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Landscape-Based Extreme Heat Vulnerability Assessment

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Extreme heat is becoming an increasingly dangerous threat to urban residents. However, unlike hazards such as storm surges which have been well studied by agencies such as the Federal Emergency Management Commission in the United States, communities lack basic knowledge of where extreme heat threats are likely to have the most impact, and who is likely to be most affected. Here, we apply a mapping approach to identify areas of New York City where people are likely to be particularly vulnerable to extreme heat-related health effects based on both exposure to biophysical elements that exacerbate heat, and sensitivity to heat-related health impacts. Unlike most studies that develop indicators of heat vulnerability at Census-based aggregations, we disaggregate population data to a fine scale, in order to more precisely identify vulnerable communities. Using a landscape-based indicator that links exposure to properties of the urban built and natural landscape, we develop an approach for informing land-based strategies for mitigating micro-urban heat islands. Our findings indicate that African Americans and households living below the poverty line are disproportionately exposed to high surface temperatures. This study illustrates an approach for identifying multiple dimensions of vulnerability to extreme heat

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with improved location precision, in a way that informs spatially strategic extreme heat mitigation efforts.

Keywords: Urban resilience; heat vulnerability; vulnerability assessment; landscape function; environmental justice; climate justice.

1. Introduction

Exposure to extreme heat in urban areas is in large part due to biophysical conditions. Mineral-based built materials such as asphalt roadways and parking lots with high specific heats trap heat and release it at night (Stone 2012). This problem can be exacerbated by configurations of the built environment, such as narrow streets which lack air circulation. By contrast, vegetation such as trees cool air and surfaces by providing shade and by converting heat energy to water vapor through processes of evapotranspiration. Surface waters can also have a major cooling effect through evaporation. Since built surfaces, vegetation and surface waters are unevenly distributed in cities, so is temperature. Remarking on uneven patterns of snowfall in London, the term “heat island effect” was first coined by Gordon Manley (1958). The urban heat island effect is now well-known to be the heat differential between urban areas and their hinterlands. However, temperature differentials within cities — known as micro-urban heat island — can be as great as (or even greater than) temperature variation between cities and their hinterlands (Lo *et al.* 1997).

People living in micro-urban heat islands are at a higher risk of mortality during warmer summer days (Smargiassi *et al.* 2009). In some cases, heat-related mortality has been more common in neighborhoods with larger minority populations, older housing stock and more vacant housing (Uejio *et al.* 2011). The elderly are also a particularly vulnerable population because they are less efficient at dispersing heat, are more likely to have co-morbidities and take medications that affect thermoregulation, and may have more limited mobility in seeking a cooler environment or finding assistance when experiencing heat-related stress. As our climate changes, heat waves are predicted to become more common and therefore heat-related illness will be an increasing concern, particularly in urban neighborhoods dominated by sealed surfaces and among vulnerable populations such as elderly, low income and disabled individuals who are less mobile or otherwise have difficulty finding relief. Therefore, it is important to understand spatial variation in not only the biophysical characteristics that create conditions for extreme heat exposure, but also spatial distributions of people who are particularly sensitive to heat-related illness and mortality.

1.1. *Vulnerability frameworks: Spaces of exposure, sensitivity and adaptive capacity*

Vulnerability is typically defined as the degree to which a system is susceptible to injury, damage or harm — the key parameters being the stress to which a system is exposed, its sensitivity and its adaptive capacity (Adger 2006; Turner *et al.* 2003; Wilhelmi and Hayden 2010). Each component of vulnerability from identifying the hazard, defining exposure, to choosing the most relevant indicator variables to assess sensitivity and adaptive capacity add complexity to empirical assessments of vulnerability. Exposure is defined differently across scholarly and practice communities. In the IPCC assessments of vulnerability to climate change impacts, the definition of exposure has shifted subtly, but importantly, from Assessment Report 4 (AR4) to Assessment Report 5 (AR5) to more explicitly include exposure to "species or ecosystems, environmental functions, services, and resources (Oppenheimer *et al.* 2014)."[1]

Many frameworks arising from diverse scholarly traditions have been used to assess vulnerability, including the risk hazards approach — which considers exposure and sensitivity, pressure-and-release — which addresses social heterogeneity of sensitivity, the hazards of place model — which considers biophysical risk and social response within geographic or areal domains (Cutter 1996) and a vulnerability framework for sustainability science which considers social-environmental causal feedbacks (Turner *et al.* 2003). Through this conceptual evolution, vulnerability research has complicated the study of vulnerability by disaggregating social groups to understand differential sensitivities, disaggregating geography to understand differential exposures, and analyzed spatial and temporal intersectionality of exposure and sensitivity to identify causal and procedural drivers of vulnerability in a more holistic way. Similarly, environmental justice scholarship has broadened to attend not only to ways in which spatial distribution of environmental threats poses disproportionate risks to communities of color, the poor and historically disenfranchised social groups, but also ways in which risk based on spatial proximity it intertwined with recognition and procedural inequity (Schlosberg 2007; Walker 2009).

1.2. *Extreme heat vulnerability*

If vulnerability is generally characterized by exposure, sensitivity and adaptive capacity, then vulnerability to extreme heat is more specifically characterized by

[1]In IPCC AR4 exposure is defined as "The presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected (Intergovernmental Panel on Climate Change (IPCC) 2012)," but updated in AR5 to "The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected (Oppenheimer *et al.* 2014)."

local climate variability and land cover patterns (biophysical exposure); social constraints (neighborhood socio-economic sensitivity); and individual and household-level and social capital, knowledge, and practices (capacity to change behaviors and conditions in response to heat threats) (Wilhelmi and Hayden 2010). Although the combination of atmospheric conditions and the extent to which the biophysical environment exacerbates or attenuates those conditions create exposure to extreme heat, characteristics of the urban social system create sensitivity and adaptive capacity, and these system parameters interact. Klinenberg's (2002) study of the heat wave that struck Chicago in 1995 found that people living in social isolation tended to be most affected, though a more full account of why over 700 people died during that heat event and why some neighborhoods were more affected than others had to do with broader economic and policy forces, including economic cycles of community abandonment and lack of disaster management response. Other factors affecting heat vulnerability are linked to heat-related mortality, illness and distress calls at the individual and neighborhood level include surface temperatures, impervious land cover, green space, minority race and ethnicity, linguistic isolation, age, level of educational attainment, income, disability, housing conditions, housing values, vacant households, and rates of access to air conditioning in the home (Hattis *et al.* 2012; Madrigano *et al.* 2015; Rosenthal *et al.* 2014; Smargiassi *et al.* 2009; Uejio *et al.* 2011).

2. Indicators of Vulnerability for Spatial Assessment

Vulnerability indicators, representing exposure, sensitivity and — to a lesser degree — adaptive capacity are used in empirical spatial assessments to identify geographies and populations that are disproportionately at risk of health and other detrimental impacts of extreme events. A range of indicator types, analytic techniques and spatial scales have been used to assess cumulative vulnerability to extreme heat. Exposure indicators measure biophysical weather conditions, landscapes and ecosystems, buildings and built environments, as well as residential populations. Specific indicators include remote sensing-derived surface temperature (Inostroza *et al.* 2016; Uejio *et al.* 2011), normalized difference vegetation index (NDVI) (Johnson *et al.* 2012), normalized built-up index (Johnson *et al.* 2012), land cover including trees, vegetation and imperviousness (Krellenberg and Welz 2017; Reid *et al.* 2009; Uejio *et al.* 2011), air temperature derived from meteorological stations (Rinner *et al.* 2010) population density (Wolf and McGregor 2013), and housing and building characteristics (Krellenberg and Welz 2017; Uejio *et al.* 2011; Wolf and McGregor 2013). Composite sensitivity indicators measure predisposition to injury based on social characteristics, representing individual and household-level coping capacities generally based on demographic population information (Wilhelmi and Hayden 2010). Sensitivity indices include various combinations of age (elderly and young), economic status, race, educational level, lack of air conditioning, social isolation, disability, and family structure indicators (Bradford *et al.* 2015; Inostroza *et al.* 2016; Johnson *et al.* 2012; Rinner *et al.* 2010). Although individuals' health conditions such as cardiovascular and respiratory diseases are also considered important sensitivity characteristics, data limitations often preclude their incorporation in vulnerability assessments. Adaptive capacity is less well represented in vulnerability assessments; however, one exception used access to communication technologies, access to water, material index, access to medical services, roads and NDVI to represent adaptive capacity (Inostroza *et al.* 2016). Wilhelmi and Hayden (2010) specify the dimensions of extreme heat vulnerability, highlighting that while sensitivity can be measured using demographic and health data, adaptive capacity — which represents a system or population's capacity to modify itself to better cope with stress — is better captured using household-level interview data and often not included in heat vulnerability assessments.

Analytic techniques are used to aggregate multiple metrics into a single vulnerability index, identify spatial clusters of vulnerability (Inostroza *et al.* 2016) and isolate independent factors (Reid *et al.* 2009). Johnson *et al.* (2012) used an extreme heat vulnerability index (EHVI) developed through factor analysis to predict expected mortality rates, finding that an EHVI which combines socioeconomic (sensitivity) and environmental (exposure) indicators performs better predicting heat-related mortality than indices representing only exposure or only sensitivity. Spatial scales at which indices are assessed include census tract (Chow *et al.* 2012; Reid *et al.* 2009; Rinner *et al.* 2010), census block group (Bradford *et al.* 2015; Johnson *et al.* 2012; Uejio *et al.* 2011), Canadian dissemination area (Rinner *et al.* 2010) or an even finer block scale where available in locales such as Santiago, Chile (Inostroza *et al.* 2016). Although exposure indicators such as surface temperature, NDVI and landscape objects are often available at a finer scale than these administrative units, aggregation of exposure and sensitivity dimensions requires averaging at the coarsest resolution of all indicators. This "common denominator" spatial scale problem inhibits the precision with which vulnerability can be located.

3. Informing Biophysical Adaptation through Landscape Structure — Function Relationships

Characteristics of urban landscapes — including built and natural land covers and three-dimensional properties — influence and can be used to estimate landscape and ecosystem functions (Bastian *et al.* 2014; van Oudenhoven *et al.* 2012). However, standard land use and land cover classifications are limited in the extent to which they capture urban dynamics and function (Inostroza *et al.* 2019). Land use/land cover systems such as the Anderson Classification scheme used in the United States (Fry *et al.* 2006) or the Corine land cover dataset developed by the European Environment Agency (Lofvenhaft *et al.* 2002) include few urban classes with limited land cover descriptiveness. Since urban environments are heterogeneous over fine spatial scales, hybrid land classifications are needed to capture relationships between landscape structure and function. The structure of urban landscapes (STURLA) classification was developed as a way to understand intra-urban heat island effects by linking compositions of landscape elements to surface temperatures at fine spatial scales (Hamstead *et al.* 2016). It provides a landscape-based proxy for temperature variation in a way that is empirically derived from a given city's potentially unique landscape characteristics, configurations and spatial patterns.

Similar to previous heat vulnerability assessment approaches, we develop indicators of exposure and sensitivity based on satellite-derived surface temperature and Census population data. However, our approach is unique in two ways. For one, we disaggregate population data in order to better align our spatial scale of analysis with the scale at which micro-urban heat islands can be detected by the satellite sensor from which our exposure indicator is derived. This spatial disaggregation approach enables comparability between exposure and sensitivity at the same relatively fine spatial scale, and more precisely locates residential populations at risk of extreme heat-related impacts. Second, we apply a landscape-based exposure indicator that represents the extent to which landscape compositions of natural and built features modify surface temperature. Unlike other indicators that represent either structure (e.g., tree canopy, NDVI) or function (e.g., surface temperature), this approach represents the relationship between the two and provides a way of considering how changes to compositions of landscapes could impact vulnerability.

4. Study Area

Although agencies in NYC have not historically been particularly focused on preparing for extreme heat, the problem has attracted attention at the city-level since Superstorm Sandy made landfall on the coasts of New York and New Jersey in the fall of 2012. With an increased focus on climate-related vulnerability, the Mayor's Office of Recovery and Resilience recognized that in addition to storm-related threats, extreme heat is one of the primary climate change-related threats that city residents face. In 2017 the NYC Mayor's Office released the Cool Neighborhoods plan (City of New York 2017), a US$100M initiative to combat heat and heat risk. The plan includes a mix of interventions from additional tree planting for cooling in high heat risk neighborhoods to "be a buddy" systems for building social cohesion and accountability during heat waves events, which are predicted to increase with climate change in the NYC region (Horton *et al.* 2015).

In NYC, demographic variables found to predict heat-related mortality among elderly in NYC include poverty, poor housing conditions, lower rates of access to air-conditioning, impervious land cover, surface temperatures and seniors' hypertension (Rosenthal *et al.* 2014). The authors also found that percent Black/African American and household poverty were strong predictors of seniors' access to air conditioning. Another study found that mortality during or immediately following a heat wave in NYC from 2000 to 2011 was more likely to occur among Black individuals, at home rather than in institutional settings, in census tracts that receive greater public assistance, and in areas of the city with higher daytime surface temperature and less green space (Madrigano *et al.* 2015). Disastrous heat waves include an event in 1966 during which mortality increased by 36 percent (Schuman 1972) and July 24, 1972 which caused 253 deaths (Ellis *et al.* 1975). According to the NYC Department of Health and Mental Hygiene, 46 heat stroke deaths resulted from two heat waves in July and August 2006, and 26 heat-related deaths occurred during the heat wave of July 2013 (NYC 2006, 2014). Between 2000 and 2011, 447 patients were treated for heat illness and 154 died (CDCP 2013).

Projecting future climate scenarios across the NYC metropolitan region, Knowlton *et al.* (2007) estimate that on average, heat-related premature mortality will increase 70 percent by the 2050s over a 1990s baseline. According to their model, most counties that comprise NYC are predicted to experience higher than average mortality increases: Bronx County (Bronx) by 89 percent; Kings County (Brooklyn) by 86 percent; New York County (Manhattan) by 83 percent; Queens County (Queens) by 95 percent; and Richmond County (Staten Island) by 80.2 percent over the 1990s baseline. The study area is defined by these five counties, which are also the five boroughs of NYC.

5. Methods and Data

We constructed vulnerability indicators of exposure and sensitivity based on surface temperature and demographic data, and developed an indicator of the landscape's contribution to heat exposure that can inform spatial prioritization of green infrastructure and other landscape-based interventions (Figure 1). All indicators

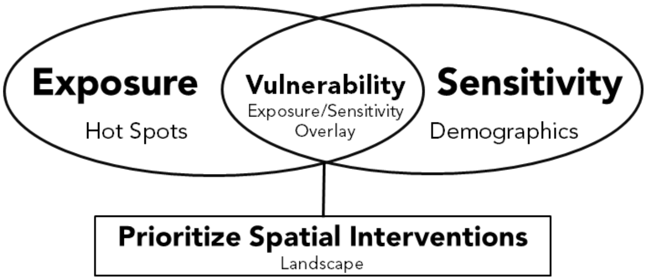

Figure 1. Methodological Framework. Exposure is Indicated by Surface Temperature Hot Spots; Sensitivity is Indicated by Demographics, and Vulnerability is Defined as Overlap Between the Two, Within Which Landscape-based Interventions Should be Prioritized

were developed at a 30 m pixel-level, chosen because it is the finest scale at which temperature data are available. As a way to identify geographic hot spots and evaluate the extent to which heat exposure represents an environmental injustice problem in the study area, we performed a surface temperature cluster analysis and computed proportions of sensitive populations living within hot spots. We then examined how a landscape-based indicator of exposure could be used to inform landscape-based interventions in communities where high exposure and high sensitivity are present.

5.1. *Sensitivity indicators*

We created sensitivity indicators based on U.S. Census demographic variables representing population types that are known to be sensitive to extreme heat events in New York City. A subset of demographic predictors could be measured using publicly-available data, including Black/African American race, poverty, and elderly. Black race was found as an important predictor of deaths during heat waves in NYC that occurred between 2000 and 2011 (Madrigano *et al.* 2015), and is a strong negative predictor of access to air conditioning, which was found to be associated with heat-related mortality among seniors in NYC between 1997 and 2006 (Rosenthal *et al.* 2014). Deaths among adults in NYC were more common in census tracts receiving higher levels of public assistance and with larger populations living below the poverty line (Rosenthal *et al.* 2014). Although heat-related mortality in NYC was also associated with poor housing conditions, lower rates of access to air conditioning, and seniors' hypertension, these predictors could not be directly measured using publicly-available data at the same spatial scale as the other indicators.

To more precisely map locations of people who are sensitive to extreme heat, we first created population maps at a finer scale than the Census block group, which is the smallest areal unit at which Census data are available. Block groups and other enumeration units include all residential and non-residential areas, and rarely reflect actual population distributions (Sleeter and Gould 2007). Dasymetric mapping is an interpolation technique that disaggregates population data by empirically sampling population values in an ancillary dataset (typically of land use) which represents the population statistical surface at a finer scale than that of the original population data. Based on this sampling procedure, weights are assigned to the classes of the ancillary dataset, and population values are disaggregated from the original spatial resolution to the finer resolution according to these derived weights (Mennis 2003). This approach is particularly useful for addressing ways in which the modifiable areal unit problem (MAUP) can mask problems of environmental justice (Mennis 2002). Geographic units of analysis are often arbitrarily defined in relation to ways in which they are applied or analyzed. When spatial data are aggregated at different areal unit sizes or extracted according to different boundary definitions, information changes (Openshaw and Taylor 1979). Thus, dasymetric and other interpolation techniques can improve the spatial precision of information, particularly for analyses in which it is necessary to detect data distributions at a fine scale. For instance, Shepard *et al.* (2012) used dasymetric mapping to identify populations who are vulnerable to storm surges in Long Island, New York. As with flood vulnerability assessments, heat vulnerability assessments are often conducted at the scale of Census units whose geographic boundaries do not precisely align with the boundaries of high exposure.

We used 2007–2011 block group-level American Community Survey U.S. Census data to retrieve populations of Black/African American individuals, elderly ($>=$ 65 years), and households below the poverty line. For comparison with the population as a whole, we also retrieved total population and total number of households. We used NYC's Bytes of the Big Apple MapPLUTO polygon tax lot dataset (NYC Department of City Planning 2011) as the ancillary dataset, representing the demographic statistical surface. NYC's tax lot dataset contains 11 land use classes, including (i) one and two family buildings; (ii) multi-family walk-up buildings; (iii) multi-family elevator buildings; (iv) mixed residential and commercial buildings; (v) commercial and office buildings; (vi) industrial and manufacturing; (vii) transportation and utility; (viii) public facilities and institutions; (ix) open space and outdoor recreation; (x) parking facilities; and (xi) vacant land. Classes 1–4 are residential, whereas classes 5–11 are non-residential. We converted this polygon dataset to raster format (30 m resolution), and reclassified it such that all non-residential classes (5–11) were assigned to the same class. We then used the U.S. Forest Service dasymetric mapping tool (Sleeter and Gould 2007) to disaggregate each of the five population datasets to 30 m resolution dasymetric maps. A coverage definition of 80 percent was used, such that pixels with at least 80 percent of a particular land use type were considered homogeneous, and otherwise areal weighting was used to redistribute population values to multiple residential land use classes according to corresponding weights. Resulting maps estimate total counts of population, households, African American individuals, elderly individuals, and households below the poverty line at the 30m-pixel scale. To compare spatial population distributions across the sensitivity indicators, we converted each into an index from 0 (low population) to 1 (high population) using a linear transformation.

6. Exposure Indicators

To identify potential exposure to micro-urban heat islands, we performed cluster analysis using the Getis-Ord Gi^* hot spot analysis in ESRI ArcGIS 10. This analysis reports z-scores of significantly clustered features, in which the difference between neighborhood-level values and the sum of all values is too large to be the result of chance. To be a statistically significant hot spot, the feature must have a high value (e.g., high temperature value) and be surrounded by other features with high values. Alternatively, cold spots emerge where features with low values are surrounded by other features with low values. We used the inverse distance conceptualization of space to define neighboring relationships. Using a zonal tool in ESRI ArcGIS 10, we computed counts of total population, total households and sensitive populations in each hot spot type.

To inform potential landscape-based interventions in vulnerable locations, we created a landscape-based heat exposure indicator based on the Structure of Urban Landscapes (STURLA) classification (Hamstead *et al.* 2016). STURLA is comprised of landscape composition elements — including built and natural components — that are common in a given urban environment. Tree canopy, grass/shrub, water, bare soil, paved, lowrise buildings (1–3 stories), midrise buildings (4–9 stories) and highrise buildings (>9 stories) are the land cover and building height elements used to construct classes at a 1 m resolution within 30 m grid cells (to align with LANDSAT temperature data) (Figure 2).

We defined the most abundant classes as those which comprise 90 percent of NYC's land area. By applying class separation analysis to a pre-processed temperature dataset, groups of STURLA classes which have distinct temperature signatures can be identified (Hamstead *et al.* 2016). This procedure was applied to a surface temperature dataset collected on July 15, 2011, derived from LANDSAT 7 ETM+ per pre-processing procedures described in Hamstead *et al.* (2016). Based on this class separation analysis, thirteen class groups representing distinct

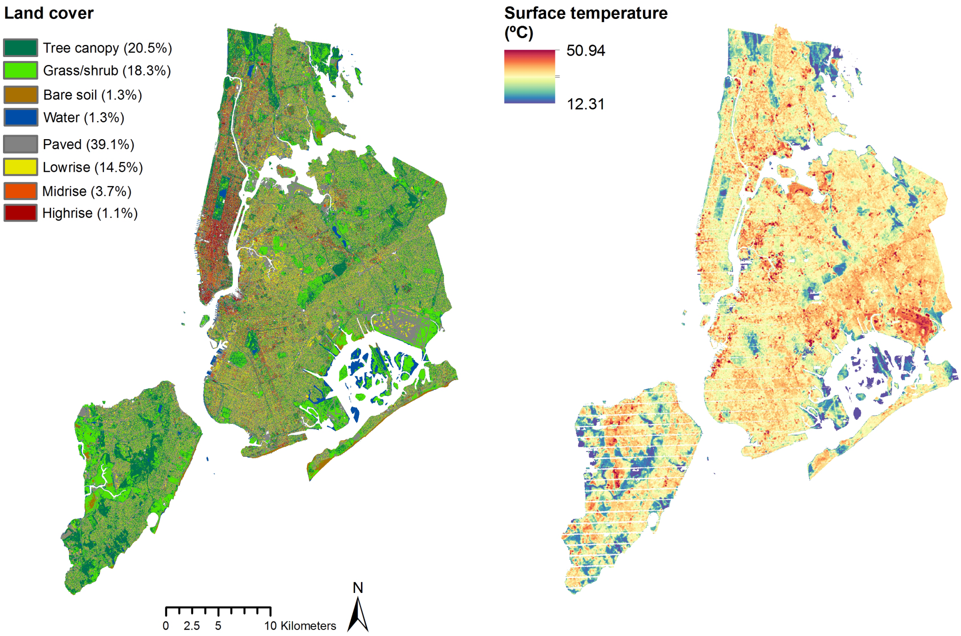

Figure 2. Base Layer for Landscape-Based Classification (Left) and Surface Temperature on July 15, 2011 (Right)

temperature signatures were identified. For each class group, we created dummy variables and performed least squares multiple regression analysis using the class group dummy variables as predictors of temperature. The coefficients for each predictor represent the relative influence of each class group on temperature. We used these coefficients as indicators of landscape-based heat exposure in the sense that they represent the extent to which a given landscape class attenuates or exacerbates heat exposure. In addition, we tested the error of the landscape-based heat exposure indicator by mapping mean temperature values of each indicator against actual temperature values. We used the landscape-based heat exposure indicator in conjunction with hot and cold spot analysis to identify landscape types that are present in the hottest locations of the city and to consider potential locations for interventions within hot spots.

7. Results

7.1. *Demographic analysis*

The sensitivity indices vary over space, with some population variables more concentrated than others. For instance, the elderly population follows a similar spatial pattern as the total population, whereas households in poverty tend to concentrate in northern Manhattan, south Bronx, and northern and central Brooklyn. Black/African American is the most concentrated of the three demographics examined — with high populations in northern Manhattan, Roosevelt Island, the south and north Bronx, Eastern and the Far Rockaways, Queens, eastern Brooklyn, and northern Staten Island (Figure 3).

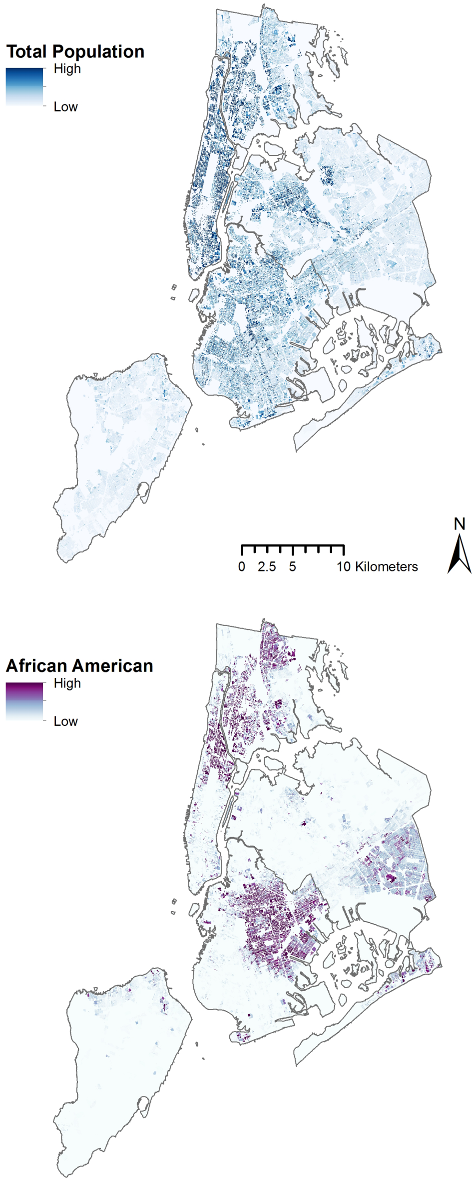

Figure 3. Disaggregated Population Maps

8. Exposure and Vulnerability Analysis

Surface temperature hot spots are located across all five boroughs, with large concentrations in east Queens, on the border of Queens and Brooklyn, Northwestern Staten Island, southwest Manhattan, and the south Bronx. Cold spots emerge where there are large natural areas and wetland in western Staten Island, Central Park, Manhattan, north Bronx near Van Cortlandt Park, Prospect Park, Brooklyn, and Jamaica Bay, Queens (Figure 4). High rates of poverty, African Americans and elderly within hot spots are found in the south Bronx. High rates of African Americans are found within nearly all major hot spots including north and central Brooklyn, eastern Queens and those which are throughout the Bronx (Figure 4).

Compared with the total population that resides within hot spots (27 percent), a smaller proportion of elderly (23 percent) and a larger proportion of African Americans (34 percent) reside within hot spots. Twenty-nine percent (29 percent) of households living below the poverty line reside within hots spots, four percent (4 percent) more than the total population of households that lives within hot spots (25 percent) (Figure 5).

Landscape-based exposure indicators derived from the regression analyses of class groups indicate that the STURLA classification defines a surface temperature exposure range of 12.1°C, with water, grass/shrub-water and tree canopy representing the coolest classes, whereas paved, grass/shrub-paved-lowrise, paved-lowrise represent the hottest classes (Table 1). Cumulatively, the STURLA classes explain 40 percent of the variation in surface temperature across NYC.

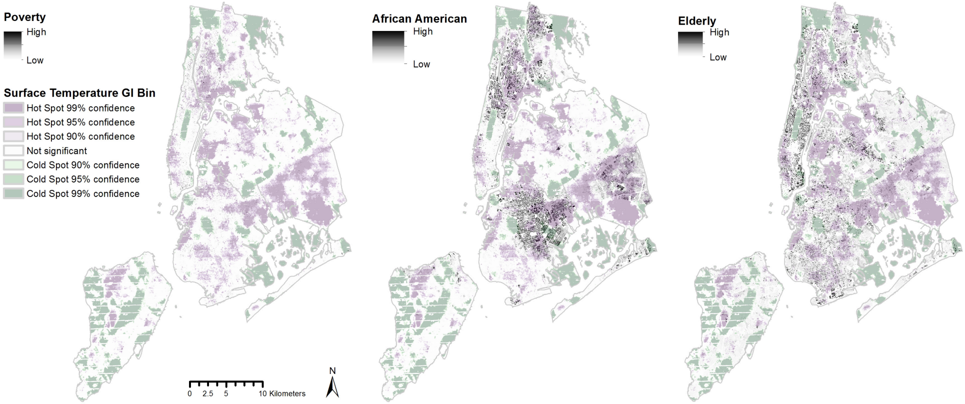

Figure 4. Temperature Hot Spots and Cold Spots Overlaid with Sensitivity Population Maps. Surface Temperature GI Bins Represent Statistical Significance Levels of Hot (High Temperature Values) and Cold (Low Temperature Values) Clusters. High Confidence Levels (CL) Represent Lower Likelihood that Clustering is the Result of Chance

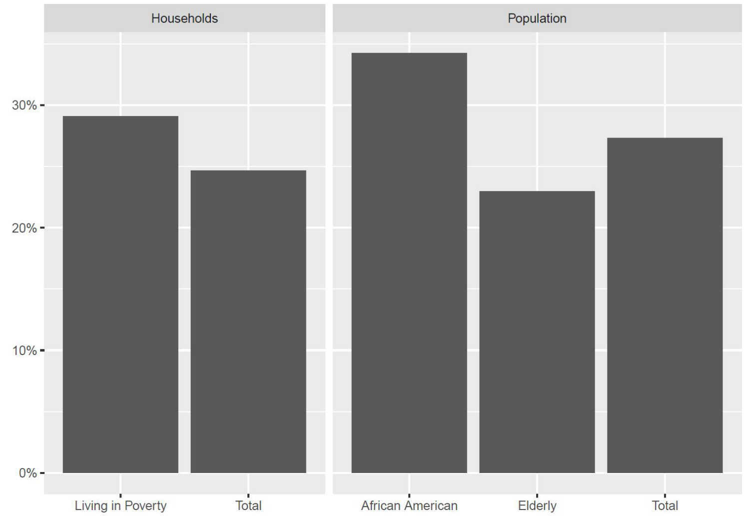

Figure 5. Populations Within All Surface Temperature Hot Spots (90–99 percent). Percentages are Grouped by their Underlying Statistical Population (All Households v. Total Population) and Correspond to the Relative Percentages Mentioned in the Text

Table 1. Structure of Urban Landscapes (STURLA) Group ST Mitigation Indicators and 95 percent Confidence Intervals. All p-values were Significant at an Alpha Level of 0.01

Group	Landscape Composition	Exposure Indicator (°C)	95 percent Confidence Interval	
1	Water	−7.77	−7.92	−7.63
2	Grass/shrub-water Tree canopy	−6.82	−6.92	−6.73
3	Tree canopy-grass/shrub-water	−4.87	−4.94	−4.81
4	Tree canopy-grass/shrub Grass/shrub	−2.69	−2.77	−2.61
5	Tree canopy-grass/shrub-water-paved Tree canopy-grass/shrub-paved	−0.96	−1.00	−0.91
6	Tree canopy-grass/shrub-bare earth-paved	−0.72	−0.82	−0.62
7	Tree canopy-grass/shrub-paved-highrise	0.44	0.35	0.54
8	Tree canopy-grass/shrub-paved-midrise-highrise	1.13	1.06	1.19
9	Tree canopy-grass/shrub-paved-midrise Tree canopy-grass/shrub-paved-lowrise-midrise-highrise	1.69	1.65	1.74
10	Tree canopy-grass/shrub-paved-lowrise-midrise Tree canopy-grass/shrub-paved-lowrise	1.78	1.70	1.82
11	Tree canopy-paved-lowrise-midrise Grass/shrub-paved	2.96	2.90	3.03
12	Tree canopy-paved-lowrise Paved	3.56	3.48	3.64
13	Grass/shrub-paved-lowrise Paved-lowrise	4.35	4.25	4.44

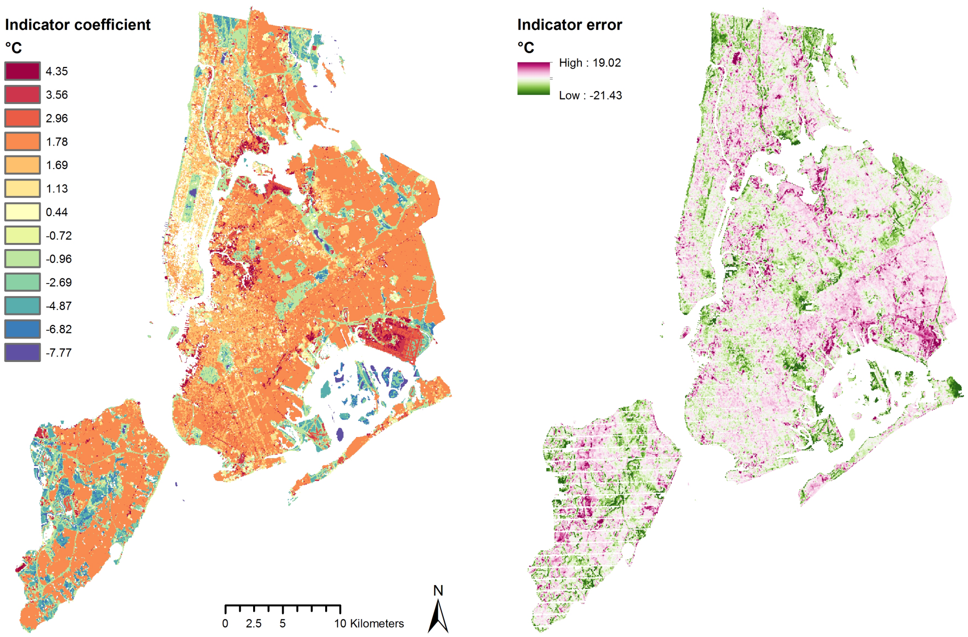

Figure 6. STURLA Landscape Indicator Coefficient and Indicator Error. Coefficients Represent the Average Impact of Each Landscape Type on Surface Temperature. Indicator Error Describes Difference Between the Mean Surface Temperature of the Landscape Type Present in Each 30 m Cell, and Actual Surface Temperature of that Cell

Landscape-based exposure indicator error ranges from -21.43 to 19.02°C, where high error values indicate areas in which temperature is underestimated, and low error values indicate areas in which temperature is overestimated. Underestimated and overestimated temperatures tend to be more prominent in relatively hot and cool areas of the city. Relatively hot areas such as John F. Kennedy Airport in Queens, and eastern Bronx near Hunts Point are underestimated. Relatively cool areas such as western Staten Island and in parks such as Southview Park in the Bronx and Prospect Park in Brooklyn are overestimated (Figure 6).

9. Discussion

Clusters of heat exposure where high proportions of sensitive populations live indicate areas that should be prioritized for minimizing the negative impacts of heat events. Mitigation techniques may involve biophysical interventions such as landscaping with street trees and other green infrastructure, or institutional and community-based interventions such as information campaigns and installation of wayfinding infrastructure to direct vulnerable people to cooling stations.

Emergency responders may proactively prioritize these areas during extreme heat events by coordinating with community-based organizations that have local knowledge of residents who may be vulnerable, and providing resources to enhance local networks. The STURLA approach provides better information about the impact of the landscape on surface temperatures than stand-alone land cover or land use indicators because it derives classes based on compositions of multiple landscape types as opposed to homogenous land uses or land covers that can vary over fine spatial scales in the urban environment.

We suggest that planning for landscape-based interventions requires vulnerability assessment at a scale that is not governed by Census units. Averaging exposure and sensitivity indicators at the scale of Census units can obscure important hot spots or high concentrations of sensitive populations, not to mention overlap between the two. Using a sample of 14 cities across the globe, Small (2009) found that most objects in the urban mosaic have a true scale between 10–20 m, though many features that impact environmental performance may be resolved at 5 m or less. Aggregating temperature and landscape indicators to census enumeration units can thus obscure important spatial dynamics.

From an environmental justice perspective, our analysis indicates that African Americans and households living below the poverty level are disproportionately exposed to high surface temperatures in New York City. This suggests that historically disenfranchised groups may be partly susceptible to heat-related illness due to the environment in which they reside. To the extent that may be the case, landscape interventions such as street trees, greening and expanding existing parkland and creating more pervious surface that allows for water infiltration can be important community-level approaches for mitigating heat exposure. Our study is limited in that is does not examine the other drivers of heat vulnerability that could be related to race. Racial and ethnic segregation patterns dating to the 1930's and 40's era of redlining and beyond have driven both the level of resources that communities are able to dedicate to public infrastructure — including parkland and other forms of greenspace — as well as individual and household-level resources that enable people to cope with heat — such as energy for cooling. The formation of the Federal Housing Authority following World War II gave households access to federally-insured home loans, which ultimately became a primary way in which middle class Americans accumulated wealth and passed on wealth to future generations. Due to the federal government's codified redlining practices combined with real estate agents' blockbusting practices, recent immigrants and people of color were institutionally denied access to this form of wealth accumulation. In 2017, White wealth in the United States was nearly twenty times that of Black wealth (Kraus *et al.* 2017). This wealth disparity may drive not only disparities in

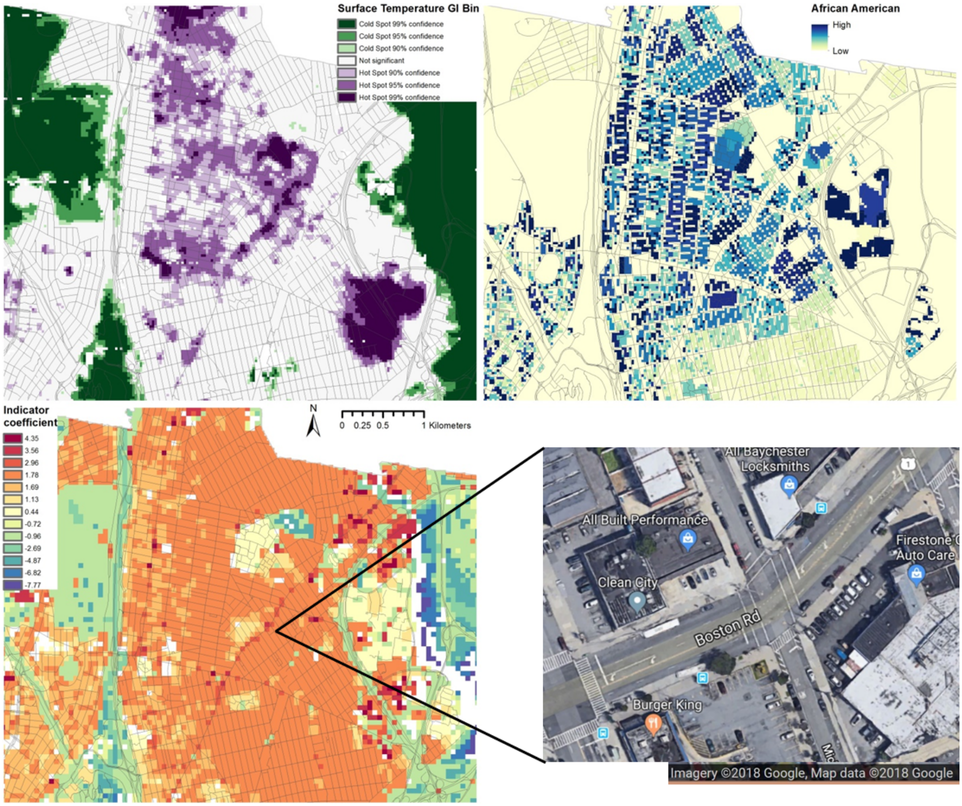

Figure 7. Exposure and Sensitivity Indicators in the Bronx From Top Left to Bottom Right: Hot and Cold Spots; African American Population; STURLA Landscape-Based Indicator and Google Map Satellite Image of the Street-Scale Landscape

the outdoor built environment to the extent that community-level infrastructure is funded through residential property taxes, but also household-level disparities in access to affordable housing and energy. In addition to comfortable outdoor environments, access to affordable housing and energy are crucial for reducing urban heat vulnerability.

Exposure and sensitivity maps, in conjunction with the STURLA classes indicate areas where the landscape may be an important driver of heat exposure. For instance, a hot spot in the Bronx runs along Boston Road, which is surrounded by predominantly African American residential neighborhoods (Figure 7). The average temperature of landscape classes along the highway are approximately 32–35°C. Boston Road and surrounding streets and land uses lack living systems and unsealed surfaces that would enable a more favorable energy-moisture balance in this community. By integrating tree canopy into the highway median and sidewalks, there is potential to reduce the temperature by several degrees. Other hot spots areas — such as north Brooklyn on its border with Queens and northern Manhattan where high populations of households in poverty and African Americans reside — are heavily impervious landscapes that would derive benefit from ecosystem-based mitigation strategies.

We argue that our approach advances planning for specific heat mitigation interventions in that it enhances the precision by which strategic locations for interventions can be planned. By combining information about heat exposure with information about current and potential landscape conditions, the STURLA landscape indicator identifies where landscape-based interventions could have the most impact on heat vulnerability. Exploration of our error analysis of the STURLA indicator illustrates that the indicator underestimates and overestimates temperatures in relatively hot and cool classes. This implies that the landscape indicator likely underestimates potential mitigation impacts (and therefore the full benefit) of land-based interventions. Further, this indicator is limited in that it accounts for only 40 percent of temperature variation across NYC and does not consider the proportion of landscape elements within classes. Increased categorical complexity may improve explained variation, reduce error and ultimately better predict potential landscape interventions.

This analysis is limited in that we did not validate the population distribution estimates produced by the dasymetric mapping technique. While the disaggregation approach maps populations with improved precision, this precision comes at the cost of some unknown level of accuracy. Further research could improve the accuracy of population disaggregation approaches by testing which land use-related indicators — including residential land use types, number of building stories, floor area ratio and others — best predict population distributions.

Our study analyzed only three demographic variables representing sensitivity, and did not consider intersectionality among them. Although age, minority race and poverty have demonstrably strong correlations with heat-related mortality in NYC as a whole, risk factors may vary at smaller neighborhood scales or when measured according to alternative areal units. Health outcomes are related to factors such as race, gender and socio-economic status, but intersections among these factors can exacerbate those health effects. Moreover, some demographic risk factors may be indicators of others — for instance in NYC, Black/African American race is a predictor of lacking air conditioning (Rosenthal *et al.* 2014). A focus on demographic variables is also limited in that it does not fully capture a population's coping and adaptive capacities. Regardless of demographic risk factors, city, community and household-level institutions can provide a protective influence during times of crisis, and demographic sensitivity analysis such as the one conducted here should be supplemented by analyses of societal adaptive capacity.

10. Conclusion

As heat waves and other extreme events are becoming increasingly common in cities, it is becoming ever more important to identify areas of vulnerability with respect to biophysical, sensitivity and adaptive dimensions. Environmental conditions to which people are exposed, capacities for coping with those exposures and the potential for adaptation interact to form overall vulnerability to heat-related illness. Our study applied a heat vulnerability assessment in New York City by overlaying social sensitivity information with surface temperature hot spots, and applying and landscape-based indicator of the extent to which landscapes exacerbate or attenuate heat exposure. Findings reveal that African Americans and households earning incomes below the poverty line are disproportionately exposed to surface temperature hot spots based on their residential locations, which raises important implications for equitable climate adaptation. While numerous studies have conducted vulnerability assessment using biophysical and population information, we did so in a more spatially-precise way, by spatially-disaggregating population information. The scale at we conducted the assessment is better suited for understanding the problem of heat-related population vulnerabilities and for designing solutions at a lot or street scale, at which planning and development interventions take place. Moreover, we applied a statistically-defined landscape classification that is intuitive and indicates potential impacts of land-based heat mitigation interventions. These approaches can be adopted many communities, since all data sources we used are readily available across the United States. City agencies should prioritize exposure hot spots — particularly those in which high proportions of elderly individuals live — for landscape design and other interventions that help mitigate the health impacts of heat. Public facilities and programs — such as senior centers and activities aimed at serving seniors — should incorporate heat exposure into siting and landscape design considerations. Further study should validate disaggregated population indicators based on surveys or other population data, examine intersectionality of social risk factors, and the relative degrees to which different risk factors contribute to vulnerability and communities' coping capacities. Assessing heat vulnerability at a fine spatial scale can help support urban decision-making for reducing heat-related risks, and for developing and designing interventions focused on improving thermal comfort in communities where heat is becoming an increasingly dangerous threat to livability and well-being.

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