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A SOCIAL VULNERABILITY STUDY OF THE URBAN HEAT ISLAND EFFECT IN BALTIMORE AND ST. LOUIS

by

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ABSTRACT

A SOCIAL VULNERABILITY STUDY OF THE URBAN HEAT ISLAND EFFECT IN BALTIMORE AND ST. LOUIS

Julia L. Heslin

Extreme heat events (EHEs) are increasing in frequency, intensity, and duration with modern climate change. An urban heat island (UHI) is a phenomenon where built environments such as cities experience elevated temperatures compared to surrounding rural areas. The UHI effect exacerbates the consequences of EHEs, leaving those in cities generally more exposed to higher temperatures. The intra-urban variability within cities, both in terms of the physical environment and demographic characteristics, can potentially leave some populations more vulnerable to EHEs. This research focuses on intra-urban vulnerability to EHEs in two cities, Baltimore and St. Louis. The study uses remote sensing and GIS methods to measure the UHI effect, correlates temperature with demographic variables by block group, creates a score measuring populations' sensitivity to EHEs, and assesses vulnerability through a heat vulnerability index. Results indicate relationships between exposure and sensitivity and how they relate to the vulnerability within the cities. Overall, there is no ubiquitous pattern of vulnerability that can be found in both cities. The results could be utilized by planners or policymakers to target vulnerable areas and implement mitigation and adaptive strategies to cope with the effects of EHEs unique to each city.

Key words: extreme heat events, urban heat islands, vulnerability, Baltimore, St. Louis

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INTRODUCTION

Background

The definition of vulnerability and its components vary across and within disciplines. A well-accepted vulnerability framework is defined in a report published by the Intergovernmental Panel on Climate Change (IPCC). In the report, the authors state that vulnerability serves as "a function of exposure, sensitivity, and adaptive capacity" (Cardona et al. 2014, 71). This definition is adapted from Wilhelmi and Hayden's (2010) extreme heat vulnerability framework (Figure 1).

Within Wilhelmi and Hayden's (2010) framework, exposure is composed of elements relating to the physical and environmental factors that contribute to a hazard, like climate variability, distribution of heat, and urban land use. Sensitivity encompasses the demographic and health inequities when it comes to responding to a hazard, like age, socioeconomic factors, and neighborhood stability. Finally, adaptive capacity extends beyond the quantitative data of exposure and sensitivity. Qualitative data at the household level to understand people's knowledge, attitudes, and practices (KAP), household resources (like air conditioning access), social capital, and access to community resources (such as early warning systems) are important when considering vulnerability to climate-related hazards like extreme heat events (EHEs).

EHEs are the leading cause of extreme weather-related fatalities in the United States (US) (CDC and EPA 2016). EHEs, along with other extreme weather events, are increasing in frequency, intensity, and duration (Perkins et al. 2012; Rahmstorf and Coumou 2012), likely the result of the changing climate (Luber and McGeehin 2008). It is predicted that EHEs have and will continue to increase in frequency, intensity, and duration in the second half of the 21st century (Meehl and Tebaldi 2004; IPCC 2007, Perkins et al. 2012).

Populations residing in urban areas are at higher risk for these EHEs due to the urban heat island (UHI) effect (CDC and EPA, 2016). UHIs, and surface urban heat islands (SUHIs) are phenomena where the ambient air temperature and land surface temperature (LST), respectively, in urban areas are higher than surrounding rural areas (Oke 1995). There are several factors contributing to temperature differences between rural and urban landscapes – the most important being land cover change. Currently, more than half of the US population live in cities (Uejio et al. 2011). As the urban population continues to grow, so does the importance of studying the UHI effect.

Demographic characteristics vary across and within urban areas. Variables pertaining to socioeconomic status, race or ethnicity, age, disability status, and household characteristics, amongst others, contribute to a population's sensitivity to environmental hazards like extreme heat (Cutter et al. 2003, Johnson et al. 2012, Yoon 2012). Studies have shown that these sensitive populations can be disproportionately affected by the UHI effect, and are thus more vulnerable to EHEs (Harlan et al. 2007, Johnson et al. 2009; Buyantuyev and Wu 2010, Uejio et al. 2011, Harlan et al. 2013).

Just as there are varying definitions vulnerability, so are the methods that measure it (Bao et al. 2015), including mathematical models or indices to integrate the components that contributes to an area's vulnerability. While authors have explored the vulnerability to natural hazards (Borden et al. 2007) and EHEs (Stone et al. 2010) across cities in the US, there is limited research comparing variations of vulnerability within multiple cities.

Two good candidates for comparing the intra-urban variability of extreme heat vulnerability are Baltimore and St. Louis. These cities are comparable when considering physical geographic characteristics, as both are within the same climate region and latitudinal range, and have major water bodies located just to the east of them. Previous studies have also indicated that both Baltimore (Brazel et al. 2000) and St. Louis (Vukovich et al. 1976) are UHIs. Highlighting the areas of high exposure and sensitivity within these cities will indicate how similar or different these two cities experience EHEs and indicate potentially vulnerable block groups. This illustrates how the UHI effect varies across cities depending upon the patterns of exposure and sensitivity

Statement of purpose

This paper will draw upon Wilhelmi and Hayden's (2010) framework by associating LST with socioeconomic, population, and household characteristics to measure the exposure, sensitivity, and potential extreme heat vulnerability within Baltimore and St. Louis. In this study, exposure is measured by LST (which is exacerbated with the occurrence of EHEs) with sensitivity measured by a group of demographic variables (which influences how populations are adversely affected by EHEs). There are four main objectives to this research, outlined below:

- Remotely sense the UHI for Baltimore and St. Louis by deriving LST for both cities;
- Run bivariate correlation tests comparing LST with sensitivity variables;
- Develop a sensitivity score by compiling the sensitivity variables in an additive model;
- Visualize and quantify areas of vulnerability through an index encompassing exposure (LST) and sensitivity scores for each city.

The results from the analysis indicate the areas where mitigation strategies could potentially be implemented to reduce the effects of the UHI, thus diminishing the exposure to EHEs.

LITERATURE REVIEW

Introduction

This research builds upon several elements of extreme heat vulnerability that have been addressed by previous studies. The first element that will be addressed is vulnerability and its various contributing factors. These factors are outlined in Wilhelmi and Hayden's (2010) extreme heat vulnerability framework. Following vulnerability is a review of EHEs and their impact on morbidity and mortality with an emphasis on city populations. Next is a review of UHIs, the factors driving urban climate, and the intra-urban variability of temperature that exists within cities. Finally, the study areas, Baltimore and St. Louis, are highlighted. The study areas discussion focuses on the demographic characteristics of Baltimore and St. Louis and previous extreme heat vulnerability studies centered around each of the cities.

Vulnerability

There are a number of frameworks and methods that have been applied within vulnerability studies relating to climate change. The IPCC presents a few different conceptual frameworks in its report (Cardona et al. 2014, 71). In relation to climate change adaptation, vulnerability is the confluence of exposure, sensitivity, and adaptive capacity (Cardona et al. 2014, 71) – a framework adapted from Wilhelmi and Hayden (2010), as seen in Figure 1. Other studies follow similar, if not the same, framework (Taubenbock et al. 2008; Romero-Lankao and Qin 2011).

Exposure. According to the IPCC, exposure "refers to the inventory of elements in an area in which hazard events may occur" (Cardona et al. 2014). In other words, if there are not any people located in an area where an extreme weather event has occurred, then no exposure occurred. Exposure to climate-related hazards is a function of geography (CARE n.d.). For instance, an individual or a population living in an urban area, particularly those living in less vegetated and crowded parts of cities (as demonstrated in Huang et al. 2011), have a higher exposure to EHEs compared to suburban or rural populations. Exposure on its own does not constitute vulnerability. While vulnerability to an extreme weather event is contingent upon whether or not an individual or a population is exposed to it, other factors also contribute to that individual or population's vulnerability.

Sensitivity. Another factor that contributes to vulnerability is sensitivity. Along with exposure, the IPCC defines sensitivity as "the physical predisposition of human beings, infrastructure, and environment to be affected by a dangerous phenomenon due to lack of resistance" (Cardona et al. 2014, 72). Variables pertaining to socioeconomic status, race or ethnicity, age, sex, and household characteristics, amongst others contribute towards a population's sensitivity to environmental hazards like extreme heat (Cutter et al. 2003). These demographic characteristics can vary across urban areas. Studies have shown that these sensitive populations can be disproportionately affected by the UHI effect, thus potentially more vulnerable to EHEs (Harlan et al. 2007, Johnson et al. 2009; Buyantuyev and Wu 2010, Uejio et al. 2011, Harlan et al. 2013).

External drivers. Wilhelmi and Hayden (2010) explain that there are external factors which drive extreme heat vulnerability. These drivers can include climate change, urbanization, population change, and large-scale social or environmental disturbances (Figure 1). Urbanization, for instance, can influence the urban land use and UHI effect, affecting exposure to extreme heat. Wilhelmi and Hayden (2010) also explain that socioeconomic perturbations, like economic recession, could affect the sensitivity of a population by decreasing neighborhood stability and socioeconomic advantage.

Adaptive capacity. Adaptive capacity is defined as "the ability of a system to adjust to climate change to moderate potential damages, to take advantage of opportunities, or to cope with the consequences" (IPCC 2001). Generally, highly sensitive populations also find themselves lacking the adaptive capacity to deal with the effects of EHEs and other hazards. Increasing adaptive capacity resources should be a priority of cities in order to adapt to the effects of the changing climate since sensitivity and exposure factors cannot or are nearly impossible to be modified.

Adaptation/response. Wilhelmi and Hayden (2010) explain that the different components that make up extreme heat vulnerability require various adaptation and responses in order to reduce that vulnerability. The authors suggest that their extreme heat vulnerability framework will target the specific indicators' importance contributing to heat-related mortality and morbidity.

Extreme heat events

EHEs, or heat waves, are prolonged periods of time of unusually hot weather conditions that have the potential to cause harm to human health (CDC n.d.). EHEs are the leading cause of hazard-related deaths in the United States (US) (EPA and CDC 2016). 1,130 deaths as a result of extreme heat were recorded from 2006-2015 in the US, surpassing tornadoes, floods, and other extreme weather events (Figure 2). Similar trends can be found in previous decades (CDC and EPA 2016).

Recent studies have explored mortality rates associated with EHEs, especially the Chicago heat wave of 1995 (Semenza et al. 1996; Whitman et al. 1997) and the European heat wave of 2003 (Johnson et al. 2005; Fouillet et al. 2006; Robine et al. 2008). During these heat waves, spikes in mortality rates increased as a result of heat-related deaths. As scholars and scientists agree that these EHEs are expected to increase in frequency, intensity, and duration (Meehl and Tebaldi 2004; Luber and McGeehin 2008; Perkins et al. 2012; Rahmstorf and Coumou 2012), the corresponding number of heat-related deaths can potentially increase as well. The effects of EHEs vary depending on spatiotemporal characteristics – particularly across the urban-rural divide. That is why it is important to study the implications of EHEs in urban areas due to the urban heat island (UHI) effect.

Urban heat islands

The UHI effect is characterized by elevated temperatures in urban areas compared to the surrounding rural areas (EPA 2017). While Oke (1997) found that the mean air temperature of a city with a population of at least one million people can be around 1-3°C warmer than the surrounding rural areas, some cities can experience temperatures up to 10-15°C higher than nearby suburban and rural areas during the summer months (EPA 2008; Baltimore Office of Sustainability 2017).

This phenomenon was first described in 1799 by Noah Webster and his observations of New York City's climate (Cerveny 2009) and corroborated by Luke Howard nearly 20 years later in his study of London's climate (Howard 1833). Oke (1978) explained that the "inadvertent climate modifications associated" with urban areas can include the transformation of "radiative, thermal, moisture, and aerodynamic characteristics" (240).

Some of the main factors contributing to these inadvertent climate modifications include urban land cover change and anthropogenic heat (Imhoff et al. 2010; Zhou et al.

2014). Impervious surfaces including buildings, roads, and other heat-absorbing infrastructure contribute to these elevated air temperatures and LSTs (EPA 2008). The prevalence of impervious surfaces over vegetation decreases latent heat and increases sensible heat, thus contributing to increased temperatures in urban areas (Imhoff et al. 2010).

Intra-urban variability

Variations in temperature can also manifest within urban areas as they do across the urban-rural divide. When compared to the history of urban climatology, intra-urban variability of UHIs has only recently been studied. The intra-urban temperature variability, much like the urban-rural temperature divide, is governed by land cover composition (e.g. the juxtaposition of vegetated and built up areas) (Jenerette et al. 2016). While one study found that the intra-urban temperature differences were as large as or larger than the urban-rural differences (Buyantuyev and Wu 2010), another concluded that there was little intra-urban temperature variability (Scott et al. 2016). Differences between these results depend upon a number of factors including land cover variation and methods for gathering temperature measurements.

Related sensitivity indicators have also recently been incorporated into the research on the intra-urban variability of the UHI effect, indicating specific areas within cities that are more vulnerable to EHEs. Scholars integrated a range of variables into these studies, including biological factors (Reid et al. 2012; Bernhard et al. 2015), pre-existing health conditions (Stafoggia et al. 2006), water use (Guhathakurta and Gober 2007), vacant land (Pearsall 2017), air conditioning (Smoyer 1998; Reid et al. 2012), and several socioeconomic indicators (Basu and Samet 2002; Uejio et al. 2011; Huang et al. 2011;

Jenerette et al. 2016). It is important to consider these vulnerability indicators within the context climate change so cities can implement appropriate mitigation and adaptive strategies in response to and anticipation of EHEs.

Study areas

Baltimore, MD and St. Louis, MO are both mid-latitude cities found within the humid subtropical climate region, according to the Köppen classification system. They are both within the same latitudinal location with major water bodies located just to their east. Both cities have a history of racial segregation, particularly when it came to housing in the early 20th century (Baltimore City Planning Commission 2009; Cultural Resources Office of St. Louis 2018). The racial divide emanates largely between the white and black populations. Overall, black residents of both cities tend to live in substandard housing tenements (Baltimore City Planning Commission 2009; Cultural Resources Office of St. Louis 2018). This dichotomy can still be seen to this day. Descriptive statistics for Baltimore and St. Louis showcasing the demographic variables chosen for this analysis can be found in Table 1.

From the information presented in Table 1, Baltimore has a population about twice and an area about 40 square kilometers (or about 15 square miles) larger than the size of St. Louis. This also accounts for a higher population density in Baltimore over St. Louis. It is interesting to note the many demographic similarities that exist between the two cities. For instance, Baltimore and St. Louis have comparable populations in terms of age (under five years old and over 65 years old), housing characteristics (group quarters and renter-occupied units), educational attainment (no high school diploma), language spoken (limited English-speaking households), disability status (adults with a disability) and employment status (unemployed).

However, other demographic variables slightly differ between the cities. While some race and ethnicity variables are relatively similar for both cities (such as Asian, Hispanic, and other races), the white and black populations for Baltimore and St. Louis vary. Both cities have a higher black than white population; but the ratio of black to white population is much higher in Baltimore than in St. Louis. Additionally, Baltimore has a higher proportion of female headed households, housing units without a vehicle available, and higher average per capita income. On the other hand, St. Louis has a higher proportion of people living alone and number of families below poverty. It is important to note these differences in the demographic composition of the cities since they affect the overall heat vulnerability landscape as these components account for a city's sensitivity.

The following paragraphs briefly introduce studies centered around the UHI effect in Baltimore and St. Louis, but a comprehensive meta-analysis of articles specifically relating to extreme heat and hazards vulnerability across different study areas can be found in Table 2.

Baltimore. Many studies have looked at the Baltimore region in relation to the drivers of the UHI effect. Imhoff et al. (2010) explored the relationship between impervious surface area (ISA) and LST across different biomes, using Baltimore as one of many cities considered. The authors found that ISA was the primary driver for temperature increase across all biomes. Zhou et al. (2014) evaluated the magnitude of this relationship specifically in the Gwynns Falls watershed (located in part of Baltimore City and County). These authors confirmed that an increase in imperviousness will increase LST and increased vegetation will decrease LST. Scott et al. (2016) recently explored the intra-urban variability of the UHI effect in Baltimore (with emphasis on Eastern Baltimore). While variability in this portion of the city was small, surface properties like vegetated or green spaces in areas dominated by impervious surface were found to be important in determining spatial variability.

Further research explores the relationship between social characteristics and the UHI effect in Baltimore. Huang et al. (2011) also studied the Gwynns Falls watershed UHI, but instead assessed the relationship between LST and socioeconomic variables (see Table 2). Basu and Samet (2002) conducted an exposure assessment amongst elderly populations in Baltimore (see Table 2).

St. Louis. There appears to be little research regarding the UHI in St. Louis. Early studies have examined and confirmed that St. Louis is a UHI (Vukovich et al. 1976; Shreffler 1978). There have been, however, a few studies on excess deaths from extreme heat in St. Louis. Clarke (1972) discussed the relationship between heat-related mortality and urban structure in St. Louis. He noted that almost half of deaths during the heat wave of 1966 were caused by excessive heat. A later study by Smoyer (1998) built upon this argument by comparing mortality rates between the 1980 and 1995 heat waves in the city. She examined how changing population characteristics (specifically elderly populations) influenced the mortality rates in St. Louis. While she found that population decreased between these two heat wave events, the overall proportion of these highly sensitive groups (elderly population) increased slightly.

A good deal of research regarding the St. Louis UHI focused on various meteorological changes like wind (Draxler 1986), thunderstorm (Rozoff et al. 2003), and precipitation changes (Dettwiller and Changnon 1976) due to the urban environment. Despite the depth of the St. Louis UHI literature, there is limited research regarding vulnerability to the UHI effect in St. Louis.

Comparison of cities. There is some research pertaining to the UHI effect and extreme heat comparing two or more cities. While Matson et al. (1978) used satellite imagery to detect the UHI effect in Baltimore and St. Louis, there were no considerations for intra-urban variability and vulnerability. Brazel et al. (2000) conducted a comparative study of the UHI effect in Baltimore and Phoenix. While the study found population density to be positively associated with temperature, the authors did not consider specific sensitivity metrics. Uejio et al. (2011) considered both Phoenix and Philadelphia in their vulnerability analysis. However, their study utilized different exposure variables (heat distress in Phoenix and heat mortality in Philadelphia) to determine vulnerability within the two cities (see Table 2). This study of Baltimore and St. Louis integrates elements from previous studies to create a new methodological framework that can be applied to other cities.

DATA

Data sources

Remotely sensed satellite imagery for both study areas was derived from USGS EarthExplorer, an online tool used to search and download remotely sensed images. Landsat 8 data were selected for this study. Imagery from this satellite was selected because of widespread use in comparable studies (Huang et al. 2011; Johnson et al. 2012; Harlan et al. 2013), relatively fine resolution, and the inclusion of thermal infrared sensor (TIRS) data. Metadata for selected imagery are found in Table 3.

American Community Survey (ACS) data were derived from the US Census Bureau. The ACS is a recurring survey providing annual population estimates in between the release of the decadal Census survey. Some scholars have begun to incorporate ACS data in their social vulnerability studies in lieu of outdated Census information (Aubrecht and Özceylan 2013; Mitchell and Chakraborty 2014; Pearsall 2017; Nayak et al. 2017). Geodatabases of 2011-2015 5-year estimates by block group, which included detailed tables and corresponding feature classes, were downloaded for Maryland and Missouri.

Criteria for data selection

Satellite imagery was selected contingent upon various conditions. Imagery was from summer months was selected as vegetation is most prominent and abundant during this time of year, an important precondition when conducting image analyses. Imagery with less than 10% cloud cover was also selected to ensure that the study areas are free of clouds.

Socioeconomic variables were chosen primarily based on Cutter et al.'s (2003) social vulnerability metrics and concepts as well as previous UHI and heat vulnerability studies (Reid et al. 2009; Huang et al. 2011; Mitchell and Chakraborty 2011; Uejio et al.

2011; Pearsall 2017). Table 2 outlines the sensitivity metrics and corresponding variables taken from the ACS. Both datasets were taken from 2015 to ensure temporal consistency.

Data preparation

Landsat imagery was imported in TerrSet, an integrated GIS and remote sensing software developed by Clark Labs (Clark University) for monitoring and modeling for sustainable development. The imagery data for both cities were imported by converting the multispectral bands to dark-object subtraction reflectance, leaving the thermal bands in their raw digital numbers, necessary for the calculation of land surface temperature in later analyses.

ACS data were prepared in ArcGIS. City block groups were selected and exported feature classes for Baltimore and St. Louis. Selected sensitivity variables from the detailed tables were joined from the detailed tables to their respective city feature classes by their unique GEOID fields. Some variables required ancillary calculations to derive the appropriate variable raw values, and all required to be converted to percentages. Table 3 lists each of the variables, a description of each, and how they were derived.

METHODS

Objective 1: Deriving LST for Baltimore and St. Louis

The normalized difference vegetation index (NDVI) while a measurement of greenness, is also a major indicator of urban climate (Yuan and Bauer 2007). NDVI is also necessary to calculate as it is used to derive emissivity. Emissivity is a surface's ability to radiate thermal energy. One can expect that land surface emissivity, unlike that of a water body, varies with land cover (Yu et al. 2014). The emissivity is derived using the thermal band from the Landsat imagery and NDVI, which is needed when calculating LST.

NDVI and emissivity were calculated in TerrSet using a macro model to automate the tasks. The following is the script from the .IML macro file that calculates NDVI and emissivity for the study areas:

```
vegindex x 2*xndvi*[band4]*[band5]
display x a*xndvi*ndvi*y
reclass x i*xndvi*xtemp1*2*0.995*-1.000*-0.185*0*-0.185*1.000*-9999*2
display x a*xtemp1*quant*y
reclass x i*xndvi*xtemp2*2*0*-1.000*-0.185*0.970*-0.185*0.157*0*0.157*1.000*-9999*2
display x a*xtemp2*quant*y
reclass x i*xndvi*xtemp3*2*0*-1.000*0.727*0.990*0.727*1.000*-9999*2
display x a*xtemp3*quant*y
reclass x i*xndvi*xtemp4*2*0*-1.000*0.157*0*0.727*1.000*-9999*2
display x a*xtemp4*quant*y
reclass x i*xtemp4*xtemp5*2*0*0*0.00001*1*0.00001*1.000*-9999*1
display x a*xtemp5*quant*y
transform x xtemp4*xtemp6a*2
display x a*x11temp6a*quant*y
scalar x xtemp6a*xtemp6b*3*0.047
display x a*xtemp6b*quant*y
scalar x xtemp6b*xtemp6c*1*1.0094
display x a*xtemp6c*quant*y
overlay x 3*xtemp5*xtemp6c*xtemp7
display x a*xtemp7*quant*y
overlay x 7*xtemp1*xtemp2*xetemp1
display x a*xetemp1*quant*y
overlay x 7*xtemp3*xetemp1*xetemp2
display x a*xtemp7*quant*y
overlay x 7*xtemp7*xetemp2*x11emissivity
display x a*xemissivity*quant*y
```

The derived emissivity raster was used to calculate the LST using TerrSet's thermal function. The thermal function provides default settings for both Landsat 4 and 5 satellite data; however, TerrSet does not provide default values for Landsat 8 imagery. The offset, gain, K1, and K2 metrics need to be input manually as well. Table 4 outlines the values taken from the Landsat 8 metadata file needed to perform the thermal function.

Once LST was derived for each of the scenes, the rasters were exported from TerrSet as an Esri binary float format, ensuring compatibility with the ArcGIS platform. Appropriate project parameters also needed to be assigned for each raster before adding the data to ArcGIS. The raster datasets were then extracted by the corresponding city boundary.

The zonal statistics as table tool in ArcMap was used to calculate the mean LST for the block groups of the cities. The tables were then joined to their respective city feature class in order to symbolize and classify these data. Mean LST by block group were visualized on both continuous and classified scales. Five classes of LST (representing temperatures from very low to very hot) were classified based on the quantile classification method, resulting in relatively equal amounts of block groups per class.

Objective 2: Bivariate correlation tests

In SPSS, mean LST and all sensitivity variables were assessed for normality using the Shaprio-Wilk test. This test was chosen due to the relatively small amount of block groups (n) for each of the cities. The Shaprio-Wilk test for both cities indicated that overall, the data were not normally distributed. Therefore, mean LST and percentages of all sensitivity variables were correlated with each other in a two-tailed Spearman's rho correlation test. SPSS flagged significance levels at 90, 95, and 99% for each correlation value. Correlograms for the each of these correlation matrices were created in R to visualize the direction, magnitude, and significance level of the bivariate relationships.

Objective 3: Developing a sensitivity score

The sensitivity variables were normalized on a zero to one scale. The following equation was used to derive the normalize values (Inostroza et al. 2016):

$$\frac{X - X_{min}}{X_{max} - X_{min}}$$

Two of the variables – percent of white population and per capita income – are important to consider, but are negatively associated with levels of sensitivity (in other words, higher percentages of white population and wealthier areas are less sensitive to climate-related hazards). These variables, therefore, needed to be inversely normalized so that the higher values reflected higher levels sensitivity. The following equation accomplished this:

$$1 - \frac{X - X_{min}}{X_{max} - X_{min}}$$

A sensitivity score was created that combines all normalized sensitivity variables through an additive model. An additive model was chosen as previous studies have utilized this method in the development of vulnerability indices (Cutter et al. 2003; Harlan et al. 2013). Very few studies have implemented a multiplicative model to some capacity in vulnerability research (e.g., Rey et al. 2009), but the application of multiplicative models when composing a sensitivity score is very limited. Other spatial statistics methods for composing a vulnerability index include a principle components analysis (PCA) (Reid et al. 2009; Harlan et al. 2013; Johnson et al. 2012; Wolf and McGregor 2013; Inostroza et al. 2016) and regression analyses (Johnson et al. 2009; Uejio et al. 2011; Loughnan et al. 2012; Declet-Barreto et al. 2016). However, an additive model considers all variables without assumptions whereas some variables would potentially be excluded in a PCA or regression model.

Objective 4: Visualizing and quantifying vulnerability

Visualizations of vulnerability were created through maps of the exposure and sensitivity scores by classifying the normalized values into quintiles to derive very low, low, medium, high, and very high risk. Bivariate choropleth maps were also created to visualize the potential vulnerability (exposure and sensitivity) within the cities. Methods for bivariate map creation were adapted from Stevens (2015). Specific block groups were highlighted to indicate areas of low exposure and high sensitivity, high exposure and low sensitivity, and high exposure and high sensitivity – the most vulnerable of these categories.

RESULTS

LST for Baltimore and St. Louis

Visualizations of LST can be found in Figures 3-6. Higher LSTs tend to be found towards the center of the cities, clustering near their respective water bodies, and generally gets cooler approaching the city boundaries. For instance, the warmest block group in Baltimore with a mean LST of 40.2°C is located in the Patterson Park neighborhood. Interestingly enough, the warmest block group in Baltimore is located very close to an anomalously cool block group in the center of the city, Patterson Park (33.4°C). The reason for Patterson Park's relatively lower temperature is due to the vegetation that promotes cool conditions. The coolest block group is located in Franklintown, bordering the city boundary on the west side, with a mean LST of 28.5°C. However, there is an anomalously warm block group that borders Baltimore's western boundary. As the neighborhood name implies, a block group within Reisterstown Station has a metro station stop located within it, with a temperature of 37.2°C.

Though there is a clear clustering of high temperatures in central St. Louis, temperature distribution tends to be quite variable across the block groups. However, there are some block groups that deviate from the overall pattern. For instance, the block group in the Forest Park neighborhood, though surrounded by high temperature block groups to the south and east, was recorded at 33.6°C. As with Patterson Park in Baltimore, the green space creates cooler temperatures. Conversely, two block groups in the northern part of the city within a neighborhood identified as Mark Twain I-70 Industrial are anomalously warm (40.3°C and 40.9°C) because of the impervious surface cover within those block groups.

It is interesting to note the spatial patterns of LST around water bodies within these cities. While one may hypothesize that the harbor and the Mississippi river would mitigate the effects of the UHI in both cities, the development that is concentrated near these water bodies contribute to the increased LST in those block groups. All of these maps, thus, indicate the intra-urban variability that exists within UHIs.

Bivariate correlation tests

Results from correlation analyses can be found in Tables 7-10. The Shapiro-Wilk tests for normality for both Baltimore (Table 7) indicated that these data were not normally distributed. Based on these results, a two-tailed Spearman's rho was the appropriate bivariate correlation analysis to run on Baltimore (Table 8). Similar results for the Shapiro-Wilk and Spearman's rho analyses for St. Louis (Tables 9 and 10). These results are also visualized for Baltimore (Figure 7) and St. Louis (Figure 8) as correlograms. The shade indicates the strength or magnitude of the correlation coefficient while the hue indicates the direction of the relationship. Significance levels are flagged at 95 (*), 99 (**) and 99.5% (***) for each correlation.

There is a similar significant relationship between mean LST and the sensitivity variables for both Baltimore and St. Louis. These significant variables include percent of population with no high school diploma, percent of families below poverty, per capita income, percent renter-occupied housing units, and percent of households without access to a vehicle. All of these variables are positively correlated with mean LST except for per capita income, which is negatively correlated, and per capita income for St. Louis, which was very weakly positively correlated with LST. These significant relationships are stronger in Baltimore than they are in St. Louis.

Sensitivity score

Small multiple maps were created of each sensitivity variable, separated into quintiles, to indicate the various levels of sensitivity (Figures 9 and 10). There is a clear divide between black and white populations in both Baltimore and St. Louis. Other variables like female-headed households, populations without a high school diploma, and families below poverty align relatively closely with the distribution of black populations in both cities. Additionally, per capita income and white population followed a similar pattern for both cities. All sensitivity variables were compiled into the sensitivity score and visualized in Figures 11 and 12. The distributions of LST did not correspond to patterns of overall sensitivity. However, the north central area of Baltimore clearly exhibited a low exposure/low sensitivity pattern, while the northern part of St. Louis showed a low exposure/high sensitivity area.

Visualizing and quantifying vulnerability

Assessing vulnerability requires the combination of both exposure and sensitivity. Exposure maps were created (Figures 13 and 14) before overlaying it with sensitivity. The results of the vulnerability maps are found in Figures 15 and 16. The classes can be broken down into high exposure/high sensitivity (purple), high exposure/low sensitivity (teal), and low exposure/high sensitivity (pink). Tables 11 and 12 indicate the top five block groups from each of these classes with the associated mean LST and sensitivity variables.

Areas of high exposure/high sensitivity have populations that are most vulnerable to extreme heat and EHEs than all other groups. In Baltimore, these block groups are somewhat dispersed and surrounds the very center of the city. In St. Louis, there are three different clusters of these highly vulnerable block groups (in this case, clustering does not refer to the statistical clustering of block groups, but rather the visual pattern they convey) around the northwest, eastern central, and south central portions of the city.

High exposure/low sensitivity block groups may not currently be vulnerable, but could indicate areas of concern if the demographic make-up of these block groups were to change. The spatial pattern of high exposure/low sensitivity block groups within Baltimore tend to be more homogeneous than of high exposure/high sensitivity. The high exposure/low sensitivity block groups are found around the Canton neighborhood. In St. Louis, these block groups are not visibly clustered around a particular area, but generally found in the central and south portions of the city.

Low exposure/high sensitivity may also not be of concern currently, but may become vulnerable if these are become more densely populated or built-up, increasing the magnitude of the UHI for these block groups. These blocks are very separated within Baltimore, but are found dispersed outside of the city’s center. In St. Louis, these block groups are also generally dispersed, mostly located in the northern portion of the city.

DISCUSSION

Summary of results

These results build upon the results found in previous studies. Like other researchers have noted, the analyses of exposure (LST) indicate the intra-urban variability of temperature that exists within UHIs (e.g. Harlan et al. 2007; Huang et al. 2011; Wolf and McGregor 2013). Baltimore and St. Louis also exhibit intra-urban variability of sensitivity metrics as well, visualized in the small multiple maps (Figures 9 and 10). In some cases, certain variables are shown to have similar patterns with each other (e.g. black population and families below poverty). However, these positive associations between sensitivity variables are not always the same across all block groups. Without the inclusion of an additive model in the analysis, the combinations of all sensitivity variables would not have been included (see Aubrecht and Özceylan 2013).

From the results of the top five high exposure/high sensitivity block groups for each city, there seem to be certain sensitivity variables that govern vulnerability. In Baltimore, housing and occupant characteristics like female headed households, people living alone, renter-occupied units, and units without a vehicle present all seem to contribute to high levels of vulnerability. Families below the poverty line and black populations also played an important role in determining vulnerability for highly exposed and highly sensitive block groups – so much so that one block group in the top five had the highest percentage of families below poverty while another had the highest percentage of black population.

There are some similarities amongst the top five most vulnerable block groups in St. Louis in terms of the sensitivity variables contributing to vulnerability. Families below poverty, units without a vehicle, and especially renter-occupied units are important variables in determining vulnerability for St. Louis. Race and ethnicity did not play a particularly significant role in determining vulnerability for St. Louis as it did with Baltimore. Age, whether very young or elderly populations, did not contribute too much towards vulnerability in either of the cities. With this information, it can be concluded that vulnerability for these two cities stems from the nature of the household or housing unit as opposed to the demographic and biophysical characteristics of the occupants.

As noted, income seemed to be an important factor in determining vulnerability as it has in previous studies. Families below poverty greatly influenced vulnerability to extreme heat in both cities, which aligns with the results from Harlan et al.'s (2007) study on the UHI in Phoenix. In it, the authors found that median household income was negatively associated with LST, indicating that richer communities tended to experience lower temperatures. The same can be said about Huang et al.'s (2011) study, which noted a negative relationship between LST and median household income and positive relationship between LST and poverty status.

Though adaptive capacity was not measured in this analysis, the results from the sensitivity analysis can suggest how vulnerable block groups might cope with extreme heat. For instance, income metrics could influence a person's access to air conditioning as it would cost money for to maintain the cooling system (especially in older houses). Rinner et al. (2010) considered the age of the housing units as a proxy for air conditioning information. Additionally, access to cooling centers may be curbed due to limited or no vehicle access. In a scenario where an individual would have to take public transit to a cooling center would only increase his/her exposure to extreme heat having, as she/he would need to travel outside. However, these are only assumptions and would need to be confirmed in further research endeavors by gathering the necessary data instead of relying on proxy data.

Within the context of Wilhelmi and Hayden's (2010) framework, specific elements within the extreme heat vulnerability framework were highlighted in this analysis. Urbanization and urban development served as an external driver of vulnerability for both Baltimore and St. Louis. While this research discussed the potential for exposure to EHEs as well as the UHI effect, exposure was measured by LST considering the intra-urban distribution of heat. Sensitivity metrics were measured based on age and various socioeconomic factors. Though adaptive capacity was not measured, household and community resources could be impacted by the socioeconomic landscape of the cities. The results from the analysis would allow planners and policymakers to make the appropriate decisions in terms of adaptation and response practices to either mitigate or prevent further heat related morbidity and mortality impacts from extreme heat.

Comparison of results

These results offer some different conclusions when compared to previous, comparable studies. For instance, in Huang et al.'s (2011) study of heat vulnerability in the Gwynns Falls watershed, the magnitude and direction of some variables differ from the results of this study. While the results followed the same general pattern, most correlation coefficients in Huang et al.'s (2011) study were higher in magnitude compared to those in this study. This can be explained by the study areas delineated for each study. While Huang et al. (2011) looked into the inequitable heat distribution across an entire watershed (which encompassed both urban and rural areas), this research focused on the variability within the city itself.

In another study focused on Baltimore, Basu and Samet (2002) focused specifically on the exposure of elevated LSTs amongst elderly populations within the city. While the study quantified the variability of demographic characteristics amongst these elderly populations, there was no method to indicate the spatial variation of these populations within the city. This study considered elderly populations amongst many other sensitivity variables to understand the distribution of sensitivity within Baltimore. Despite these comparisons amongst studies within Baltimore, no studies have looked at sensitivity to EHEs or compiled a vulnerability index for St. Louis. This research offers the first glimpse into the sensitivity and vulnerability of St. Louis to EHEs.

Limitations of the study

While this study expanded upon previous extreme heat vulnerability studies relating to heat stress and the UHI effect, there are some components of this study that could be addressed in future research. One of the most obvious was the lack of an adaptive capacity component that would indicate the cities' overall vulnerability as opposed to just potential vulnerability. Reid et al. (2009), for instance, have considered the factors like air conditioning access to indicate adaptive capacity resources in their study. These data were not available at the same resolution and time frame to do an appropriate comparative analysis at the block group level. The incorporation of multilevel statistical analyses encompassing more variables available at various scales could be implemented in future studies. This study did not also consider the possibility of how the UHI within these two cities changed over time, as some previous UHI studies have noted. If given more time, these limitations could be addressed.

Further research

Future studies should consider comparing intra-urban vulnerability to the UHI effect across different cities to understand how patterns of exposure, sensitivity, and vulnerability vary. Baltimore and St. Louis showed similar spatial relationships in terms of the distribution of heat and the divide amongst sensitive populations. For instance, higher LSTs in both cities were clustered near the center of each city. Additionally, the racial and economic divide within both cities was indicated by the clustering of block groups in certain sensitivity variable maps. Scholars should consider implementing surveys to acquire information on adaptive capacity resources that are not currently available, for these cities and others. This information will contribute to the understanding of how certain block groups can cope with and manage the effects of climate-related hazards such as EHEs. Further, scholars may also consider data on heat-related hospital admittances or heat mortality and how those relate to sensitivity, as other studies have considered (see Uejio et al. 2011 and Navak et al. 2017).

For planners and policymakers

This study could serve as a resource for the planners and policymakers of these cities. Perhaps this study offers these decision makers new variables to consider when preparing for and responding to EHEs. The areas identified as highly vulnerable could be targeted to implement mitigation strategies in order to diminish the effects of the UHI. Methods like cool and green roofs, vegetation, community pools, and cooling centers are just a few ways that cities can help reduce the effects of EHEs. With vacant buildings being an issue for both cities due to their shrinking populations, transforming or repurposing those areas to mitigate the UHI effect would be a good starting point. The concept of urban community gardens would not only be a way of cooling areas, but it could also potentially bring economic revenue and provide good food to food insecure areas.

CONCLUSIONS

This study focused on the potential vulnerability to EHEs within two cities found to be UHIs – Baltimore and St. Louis. In this study, remotely sensing the UHI by deriving LST for each city by block group was achieved. The mean LST values by block group were correlated with indicators of sensitivity to EHEs. A sensitivity score was developed in an additive model, combining all sensitivity variables. Finally, areas of vulnerability were visualized and quantified through an EHE vulnerability index.

Correlation results indicated statistically significant relationships between mean LST and the following in both cities: percent of population with no high school diploma, percent of families below poverty, per capita income, percent renter-occupied housing units, and percent of households without access to a vehicle. All sensitivity variables along with exposure (or mean LST) were combined to reveal the high exposure/high sensitivity block groups. While these block groups are generally located just around the urban center of Baltimore, there is no real pattern of the distribution of these block groups in St. Louis.

This research built upon the already well-established field of UHIs and vulnerability by integrating methods and considerations that were not encompassed in one study alone. As EHEs become more pervasive, and as urban populations grow, the ramifications of these climate-related hazards will affect more and more people. These hazards are an important topic concerning the relationship and dichotomy of nature and society. Though it is taught that Mother Nature does not discriminate, discrimination has become institutionalized in society. Not only do we need to make efforts to mitigate and adapt to the changing climate; but we must also make strides to change societal standards that relegate certain populations as highly sensitive. Until then, we all put ourselves at risk.

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Tables

Table 1. Descriptive statistics, Baltimore and St. Louis

	Baltimore	*St. Louis*
Total population	622,454	317,850
Area (km^2)	210.606849	171.10734
Population density (persons/km^2)	2955.525915	1857.605875
Social variables (%)		
Under 5 years old	6.67	6.70
Over 65 years old	12.06	11.22
White	30.31	45.75
Black/African-American	62.84	47.68
Asian	2.57	2.84
Other race	6.55	6.35
Hispanic	4.58	3.73
Female-headed households	22.36	17.88
Living alone	39.23	44.39
Group quarters	3.94	3.47
Renter-occupied units	43.18	44.59
No vehicle available	24.31	17.24
No high school diploma	15.71	15.89
Limited English-speaking households	2.15	2.23
Families below poverty	18.96	21.70
Per capita income (average $)	24986	23158
Adults with a disability	18.10	18.09
Unemployed	8.08	8.02

Table 2. Meta-analysis of relevant extreme heat vulnerability case studies

Author, year	*Study area*	*Data*	*Methods*	*Results*
Aubrecht and Özceylan 2013	National Capital region (Washington, DC and surrounding metropolitan area)	Global Historical Climatology Network (GHCN) (heat wave frequency and duration), National Land Cover Database (land cover patterns), American Community Survey (ACS) census block estimates (sensitivity variables) Social variables: Ratio of elderly people 65 years of age and older; Ratio of elderly householders that live alone; Ratio of poverty status of individuals in the past 12 months; Ratio of households that do not speak English well or at all; Ratio of individuals 25 years and older with less than a high school education	Heat stress index (HSI) of heat wave day counts; heat stress vulnerability index (HSVI) with normalized vulnerability indicators (unweighted quantitative aggregation); heat stress risk index (HSRI) created by multiplying two previous indices	Less heat wave days in north, northwest portion of region compared to south, southeast; urbanized blocks generally more sensitive than others; HSRI indicates that Washington, DC accounts for majority of highly vulnerable blocks
Basu and Samet 2002	Baltimore, MD	Participant data from a group of 42 elderly (65 years and older) individuals (body and ambient temperature, heart rate, activity level, demographic information, survey questions)	Individual linear regressions between body temperature, heart rate, activity level, and ambient temperature	Positive association between body temperature and ambient temperature, yet no relationship between heart rate/activity level and body or ambient temperature; while demographic information was collected, it was not analyzed against ambient temperature
Cutter et al. 2003	United States	County-level census data (social data) Social variables: Median age; Per capita income; Median dollar value of owner-occupied housing; Median rent; Number of physicians per 100,000 population; Vote cast for president (percent voting for leading party [Democrat]); Birth rate; Net international migration; Land in farms as a percent of total land; Percent African-American; Percent Native American; Percent Asian; Percent Hispanic; Percent of population under five years old; Percent of population over 65 years old; Percent of civilian labor force unemployed; Average number of people per household; Percent of households earning more than $75,000; Percent living in poverty; Percent renter-occupied housing units; Percent rural farm population; General local government debt revenue; Percent of population 25 years or older with no high school diploma; Number of housing units per square mile; Number of housing permits per new residential construction per square mile; Number of manufacturing establishments per square mile; Earnings in all industries per square mile;	Factor analysis of social variables; additive model combining all factors creating a social vulnerability index (SoVI)	Most vulnerable counties appear in the southern half of the nation (regions with greater ethnic inequality and rapid population growth); weak, negative relationship between frequency of presidential disaster declarations and higher SoVI scores

		Number of commercial establishments per square mile; Value of all property and farm products sold per square mile; Percent of the population participating in the labor force; Percent employed in primary extractive industries (farming, fishing, mining, and forestry); Percent employed in transportation, communications, and other public utilities; Percent employed in service occupations; Per capita residents in nursing homes; Per capita number of community hospitals; Percent population change; Percent females; Percent female-headed households, no spouse present; Per capita Social Security recipients		
Harlan et al. 2007	Phoenix, AZ	Landsat 7 ETM+ (vegetation abundance and LST), digital elevation model (slope and elevation), census tract data (population characteristics), interview data from households (housing quality and upkeep) Social variables: Population density; Median income; Percent Hispanic; Year house was built	Creation of human thermal comfort index (HTCI); Pearson correlation analysis; bivariate linear regression analysis between social stratification and local temperatures	Correlations between social variables and temperature were higher than some environmental variables; regression results showed for every 0.5°F decrease in temperature, there was a $10,000 increase in median income (affluent people “buy” more favorable microclimates)
Huang et al. 2011	Gwynns Falls Watershed (Baltimore City and County, MD)	Landsat 7 ETM+ (LST), census block groups (sensitivity data) Social variables: Percentage of households in a block group which have an income below the poverty line; Annual household median income; Percentage of people in a block group who received a bachelor’s degree; Percentage of people in a block group who received less than nine-years of education; Percentage of people in a block group who are White; Percentage of people in a block group who are older than 65; Percentage of households in a block group which have only one person; Total crime index of a block group	Pearson correlation between LST and social variables; mapping LST and social variables to indicate vulnerable “hot spots”	Higher LST correlated with low income and education, large proportion of ethnic minorities, elderly, impoverished, and high crime risk; most vulnerable “hot spots” found within city’s boundary
Inostroza et al. 2016	Santiago, Chile	Landsat TM/ETM+ (built up surfaces, vegetation, LST), Instituto Nacional de Estadistica de Chile census tracts (sensitivity and adaptive capacity data), Mapcruzin (adaptive capacity data) Social variables: Inhabitants per hectare above 60 years old; Inhabitants per hectare below 5 years old; Inhabitants per hectare handicapped; Inhabitants per hectare single; Inhabitants per hectare with lower education; Inhabitants per hectare without a permanent employment	Principle components analysis (PCA); Pearson correlation analysis; summatory model combining exposure, sensitivity, and adaptive capacity variables using weighted variance from principle components; Anselin Local I Moran cluster analysis	Clear pattern of exposure based on LST distribution; various spatial patterns of exposure, sensitivity, and adaptive capacity; in general, higher exposure and lower adaptive capacity result in high HVI clusters
Nayak et al. 2017	New York State (excluding New York City)	National Land Cover Database (environmental data), heat stress emergency department visits from NYS Dept. of Health; American Community Survey census tracts (social data)	Spearman’s correlation between social variables; PCA;	Most variables were positively correlated with each other; four components: social/language,

		Social variables: Percentage population that is Hispanic; Percentage population that is foreign born; Percentage population who speak English less than 'very well'; Percentage population with income below poverty level; Percentage population that is Black; Percentage population over 65 years of age; Percentage population over 65 years of age and living alone; Percentage population (18-64 years) that has a disability; Percentage population (18-64 years) that are unemployed; Percentage of houses built before 1980; Density of housing units per square mile	creation of heat vulnerability index (HVI) based on principle components; comparison of heat stress cases with HVI score	socio-economic, environmental/urbanicity, social isolation/elderly; most vulnerable areas located in urban and metropolitan census tracts; increasing prevalence of heat related illnesses with increase in HVI scores
Pearsall 2017	Philadelphia, PA	Landsat 8 (LST and vegetation), National Land Cover Database (impervious surfaces), City of Philadelphia land use (vacant lots), ACS census block group data (demographic data) Social variables: Families living in poverty; Median household income; Percentage non-white; Percentage in labor force	OLS and geographically weighted regression and hot spot analyses to compare relationship between LST, vacant land, vegetation, and impervious surface; difference between means test to compare social indicators with hot spots	Social vulnerability spatially varies across the city; statistically significant difference for all social indicators; one-third of families in one hotspot live in poverty; median household income was $12,000 less in a hotspot, and a smaller percentage of people were in the labor force; higher percent of non-white population in hotspots compared to city's average
Rinner et al. 2010	Toronto, Canada	Natural Resources Canada imagery (LST); Canadian census and Community Social Data Strategy (sensitivity data) Social variables: Pre-existing/chronic illness; Cognitive impairment; Elderly residents; Infants and young children; Low-income households; Rental households; Socially isolated people; Homeless; Low education level; Not English speaking; Recent immigrants; Racialized groups	Ordered weighted averaging (OWA) multi-criteria analysis; hot spot analysis using local indicators of spatial association (LISA) method (proportion of heat-related 911 calls by Toronto neighborhoods); focus on mapping variables and overall vulnerability	OWA analysis provided optimistic, neutral, and pessimistic strategy maps for decision makers (based on decision-makers attitude towards risk); clusters of low vulnerability towards the city center; emphasis on visual interpretation of results from maps
Uejio et al. 2011	Philadelphia, PA and Phoenix, AZ	Heat distress calls (Phoenix), heat mortality (Philadelphia), ASTER data (LST and vegetation), National Land Cover Database (impervious surface), Census block groups (sensitivity data) Social variables: Percentage of residents below the poverty line; Percentage of households renting; Population age 65 or older; Percentage of population age 65 or older; Percentage of people living alone; Percentage of people with disabilities; Percentage of linguistically isolated households; Percentage of households with seven or more residents; Percentage of residents in race categories (Black, Hispanic, American Indian, and Asian American);	Generalized linear and mixed models (GLMM) and reported odds ratios and incidence ratios	In Philadelphia, heat exposure was not related to mortality, rather percent black population, year house was built, vacant households, and total population; In Phoenix, exposure/built environment, socioeconomic factors, and neighborhood stability were all important in explaining heat

		Percentage of residents changed households past 5 years; Percentage of vacant households; Year house built (median) Housing value (median) – US Dollars		distress calls, especially Black, Hispanic, and linguistically and socially isolated residents, and vacant households
Wolf and McGregor 2013	London, United Kingdom	MODIS (LST); census district data (sensitivity and heat exposure variables) Social variables: Population above 65 years old; Population with long-term limiting illness; Population with self-reported health status of "not good"; Receiving any kind of social benefit; Single pensioner households; Ethnic group other than "White British"; Population living in any kind of communal establishment	Assessment of risk factors and choosing appropriate proxy data; PCA; weighted variables based on principle components and sum together to created heat vulnerability index (HVI); Hot Spot Analysis Getis Ord Gi*	HVI shows spatial heterogeneity for London; hot spot analysis shows highly vulnerable areas are in north London

Table 3. Satellite imagery metadata

Study area	*Baltimore, MD*	*St. Louis, MO*
Date acquired	08-17-2015	07-31-2015
Path, row	15, 33	24, 33
UTM zone	18N	15N

Table 4. Sensitivity metrics and variables*

Metrics	*Variables (%)*
Age	Under 5 years old
	Over 65 years old
Race and ethnicity	White
	Black/African-American
	Asian
	Other race
	Hispanic
Housing/occupant characteristics	Female headed households
	Living alone
	Group quarters
	Renter-occupied units
	No vehicle available
Education	No high school diploma
Language spoken	Limited English-speaking households
Socioeconomic status	Below poverty line
	Per capita income ($)
Disability status	Adults with a disability
Employment status	Unemployed

*metrics derived from Cutter et al. (2003)

Table 5. Sensitivity variables and associated letter code

Letter	*Variable (%)*
A	Under 5 years old
B	Over 65 years old
C	White
D	Black/African-American
E	Asian
F	Other race
G	Hispanic
H	Group quarters
I	Female headed households
J	Living alone
K	No high school diploma
L	Limited English-speaking households
M	Families below poverty
N	Per capita income ($)
O	Adults with a disability
P	Unemployed
Q	Renter-occupied units
R	No vehicle available

Table 6. Thermal function parameters for Landsat 8 imagery

Variable	*.MTL file code*	*Value*
Offset	RADIANCE_ADD_BAND_10	0.1
Gain	RADIANCE_MULT_BAND_10	0.0003420
K1	K1_CONSTANT_BAND_10	774.8853
K2	K2_CONSTANT_BAND_10	1321.0789

Table 7. Shapiro-Wilk test for normality, Baltimore

Variable	*Statistic*	*df*	*Sig.*
Mean LST	.986	648	.000
A	.906	648	.000
B	.830	648	.000
C	.389	648	.000
D	.699	648	.000
E	.542	648	.000
F	.289	648	.000
G	.954	648	.000
H	.970	648	.000
I	.931	648	.000
J	.317	648	.000
K	.893	648	.000
L	.317	648	.000
M	.893	648	.000
N	.844	648	.000
O	.933	648	.000
P	.929	648	.000
Q	.978	648	.000
R	.941	648	.000

Table 8. Spearman's rho correlation matrix, Baltimore

	Mean LST	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Mean LST	1.000	.005	-.240**	-.068	.055	-.001	-.049	.083*	-.059	.089*	.110**	.330**	.094*	.251**	-.250**	.108**	.135**	.269**	.368**
A	.005	1.000	-.187**	-.013	.041	-.077	.095*	.047	-.041	.234**	-.122**	.093*	.090*	.263**	-.160**	-.073	.157**	.123**	.065
B	-.240**	-.187**	1.000	-.157**	.219**	-.163**	-.149**	-.179**	.039	-.079*	.215**	.088*	-.112**	-.126**	.115**	.350**	-.037	-.187**	.013
C	-.068	-.013	-.157**	1.000	-.936**	.525**	.360**	.480**	.121**	-.637**	.083*	-.352**	.271**	-.363**	.595**	-.394**	-.412**	-.026	-.403**
D	.055	.041	.219**	-.936**	1.000	-.584**	-.482**	-.507**	-.082*	.665**	-.062	.376**	-.319**	.387**	-.551**	.414**	.454**	.003	.392**
E	-.001	-.077	-.163**	.525**	-.584**	1.000	.271**	.303**	.055	-.474**	.167**	-.285**	.314**	-.268**	.414**	-.368**	-.284**	.156**	-.160**
F	-.049	.095*	-.149**	.360**	-.482**	.271**	1.000	.459**	.101**	-.198**	-.012	-.099*	.251**	-.109**	.192**	-.136**	-.125**	.105**	-.103**
G	.083*	.047	-.179**	.480**	-.507**	.303**	.459**	1.000	.109**	-.251**	-.018	-.048	.405**	-.108**	.222**	-.210**	-.156**	.114**	-.106**
H	-.059	-.041	.039	.121**	-.082*	.055	.101**	.109**	1.000	-.074	.071	-.021	.049	-.022	.031	-.006	-.106**	.026	.022
I	.089*	.234**	-.079*	-.637**	.665**	-.474**	-.198**	-.251**	-.074	1.000	-.398**	.397**	-.188**	.535**	-.582**	.269**	.488**	.016	.333**
J	.110**	-.122**	.215**	.083*	-.062	.167**	-.012	-.018	.071	-.398**	1.000	-.021	.100*	-.101**	.116**	.084*	-.162**	.374**	.261**
K	.330**	.093*	.088*	-.352**	.376**	-.285**	-.099*	-.048	-.021	.397**	-.021	1.000	-.005	.465**	-.590**	.529**	.386**	.249**	.537**
L	.094*	.090*	-.112**	.271**	-.319**	.314**	.251**	.405**	.049	-.188**	.100*	-.005	1.000	-.093*	.076	-.157**	-.140**	.205**	.058
M	.251**	.263**	-.126**	-.363**	.387**	-.268**	-.109**	-.108**	-.022	.535**	-.101**	.465**	-.093*	1.000	-.595**	.365**	.426**	.250**	.448**
N	-.250**	-.160**	.115**	.595**	-.551**	.414**	.192**	.222**	.031	-.582**	.116**	-.590**	.076	-.595**	1.000	-.465**	-.421**	-.213**	-.563**
O	.108**	-.073	.350**	-.394**	.414**	-.368**	-.136**	-.210**	-.006	.269**	.084*	.529**	-.157**	.365**	-.465**	1.000	.245**	.116**	.447**
P	.135**	.157**	-.037	-.412**	.454**	-.284**	-.125**	-.156**	-.106**	.488**	-.162**	.386**	-.140**	.426**	-.421**	.245**	1.000	.068	.303**
Q	.269**	.123**	-.187**	-.026	.003	.156**	.105**	.114**	.026	.016	.374**	.249**	.205**	.250**	-.213**	.116**	.068	1.000	.614**
R	.368**	.065	.013	-.403**	.392**	-.160**	-.103**	-.106**	.022	.333**	.261**	.537**	.058	.448**	-.563**	.447**	.303**	.614**	1.000

Table 9. Shapiro-Wilk test for normality, St. Louis

Variable	*Statistic*	*df*	*Sig.*
Mean LST	.993	360	.082
A	.936	360	.000
B	.932	360	.000
C	.886	360	.000
D	.865	360	.000
E	.597	360	.000
F	.698	360	.000
G	.635	360	.000
H	.326	360	.000
I	.933	360	.000
J	.995	360	.366
K	.956	360	.000
L	.573	360	.000
M	.915	360	.000
N	.919	360	.000
O	.969	360	.000
P	.919	360	.000
Q	.993	360	.086
R	.954	360	.000

Table 10. Spearman's rho correlation matrix, St. Louis

	Mean LST	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Mean LST	1.000	.008	-.203**	.161**	-.158**	.244**	.179**	.160**	.126*	-.143**	.177**	-.035	.170**	.037	.087	-.157**	-.077	.308**	.091
A	.008	1.000	-.284**	-.008	.024	-.046	.128*	.137**	-.080	.274**	-.303**	.162**	.187**	.238**	-.192**	.042	.164**	.063	.094
B	-.203**	-.284**	1.000	-.075	.097	-.135*	-.116*	-.199**	.061	-.040	.198**	.095	-.194**	-.135*	.078	.373**	-.007	-.260**	.103
C	.161**	-.008	-.075	1.000	-.967**	.340**	.281**	.398**	.032	-.664**	.058	-.537**	.193**	-.588**	.688**	-.425**	-.585**	-.086	-.574**
D	-.158**	.024	.097	-.967**	1.000	-.404**	-.367**	-.421**	-.017	.685**	-.047	.539**	-.215**	.595**	-.663**	.443**	.591**	.093	.592**
E	.244**	-.046	-.135*	.340**	-.404**	1.000	.297**	.247**	.132*	-.386**	.154**	-.255**	.366**	-.276**	.361**	-.310**	-.252**	.147**	-.190**
F	.179**	.128*	-.116*	.281**	-.367**	.297**	1.000	.428**	.043	-.220**	.048	-.030	.250**	-.126*	.169**	-.062	-.185**	.154**	-.124*
G	.160**	.137**	-.199**	.398**	-.421**	.247**	.428**	1.000	.054	-.244**	-.055	-.046	.426**	-.181**	.188**	-.153**	-.191**	.125*	-.168**
H	.126*	-.080	.061	.032	-.017	.132*	.043	.054	1.000	-.054	.167**	.123*	.059	.038	-.091	.042	-.038	.157**	.140**
I	-.143**	.274**	-.040	-.664**	.685**	-.386**	-.220**	-.244**	-.054	1.000	-.409**	.545**	-.111*	.621**	-.703**	.412**	.558**	.053	.478**
J	.177**	-.303**	.198**	.058	-.047	.154**	.048	-.055	.167**	-.409**	1.000	-.048	-.022	-.134*	.189**	.004	-.190**	.290**	.144**
K	-.035	.162**	.095	-.537**	.539**	-.255**	-.030	-.046	.123*	.545**	-.048	1.000	.051	.595**	-.695**	.587**	.454**	.103	.552**
L	.170**	.187**	-.194**	.193**	-.215**	.366**	.250**	.426**	.059	-.111*	-.022	.051	1.000	-.018	-.002	-.073	-.071	.197**	.043
M	.037	.238**	-.135*	-.588**	.595**	-.276**	-.126*	-.181**	.038	.621**	-.134*	.595**	-.018	1.000	-.725**	.400**	.516**	.241**	.550**
N	.087	-.192**	.078	.688**	-.663**	.361**	.169**	.188**	-.091	-.703**	.189**	-.695**	-.002	-.725**	1.000	-.514**	-.552**	-.115*	-.581**
O	-.157**	.042	.373**	-.425**	.443**	-.310**	-.062	-.153**	.042	.412**	.004	.587**	-.073	.400**	-.514**	1.000	.313**	-.052	.484**
P	-.077	.164**	-.007	-.585**	.591**	-.252**	-.185**	-.191**	-.038	.558**	-.190**	.454**	-.071	.516**	-.552**	.313**	1.000	.075	.375**
Q	.308**	.063	-.260**	-.086	.093	.147**	.154**	.125*	.157**	.053	.290**	.103	.197**	.241**	-.115*	-.052	.075	1.000	.417**
R	.091	.094	.103	-.574**	.592**	-.190**	-.124*	-.168**	.140**	.478**	.144**	.552**	.043	.550**	-.581**	.484**	.375**	.417**	1.000

Table 11. Relationships between exposure and sensitivity amongst block groups, Baltimore

Baltimore	*Exposure*	*Sensitivity Variables*																	
Block Group ID	Mean LST	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
High exposure/high sensitivity																			
15000US245100602001	39.93007	0.16	0.065	0.13	0.515	0	0.657	0.485	0	0.222	0.58	0.101	0.383	0.324	27167	0.082	0.268	0.343	0.195
15000US245102805002	38.758892	0.04	0.019	0.206	0.779	0	0.031	0	0.405	0.581	0.419	0.369	0	0.651	10747	0.317	0.096	1	0.784
15000US245100702003	40.11352	0.044	0.046	0.01	0.91	0	0.079	0.09	0	0.452	0.324	0.338	0.036	0.325	11793	0.224	0.106	0.599	0.629
15000US245102805004	37.249404	0.058	0.312	0	1	0	0	0	0	0.227	0.616	0.44	0	0.864	7196	0.516	0.152	0.843	0.725
15000US245102610002	39.696664	0.178	0	0.463	0.527	0	0.02	0.247	0.004	0.512	0.254	0.454	0.34	0.65	7830	0.14	0.112	0.726	0.405
Low exposure/high sensitivity																			
15000US245101510003	32.472351	0.165	0.051	0.118	0.772	0.024	0.155	0	0	0.407	0.384	0.105	0	0.698	10930	0.29	0.096	0.632	0.35
15000US245102710024	32.435322	0.147	0.061	0.015	0.971	0	0.028	0	0	0.545	0.336	0.163	0	0.261	13603	0.258	0.216	0.512	0.299
15000US245102803013	28.960111	0.148	0.123	0.099	0.803	0.021	0.152	0.043	0	0.245	0.59	0.115	0	0.19	19671	0.328	0.008	0.826	0.396
15000US245101607004	31.564054	0.041	0.172	0	0.97	0	0.059	0.017	0	0.272	0.541	0.205	0	0.353	12053	0.222	0.063	0.47	0.515
15000US245102604031	31.526443	0.089	0.065	0.003	0.972	0	0.042	0	0	0.309	0.5	0.153	0	0.265	19625	0.148	0.142	0.732	0.355
High exposure/low sensitivity																			
15000US245102609001	39.35884	0.122	0.144	0.897	0.034	0	0.099	0.035	0.011	0.017	0.598	0.201	0.033	0.056	34609	0.164	0.069	0.331	0.265
15000US245102609002	39.289158	0.116	0.1	0.862	0.093	0	0.081	0.215	0	0.129	0.217	0.061	0.026	0	39812	0.097	0.025	0.311	0.051
15000US245102609003	39.233953	0.053	0.093	0.897	0.029	0.049	0.049	0.009	0	0.012	0.504	0.094	0	0	61663	0.113	0.029	0.516	0.058
15000US245102610004	39.188156	0.088	0.078	0.692	0.258	0	0.099	0.251	0	0.132	0.373	0.289	0	0	26516	0.151	0.016	0.13	0.018
15000US245100101001	38.964107	0.048	0.128	0.901	0	0.085	0.027	0.102	0	0.014	0.331	0.04	0.014	0.042	57266	0.052	0.011	0.33	0.026

Table 12. Relationships between exposure and sensitivity amongst block groups, St. Louis

St. Louis	*Exposure*	*Sensitivity Variables*																	
Block Group ID	Mean LST	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
High exposure/high sensitivity																			
15000US295101184001	40.769102	0	0.046	0.61	0.268	0.086	0.067	0.029	0.693	0	0.898	0.341	0.014	0.571	6225	0.592	0.029	0.71	0.509
15000US295101164004	39.760091	0.163	0.068	0.216	0.666	0.027	0.165	0.265	0	0.472	0.391	0.51	0.062	0.377	8172	0.288	0.168	0.676	0.271
15000US295101163022	40.543943	0.018	0.042	0.342	0.293	0.328	0.037	0.18	0	0.074	0.634	0.454	0.276	0.31	18052	0.246	0.036	0.665	0.248
15000US295101161004	40.07824	0.09	0.085	0.385	0.268	0.062	0.57	0.217	0	0.175	0.611	0.225	0.221	0.486	18214	0.09	0.156	0.612	0.309
15000US295101212001	40.420471	0.226	0.039	0.042	0.943	0	0.023	0	0	0.591	0.346	0.211	0	0.567	8968	0.132	0.172	0.766	0.304
Low exposure/high sensitivity																			
15000US295101156004	36.043595	0.069	0.125	0.58	0.274	0.056	0.18	0.356	0	0.271	0.537	0.267	0.121	0.352	8838	0.449	0.083	0.608	0.287
15000US295101097001	36.292187	0.128	0.06	0.007	0.993	0	0	0.014	0	0.355	0.433	0.461	0	0.642	11029	0.143	0.16	0.544	0.339
15000US295101054001	36.218538	0.11	0.153	0.123	0.774	0	0.172	0.114	0	0.379	0.418	0.241	0.061	0.348	13357	0.322	0.075	0.584	0.349
15000US295101066002	36.282858	0.111	0.067	0	0.985	0	0.015	0	0	0.326	0.353	0.242	0	0.561	10617	0.243	0.153	0.601	0.39
15000US295101063004	35.840332	0.141	0.164	0	0.937	0	0.104	0.008	0	0.458	0.347	0.229	0	0.351	10408	0.452	0.179	0.383	0.077
High exposure/low sensitivity																			
15000US295101255003	43.41531	0.016	0	0.794	0.158	0.021	0.026	0.026	0	0	0.663	0	0	0	59938	0	0	0.531	0.033
15000US295101255001	41.304887	0.075	0.015	0.769	0.164	0.06	0.015	0.012	0.066	0.044	0.668	0.087	0.012	0.12	56882	0.05	0.02	0.401	0.025
15000US295101135004	40.705233	0	0.179	0.966	0	0.013	0.04	0	0	0.078	0.556	0.064	0.03	0	37944	0.122	0.023	0.292	0.101
15000US295101051981	40.328101	0.043	0.048	0.656	0.22	0.099	0.051	0.036	0.002	0	0.261	0	0	0	30664	0.008	0.024	0.562	0.018
15000US295101162006	39.955515	0.098	0.006	0.846	0.023	0.1	0.051	0.012	0.021	0	0.401	0.004	0.047	0	32601	0.038	0.043	0.476	0

Figures

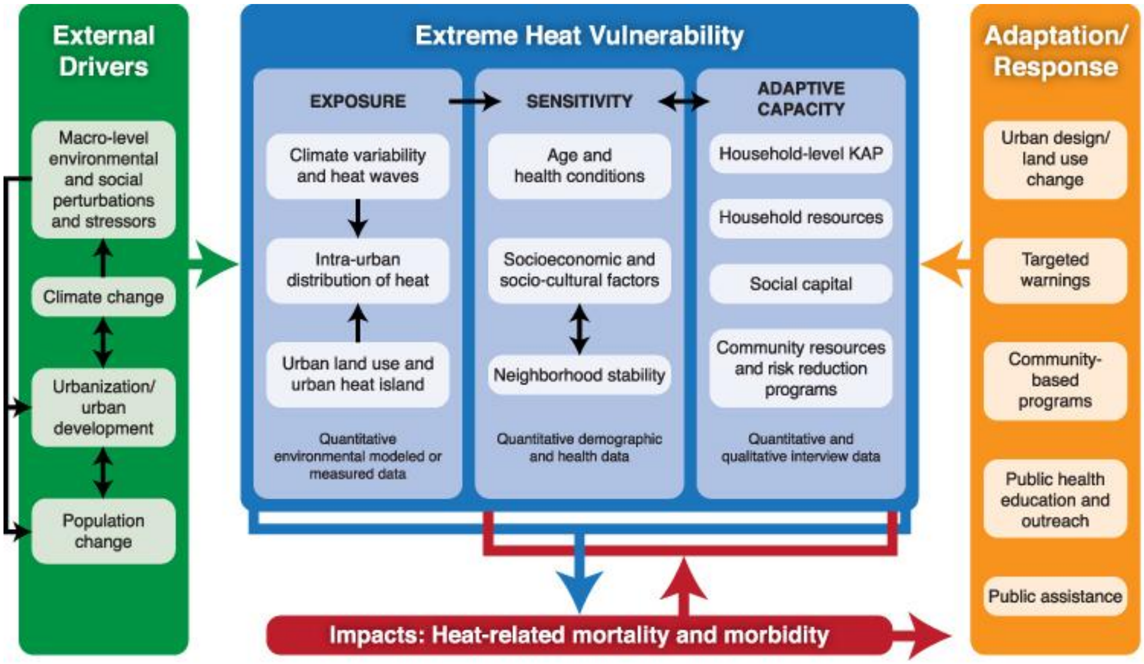

Figure 1. Extreme heat vulnerability analysis framework (Source: Wilhelmi and Hayden 2010).

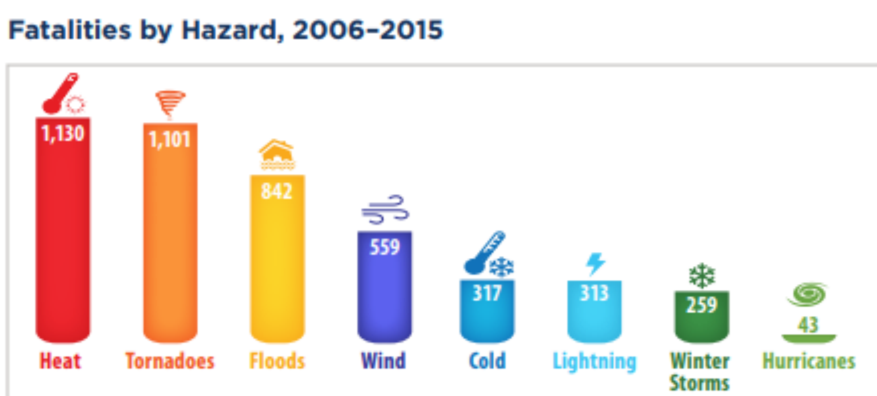

Figure 2. Fatalities by hazard in the United States, 2006-2015 (Source: EPA and CDC 2016).

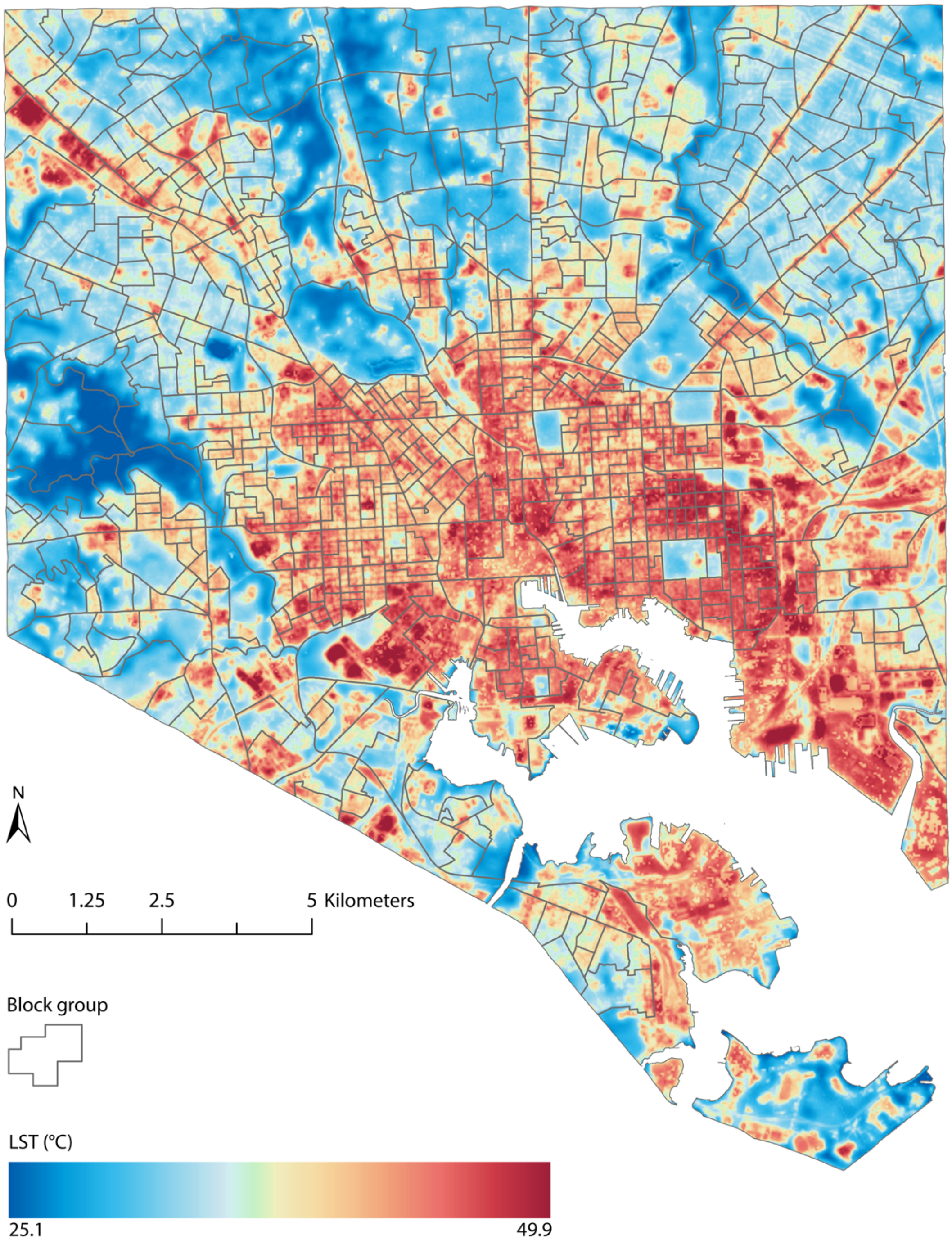

Figure 3. LST with block group boundaries, Baltimore

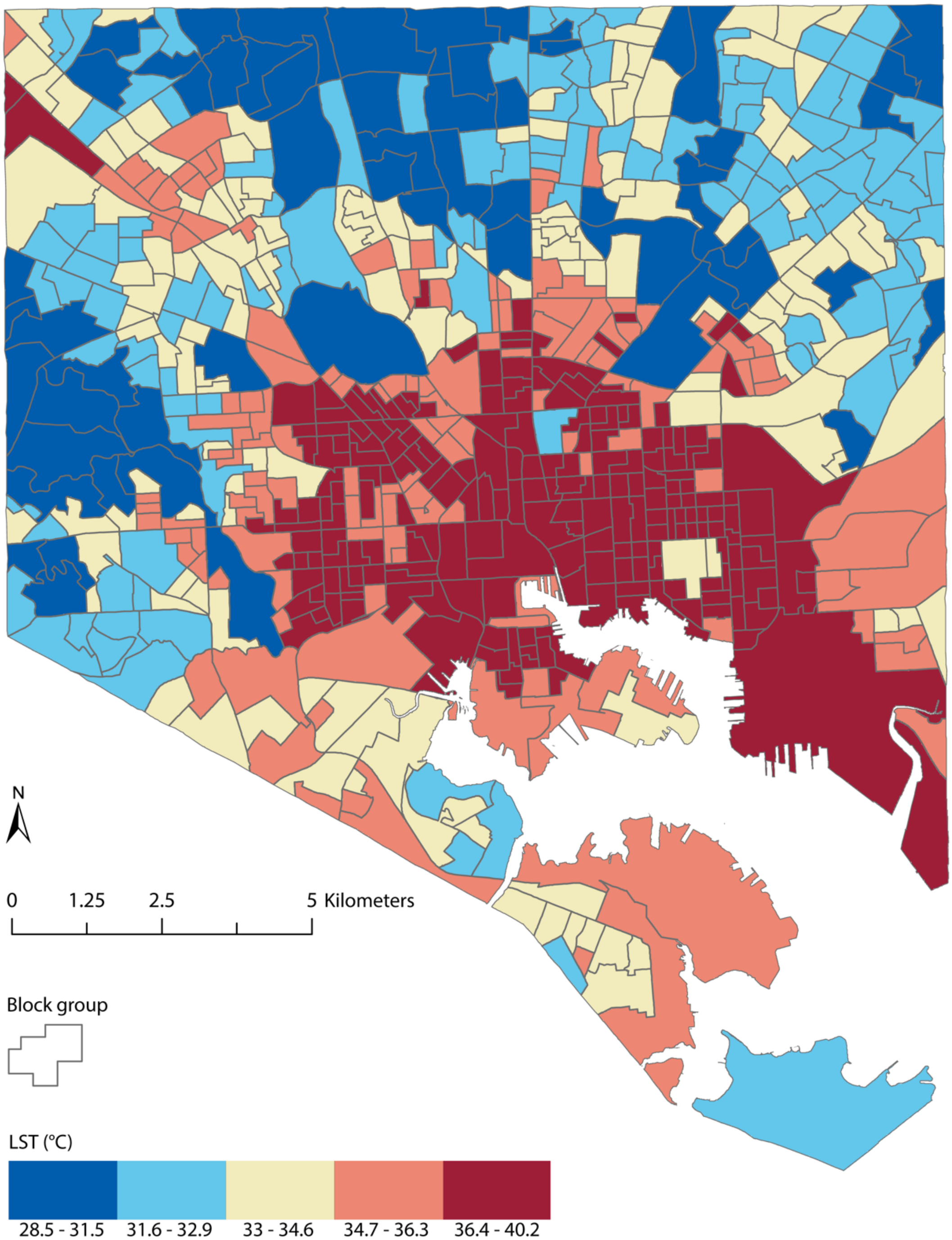

Figure 4. Mean LST class by block group, Baltimore

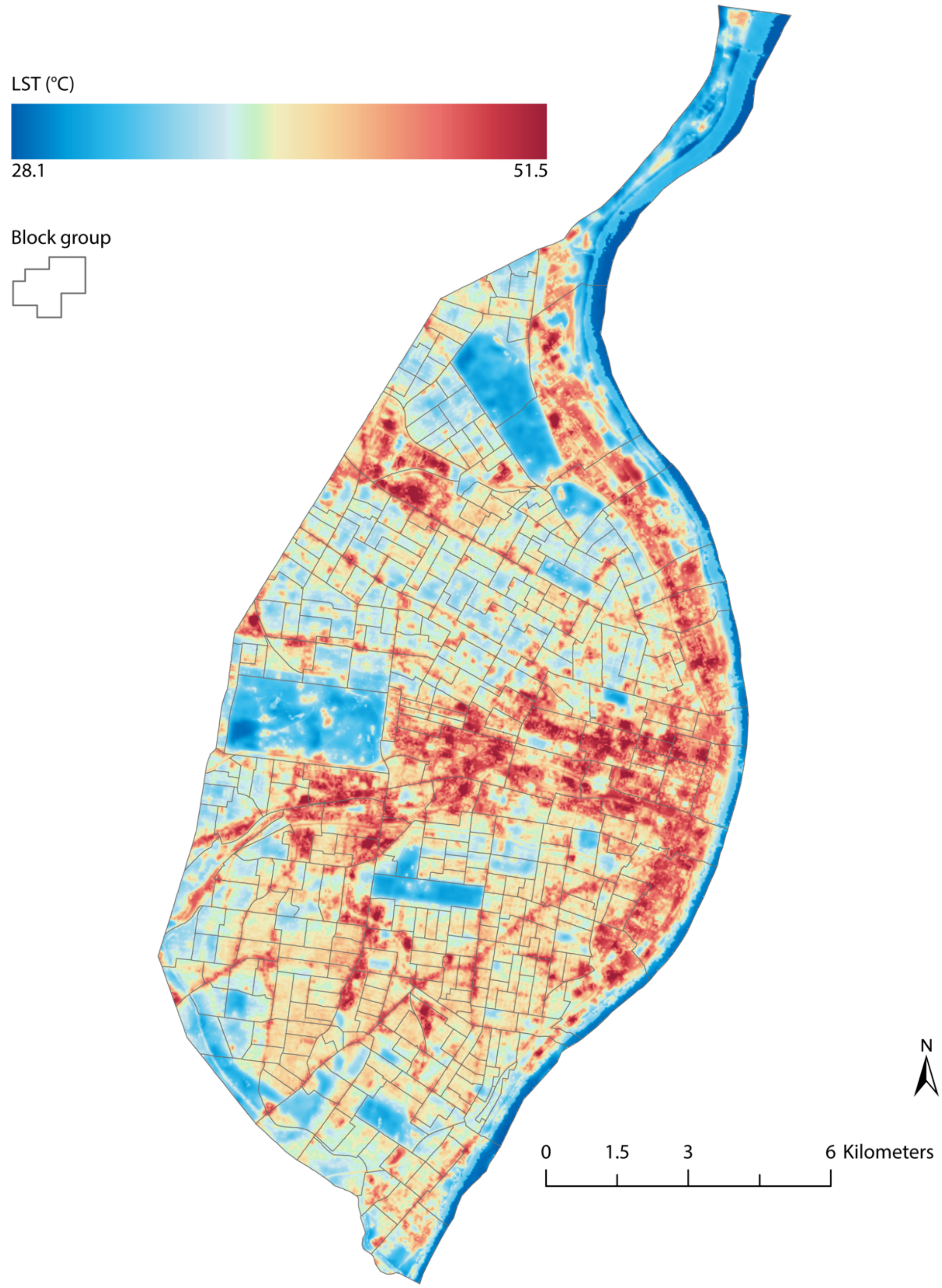

Figure 5. LST with block group boundaries, St. Louis

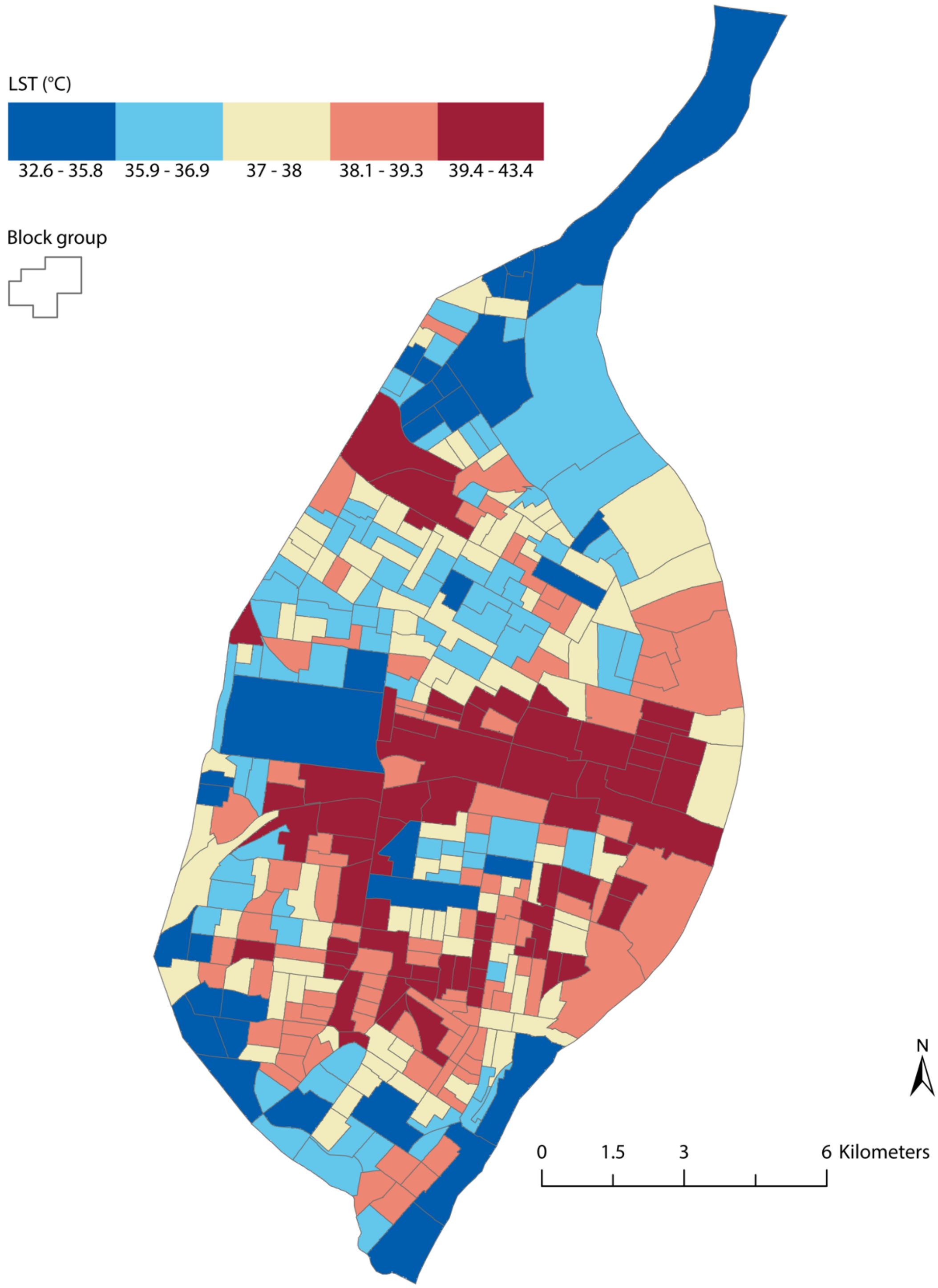

Figure 6. Mean LST class by block group, St. Louis

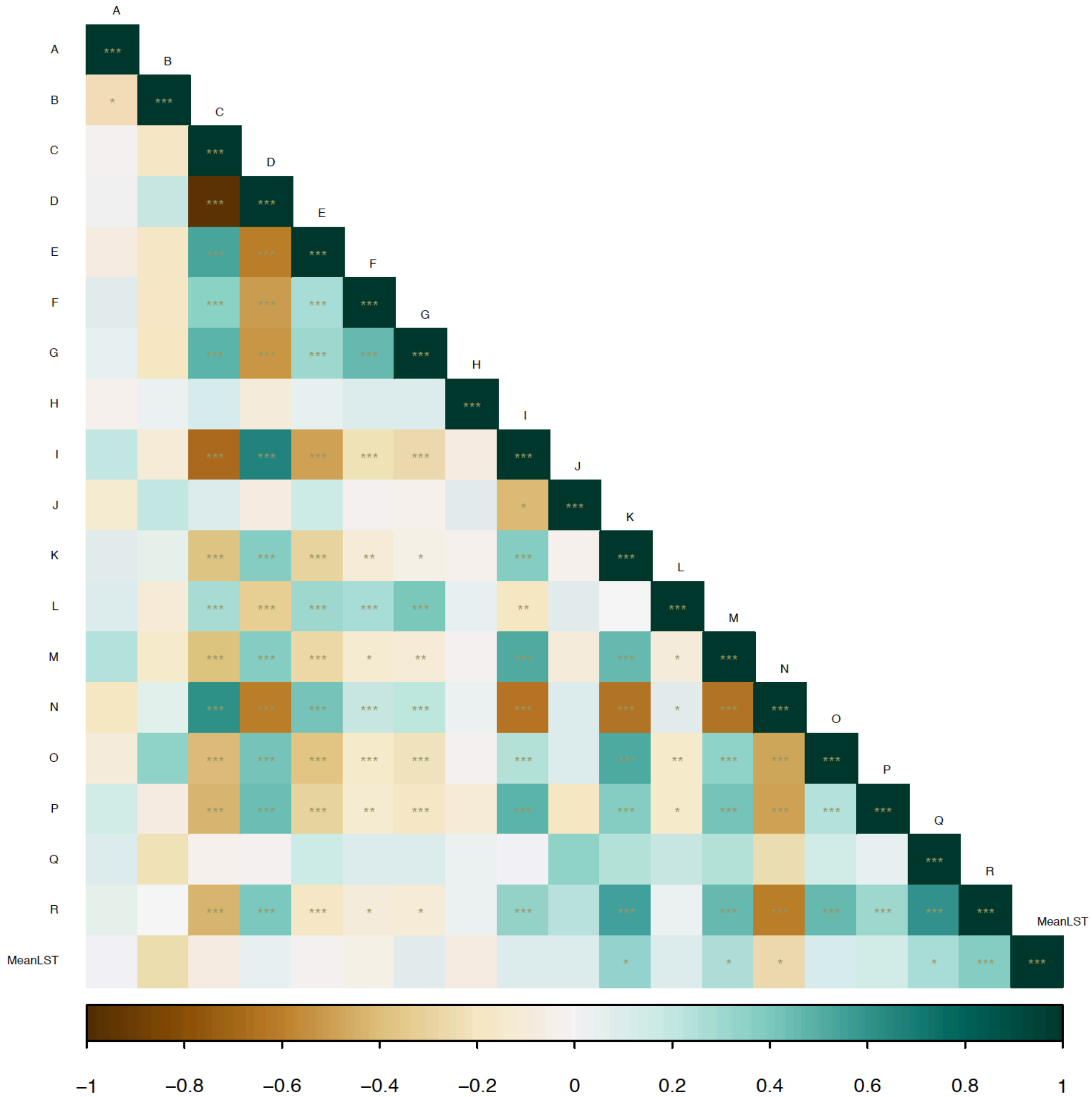

Figure 7. Correlogram of Spearman's rho results, Baltimore. Significance flagged at 95 (*), 99 (**) and 99.5% (***)

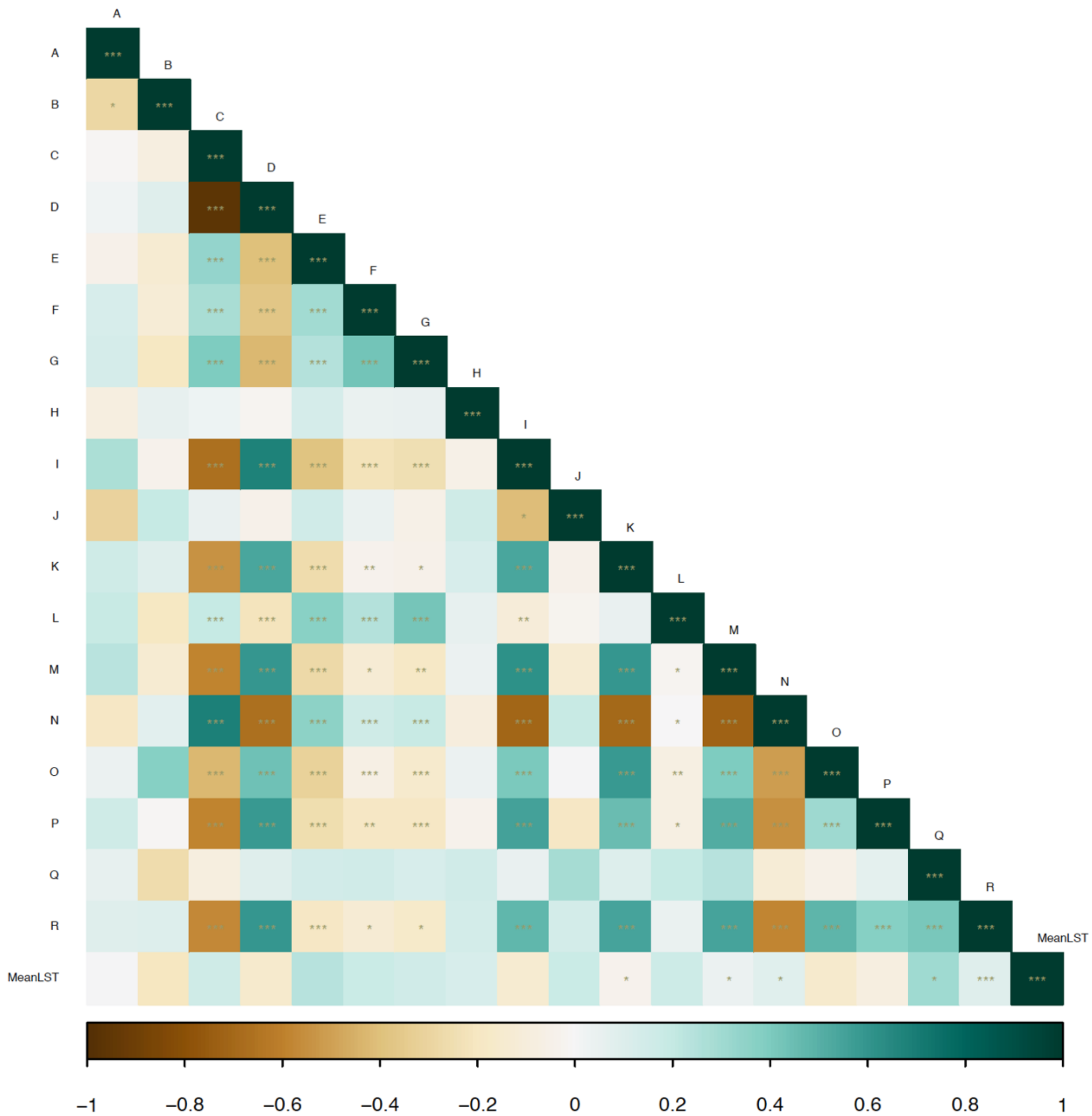

Figure 8. Correlogram of Spearman’s rho results, St. Louis. Significance flagged at 95 (*), 99 (**) and 99.5% (***)

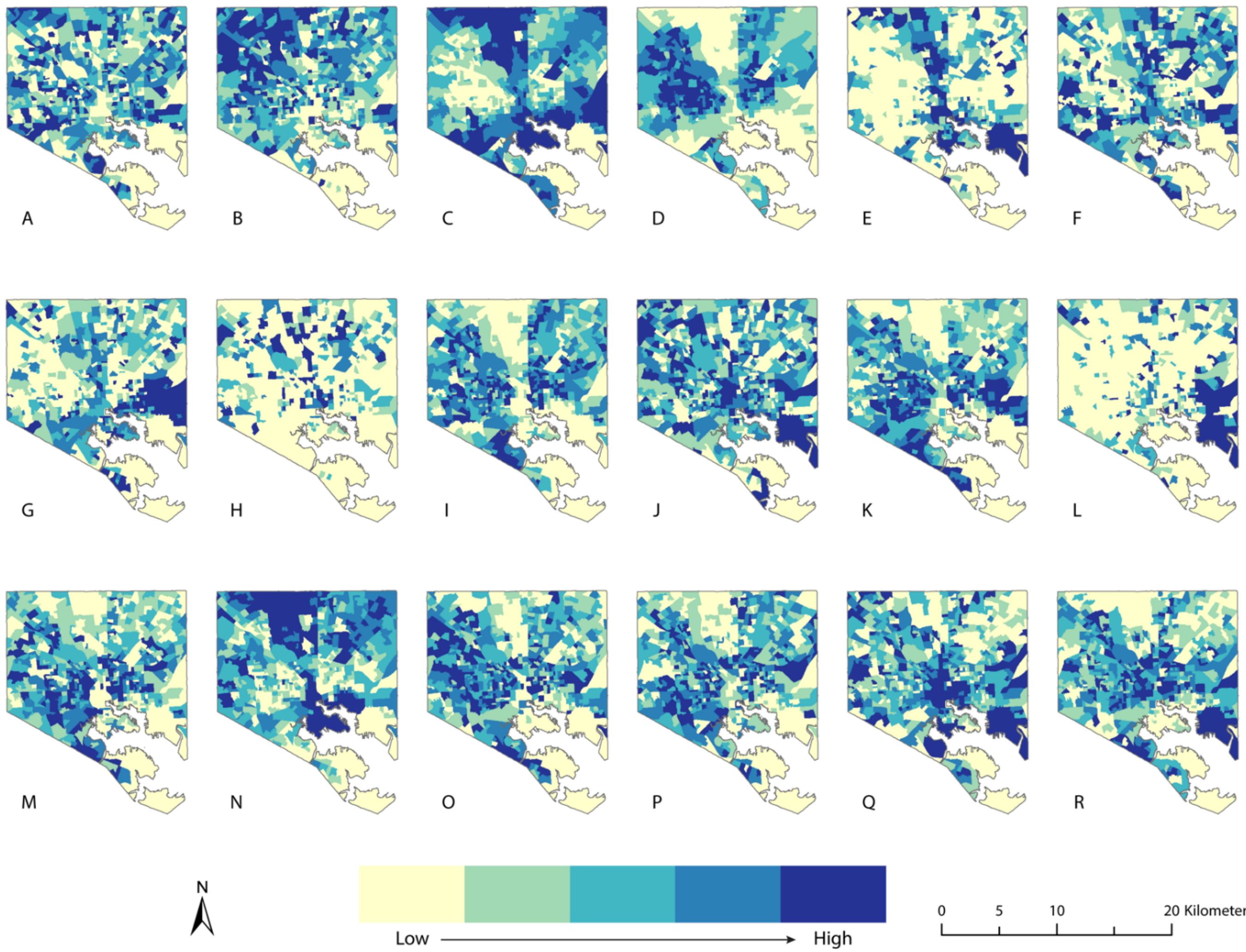

Figure 9. Small multiple maps of sensitivity variables, Baltimore

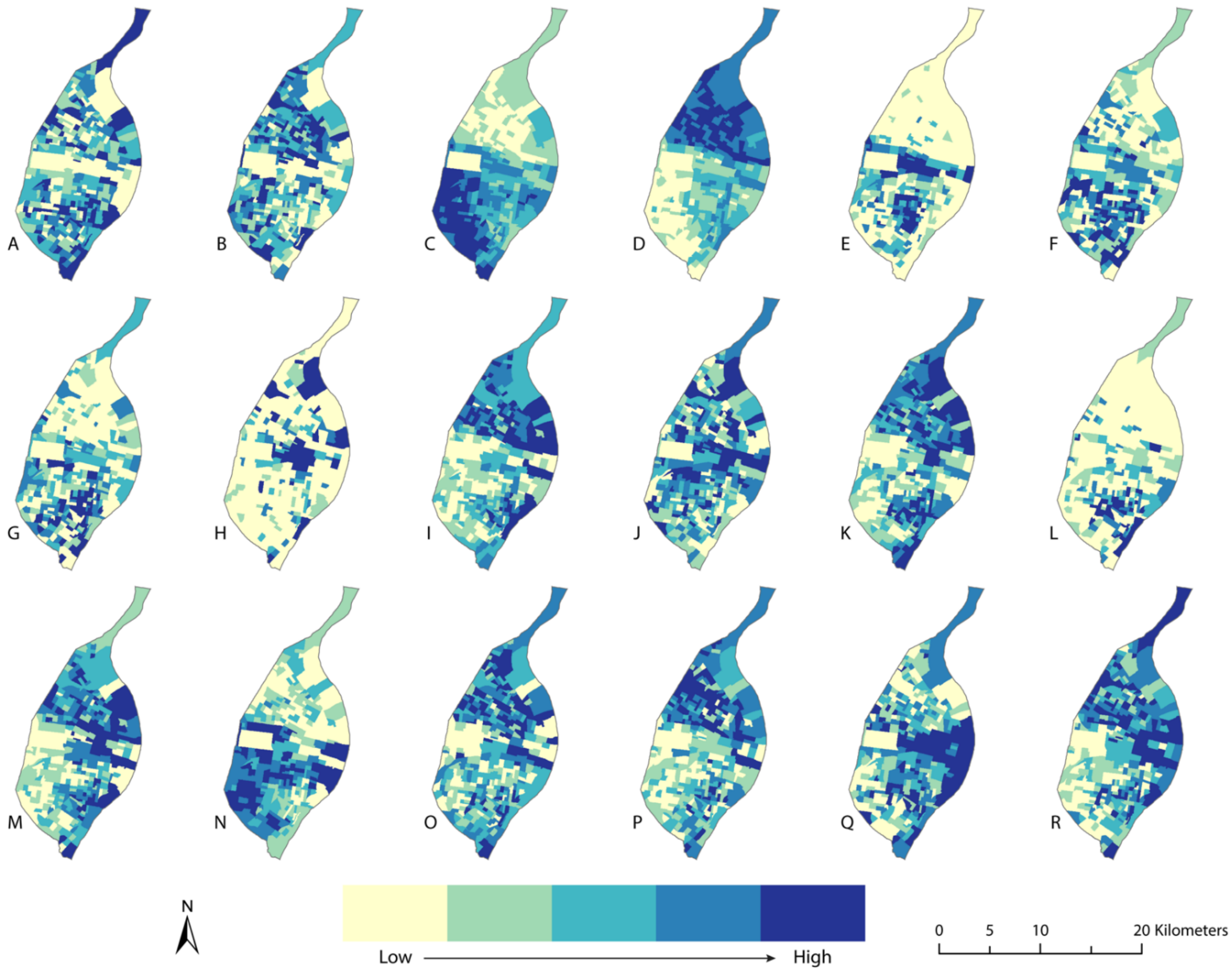

Figure 10. Small multiple maps of sensitivity variables, St. Louis

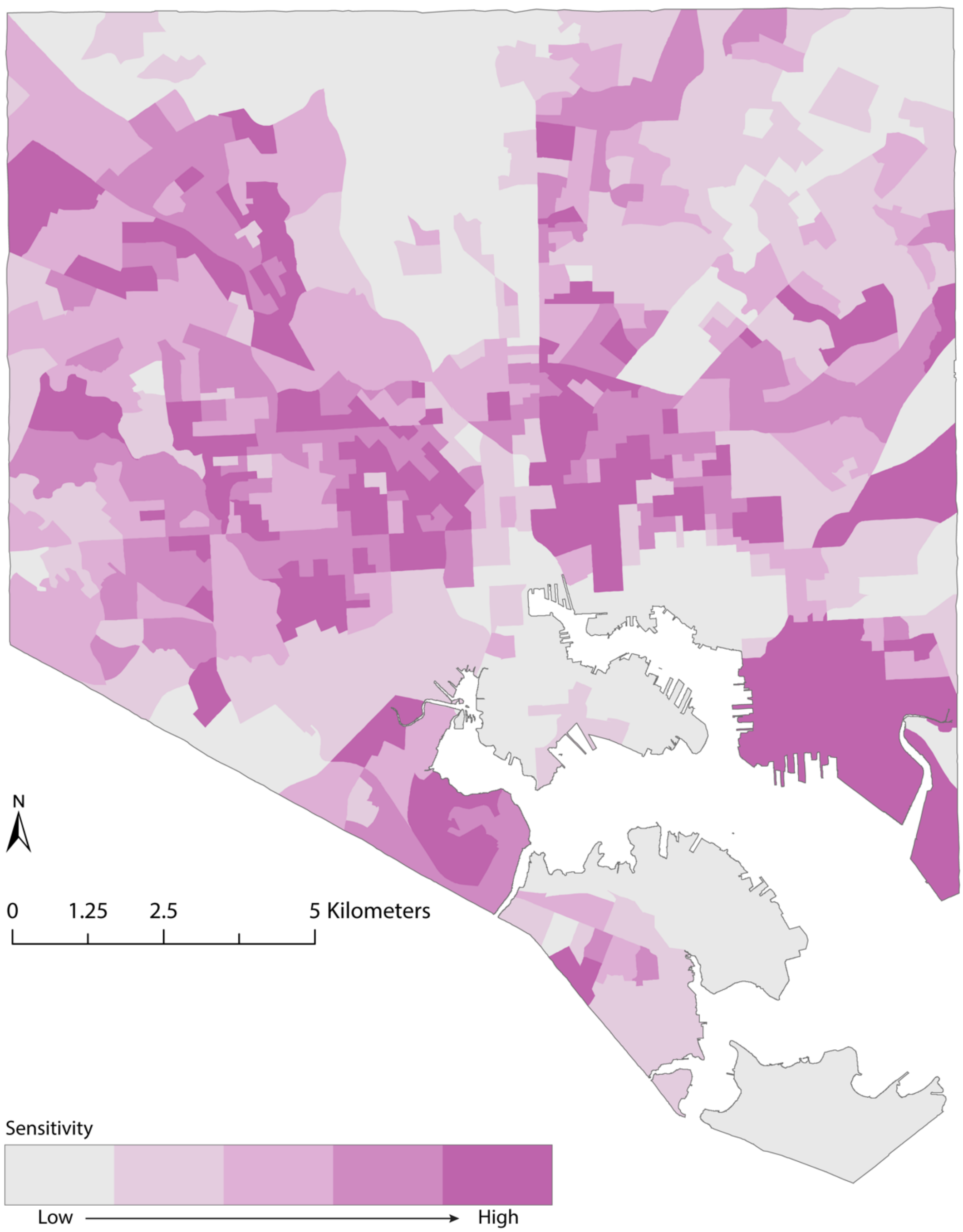

Figure 11. Sensitivity choropleth map, Baltimore

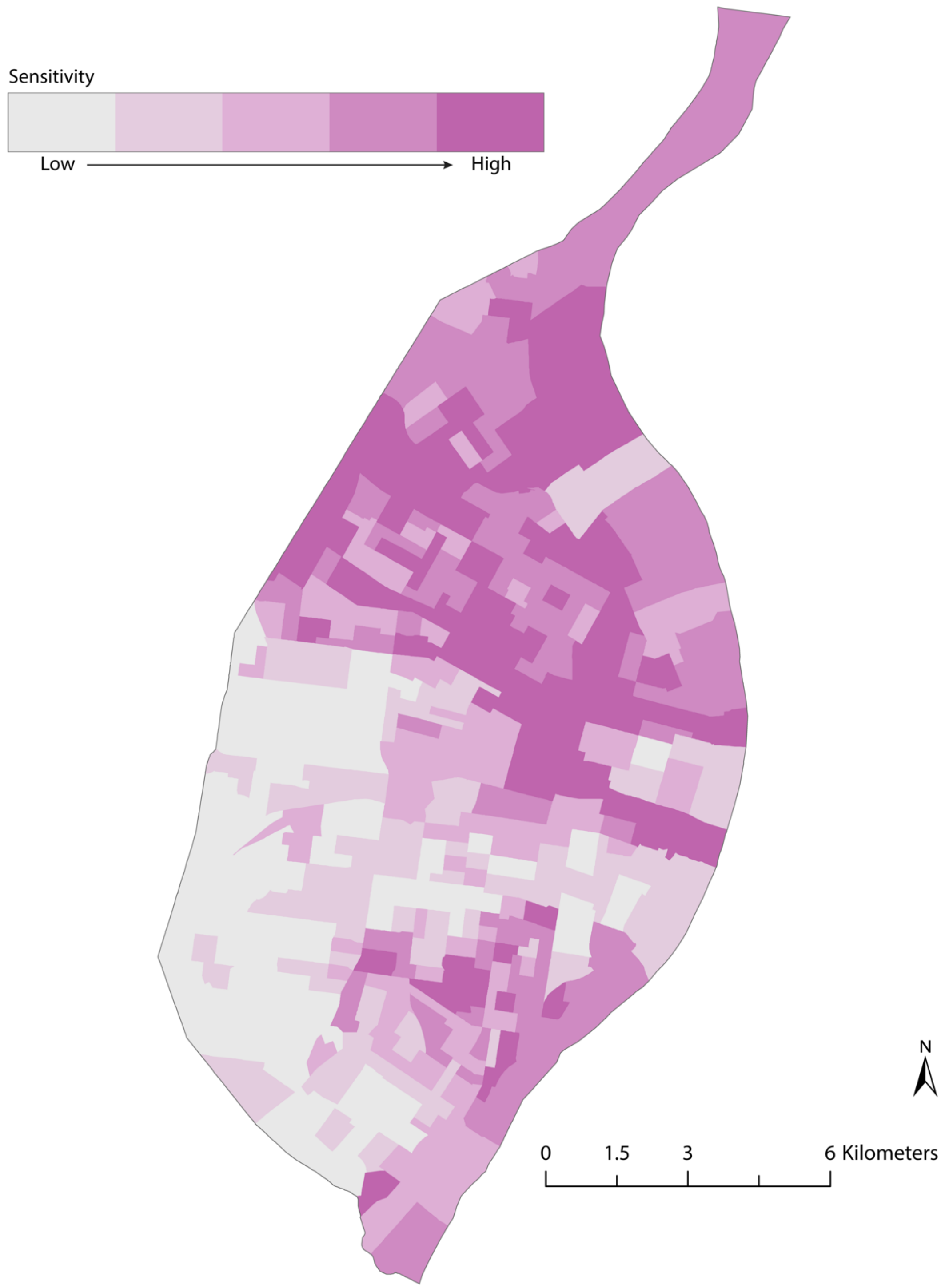

Figure 12. Sensitivity choropleth map, St. Louis

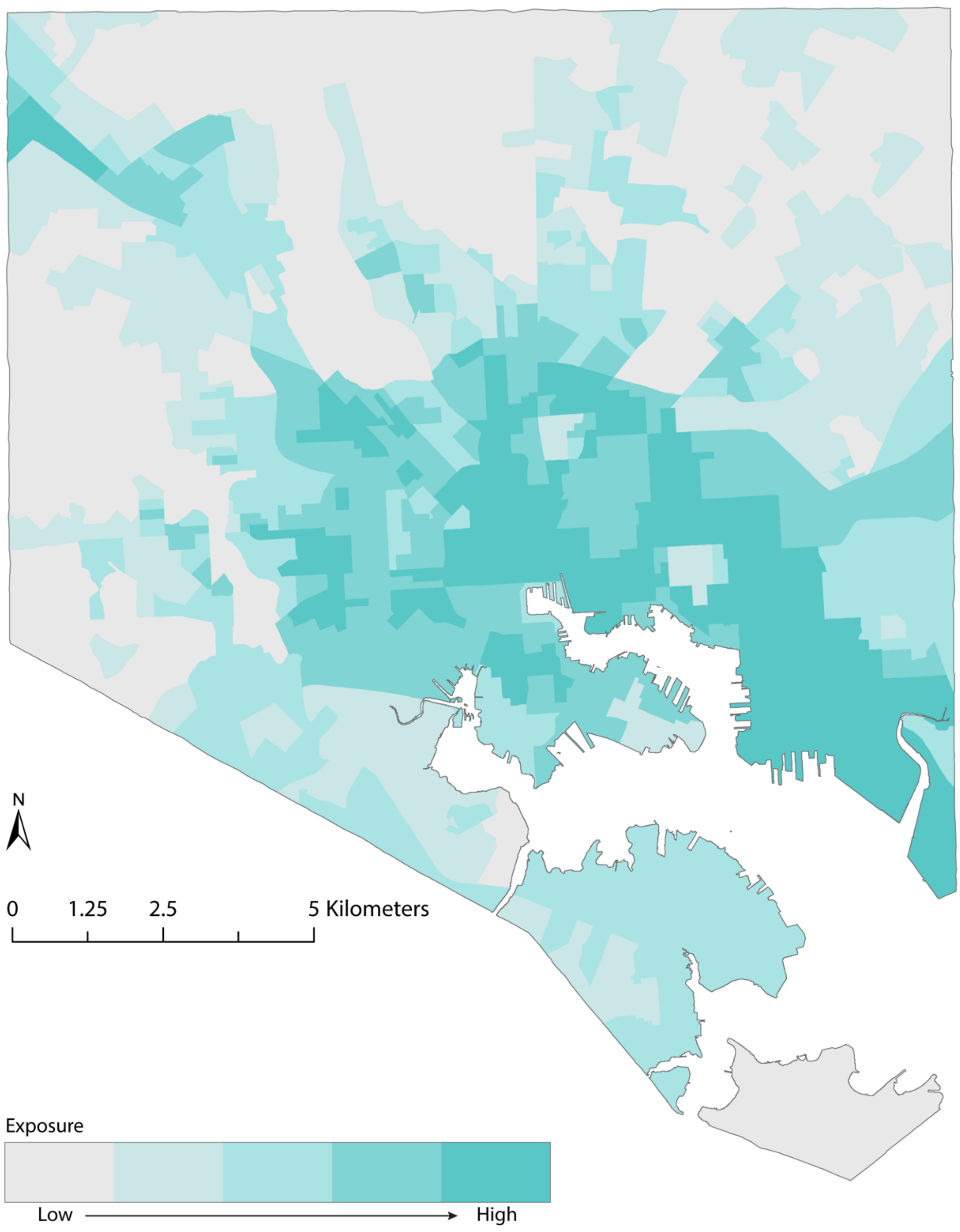

Figure 13. Exposure choropleth map, Baltimore

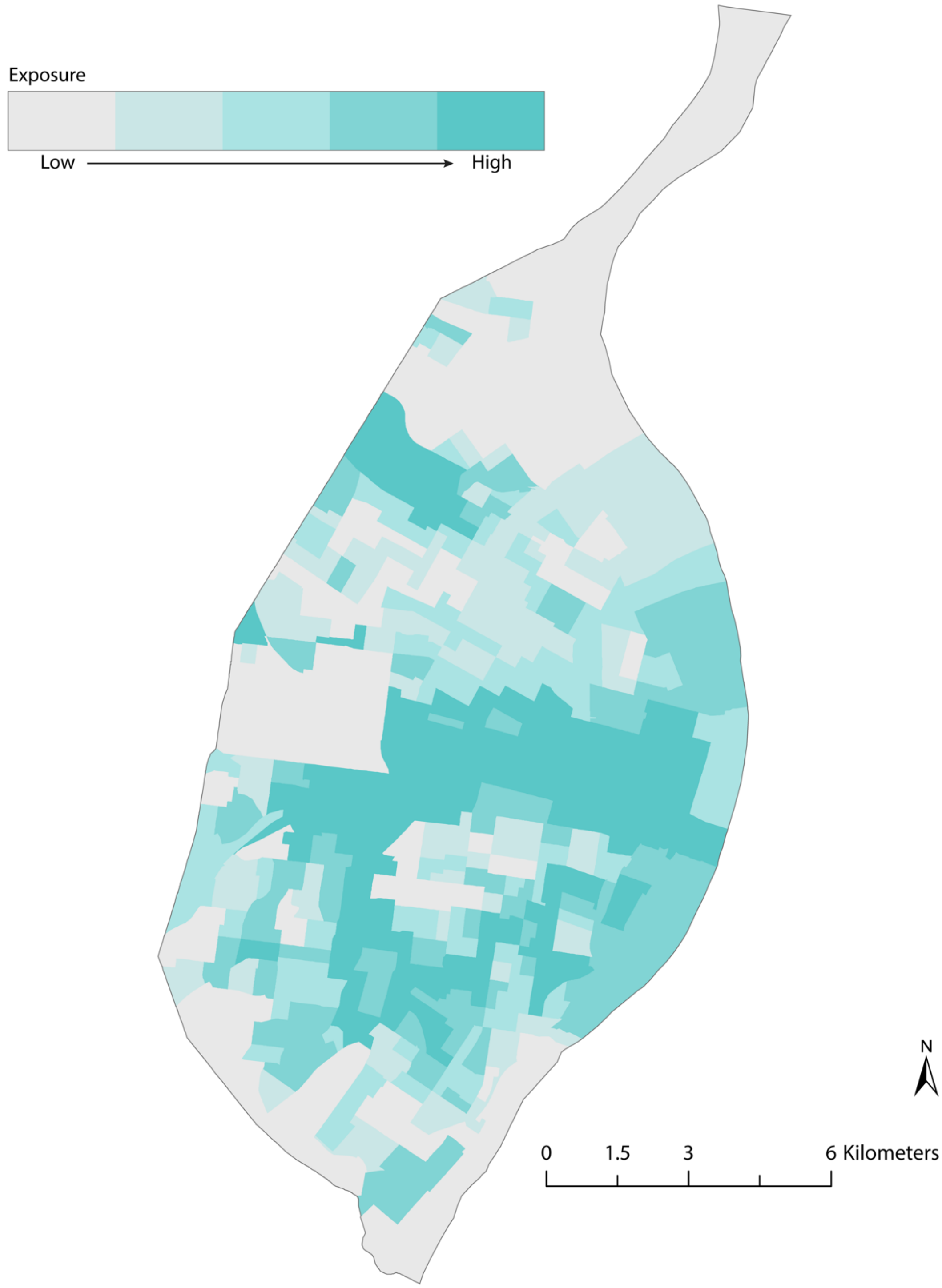

Figure 14. Exposure choropleth map, St. Louis

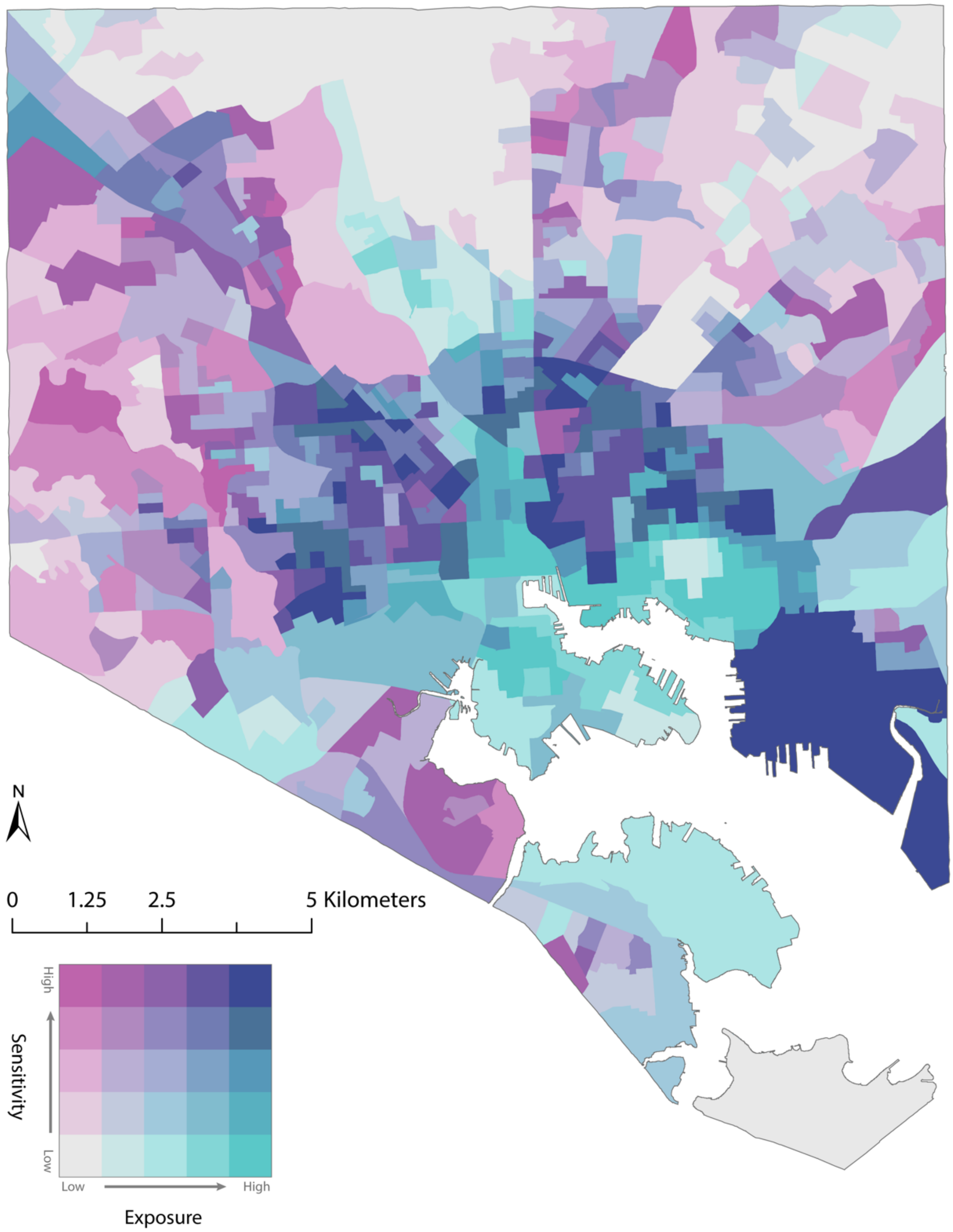

Figure 15. Bivariate choropleth map comparing exposure and sensitivity, Baltimore

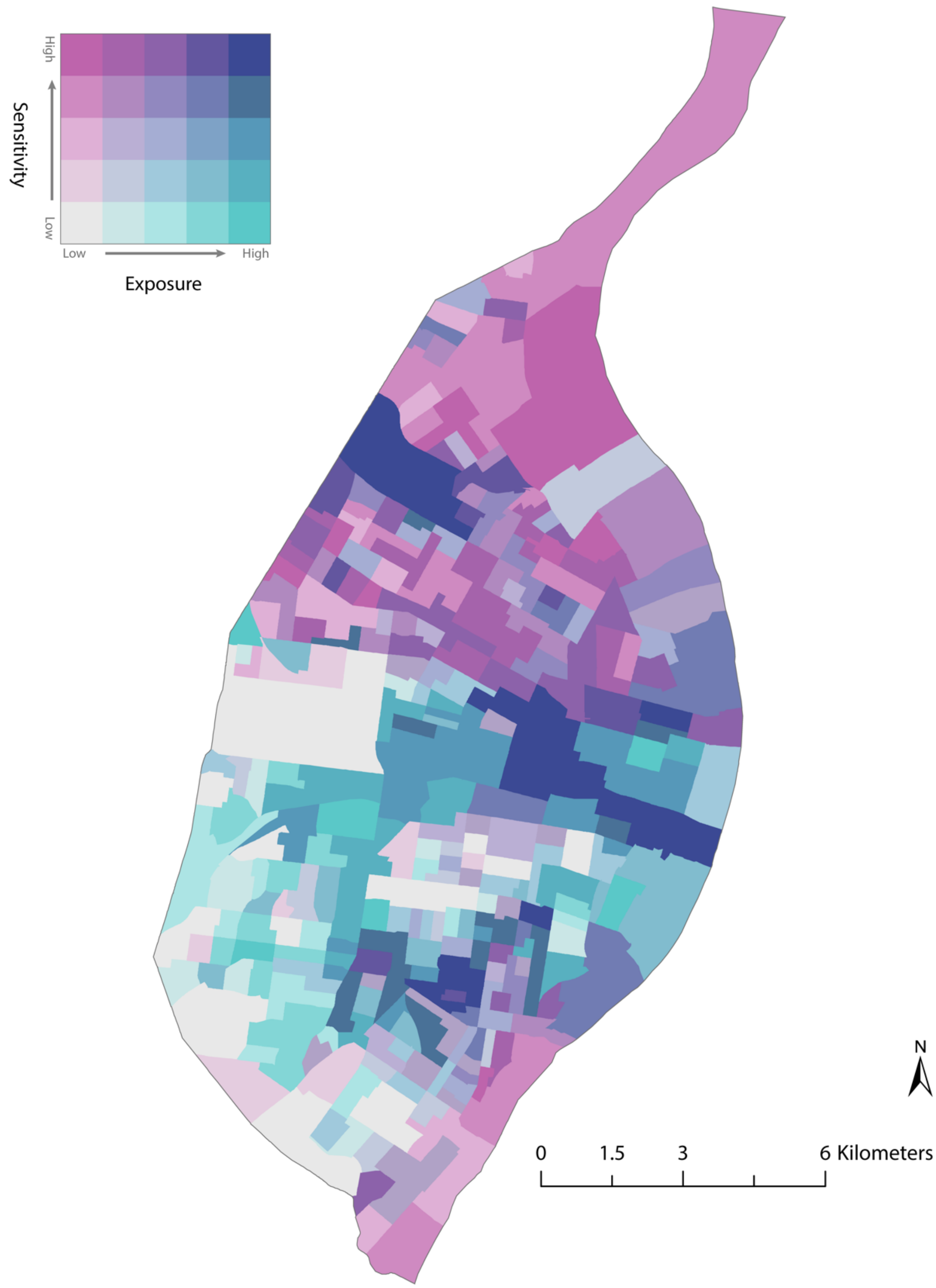

Figure 16. Bivariate choropleth map comparing exposure and sensitivity, St. Louis

CURRICULUM VITA

JULIA HESLIN
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Education

Towson University, Towson, MD
M.A. Geography, January 2018
Current GPA: 3.929
Areas of Interest: Geographic Information Systems, Environmental Justice, Cartography, Urban Heat Islands

B.A. International Studies, Geography Minor, May 2015
Overall GPA: 3.905
Areas of Interest: African and European Studies, Italian Language and Culture, International Development

The American University in Rome, Rome, Italy
Semester Abroad, TU in Italy Program, January-May 2014
Term GPA: 3.873
Focus on Italian language (intermediate level) and perceptions of Italy through media, the arts, and literature

Employment

Teaching Assistant, August 2016-present
Towson University Dept. of Geography and Environmental Planning, Towson, MD
As a teaching assistant for the Department of Geography and Environmental Planning, I assist professors with introductory courses in physical geography, world regional geography, and GIS. My responsibilities include grading students' work, facilitating review sessions, proctoring exams, helping students in and out of class, monitoring GIS labs, and preparing and giving class lectures.

Summer of Maps Fellow, *June 2017-August 2017*
Azavea, Philadelphia, PA
The Summer of Maps Fellowship offers stipends to student GIS analysts to perform geospatial data analysis for non-profit organizations. I was matched with the Common Market and was tasked with mapping their impact on the regional economy, food security, and agricultural sustainability. I also worked with the Speak to Your Health! Community Survey, mapping the effects of the Flint Water Crisis on individual and community health results from the survey.

Communications and Outreach Coordinator, June 2016-May 2017
Maryland Geographic Alliance, Towson, MD

During my time with the Maryland Geographic Alliance, I maintained the website, Facebook page, and blog for the alliance, coordinated events and workshops, attended meetings and conferences, kept in touch with current members, and reached out to prospective members

Software Knowledge

Adobe Illustrator, *Intermediate*
ArcGIS, *Intermediate to Advanced*
Leaflet, *Intermediate*
Microsoft Office Suite, *Advanced*
Notepad ++, *Intermediate*
RStudio, *Novice to Intermediate*
SPSS, *Intermediate*
TerrSet*, Intermediate*

Programming Languages

CSS, *Intermediate*
HTML, *Intermediate*
JavaScript, *Intermediate*
Python, *Novice*
R, *Novice to Intermediate*

Selected Presentations

***Mid-Atlantic AAG Conference**, November 2017*
College Park, MD

Mother Africa: A Feminist Geopolitical Approach to Post-Colonial Development in Sub-Saharan Africa

***Mid-Atlantic AAG Conference**, November 2016*
Fairfax, VA

Baltimore City's Urban Heat Island: A Problem-Based Approach

***MSGIC Quarterly Meeting**, July 2016*
Salisbury, MD

Maryland Geographic Alliance: Promoting Geographic Literacy from the Eastern Shore to Garrett County

Honors and Recognitions

Mid-Atlantic AAG Conference
Student paper award, November 2017
Awarded $150 for research paper from a pool of Master's and Ph.D. candidates

TUGis: Maryland's Geospatial Conference
Student map winner, March 2017
Awarded first place in student map poster category

Towson University
Summa Cum Laude, May 2015
Ranked in the top 2% of my graduating class

Dean's List Scholar, August 2011-May 2015
Named to the Dean's List each semester

National Society of Collegiate Scholars Member, *August 2011-May 2015*
Recognized for my commitment to and achievements in leadership, academics, and service

Groups and Organizations

American Association of Geographers (AAG), *January 2018-present*

Association for Women in Science (AWIS), *March 2017-present*

Maryland State Geographic Information Committee (MSGIC), *July 2016-present*

Maryland Geographic Alliance, *June 2016-present*