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MI-Environment: Geospatial Patterns and Inequality of Relative Heat Stress Vulnerability in Michigan

Patricia D. Koman[a], **Frank Romo**[b], **Peter Swinton**[b], **Graciela B. Mentz**[c], **Ricardo F. de Majo**[c], **Natalie R. Sampson**[d], **Michael J. Battaglia**[e], **Kimberly Hill-Knott**[f], **Guy O. Williams**[g], **Marie S. O'Neill**[h], **Amy J. Schulz**[c]

[a]University of Michigan School of Public Health, Environmental Health Sciences Department, 1415 Washington Heights, Ann Arbor, MI 48109, USA

[b]University of Michigan Taubman College of Architecture and Urban Planning, 2000 Bonisteel Blvd, Ann Arbor, MI 48109, USA

[c]University of Michigan School of Public Health, Department of Health Behavior and Health Education, 1415 Washington Heights, Ann Arbor, MI 48109, USA

[d]University of Michigan -Dearborn, Department of Health & Human Services, 19000 Hubbard Drive, Fairlane Center South, Dearborn, MI 48126, USA

[e]Michigan Technological Research Institute, Michigan Technological University, 3600 Green Road, Suite 100, Ann Arbor, MI 48105, USA

[f]Future Insight Consulting, LLC, Detroit, MI 48201, USA

[g]Detroiters Working for Environmental Justice, 4750 Woodward Ave, Detroit, MI 48201, USA

Corresponding author: Patricia D. Koman, Ph.D., MPP, Research Investigator, University of Michigan School of Public Health, Environmental Health Sciences Department, tkoman@umich.edu, 734-764-0552, 1415 Washington Heights, Ann Arbor, MI 48109, USA.

Patricia D. Koman, University of Michigan School of Public Health, Environmental Health Sciences Department, 1415 Washington Heights, Ann Arbor, MI 48109, USA

Frank Romo, University of Michigan Taubman College of Architecture and Urban Planning, 2000 Bonisteel Blvd, Ann Arbor, MI 48109, USA

Peter Swinton, University of Michigan Taubman College of Architecture and Urban Planning, 2000 Bonisteel Blvd, Ann Arbor, MI 48109, USA

Graciela B. Mentz, University of Michigan School of Public Health, Department of Health Behavior and Health, Education (at the time of the research), Current affiliation: University of Michigan, Medical School, Department of Anesthesiology, North Campus Research Center, Ann Arbor, MI 48109, USA

Ricardo F. de Majo, University of Michigan School of Public Health, Department of Health Behavior and Health Education, 1415 Washington Heights, Ann Arbor, MI 48109, USA

Natalie R. Sampson, University of Michigan -Dearborn Department of Health & Human Services, 19000 Hubbard Drive, Fairlane Center South, Dearborn, MI 48126, USA

Michael J. Battaglia, Michigan Technological Research Institute, Michigan Technological University, 3600 Green Road, Suite 100, Ann Arbor, MI 48105, USA

Kimberly Hill-Knott, Detroiters Working for Environmental Justice (at the time of the research) (Currently) Future Insight Consulting, LLC, P.O. Box 442537, Detroit, MI 48244, USA

Guy O. Williams, Detroiters Working for Environmental Justice, 4750 Woodward Ave, Detroit, MI 48201, USA

Marie S. O'Neill, University of Michigan School of Public Health, Department of Epidemiology and Environmental Health Sciences Department, 1415 Washington Heights, Ann Arbor, MI 48109, USA

Amy J. Schulz, University of Michigan School of Public Health, Department of Health Behavior and Health Education, 1415 Washington Heights, Ann Arbor, MI 48109, USA

[h]University of Michigan School of Public Health, Department of Epidemiology and Environmental Health Sciences Department, 1415 Washington Heights, Ann Arbor, MI 48109, USA

Introduction

Increased temperatures and heat waves can have significant effects on health, resulting in illness, hospitalization, or death (Basu and Ostro, 2008; Luber and McGeehin, 2008; O'Neill et al., 2009; Xu et al., 2012a). Increased hospitalization rates for respiratory and cardiovascular diseases can also occur as a consequence of extreme heat exposure (Ostro et al., 2009). A heat wave in Chicago killed over 700 people in Chicago in July 1995 (Semenza et al., 1999) and one in Europe killed more than 70,000 people in August 2003 (Robine et al., 2008). The Intergovernmental Panel on Climate Change (IPCC) identified vulnerability to climate change as a combination of susceptibility to geophysical, biological, and socioeconomic systems and differentials in ability to adapt or cope with the impacts of climate change (Intergovernmental Panel on Climate Change IPCC, 2013). Vulnerability to heat is linked to characteristics of places (e.g., heat island effect in urban areas), ambient temperature, and susceptibilities among people.

Young children, the elderly and people with respiratory or cardiovascular diseases, diabetes mellitus, obesity, or chronic mental health conditions are at greatest risk of experiencing adverse health effects during heat waves (Gronlund et al., 2016; Kovats and Hajat, 2008; Zanobetti et al., 2012). Occupational exposure to heat can also be a factor. Among the general population, some individuals have pre-existing conditions that reduce their ability to sense heat (e.g., diabetes mellitus) (Zanobetti et al., 2012), or the effectiveness of sweating to cool (e.g., obesity) (Chung and Pin, 1996). Those taking medications that affect thermoregulation, such as some medications for hypertension (Kenny et al., 2010), are also at heightened risk. Others may be unable or unwilling to drink fluids needed for cooling, including children under 5 (Xu et al., 2012b), the elderly or very frail (Gronlund et al., 2016; Zanobetti et al., 2012), and those whose religious practices call for periodic fasting or abstaining from water. Furthermore, certain socially vulnerable populations (e.g., those experiencing poverty, with limited education or living in substandard housing) are more at risk in heat events as they have fewer resources to mitigate the effects of heat (Gronlund, 2014a; Harlan et al., 2006; Reid et al., 2009). These populations may be more likely to also experience other environmental exposures in Michigan (Grier et al., 2019; Schulz et al., 2016).

Heat-related illness is expected to rise with increases in frequency and duration of hot days and nights (heat waves) and average temperatures due to climate change (Intergovernmental Panel on Climate Change IPCC, 2013). In the IPCC Fifth Climate Assessment, ensemble climate modeling (CMIP5) projects very likely increases in mean annual temperature over North America in the mid- and late-21st-century periods compared to 1961–1990 baseline (Ebi, K.L., J.M. Balbus, G. Luber, A. Bole, A. Crimmins, G. Glass, S. Saha, M.M. Shimamoto, J. Trtanj, and J.L. White-Newsome, 2018). These increases are projected to exceed 2°C as early as the mid-21st-century period and to exceed 4°C in the late-21st-century period (2071–2100). For daily-scale extremes, almost all areas of North America are projected to have very likely increases of at least 5°C in the warmest daily maximum temperature by the late-21st-century period, resulting in an increase in extreme heat events and corresponding increases in heat-related illnesses and deaths (Altman et al., 2012; Ebi, K.L., J.M. Balbus, G. Luber, A. Bole, A. Crimmins, G. Glass, S. Saha, M.M. Shimamoto, J. Trtanj, and J.L. White-Newsome, 2018). The IPCC recommended vulnerability mapping as a transitional adaptation policy in response to these changes (Campbell-Lendrum et al., 2014). Such mapping can help policymakers and the public understand potential health risks related to climate change. Mapping can also inform efforts to address impacts on public health: for example, by identifying locations that would benefit from cooling interventions or early warning systems and by informing efforts to address health inequities (Campbell-Lendrum et al., 2014).

Over the last decade, a global body of research has emerged that explores methods to create heat vulnerability indices and maps (Bao et al., 2015). For example, spatial heat vulnerability assessments have been conducted in Santiago, Chile, (Inostroza et al., 2016) and Toronto, Canada (Rinner et al., 2010) to identify exposures among those most vulnerable to heat stress in order to inform mitigation efforts. At the regional scale, Henderson et al. (2013) in their study of temperature and mortality in ecoregions in Canada report that populations in the coldest ecoregions were most sensitive to hot weather compared to the population of the hottest ecoregion, which was least sensitive (Henderson et al., 2013). In the U.S. at the national level, Reid et al. (2009) analyzed and mapped multiple vulnerability factors and provided a template for communities to make local heat vulnerability maps. At the state level, Nayak and colleagues (2017) examined factors in New York State related to urban heat island effects as well as population response and vulnerability characteristics (Nayak et al., 2017). These heat vulnerability index (HVI) studies suggest that mitigation and adaptation strategies can be usefully informed by identification of areas with the greatest vulnerability; physical land use attributes, exposure, and population characteristics contribute to overall vulnerability; and spatial scale and other risk factors are important considerations in these analyses.

Characterizing climate change-related exposures and vulnerabilities, especially regarding heat stress, can be particularly important in northern U.S. states such as Michigan in which the population, infrastructure, and practices to mitigate heat stress may not be well adapted (O’Neill, 2003; Sampson, 2014). Current temperature and precipitation trends and future projections suggest that the most likely impacts from climate change in Michigan are: extreme heat events, defined as prolonged periods of increased temperatures and humidity; changes in precipitation patterns, including excess rain leading to flooding; and extreme weather such as heavy snow and freezing rain (Ebi, K.L., et al., 2018; Intergovernmental Panel on Climate Change IPCC, 2013; Melillo and Yohe, 2014). These changes are already affecting public health in Michigan (Climate Change in the Midwest A Synthesis Report for the National Climate Assessment, 2014). The Michigan Department of Health and Human Services has identified five priority climate-related health outcomes in the state: heat related illnesses, respiratory diseases, waterborne diseases, vector-borne diseases, and injuries, including carbon monoxide poisoning (Cameron, L., A. Ferguson, R. Walker, D. Brown, 2015). Michigan is a populous state with racial/ethnic and income disparities in exposure to other environmental contaminants (Grier et al., 2019; Schulz et al., 2018). In surveys of local public health officials and local planning officials, Michigan's local governments report being under-prepared for the consequences of climate change and lacking necessary tools (Maibach et al., 2008; Norton et al., 2018; White-Newsome et al., 2014).

To better prepare communities and inform health decisions, the National Academy of Sciences recommends cumulative environmental risk frameworks because populations can experience multiple environmental exposures (NAS, 2017; National Research Council, 2009). California has been a leader in cumulative risk frameworks and recently implemented a third version of their cumulative exposure index in the Cal EnviroScreen tool (Huang and London, 2012; Knowlton et al., 2009; Liévanos, 2018; Morello-Frosch et al., 2011; Solomon et al., 2016). In addition to developing cumulative environmental approaches, California legislation requires the use of these frameworks to designate and provide funds from permit fees to environmentally disadvantaged communities, defined as those in the top 25% of cumulative exposure and population vulnerabilities scores pursuant to Senate Bill 535 (De Leon, Chapter 830, Statutes of 2012) and Assembly Bill 1550 (Gomez, Chapter 369, Statutes of 2016). Cal EnvironScreen uses a cumulative exposure framework, developed via multiple geospatial layers that are aggregated to identify the areas with the highest relative exposures in California. However, at this time, Cal EnviroScreen v3.0 does not contain a heat vulnerability index layer (Faust et al., 2017; Liévanos, 2018). Recognizing the public health impact of heat, researchers (Morello-Frosch, 2015) have proposed methods for California that may be relevant to other areas, and in this paper we explore their application in Michigan.

Vulnerability to heat can vary across large regions due to geospatial and sociodemographic characteristics (e.g., poverty and race) (Reid et al., 2009). Heat stress vulnerability can be exacerbated by a number of factors such as: local land use (Ye et al., 2012); increasing temperatures; populations with deteriorating health, social isolation, or age characteristics that increase susceptibility to deleterious effects of heat. In Michigan, land cover by impervious surfaces, lack of tree canopy, minority racial status, age and advanced age-related infirmity, and low socioeconomic status have been reported to increase vulnerability heat stress (Gronlund, 2014b; Gronlund et al., 2019, 11; Gronlund CJ, Zanobetti A, Wellenius GA, Schwartz JD, and O'Neill MS, 2016).

Using the Cal EnviroScreen v2.0 as a cumulative exposure model and the specific heat vulnerability techniques used by Morello-Frosch and colleagues (2012), we created a HVI and geospatial tool (one component of the MI-Environment platform) for the state of Michigan focusing on heat stress, a priority health-related aspect of climate change impacts. The objectives of this research are (1) to identify geographic areas in Michigan that are more vulnerable to heat stress relative to other areas in Michigan and (2) to examine the geospatial location and quantitative extent of racial or socioeconomic inequities in exposure to these heat-related factors.

Applying techniques from California, the MI-Environment HVI combined three categories of vulnerability indicators -- Place, Temperature, and People -- in order to describe and assess spatial patterns in Michigan's overall heat stress vulnerability. Our long-term goal is to create a cumulative environmental exposure framework; in this paper, we focus specifically on heat stress vulnerability. Accordingly, the MI-Environment visualization tool can help communities prepare by identifying census tracts in Michigan with the most vulnerable residents and highest potential relative exposures. Public and private investment in mitigation or adaptation strategies can be focused more equitably on areas with the greatest vulnerability.

Data and Methods

Community Engagement

We worked with Michigan community leaders to formulate and address the central research questions of this analysis and to assure that the mapping tool was informed by multiple perspectives. Specifically, we developed a partnership agreement with a Michigan non-profit organization Detroiters Working for Environmental Justice, and we consulted with researchers from the Michigan Lifestage Environmental Exposures and Disease (MLEEaD) Community Engagement Core (CEC) during the hypothesis formulation and data selection process. In the analysis and outreach process, we presented the tool to the Stakeholder Advisory Board (SAB) for the MLEEaD CEC, which includes Detroiters Working for Environmental Justice, to solicit their input. The Detroiters Working for Environmental Justice, Michigan state agency, and health care representatives were interested in utilizing publicly available data and platforms to ensure widespread availability and to examine rigorously the distribution of HVI related to race and income factors. The use and interpretation of future climate modeling was strongly supported because although these data are publicly available, technical barriers to their analysis and interpretation prevent its accessibility to the community. Following development of the tool, we presented the preliminary tool at a Detroiters Working for Environmental Justice stakeholder event in Detroit. We also organized a Science Café, which is a technique intended to create a multi-directional and relatively informal discussion about the contemporary ideas of science that are impacting society (Ahmed et al., 2014). Detroit Hispanic Development Corporation, a member of the M-LEEaD SAB, hosted the MI Environment Science Café in Detroit in March 2016, with the goal of sharing the tool and obtaining additional community and expert user input on the maps and data visualization tool. Our Science Café involved scientists, public health and medical professionals, community members, government officials, and other interested parties; it featured brief presentations and refreshments, followed by a hands-on guided exploration of the MI-Environment visualization tool in a computer lab. Discussion and feedback on the visualization tool in this context informed the approach in the tool (version 2019) and our future plans for enhancement.

Indices and Mapping

We adapted the Morello-Frosch et al. approach from California to describe relative heat stress vulnerability in Michigan's census tracts (Morello-Frosch, 2015). Because these factors have been shown in previous studies to be related to heat-related morbidity and mortality in the upper Midwest (Gronlund, 2014b; Gronlund et al., 2019, 11; Gronlund CJ, Zanobetti A, Wellenius GA, Schwartz JD, and O'Neill MS, 2016), we used three primary geospatial components to create heat stress vulnerability indices (HVI): physical features including tree canopy and impervious surface; locations of projected future temperature exposures; and location of populations vulnerable and susceptible to heat stress. As shown in Table 1, we gathered data on 9 components characterizing these three indices. These components were averaged or allocated to the census tract level to form an aggregated HVI and maps for the State of Michigan.

Using publicly available data for Michigan, we obtained data from the 2011 National Land Cover Database (NLCD) (Multi-Resolution Land Characteristics Consortium, 2011), the US Census Bureau (2008–12) (U.S. Census Bureau, 2010) and the Behavioral Risk Factor Surveillance System (BRFFS) (Centers for Disease Control, 2010), in addition to outputs from ensemble climatic modeling [Coupled Model Intercomparison Project Phase 3 (CMIP3)] (Melillo, J.M., et al., 2014).

In Table 2 we describe and compare the data and calculations used in the California method and the MI-Environment analyses; some modifications were made for Michigan index components. Where more recent data were available, we used updated sources. For instance, we used a more recent version of the NLCD (2011) for the two Place components. We did not have access to downscaled climate modeling or to the specific variables to represent Temperature; thus, we used available ensemble modeling from the Third National Climate Assessment Coupled Model Intercomparison Project (CMIP3). We used more recent American Community Survey data (2008–12).

We added an additional component of age-adjusted obesity prevalence because obesity is understudied but it contributes to susceptibility to heat stress. Individuals with obesity are more physiologically vulnerable to heat because obesity is a known risk factor for problems with thermoregulatory functions (Bricknell, 1996, 1995; Grogan, 2002). Heat-dissipating and heat-sensing abilities may be impaired among the obese. Additionally, it is more difficult for obese people to lower their body temperature because of the difficulty transferring heat from core body to the skin given that fat is an effective thermal insulator (Dehghan et al., 2013a). Moreover, obese individuals experience reductions in the ability to sweat as a means of cooling the body because of a smaller ratio of body surface area to body mass compared to normal weight persons of the same height (Dehghan et al., 2013b). In Michigan, obesity prevalence differs from California and is above national averages in many Michigan communities, and the geospatial patterns are not as concentrated in urban areas in Michigan as other vulnerability factors. As a result, we included this factor that was not part of the California indicators.

Young children and those in poverty can also be vulnerable to heat stress. CalEnviroScreen 2.0 and the national EJ-Screen indices included factors related to both children and poverty and geospatial data were readily available from the US Census Bureau. Thus, we included these two factors in our People index. Children are physiologically more susceptible to the effects of heat (Bennett and Friel, 2014; Bunyavanich et al., 2003; Xu et al., 2012b); accordingly, we included a measure of percent children < age 5 (Table 2). In addition, people experiencing poverty have less of an ability to control or mitigate exposures to heat or factors that contribute to heat stress vulnerability (Bao et al., 2015; Curriero et al., 2002; Naughton et al., 2002). We included the percent of the population in a census tract below the poverty level (Table 2). We considered other indicators, such as mental health conditions, medication use, and occupational exposure; however, adequate quality geospatial data sets were not readily available.

Using the data described in Table 2, we calculated the three index categories (described in more detail below) with ArcGIS (v.10.3) and then created an aggregate HVI score for each census tract by averaging the three categories and normalizing the final HVI for values between 0 – 100. The HVI was mapped by census tract across Michigan to display spatial patterns using quintiles of HVI scores. Larger scores indicate relatively higher vulnerability to heat stress.

Place

The Place index is comprised of the average of two factors: tree canopy coverage and impervious surface data. The California model we emulated also used these two indicators, datasets and averaging but used the 2001 NLCD which was the most current year available at the time.

We obtained percent tree canopy (subtracted from 100 to convert to lack of tree canopy) i and percent impervious surface data from the 2011 NLCD at a 30m resolution raster data set (Multi-Resolution Land Characteristics Consortium, 2011). We geo-located the raster data to each census tract and averaged the data within census tracts to create one value for each census tract. For the two factors, using ArcGIS we calculated and then averaged percent lack of tree canopy and impervious surface coverage to create an aggregate Place score for each census tract and normalized the Place index from 0–100. Larger values indicate more heat exposure due to less tree canopy and/or a higher percentage of impervious surfaces.

Temperature

Using decade or longer time horizons to reflect climate, the Temperature index combines projected future average or seasonal temperatures and projected future extreme temperatures to gauge potential exposures to the community. As shown in Table 2, the California model we were emulating used finer scaled modeling from Cal ADAPT and the National Center for Atmospheric Research’s downscaled Community Climate System Model, Scenario B1, ensemble average. Factors such as change in number of warm nights were not available for Michigan; accordingly, we used two factors to represent future average temperature weighting the number of hot days factor more heavily to simulate the California approach. We performed several exploratory analyses using historic 30-year temperature averages for a more precise temperature profile and examining sensitivity to other weighting schemes for both temperature measurements and modeling (results not shown).

The Temperature index model output was obtained from the Great Lakes Integrated Sciences Assessment based on Coupled Model Intercomparison Project Phase 3 (CMIP3) climate projections at the spatial resolution of Michigan’s 10 climatic divisions (Hayhoe, Katharine, 2013; Melillo, Jerry M., Terese (T.C.) Richmond, and Gary W. Yohe, 2014; National Oceanic and Atmospheric Administration (NOAA), 2016) For each indicator, the data were geo-located and converted to a raster format in ArcGIS. The raster values were then averaged across each census tract and indexed on a scale ranging from 0 to 100. Each census tract had two values: days-over-90-degrees and average seasonal temperature. Finally, a weighted average index, normalized from 0–100, was constructed by weighting the days-over-90-degrees index more heavily (0.75) than the average seasonal temperature index (0.25) to more closely approximate the three California indicators. Larger values indicate more heat exposure due to higher expected climatic temperatures.

People

The People index represents population susceptibility and vulnerability using five metrics by census tract for the percentage of the population who are one of the following: over 65 years old and living alone; have no access to a personal vehicle; are obese, defined as having a body mass index (BMI) of ≥ 30.0 kg/m^2; are under 5 years old; or are experiencing poverty.

The California model we were emulating was situated in a more fully formed cumulative environmental exposure platform that included two factors in the HVI layer and additional distinct layers of social vulnerability. The California model had two factors from the U.S. Census: percent elderly population living alone and percent lack of vehicle ownership. Age, obesity, and poverty were included in our final People Index (Table 2) because of their presence in the California cumulative index and the impact these components have on a population's ability to mitigate the effects of heat (Chung and Pin, 1996; Gronlund et al., 2016; Kenny et al., 2010; Kovats and Hajat, 2008). We included these factors in an additive fashion although the California EnviroScreen approach hypothesized a multiplicative effect of factors such as poverty.

Census tract level data were obtained from the 2008–2012 American Community Survey (ACS) as indicated in Table 2 (U.S. Census Bureau, 2010). Obesity prevalence data were obtained at the county level from Behavioral Risk Factor Surveillance System conducted by the Centers for Disease Control and Prevention (Centers for Disease Control, 2010). Because the county is the smallest available geographical unit for obesity prevalence, we assigned the county level value to all the census tracts within a county. Each of the five factors were then normalized on a 0–100 scale. Finally, we averaged the percentages of people over 65 years old and living alone, people lacking access to a personal vehicle, people under 5 years old, and people living under the poverty line with the normalized obesity data to create a People Index score for each census tract and normalized this index on a scale of 0–100. For the inequality assessment, we also created an analytical version of the People Index (and resulting Analytic HVI) excluding the poverty indicator, as described below.

Heat Stress Vulnerability Index

To assemble the MI-Environment's HVI, we averaged the Place, Temperature, and People indices for each census tract in Michigan and normalized this aggregate index on a scale of 0–100. We created quintiles to map the relative heat stress vulnerabilities for all tracts in Michigan, with quintile 1 representing the census tracts with the lowest relative scores and quintile 5 representing census tracts with the highest relative scores on the HVI.

Indicators of Population Vulnerability

We obtained data for factors related to population vulnerability at the census tract level from the 2008–2012 ACS for 7 factors to examine the extent to which heat stress indices were equally distributed (Schulz et al., 2016). We obtained the following 7 population characteristics for Michigan: percent people of color, percent people over 25 years with less than a high school education, percent residents living in rented households, median housing value, percent below poverty line, percent below twice the poverty line, and a measure of linguistic isolation: those living in households where no one over the age of 18 speaks English.

Analysis Methods

We created descriptive statistics and examined Pearson correlations among variables and indicators to measure the extent to which exposures to heat stress factors are associated across census tracts in Michigan. Census tracts in Michigan have varying racial compositions, socioeconomic and age-related vulnerabilities. We drew on techniques described by Su and colleagues (2009) to assess inequalities in the distribution of cumulative environmental hazards (Su et al., 2009). Our research objective was to describe the extent to which the HVI might be unequally distributed according to percent of population below the poverty line in a census tract, for example, with lower income census tracts exhibiting disproportionately higher HVI scores. In order to address this question and because our overall aggregate HVI contains a measure of poverty in the People index, we first constructed an analytic index that excluded the percent of population in a census tract experiencing poverty (called Analytic People index). In the analyses reported below, we used the Analytic People index alone, and in combination with the Place and Temperature indices to form the Analytic HVI (excluding poverty).

Next, as illustrated in Figure 1, we plotted at the census tract level the cumulative share of the Analytic HVI against cumulative proportion of the population, ordered by area-based indicators of population vulnerability, including education, socioeconomic status, and proportion people of color. The vertical axes on these graphs reflect the exposure of interest (e.g., Analytic HVI) and the horizontal axes are population indicators of vulnerability (e.g., percent population in a census tract below the poverty line). In these plots, the horizontal axes are shown with increasing levels of advantage (e.g., census tracts with highest to lowest percentage of people below the poverty line). Equality is defined as the 45-degree 1:1 line or identity line; that is, in the case in which each population across the spectrum of vulnerability indicator has the same share of the exposure to the environmental hazard, the curve coincides with the diagonal equality line (Figure 1, red dotted line). If the curve lies above the equality line, the inequality index is negative, indicating that more disadvantaged groups encounter greater environmental exposure or vulnerability burdens (Figure 1, solid blue curve). If the curve lies below the equality line (Figure 1, dashed curve), then more advantaged groups carry a higher proportion of environmental exposure burdens. A summary measure of inequality is defined as twice the area between the curve and the equality line:

$$I = 1 - 2\int_{1}^{n} e(s)\, ds$$

This measure gives a quantitative summary of inequality among groups based on indicators of population vulnerability. In order to assess the integral we used the “trapezoidal rule” (Atkinson, 1989) to approximate the region under the graph of the function e(s).The value of 0 is the lowest level of inequality where all groups have same exposure to the variable of interest. When the inequality score is negative, it indicates that less advantaged groups bear a disproportionate burden of exposure: The highest level of inequality, where disadvantaged groups bear the burden of all the exposure is −1 (Kakwani et al., 1997).

Using the approach described above, we examined to what extent heat stress vulnerability is equally distributed across census tracts with varying sociodemographic vulnerability indicators. Accordingly, we examined the extent to which the analytic HVI was (un)equally distributed by the following 7 population characteristics at the census tract level: percent people of color, percent people over 25 years with less than a high school education, percent residents living in rented households, median housing value, percent below poverty line, percent below twice the poverty line, and a measure of linguistic isolation those living in households where no one over the age of 18 speaks English.

The inequality curve is sensitive to change in several factors. The curve depends on the distribution of the individual factor or cumulative environmental index (e.g., Analytic HVI), the distribution of the vulnerability factor used to describe the population, and their joint covariation. The inequality curve is also sensitive to the level of aggregation, which varies between the three indices especially if there are not a large number of aggregation units such as the Temperature index.

To further explore geospatial patterns, we also conducted sensitivity analyses to assess the extent to which state-wide results were influenced by Michigan’s largest metropolitan area of Detroit. Specifically, using Tukey’s pairwise comparisons, we tested for the tri-county Detroit area alone and the rest of the state with the tri-county metro Detroit area data removed at the 95% confidence level. We also stratified by rural and non-rural census tracts to determine the extent to which this factor might be confounding our results. We also performed descriptive statistics and inequality curves with the geographic stratifications (see supplemental materials).

Results

We summarize nine variables in three component indices in Michigan census tracts in Table 3. The Place index has the widest distribution with a mean of 46.5 (S.D. 20.2), compared to the Temperature index with a mean of 65.2 (S.D. 15.0), and the People index 43.8 (S.D. 13.8).

The Place index is highly correlated with aggregate HVI (87%, $p<0.0001$); the Temperature index is also highly correlated with HVI (73%, $p<0.0001$). Pairings of (1) Temperature and People and (2) Place and People indices are less correlated (8.1% and 27%, respectively).

The resolution of the original indicators (e.g., continuous raster data, 10 climatic divisions, census tract, and county level) can be observed in the resulting spatial patterns of the indices. We present maps of each index and the combined HVI.

Figure 2 shows the Place Index distribution of census tracts, rank-ordered by land use characteristics observed by remote sensing. These data have finer spatial resolution throughout the state compared to other components that have coarser resolution. The Place index shows urban areas distinctly. The more rural upper peninsula and northern portion of the lower peninsula have more tree canopy and less impervious surface based on satellite measures and evince lower place-based heat stress vulnerability, compared to more urban and southern areas of the peninsula. Using Tukey's pairwise comparisons, the means of the Place index are different in the Tri-County Detroit metro area compared to the rest of the state at the 95% confidence level (see Supplemental Tables S-5 and S-6).

The Temperature index (Figure 3) is based on climatic modeling with lower spatial resolution (10 climatic divisions) that appears in broad bands. Because of the underlying spatial resolution, this index has less variability than the other two indices. Due to the more homogenous nature of temperature as well as the spatial resolution of the modeling, we would expect outcomes in census tracts to be more correlated with neighboring census tracts than for the other indicators. The Temperature index shows a smooth pattern with future higher exposures in the southern portion of the lower peninsula with scant demarcation of urban areas nor effects near the Great Lake shores. Based on pairwise comparisons, the means of the Temperature index are different in the Tri-County Detroit metro area compared to the rest of the state at the 95% confidence level (see Supplemental Tables S-5 and S-6).

Some of the largest climatic temperature changes will occur in areas that are also likely to have further heat island effects due to impervious surface and lack of shade from tree canopy. This can be especially important in geographic areas such as major cities in Michigan.

The People index (Figure 4) is based on historic census and survey data available at the census tract and county level (BRFFS 2010 obesity prevalence). The People index is generally distributed throughout the state of Michigan. Based on Tukey's pairwise comparisons, the means of the People index are not different between the Tri-County Detroit area and the rest of the state of Michigan, although four of the components show difference (See Supplement Table S-5 and S-6). Specifically, there are differences between the census tract means of obesity prevalence, percent aged 65 and older and alone, percent no personal transportation, and percent below the poverty line, but mean of percent children ≤ 5 years did not differ at the 95 % confidence level.

The HVI index (Figure 5) averages the three previous indices, showing overall relative vulnerabilities by census tract. Highest scores are concentrated in the urban areas of the lower peninsula. The census tracts with the highest scores are in Detroit, which is also the state's largest urban area. The more rural upper peninsula evinces the lowest relative vulnerability. Based on pairwise comparisons, the means of the HVI are different in the Tri-

County Detroit metro area compared to the rest of the state at the 95% confidence level (see Supplemental Tables S-5 and S-6).

Inequality Analysis

We observed consistent results at the statewide level from analyses quantifying the extent of equality of the aggregated Analytic HVI, and the three sub-indices of Place, Temperature, and Analytic People in Michigan. Inequality curves for the aggregate Analytic HVI, as well as for each of its three components (Place, Temperature and Analytic People indices) are summarized in Table 4 and in Figures 6–8.

When assessing inequality of the aggregate Analytic HVI compared to the 7 vulnerability factors at the census tract level (e.g., percent people of color, percent below poverty line, Table 4), we observed the greatest inequality in heat vulnerability in relation to median household value (C = −0.142 [95% CI −0.134,−0.150]) (Figure 6a), followed by the percent people of color (C = −0.115 [95% CI −0.108,−0.122]) (Figure 6b). Although different in magnitude, all categories of social disadvantage except linguistic isolation (Figure 7b), showed significant differences from what is expected under equality. In Michigan at the statewide level, census tracts with lower median home values, higher proportions of people of color, greater proportions of people living below the poverty line and below two times the poverty line, and lower levels of education are disproportionately likely to experience heightened heat-related vulnerability. Census tracts in Michigan with higher percent of linguistic isolation showed a positive but not significant deviation from equality in heat-related vulnerability.

Given the particular importance of the City of Detroit in state-wide analysis we conducted sensitivity analyses of inequality using two different clustering of census tracts: 1) Tri-County Detroit Metro Area (n=1,166 census tract) and 2) Without Tri-County Detroit Metro or the rest of Michigan (n=1,647 census tracts). The means for the Place and Temperature indices are different between the Tri-County Detroit Metro and the rest of Michigan at the 95% confidence level. Although the means of the Analytic People index did not vary over this geographic split, the components of obesity prevalence, percent elderly living alone, and percent with no personal transportation differed between Tri-County Detroit Metro and the rest of Michigan (See Table S-6). The Detroit metro-specific analysis (Supplement Tables S-2 – S-6) showed that median home value (−0.171 [95% CI −0.163,−0.180]), the proportion of residents living twice below the poverty line (−0.145 [95% CI −0.137,−0.153]), and the proportion of residents living below the poverty line (−0.134 [95% CI −0.126,−0.141]) had the highest inequalities with Analytic HVI. All inequality curve analyses for Detroit metro area showed that heat stress vulnerability was higher in census tracts with greater proportions of people of color, and heightened concentrations of poverty.

Even without Detroit's influence, our inequality curve analysis shows that Analytic HVI is disproportionately distributed along racial and socioeconomic lines in the rest of Michigan, but to a smaller extent (see Supplement Tables S-5 – S-6 and Figures S1 – S-20). Without Detroit, the same indicators as statewide had the most unequal distribution with heat stress: median house value (−0.102 [95% CI −0.095,−0.109]), the proportion of residents living below twice the poverty line (−0.081 [95% CI −0.075,−0.087]), and the proportion of residents living below the poverty line (−0.074 [95% CI −0.068,−0.081]). The aggregate Analytic HVI shows inequalities between heat stress vulnerability and census tracts with higher percent of people of color (−0.056 [95% CI −0.050,−0.061]), the proportion of residents living below the poverty line, the proportion of residents living twice below the poverty line, the proportion of residents renting their residence (0.071 [95% CI −0.065,−0.077]), lower median home value, and the proportion of the population over age 24 without a high school diploma (−0.068 [95% CI −0.062,−0.074]) at a $p<0.001$ level.

We also stratified by rural status. Among the smaller number of rural areas tracts (n=466), there is less evidence of inequalities; among non-rural areas (n=2,347), all factors except for linguistic isolation were significantly different from equality (see Supplement Table S-4 and Figures S-21 – S-40).

Discussion

Around the world, community, academic, and government leaders are working to identify strategies for assessing cumulative environmental impacts that may be integrated into policies to enhance health, including in the U.S. The MI-Environment platform for Michigan is responsive to these ongoing efforts. Specifically, MI-Environment was developed as an analytical and visualization tool based on publicly available data to inform statewide and local efforts to adapt to climate change in Michigan. Using techniques from California, we created a relative heat vulnerability index and geospatial tool (one component of the MI-Environment platform) for the state of Michigan for relative heat stress vulnerability. The objectives of this research were (1) to identify geographic areas in Michigan that are relatively more vulnerable to heat stress and (2) to examine the geospatial location and quantitative extent of racial or socioeconomic inequities in exposure to these heat-related factors.

Accordingly, as proof of concept, we demonstrated that data are publicly available to create HVIs. Our geospatial analyses illuminate varied spatial patterns of relative vulnerability of census tracts in Michigan to heat stress factors depicted in the maps (Figures 3–5). In Michigan, more densely populated urban areas are more vulnerable to heat stress than less densely populated areas; based on our analyses, areas near Detroit, Flint, Saginaw, Grand Rapids, Muskegon, and Lansing have higher values of heat stress vulnerability.

The three indices of Place, Temperature, and People have different spatial resolution and ranges of values in the underlying data. Interpretation of patterns of the aggregate HVI should acknowledge the effects of heterogeneity in the underlying data. For example, the raster data for the Place index have finer spatial resolution throughout the state compared to other components that have coarser resolution. Consequently, the influence of Place may be an artifact of the spatial resolution and range, which would merit further exploration with finer resolution Temperature index modeling, for example. Additional strengths and limitations are discussed below.

With respect to our second research objective, inequalities in exposure were identified for Michigan. The aggregate Analytic HVI (excluding poverty), when compared to 7 sociodemographic vulnerability indicators, was significantly different than what is expected under equality conditions. For example, Michigan census tracts with a higher percentage of people of color had larger exposures to Analytic HVI ($p<0.001$). Similar results were observed for Michigan census tracts with higher percentage of people experiencing poverty. The directionality of these results remained constant when the Tri-county Detroit Metro area was excluded, although the degree of inequality was smaller. The Tri-county Detroit area had some of the highest HVI values and some of the largest inequalities. Inequalities related to median housing values deserve further exploration because of the connection between low housing value and factors related to the heat profile of the residence (e.g., insulation, presence of air conditioning, neighborhood amenities). Inequities have been identified in other environmental factors (Jesdale Bill M. et al., 2013; Woodruff et al., 2003) and in Michigan (Kannan et al., 2010; Schulz et al., 2016). Our framework quantitatively examines inequalities in the distribution of cumulative heat exposure in an integrated manner. Our future research goal is to situate this information in a cumulative environmental exposure framework (Kuruppuarachchi et al., 2017).

Strengths

By adapting methods from California to Michigan, this analysis offers several advantages. The MI-Environment tool provides a statewide index of publicly available information to help communities and decision-makers in Michigan understand which areas at the census tract level may be the most vulnerable so that more study, resources, and action can be directed toward determining and implementing appropriate solutions. The multiple dimensions that contribute to the vulnerability index offer added insight into the makeup of Michigan from built environment, climatic and social perspectives. Our HVI construction and analysis shows the extent to which physical factors such as land use factors or projected climatic temperature exposures correspond with potentially susceptible populations. Our method addresses inequality and some aspects of cumulative effects together, which facilitates a more robust understanding sources of inequalities and strategies to address them. The analyses help identify regions for more detailed examination of localized patterns and drivers of those inequalities.

This analysis is novel because it uses climate modeling and provides future projections. The ensemble climate modeling we used has been evaluated and characterized elsewhere, and although these evaluations did not focus specifically on the Midwest, the ensemble temperature means across all models show that over most of the Midwest, temperature bias is slightly negative (Climate Change in the Midwest A Synthesis Report for the National Climate Assessment, 2014). Data collected for this study come from sources for which uncertainties are characterized and which are relatively easy and inexpensive to access, allowing the analysis to be built upon or replicated in community-participatory research settings.

Limitations

We were not fully able to replicate the California analyses due to lack of readily available data such as climate modeling projections resolved to the census tract level for Michigan or the output of particular indicators (such as the warm night indicator). We updated to the most recent year available (e.g., for the Place index, the California analysis used data published in 2001 and MI-Environment used 2011 NLCD data). Moreover, the California model we emulated was situated in a more fully formed cumulative environmental exposure platform (Cal EnviroScreen) that included both more extensive statewide community engagement as well as additional data and distinct layers of social vulnerability. We included population susceptibility factors in an additive manner although a multiplicative effect for factors such as poverty might be more appropriate; during a validation step both approaches could be tested but this was beyond the scope of our analyses. Our analyses were further limited by lack of readily available geospatial datasets regarding mental health conditions, medication use, and occupational exposure.

Although including a climatic projection is an advantage in a situation in which the historic climatic temperatures may not predict future potential for exposures, there are limitations with this approach. First, difficulties in interpretation may arise from combining projections with other historically observed geospatial or demographic data which do not reflect future change. Utilizing future temperature projections creates barriers to validation with past heat-related health observations; however, the elements presented here have been studied relative to the role in morbidity in other areas especially for tree canopy and impervious surfaces, although not always associated with health risk (Gronlund, 2014a; Uejio et al., 2011; Zanobetti et al., 2012). The available modeled climate data have limitations for use at the census tract level (Climate Change in the Midwest A Synthesis Report for the National Climate Assessment, 2014). For example, data are only available for the ten climatic divisions in Michigan, the influence of the Great Lakes is not considered, and emissions scenarios in which the goals of the Paris Climate Accord are achieved are included. Finer scale historic temperature data shows the localized effect of the lake shores.

Other geospatial issues limit our analysis. Spatial scales besides the state-level should be considered and the relative rankings are dependent on the spatial boundary selected. The spatial scales of the factors comprising the HVI have limitations. For instance, population susceptibility indicators such as obesity prevalence were only readily available at the county level, which we disaggregated to the census tract level. Averaging raster data (for Place and Temperature variables) over census tracts results in the loss of extremes, which can be an issue in smaller cities that combine urban and suburban areas. In addition, the combination of a variety of units can make interpretation of the HVI value to be difficult. The inequality curve is sensitive to the level of aggregation used to describe the population, the distribution of the factors and their covariance, and the number of population-based units, in this case census tracts. The inequality assessment is limited to comparison within the U.S. context.

Conclusion

To respond to urgent health challenges related to climate change, community, academic, and government leaders are working to identify strategies for assessing cumulative environmental impacts that may be integrated into policies to enhance health, including in Michigan. The statewide MI-Environment Heat Stress Vulnerability Index shows different patterns for the 2,767 census tracts in Michigan for three underlying elements: Place, Temperature, and People. Each category has a differently patterned spatial distribution, yet urbanized areas are relatively more vulnerable to heat stress in Michigan, and inequalities based on race and socioeconomic status were identified. In Michigan, census tracts with lower median home values, higher proportions of people of color, and greater proportions of people living below the poverty line and below two times the poverty line are disproportionately likely to experience heightened heat-related vulnerability. This analysis showed that climate vulnerability disproportionately affected impoverished communities (−0.101 [95% CI −0.094, −0.107]) and communities of color (−0.115 [95% CI −0.108, −0.122]). These effects were strongest in the Tri-county Detroit Metro area, but inequities were similar in other parts of the state. The MI-Environment maps can help communities and decision makers to visualize the most vulnerable areas statewide so that more resources can be directed toward determining appropriate solutions. Strengths of this index are the inclusion of climatic modeling for future average temperature projections and publicly available data which can be replicated in other states. Limitations include the geographic scale of the future climate projections (output at only 10 climatic regions), lack of inclusion of the Great Lakes in that modeling, and selection of a future scenario in which major emission reductions are estimated which are no longer consistent with current federal policy. The lack of validation with health data is a limitation, which can be challenging for an index with a future projection. In spite of these limitations, the MI-Environment visualization tool can help communities prepare for climate change and resolve inequities by identifying census tracts with the most vulnerable residents and highest potential exposures.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights:

1. MI-Environment identifies census tracts most vulnerable to heat stress in Michigan.
2. Michigan's densely populated urban areas are especially vulnerable to heat stress.
3. We identified inequalities in heat vulnerability based on race and SES in Michigan.
4. Inequities were strongest in the Detroit Metro area with similar patterns statewide.
5. Finer spatial scale needed for climate projections to inform exposure patterns.

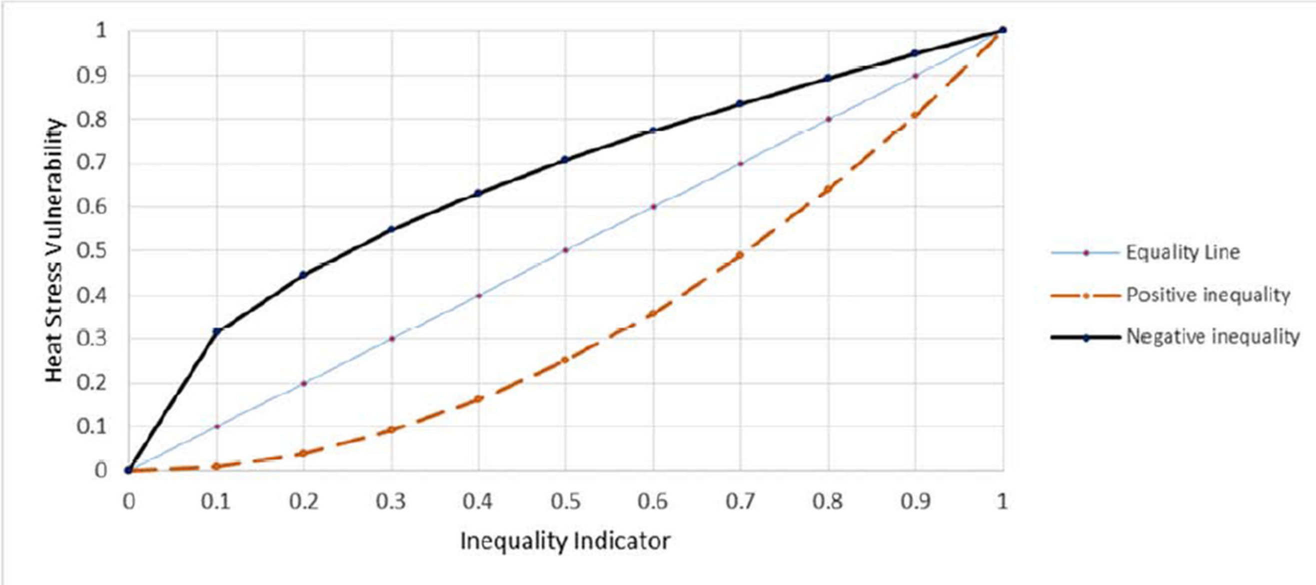

Figure 1:

Inequality Curve: a positive curve (below the equality line, dashed curve) indicates census tracts with lower percentage shares of heat stress vulnerability. A negative curve (above the equality line, solid curve) indicates census tracts with higher percentage shares of heat stress vulnerability. The equality line (dotted 1:1 identity line) indicates where there is no environmental inequality related to the share of heat stress vulnerability at the census tract level.

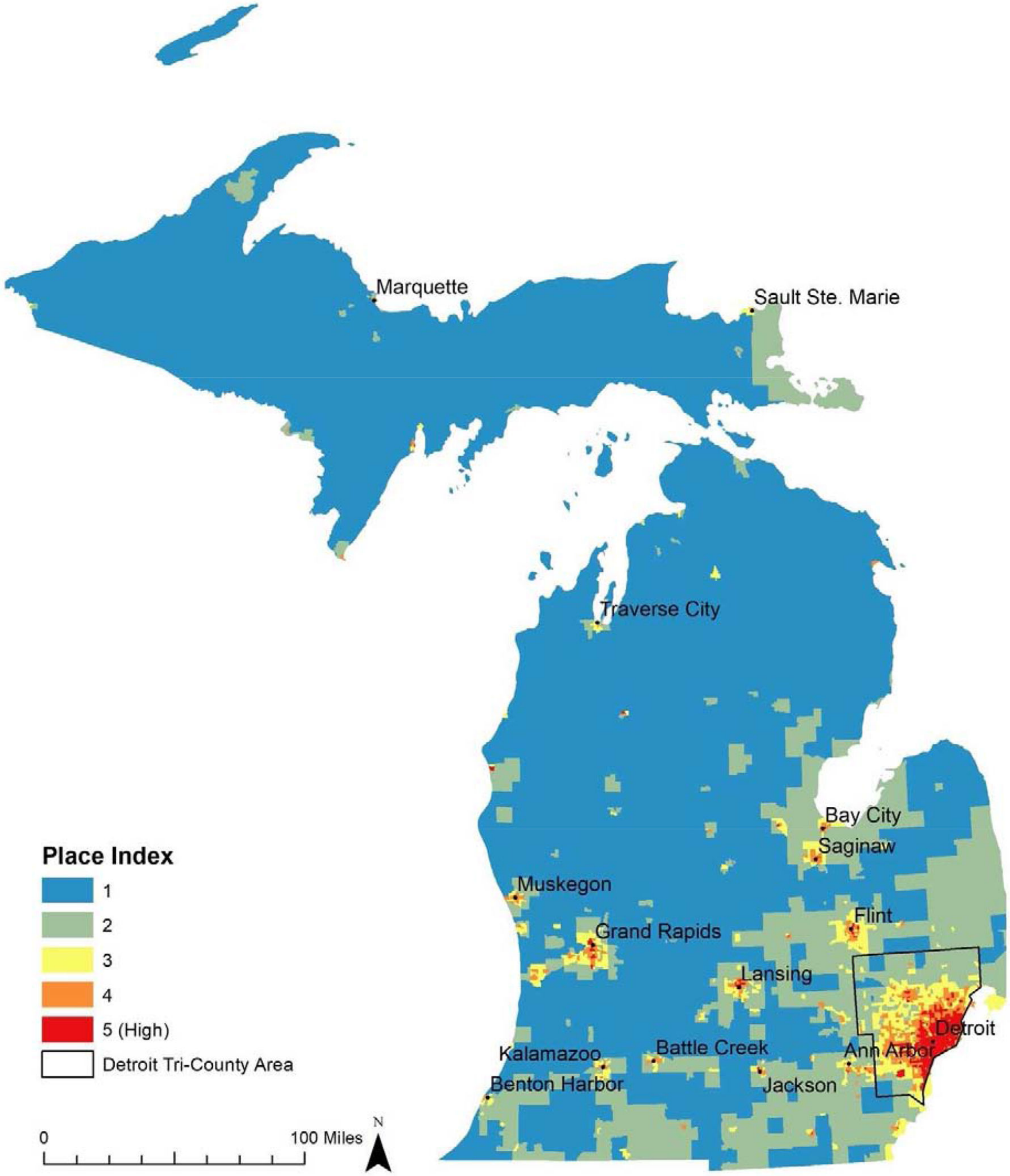

Figure 2. Quintiles of Place index by census tract in Michigan.

The Place index is comprised of the average of the Lack of Tree Canopy Coverage and Impervious Surface Coverage components.

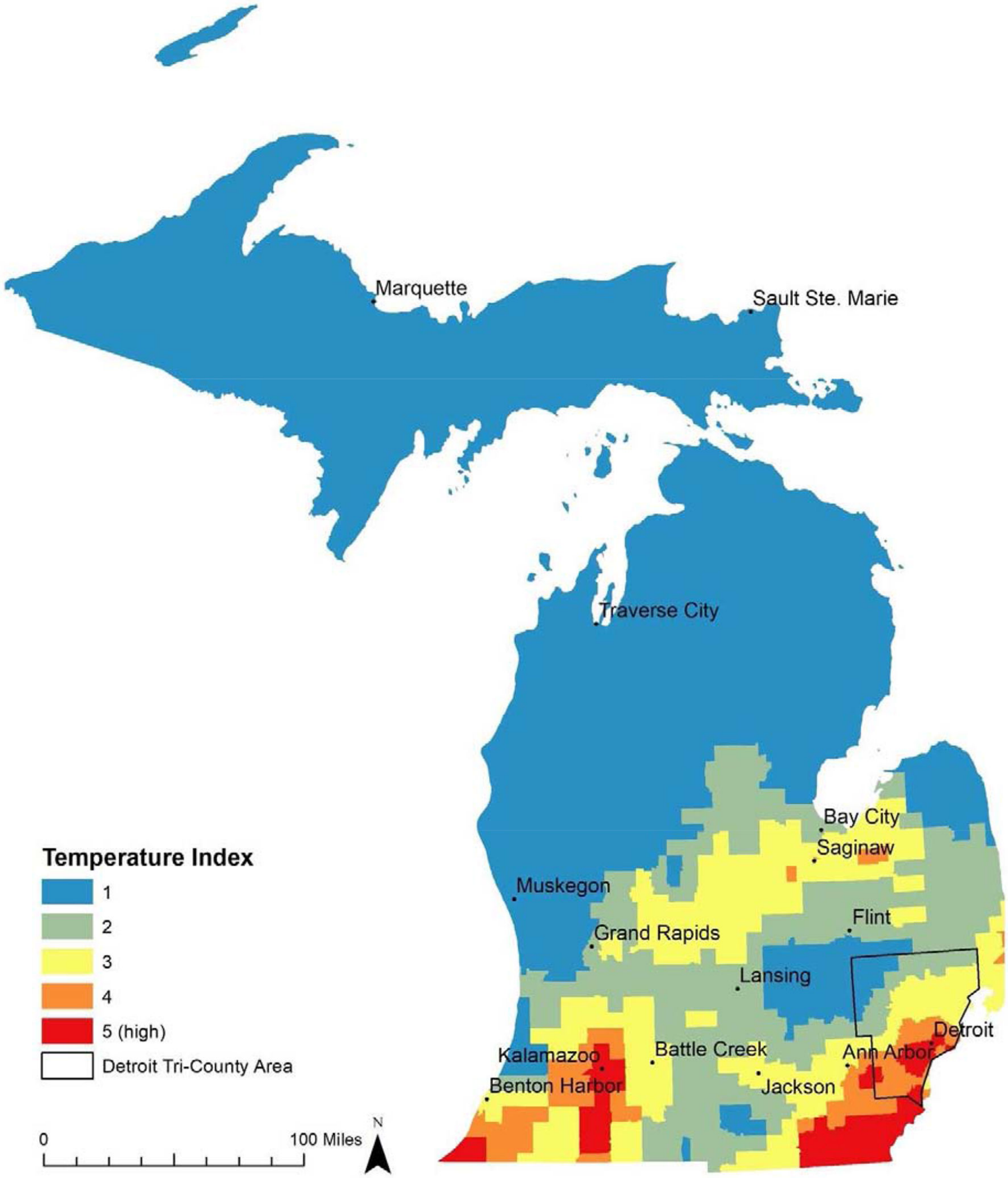

Figure 3. Quintiles of Temperature index by census tract in Michigan.

The Temperature index is a weighted average of the Average Seasonal Temperature and the Extreme Heat components.

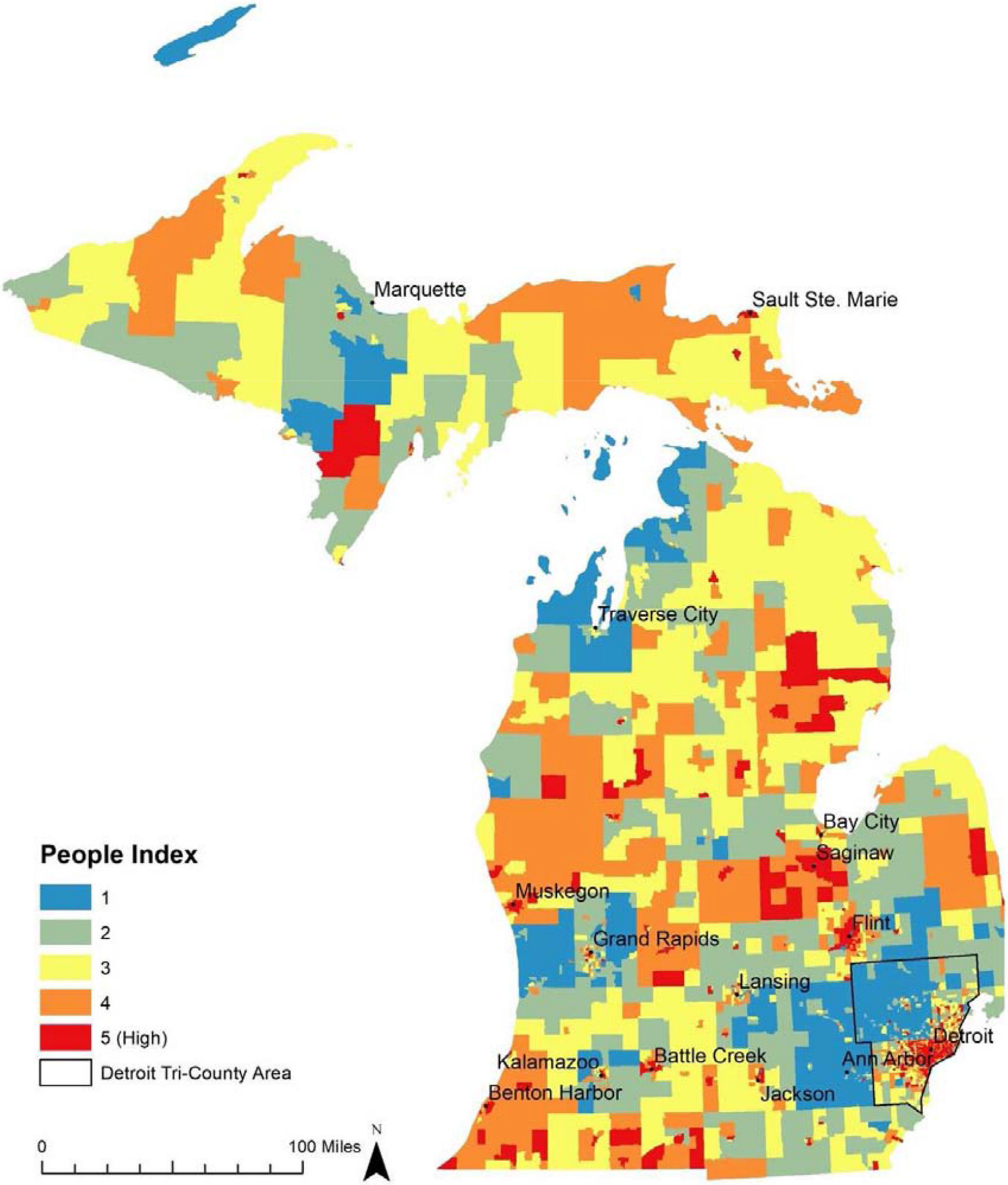

Figure 4. Quintiles of People Index by census tract in Michigan.

The People index is comprised of the average of five components: percent age > 65 years and living alone, percent no car ownership, age-adjusted obesity prevalence, percent age < 5 years , and percent population below poverty line.

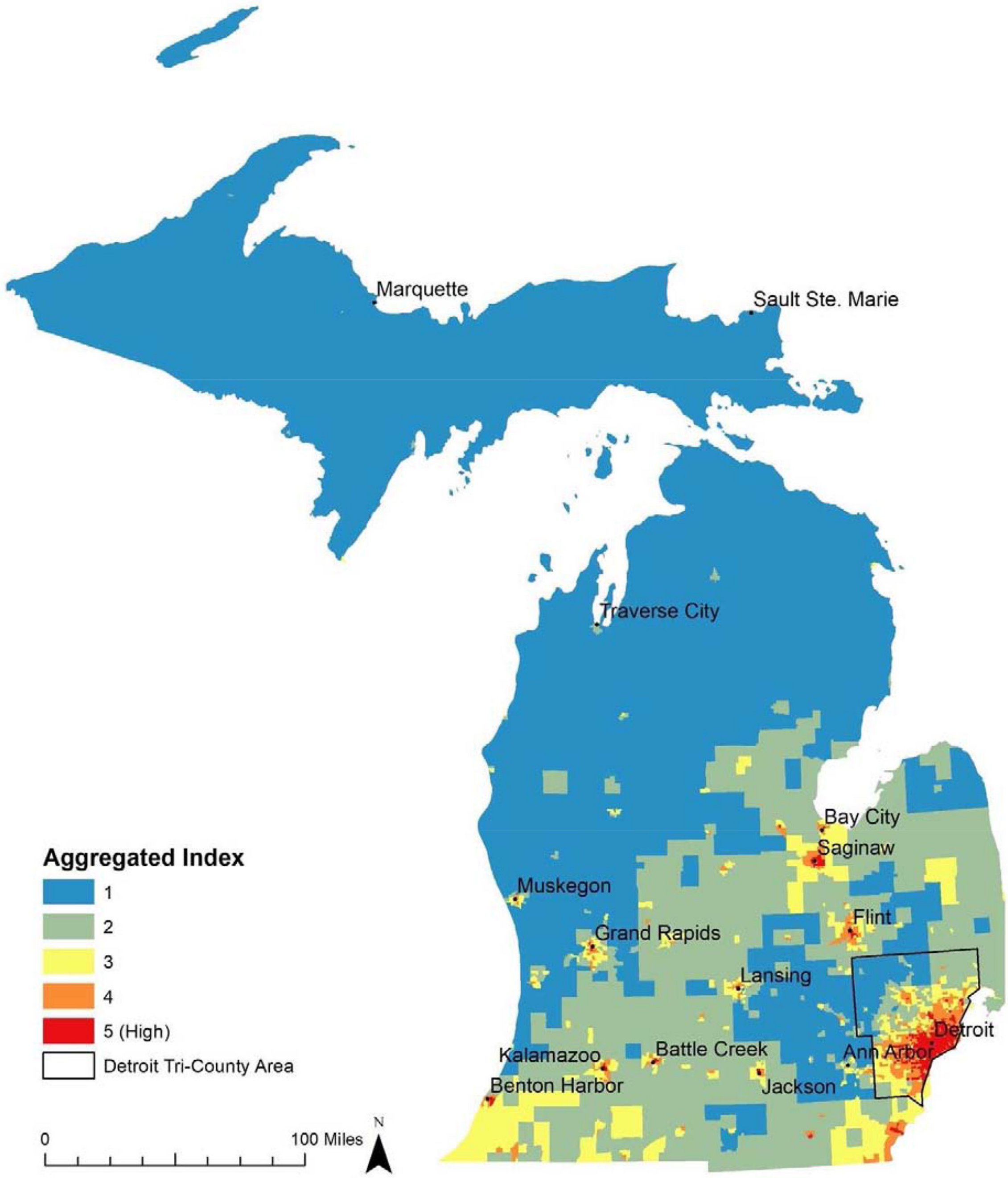

Figure 5.

Quintiles of relative Heat Vulnerability Index by census tract combining exposures from Place, Temperature and People Indices.

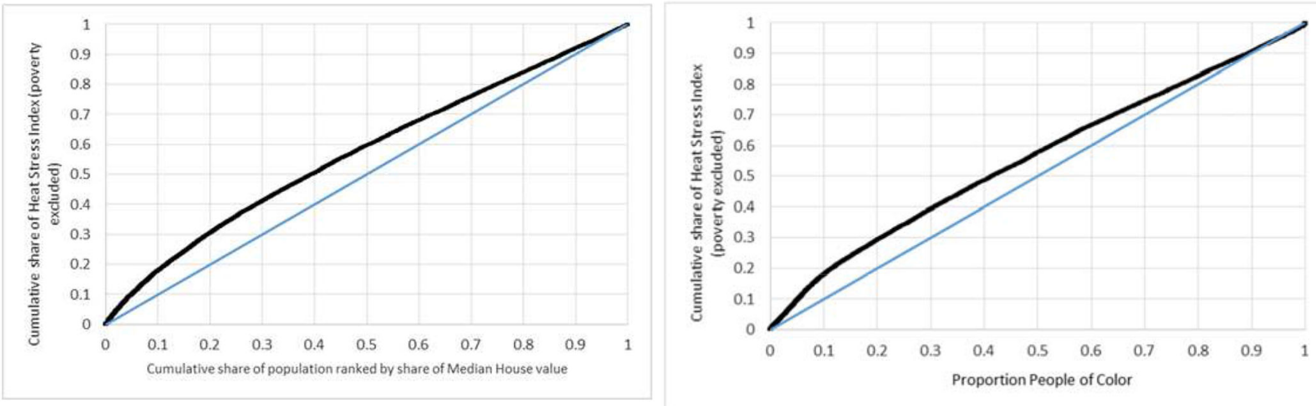

Figure 6.

Inequality curves showing the distribution of heat stress vulnerability (Analytic HVI) based on a) median home value in census tract (left) and b) based on racial minority status at the census tract level (right)

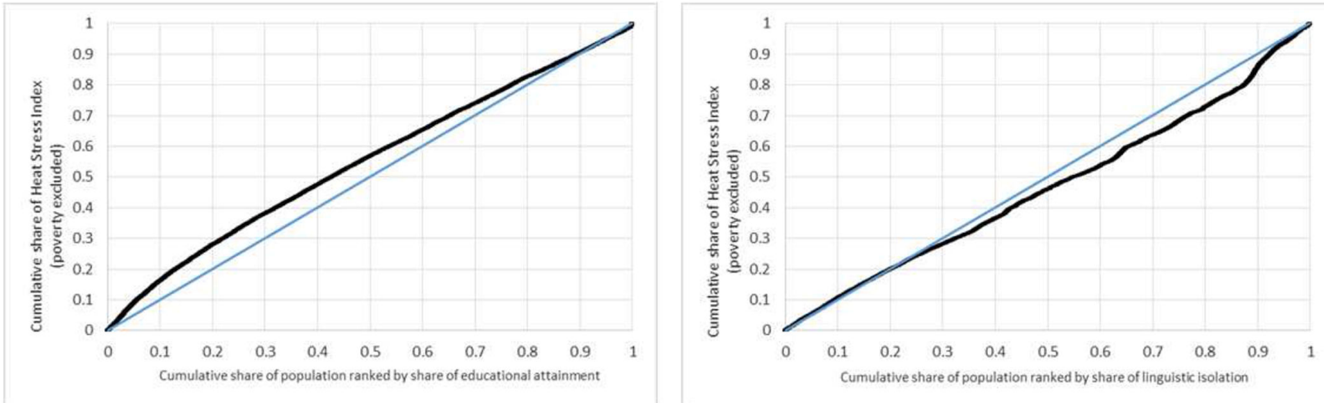

Figure 7.
Inequality curves showing the distribution of heat stress vulnerability based on a) education (left) and b) linguistic isolation (right) indicators at the census tract level

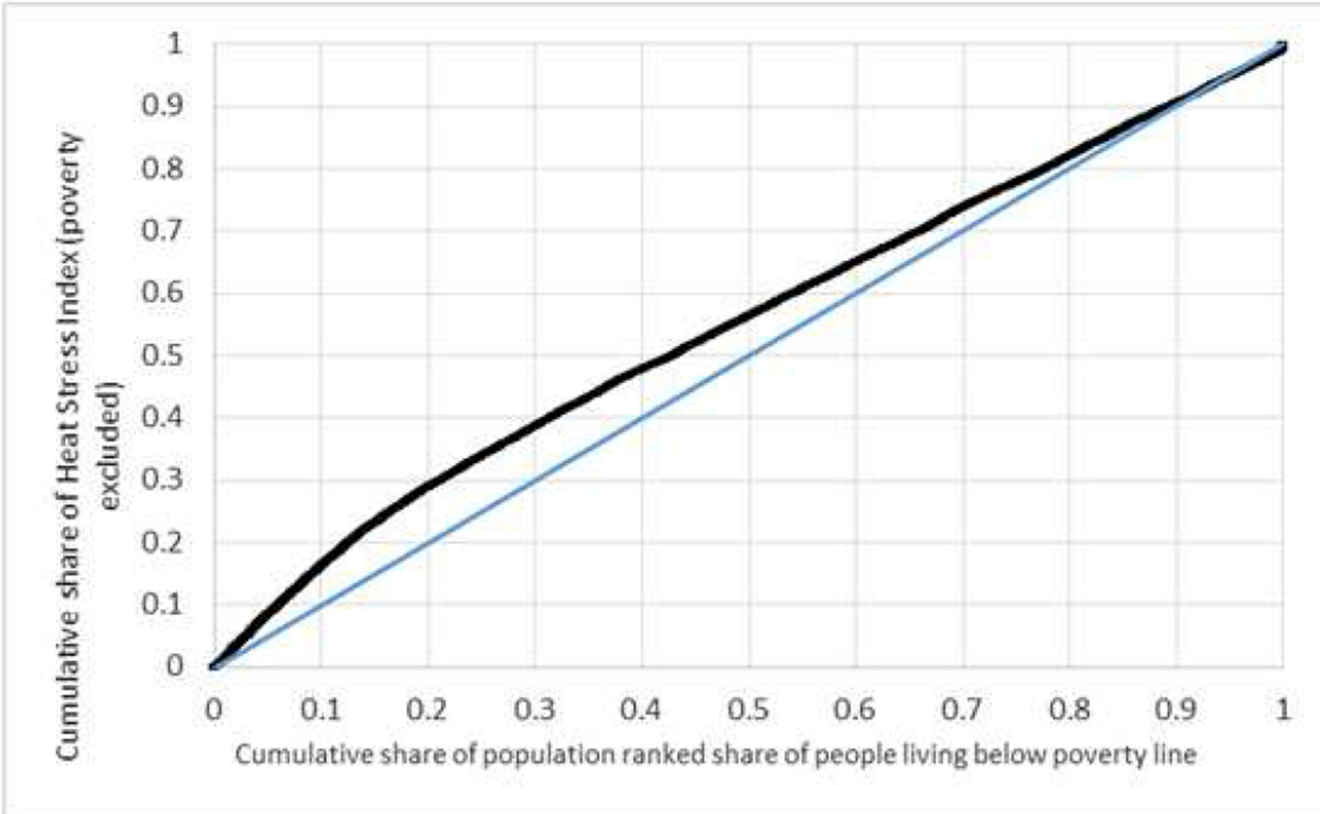

Figure 8.
Inequality curve showing the distribution of heat stress vulnerability (Analytic HVI) based on poverty

Table 1.

Heat stress vulnerability indicators included in the MI-Environment model

Index	Component
Place Index	Percent lack of tree canopy coverage Percent impervious surfaces
Temperature Index	Projected days over 90 degrees F Projected average seasonal temperature
People Index	Percent elderly and living alone Percent households without vehicle Age-adjusted prevalence of obesity (Body mass index (BMI) > 30 m/kg^2) Percent children < 5 years Percent population below the poverty line*

For the inequality assessment used to address our second research question, we removed the poverty factor from the HVI, to create an Analytic People index and an Analytic HVI.

Table 2.

Comparison of California and MI-Environment data sources and equations by indicator

Index	California Indicators	MI-Environment Indicators	Data Sources and Notes
Place Index	% Lack of tree canopy coverage (2001)[1] % Impervious surface[1]	% Lack of tree canopy coverage (2011)[2] % Impervious surface[2]	[1]2001 National Land Cover Database [2]2011 National Land Cover Database (Multi-Resolution Land Characteristics Consortium, 2011)
	Place index: ((Lack of tree canopy + impervious surface)/2)		
Temperature Index	Projected maximum monthly temperature (2050-2059)[3]	Number of projected hot days (over 90 degrees Fahrenheit or 32.2 degrees Celsius) (2041-2070)[4]	[3]Cal-Adapt http://v1.caladapt.org/research/ [4]Third National Climate Assessment Coupled Model Intercomparison Project Phase 3 (CMIP3), (Melillo, Jerry M., Terese (T.C.) Richmond, and Gary W. Yohe, Eds., 2014)
	Projected change in maximum monthly temperature (2050-2059) - (2000-2009)[3]	Projected change in average seasonal temperature ((2041-2070) - (1981-2010))[4]	
	Change in number of degree-days of warm nights (66.2 degrees F or 19 degrees Celsius) - ((2050-2059)-(2000-2009))[3]	N/A	
	Temperature index: (Monthly Max + Monthly Temp Change + Warm Night Change)/3	Temperature index: (0.25* Seasonal Temp Change) + (0.75*Hot Day)	Weighting was added to account for the emphasis on peaks in the California data
People Index	% Population older than 65 years and living alone (2005-2009)[5]	% Population older than 65 years and living alone (2008-2012) [6]	[5]American Community Survey 2005-2009 [6]American Community Survey 2008-12 (U.S. Census Bureau, 2010) [7]Behavioral Risk Surveillance System (Centers for Disease Control, 2010) [8]Cal EnviroScreen's framework incorporates this component into its cumulative index but it was not present in the heat stress layer [9]We removed this factor to create the Analytic People Index and the Analytic HVI
	% Households with no access to a personal vehicle (2005-2009) [5]	% Households with no access to a personal vehicle (2008-2012) [6]	
	Age-adjusted obesity prevalence by county (2016)[7]		
	% Population under 5 years (2008-2012) [6, 8]		
	% Population below poverty line (2008-2018) [6,8,9]		

$$\textbf{MI} - \textbf{Environment Heat Vulnerability Index} = \frac{\textbf{(Place Index + Temperature Index + People Index)}}{\textbf{3}}$$

Table 3.

Descriptive statistics for Heat Stress Vulnerability Index and its three elements of Place, Temperature and People and vulnerability indicator demographics of Michigan census tracts (n=2767)

	Mean (SD)
MI-Environment Heat Stress Vulnerability Index *	51.7 (17.0)
Place Index	46.5 (20.2)
Percent Lack of Tree Canopy Coverage	(17.1)
Percent Impervious Surface Coverage	(23.2)
Temperature Index	65.2 (15.0)
Average Seasonal Temperature	92.1 (20.7)
Extreme Heat (Number Hot Days)	56.3 (14.8)
People Index *	43.8 (13.8)
Percent Age ≥ 65 Years + Living Alone	25.3 (13.6)
Percent No Car Ownership	8.9 (9.8)
Age-adjusted Obesity Prevalence	52.9 (20.9)
Percent Age ≤ 5 Years	27.3 (12.1)
Percent Population Below Poverty Line	18.2 (14.9)
<u>Equality Analysis Population Vulnerability Indicators</u>	
Percent people of color	24 (29.7)
% Age ≥ 25 years with < high school education	12.3 (8.8)
Percent living in rented households	28.3 (21.1)
Median house value	129,084 (69,660)
Percent below poverty line	18.2 (14.9)
Percent below twice the poverty line	37.1 (19.9)
Percent Linguist isolation: Age ≥ 5 years + living in households where no one age ≥18 speaks English	0.3 (0.9)

* Analytic HVI excluding the poverty indicator: Mean of 51.8 (12.1), range (15, 85), Analytic People Index excluding the poverty indicator: Mean of 28.6 (8.4), range (2.1,62.6)

Table 4.

Significance tests of inequality in aggregate heat vulnerability index based on sociodemographic vulnerability indicators. (Michigan, n=2,813 census tracts)

Vulnerability Index	Category of Vulnerability Indicator	Michigan	
		Inequality Index[a]	95% CI
Analytic Heat Stress Vulnerability Index (Excluding Poverty)	Proportion people of color	−0.115	(−0.108,−0.122)[***]
	Proportion residents living below poverty line	−0.101	(−0.094,−0.107)[***]
	Proportion residents living 2X below poverty line	−0.106	(−0.099,−0.113)[***]
	Proportion living in rented households	−0.103	(−0.096,−0.110)[***]
	Median house value	−0.142	(−0.134,−0.150)[***]
	Proportion over age 24 without high school completion	−0.099	(−0.093,−0.106)[***]
	Linguistic Isolation	0.065	(−0.121,0.252)[*]

[*] 0.1<p<0.05

[**] 0.05<p<0.001

[***] p<0.001

[a] A negative inequality score indicates that less advantaged groups bear a disproportionate burden of expos-ure. The highest level of inequality, where disadvantaged groups bear the burden of all the exposure is −1 (Kakwani et al., 1997).