPATIAL REGRESSION ANALYSIS: SPATIAL-ERROR MODEL

SAR modeling was employed to account for the significant and positive spatial autocorrelation indicated by the OLS regression residuals. Results of SAR analysis, using a spatial-error model specification, indicate several improvements from the OLS model (Table 3). For both SAR models (contiguity-based and distance-based), the Moran's *I*-statistic is near zero and statistically nonsignificant (p<.10), while the spatial-error term (λ) is highly significant (p<.001). This implies that the effects of spatial autocorrelation have been mostly eliminated from this regression model using either the contiguity- or distance-based methods. Additionally, the pseudo *R*-squared (0.473 and 0.467) shows an improvement in goodness-of-fit compared to the OLS model. Finally, the Akaike Information Criterion (AIC) scores from the spatial-error models are also lower than the AIC from the OLS model, indicating considerable improvement in model performance.

Differences between the two methods of neighbor selection for the SAR models, contiguity (queen) and distance (2,400 meters) are evaluated by comparing the relative value of the Moran's *I*-statistic. While both measures are nonsignificant (p>.10), the distance-based weights matrix of the SAR model yields only a slightly lower Moran's *I* (0.008 versus -0.018). Consequently, both SAR models yield Moran's *I* values close to zero, and reduce spatial autocorrelation when compared to the OLS model.

Results of both SAR models indicate that several independent variables are significantly and positively associated with LST ($p<.10$). Census tracts with higher average LST are characterized by significantly greater population density and poverty rates, as well as a higher percentage of Asian residents. Coefficients for non-Hispanic Black and Hispanic percentages in the spatial-error model are positive, but nonsignificant in presence of the other variables. Rates of homeownership show a negative association with mean LST, and this relationship was also statistically significant ($p<.01$) in the SAR models. The results of the SAR distance model are consistent with the OLS model in which population density, percent Asian, percent below poverty, and percent homeowner-occupied were all significantly related to LST.

Concluding Discussion

Climate justice has focused primarily on the inequitable distribution of the adverse impacts of climate change on economically, politically, and socially marginalized communities around the world. In the case of urban heat, the effects of the UHI are compounded by climate change. Socially vulnerable groups in cities are inequitably exposed to a hazard that is amplified by human-induced climate change and the built structure of urban environments. As this important subfield of environmental justice research continues to develop, a rigorous empirical methodology is required to examine the interconnection among the built urban environment, urban heat, and socio-demographic characteristics of urban residents. Following recent studies on social inequities in exposure to extreme heat (Grineski and others 2012, 2013), our article contributes to climate justice research by: focusing on the use of high-resolution thermal remote sensing of land surface temperature (LST); and implementing geostatistical techniques that explicitly account for spatial dependence in the data.

From an empirical perspective, our case study reveals significant statistical relationships between where particularly vulnerable groups live and their level of exposure to elevated urban heat. Specifically, the findings clearly indicate that urban heat is distributed inequitably with respect to race, ethnicity, and socioeconomic status in the study area of Pinellas County, Florida. The results of bivariate correlation analysis revealed mean LST to be significantly greater in neighborhoods with higher population density, higher proportions of non-Hispanic Black, Hispanic, Asian (specifically Southeast Asian), and elderly residents, as well as those with higher poverty and lower homeownership rates. Multiple regression analysis confirmed that LST is significantly greater within census tracts that contain higher percentages of certain minority subgroups, higher poverty rates, and lower percentages of homeownership, even after controlling for contextual factors such as population density and the effects of spatial autocorrelation. Taken together, this indicates higher urban heat levels in impoverished and racially segregated census tracts, which may be considered more socially vulnerable. Many of these socially vulnerable neighborhoods are located in areas away from the coast and toward the center of the peninsula, where LST levels are substantially higher. Exposure to urban heat is particularly high in central Pinellas County (areas of East Lealman, West Lealman, and Pinellas Park), where a relatively large percentage of individuals of Southeast Asian origin reside. Overall, these findings are consistent with prior studies in other metropolitan areas (e.g., Harlan and others 2006; Chow and others 2012; Hondula and others 2012) and support the primacy of race, ethnicity, and poverty in explaining patterns of thermal inequity.

Our findings suggest that the urban built environment itself should be considered as an important factor influencing the spatial distribution of urban heat across different, and sometimes more vulnerable, demographic and socioeconomic groups. This association of urban heat and socially vulnerable groups reveals the presence of what can be characterized as a *landscape of thermal inequity* within this metropolitan area. The geographic distribution of urban heat and its adverse effects on vulnerable populations is a rapidly growing research area, especially considering the recent pattern of heat waves in North American cities (Gaffen and Ross 1998; Stone and others 2010). Because of the socio-technical nature of the hazard and its embeddedness within the built structure of the urban environment, comprehensive modes for surveying urban heat provide a tool for enhancing adaptation and mitigation strategies as the impacts of global climate change become more pronounced.

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