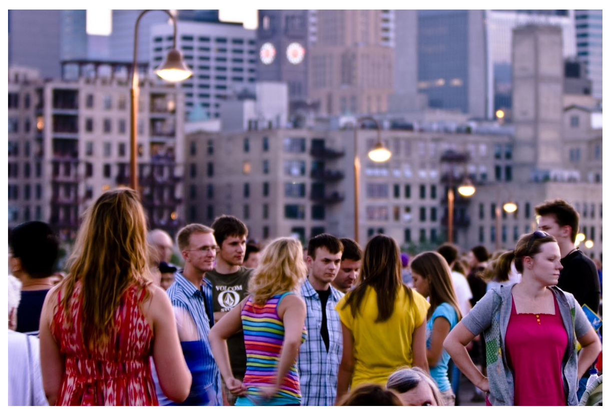
Technical Report: Minneapolis Climate Change Vulnerability Assessment



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Technical report purposes

This document details the methodology used to produce indices associated with climate change vulnerability within the City of Minneapolis, MN. These indices were used to perform a climate change vulnerability assessment of Minneapolis by way of map-based spatial analysis. This report and vulnerability assessment were developed for the City of Minneapolis' Sustainability Office and Department of Health as a part of a grant received from the Public Health Institute's Center for Climate Change and Health in October of 2015. This report and the vulnerability assessment were prepared by a graduate capstone team at the Humphrey School of Public Affairs (University of Minnesota) with the collaboration and support of many professionals and experts. The City of Minneapolis asked that a comprehensive technical document be created to support the ability for staff to integrate additional indices, updated data sets, and expanded data sets into future assessments of Minneapolis' climate change vulnerability.

The document serves three purposes:

- To provide the methodology by which indices were selected, how the data supporting those indices was accessed and acquired, as well as how that data was used to create maps for the climate change vulnerability assessment of Minneapolis.
- To document the method by which the assessment was performed for replicability.
- To create a guide for future staff and collaborators to be able to develop a competency with the methodology of the assessment's GIS-analysis and data acquisition for understanding and communication.

Organization of technical report

This document consists of five primary sections that are organized in the following manner:

- Section 1 provides the overarching theory and rationale behind the selection of vulnerability indices, as well as how indices were defined and grouped for distinction, e.g., environmental and social vulnerabilities
- Sections 2, 3, 4 and 5 detail the methodology supporting the analysis of the city's flooding, heat, and social vulnerabilities, respectively. Each vulnerability index is organized in the following general subsection format for consistency:
    - Data Details
    - Mapping Methodology
    - Limitations and Additional Information (where necessary)

  The document does acknowledge when data/information was not relevant or available under each subsection.
- Section 6 details the methodology used to map the cumulative impact of landscape and social vulnerability.

1. Assessment design

The following sections detail the design stage of this climate change vulnerability assessment, from the theory underpinning the place-based vulnerability approach to the rationale for selecting key indicators of climate change vulnerability.

1.1 The place vulnerability model

Vulnerability to natural hazards is dependent upon characteristics of the landscape as well as characteristics of the people that live there. Cutter defines a hazards-of-place vulnerability model that distinguishes social vulnerability from biophysical vulnerability and emphasizes that both are critical to understanding overall place vulnerability. This basic conception of vulnerability as a cumulative feature of place underpins the framework for this City of Minneapolis climate change vulnerability assessment, and justifies the use of GIS-based spatial analysis as the primary mode of assessment.

FIGURE 1

The Hazards-of-Place Model of Vulnerability (Modified from Cutter, 1996)

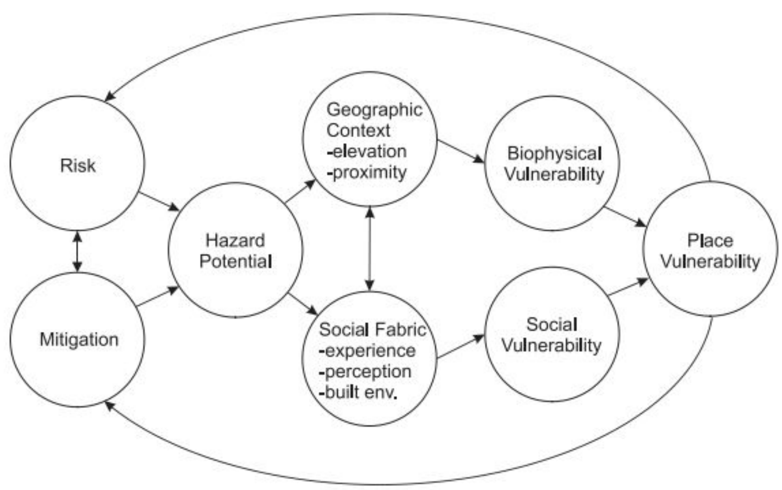


Figure 1: The Hazards-of-Place model recognizes that vulnerability can be attributed to a place and depends on a variety of different factors. Susan L. Cutter, Bryan J. Boruff, W. Lynn Shirley. “Social Vulnerability to Environmental Hazards”**,** Social Science Quarterly, June, 2003. 10.1111/1540-6237.8402002.

1.2 Variable selection

The first stage of almost all climate change vulnerability assessments is to select variables that measure vulnerability at the scale intended. For this project, an iterative process was used to select variables for inclusion. Because this assessment relied upon spatial analysis, a fundamental requirement for consideration was the ability for the data to be expressed in spatial format at a finer geographic scale than the municipality.

Indicator selection was based on a literature review of previous climate vulnerability assessment work at many scales (city, regional, state and national) and Minneapolis City staff suggestions. Existing climate change vulnerability assessments each use a custom set of indicators that are heavily context-dependent and may differ based on geographic location, localized climate change risks, and the degree of health and equity focus in the assessment. Final variables were selected in part to mirror those defined by a 2014 statewide climate vulnerability assessment conducted by the Minnesota Department of Health[1], and were revised both to fit the smaller geographic area of the City and to reflect available data. Selected indicators were also vetted by City staff from many departments early in the assessment process.

This climate vulnerability assessment makes two important methodological distinctions. First, the assessment design distinguishes between *social vulnerability* and *landscape vulnerability.* In this study, social vulnerability is defined as characteristics of individuals or households, measured at a community scale, that may mean communities are more susceptible to climate change risks. In contrast, landscape vulnerability is defined as characteristics of the built or unbuilt environment. Second, in the case of the landscape vulnerability indicators, this assessment distinguishes between vulnerability to *extreme heat* and *flooding*. Both of these are very different climate change risks in Minneapolis and were examined separately as a result.

The final climate change vulnerability calculations narrow the concept of climate change vulnerability in Minneapolis to three landscape indicators of extreme heat and nine indicators of social vulnerability. In contrast, the assessment of flooding is more qualitative, focusing on six landscape factors of flooding that City staff confirmed would add value to the City's work.

Overall, data collection was an iterative process that involved many data requests and consultation with governmental and non-governmental experts. As the data collection process progressed, many indicators were removed from consideration due to lack of data. Conversely, other indicators were added as new data was discovered.

1.3 Overview of assessment scheme

In alignment with the place vulnerability model, the initial assessment scheme concept combined the effects of two landscape vulnerability variables (flooding and heat) as well as social vulnerability into one overall final climate change vulnerability map of the City of Minneapolis. However, it became evident during the data collection phase that these three vulnerability factors could not be given equal treatment in a final map concept. Data availability constraints and the level of complexity associated with flooding led to a pivot in the flooding analysis approach that resulted in a more qualitative flooding vulnerability assessment rather than a quantified spatial vulnerability map. The

[1] Minnesota Climate & Health Profile Report. Minnesota Department of Health. St. Paul, MN. February 2015.

landscape vulnerability to heat and social vulnerability components both retained a quantified spatial approach.

Figure 2 gives an overview of what was produced in the different components of this assessment, the final result of each vulnerability component and the point at which separate vulnerability components were combined.

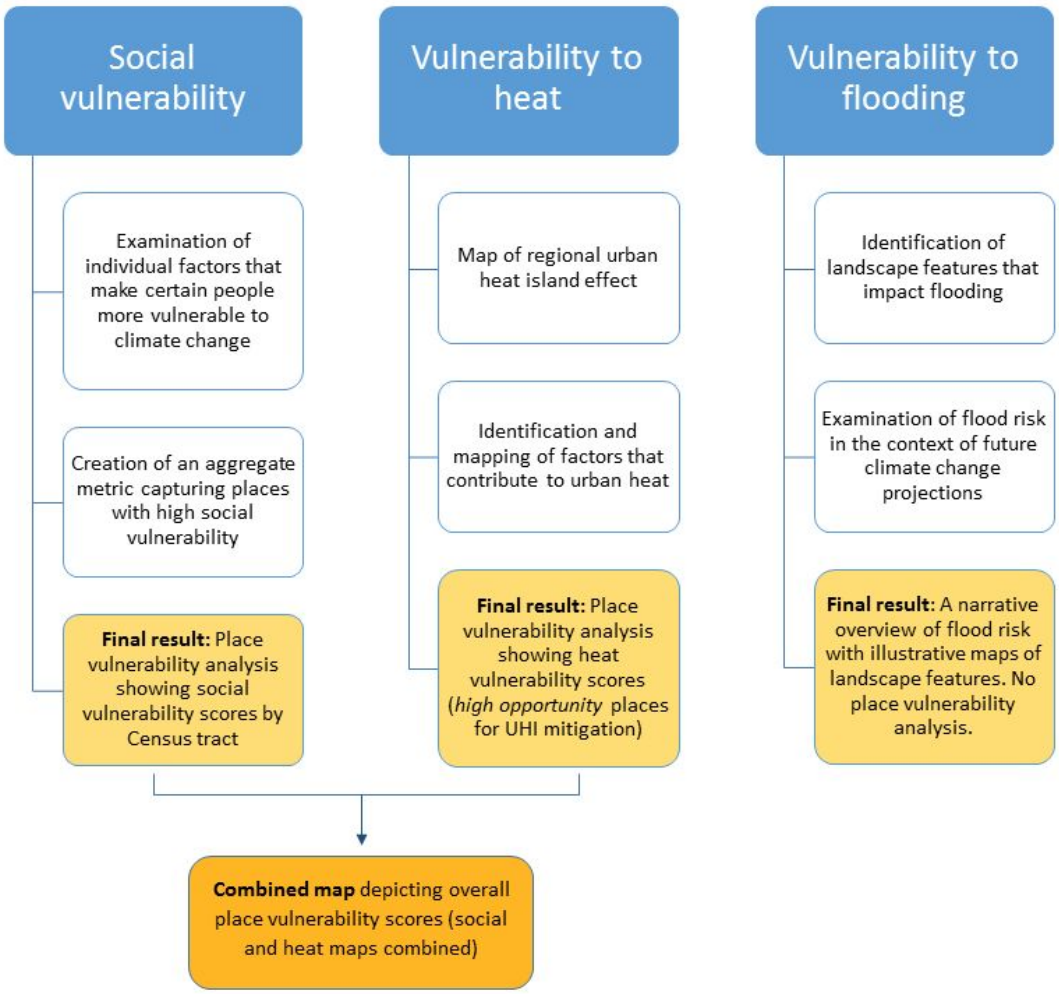


Figure 2: This schematic details the different outcomes from each of the three components of this climate change vulnerability assessment.

1.4 Landscape vulnerability: Background and overview

Vulnerability to climate change is influenced by the physical environment. For this assessment, a “landscape vulnerability indicator” is defined as a physical characteristic of the built or unbuilt environment that can mitigate or exacerbate the effects of climate change. There are many potential environmental effects of climate change to consider.

The landscape vulnerability indicators examined in this assessment can be categorized along a spectrum. At one end of this spectrum are physical landform characteristics such as the elevation gradient and floodplain areas, and weather characteristics such as temperature and precipitation. These factors are the result of geomorphological and climatic processes that are global in nature and not primarily due to Minneapolis influence. At the other end of this spectrum lie characteristics which are wholly due to local human influence over the physical landscape. This latter category, which includes the amount of impervious surface cover and the remaining amount of vegetation, represents the largest opportunity areas for the City of Minneapolis to reduce landscape vulnerability to climate change. Between these two extremes exist a variety of hybrid factors which represent the outcomes of the intersection between humans and the landscape.

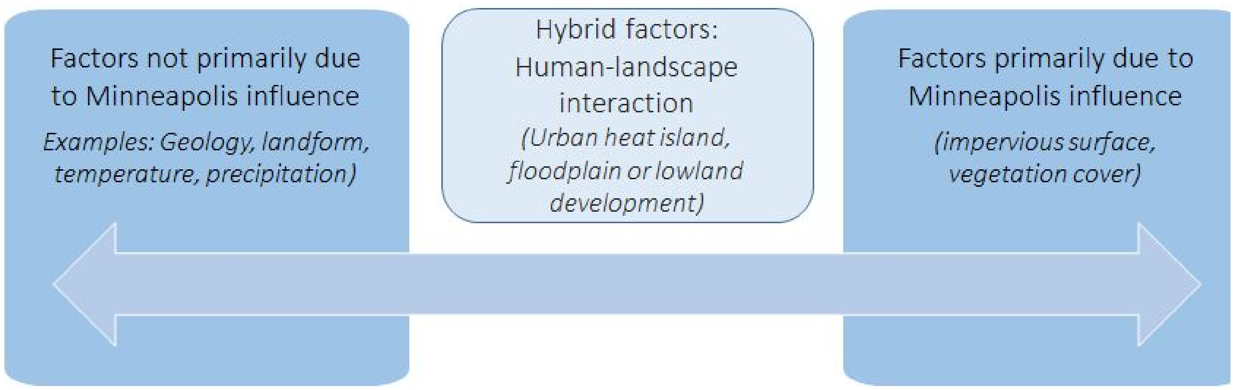


Figure 3: This schematic illustrates the global to local spectrum of influence over landscape vulnerability indicators. The box in the middle indicates hybrid factors that are a result of human interactions with landscape.

Because of the semester-long nature of this capstone project, the scope of the landscape vulnerability component of this assessment is limited to two areas: (1) vulnerability to extreme heat exposure and (2) vulnerability to flooding impact. These two focus areas were determined during the project planning phase in collaboration with City of Minneapolis staff because of their importance to health-related vulnerability.

Increases in flooding and heat are important environmental effects of climate change that the City of Minneapolis must plan for and adapt to. According to projections developed by the Great Lakes Integrated Sciences + Assessments Center at the University of Michigan (GLISA), temperatures in Minneapolis are expected to rise in the coming decades and precipitation is expected to become more variable. Maps developed by GLISA are included on the following page. The set of precipitation maps demonstrates projected temperature and precipitation changes by 2041-2070 for both a “Lower emissions scenario” and a “Higher emissions scenario.” The “lower emissions scenario” is based on the B1 scenario developed by the Intergovernmental Panel on Climate Change (IPCC). The “higher emissions scenario” is based on the A2 scenario developed by the IPCC. The set of heat maps includes a map of the historical number of days over 90 degrees and the projected number of days over 90 degrees (using the A2 “higher emissions scenario” developed by the IPCC. Full descriptions of each of these scenarios are quoted in the box below.

Figure 4: Emissions scenarios developed by the Intergovernmental Panel on Climate Change

Scenario B1 (Lower emissions scenario used by GLISA)

“B1 illustrates the possible emissions implications of a scenario in which the world chooses consistently and effectively a development path that favors efficiency of resource use and "dematerialization" of economic activities. The scenario entails in particular:

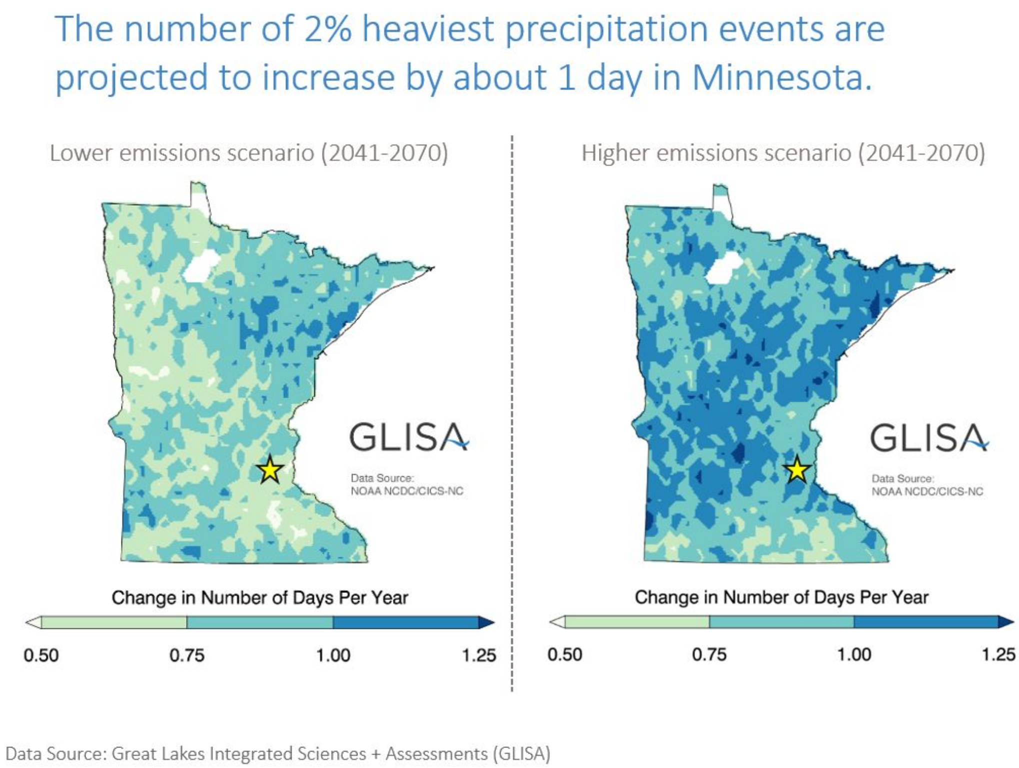
- Rapid demographic transition driven by rapid social development, including education.
- High economic growth in all regions, with significant catch-up in the presently less-developed regions that leads to a substantial reduction in present income disparities.
- Comparatively small increase in energy demand because of dematerialization of economic activities, saturation of material- and energy-intensive activities (e.g., car ownership), and effective innovation and implementation of measures to improve energy efficiency.
- Timely and effective development of non-fossil energy supply options in response to the desire for a clean local and regional environment and to the gradual depletion of conventional oil and gas supplies.”

Scenario B2 (Higher emissions scenario used by GLISA)

“Overall, the A2-ASF quantification is based on the following assumptions (Sankovski et al., 2000):

- Relatively slow demographic transition and relatively slow convergence in regional fertility patterns.
- Relatively slow convergence in inter-regional GDP per capita differences.
- Relatively slow end-use and supply-side energy efficiency improvements (compared to other storylines).
- Delayed development of renewable energy.
- No barriers to the use of nuclear energy.”

Source: Intergovernmental Panel on Climate Change. Emissions scenarios.
http://www.ipcc.ch/ipccreports/sres/emission/index.php?idp=98



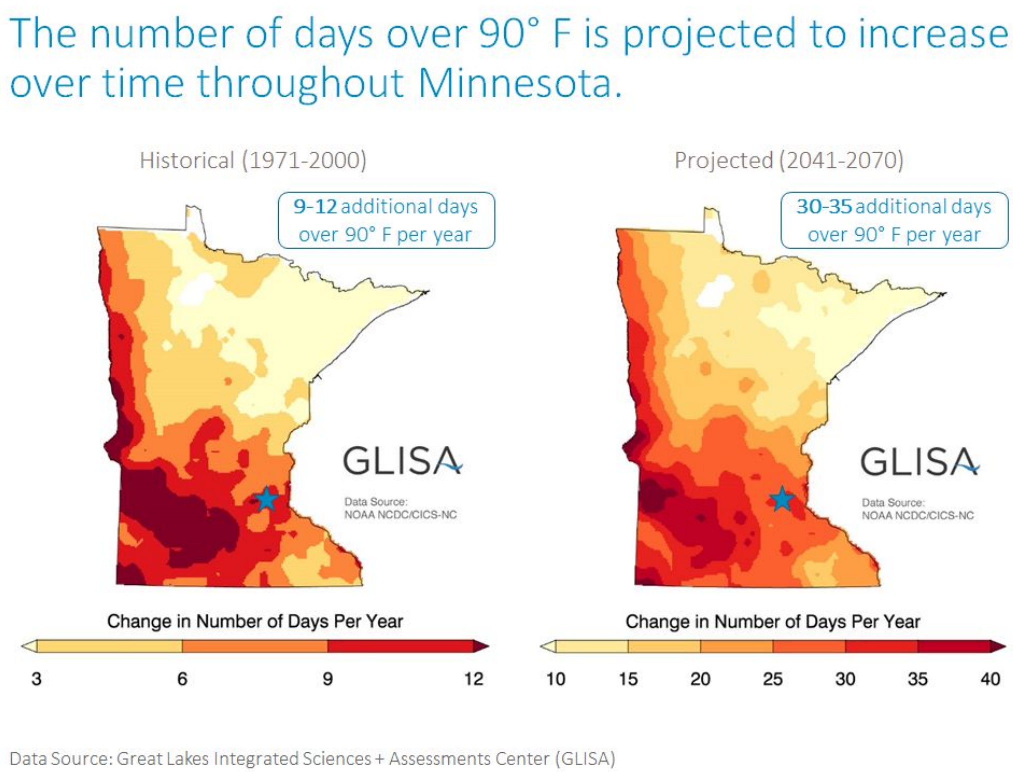


Figure 5: The maps above indicate temperature and precipitation projections for Minnesota. Source: Great Lakes Integrated Sciences + Assessments Center (GLISA).

The tables below summarize the final variables examined in the landscape vulnerability assessment, their data sources, and the location in this document where each variable is described in greater detail.

Figure 6: Landscape vulnerability to heat: Indicators chosen for this assessment		
Heat Indicator	*Data source*	*Section of technical document*
Urban heat island effect	University of Minnesota	3.1
Impervious land cover	University of Minnesota	3.2
Vegetation: Normalized Difference Vegetation Index	United States Geological Survey	3.3

Figure 7: Landscape vulnerability to flooding: Indicators chosen for this assessment		
Flooding Indicator	*Data source*	*Section of technical document*
Surface Water Flow Accumulation	Digital Elevation Model provided by the City of Minneapolis	2.1
FEMA Floodplains	Federal Emergency Management Agency	2.2.1
Elevation	City of Minneapolis Open Data	2.2.2
Slope	Digital Elevation Model provided by the City of Minneapolis	2.2.3
Land Cover (vegetation and impervious cover)	University of Minnesota; United States Geological Survey	2.2.4

1.5 Social vulnerability: Background and overview

In the context of this assessment, a "social vulnerability indicator" refers to an indicator that pertains to a human-oriented characteristic rather than a physical feature of the landscape or infrastructure. Social vulnerability variables may be demographically descriptive in nature, or they may refer to a secondary characteristic indicative of access to a particular resource or lifestyle. From the University of South Carolina's Hazards and Vulnerability Research Institute comes this definition of the term:

> Social vulnerability is represented as the social, economic, demographic, and housing characteristics that influence a community's ability to respond to, cope with, recover from, and adapt to environmental hazards.[2]

While this definition of social vulnerability is accepted within vulnerability assessment literature, the task of creating an effective social vulnerability metric in the context of a locally-specific natural hazard is more challenging. The pre-eminent work by Cutter et. al[3] and the development of the "SoVI" index creates a theoretical foundation for the concept of "social vulnerability to natural hazards". The original SoVI index named 32 distinct indicators that can be used to measure social vulnerability to natural hazards (see Figure 8). These variables were reduced and combined into an index using principal components analysis. This index was developed at a comprehensive national scale for county-level assessment.

Variable Names and Descriptions

Name	Description
MED_AGE90	Median age, 1990
PERCAP89	Per capita income (in dollars), 1989
MVALOO90	Median dollar value of owner-occupied housing, 1990
MEDRENT90	Median rent (in dollars) for renter-occupied housing units, 1990
PHYSICN90	Number of physicians per 100,000 population, 1990
PCTVOTE92	Vote cast for president, 1992—percent voting for leading party (Democratic)
BRATE90	Birth rate (number of births per 1,000 population), 1990
MIGRA_97	Net international migration, 1990–1997
PCTFARMS92	Land in farms as a percent of total land, 1992
PCTBLACK90	Percent African American, 1990
PCTINDIAN90	Percent Native American, 1990
PCTASIAN 90	Percent Asian, 1990
PCTHISPANIC90	Percent Hispanic, 1990
PCTKIDS90	Percent of population under five years old, 1990
PCTOLD90	Percent of population over 65 years, 1990
PCTVLUN91	Percent of civilian labor force unemployed, 1991
AVGPERHH	Average number of people per household, 1990
PCTHH7589	Percent of households earning more than $75,000, 1989
PCTPOV90	Percent living in poverty, 1990
PCTRENTER90	Percent renter-occupied housing units, 1990
PCTRFRM90	Percent rural farm population, 1990
DEBREV92	General local government debt to revenue ratio, 1992
PCTMOBL90	Percent of housing units that are mobile homes, 1990
PCTNOHS90	Percent of population 25 years or older with no high school diploma, 1990
HODENUT90	Number of housing units per square mile, 1990
HUPTDEN90	Number of housing permits per new residential construction per square mile, 1990
MAESDEN92	Number of manufacturing establishments per square mile, 1992
EARNDEN90	Earnings (in $1,000) in all industries per square mile, 1990
COMDEVDN92	Number of commercial establishments per square mile, 1990
RPROPDEN92	Value of all property and farm products sold per square mile, 1990
CVBRPC91	Percent of the population participating in the labor force, 1990
FEMLBR90	Percent females participating in civilian labor force, 1990
AGRIPC90	Percent employed in primary extractive industries (farming, fishing, mining, and forestry), 1990
TRANPC90	Percent employed in transportation, communications, and other public utilities, 1990
SERVPC90	Percent employed in service occupations, 1990
NRRESPC91	Per capita residents in nursing homes, 1991
HOSPTPC91	Per capita number of community hospitals, 1991
PCCHGPOP90	Percent population change, 1980/1990
PCTURB90	Percent urban population, 1990
PCTFEM90	Percent females, 1990
PCTF_HH90	Percent female-headed households, no spouse present, 1990
SSBENPC90	Per capita Social Security recipients, 1990

Figure 8: From Cutter et. al. 2003., a listing of the 42 independent variables that formed the SoVI index.

[2] Social Vulnerability Index | Frequently Asked Questions <http://webra.cas.sc.edu/hvri/products/sovifaq.aspx>

[3] Cutter et. al. "Social Vulnerability to Environmental Hazards." *Social Science Quarterly*, Volume 84, Number 2, June 2003.

While the SoVI index shows that many distinct variables contribute to overall social vulnerability, the concept of social vulnerability has frequently been narrowed or adapted to fit the assessment or the specific hazard in question, such as Reid et. al's 2009 effort to locate populations with high vulnerability to heat using nine social vulnerability criteria[4] (see Figure 9) or the efforts by Jerrett et. al to generate an assessment tool capturing social vulnerability to extreme heat in the Los Angeles and Fresno areas of Southern California (see Figure 10). The development of a singular, comprehensive and effective social vulnerability measurement tool remains somewhat elusive, and most climate change vulnerability assessments that incorporate social vulnerability are developed in an ad hoc manner with indicators selected based on the parameters of the study area in question.

Category	Data source (year)	Variable definition	Percent mean (range)
Demographic variables	U.S. Census (2000)	Percent population below the poverty line	12.57 (0.00–100.00)
		Percent population with less than a high school diploma	19.97 (0.00–85.88)
		Percent population of a race other than white	30.20 (0.00–100.00)
		Percent population living alone	10.28 (0.00–68.86)
		Percent population ≥ 65 years of age	12.21 (0.00–94.28)
		Percent population ≥ 65 of age living alone	27.38 (0.00–100.00)
Land cover	National Land Cover Database (2001)	Percent census tract area not covered in vegetation	61.15 (0.03–100.00)
Diabetes prevalence	Behavioral Risk Factor Surveillance System (2002)	Percent population ever diagnosed with diabetes	6.95 (2.38–11.10)
Air conditioning	American Housing Survey (2002)[a]	Percent households without central AC	44.43 (2.10–95.13)
		Percent households without any AC	18.47 (0.00–95.13)

Figure 9: A selection of indicators used to map vulnerability to extreme heat at the county level across the United States. Reid, Colleen E. et al. "Mapping Community Determinants of Heat Vulnerability." *Environmental Health Perspectives* 117.11 (2009): 1730–1736.*PMC*. Web. 20 Feb. 2016.

Table 3. Data Sources Used to Estimate Environmental, Social, and Health Risks Related to Climate Change and Vulnerability

Data	Year(s)	Original Data Level	Source
Air Conditioning Usage	2000	ZIP Code/Tract	CEC RASS
Air Pollution Monitoring	1999–2005	At monitoring locations	U.S. EPA
Birth Outcomes	2000–2006	Census Tract	CDPH
Elderly Living Alone	2000	Census Tract	ACS
Household Car Access	2000	Census Tract	ACS
Weather data for heat stress	2001–2005	At monitoring locations	CIMIS
Impervious Surface	2001	30 meter raster	NLCD
Tree Canopy	2001	30 meter raster	NLCD
Race-ethnicity and Socioeconomic Status	2000	Census Tract	U.S. Census

Figure 10: A selection of indicators used to map vulnerability in two select municipalities in California. Jerrett et. al, (University of California, Berkeley). 2012. Mapping Climate Change Exposures, Vulnerabilities, and Adaptation to Public Health Risks in the San Francisco Bay and Fresno Regions. California Energy Commission. Publication number: CEC-500-2012-041.

[4] Reid, Colleen E. et al. "Mapping Community Determinants of Heat Vulnerability." *Environmental Health Perspectives* 117.11 (2009): 1730–1736.*PMC*. Web. 20 Feb. 2016.

The social vulnerability index developed for this City of Minneapolis assessment includes nine critical indicators, selected as variables contributing to social vulnerability to climate change in the Minneapolis context. Although initially the intent was to create separate social vulnerability indices for extreme heat and flooding, the index was eventually collapsed to create a single social vulnerability index to capture both climate change phenomena due to redundant rationale and an interest in simplifying the study methodology.

The table below (Figure 11) summarizes the final variables examined in the social vulnerability assessment, their data sources, and the location in this document where each variable is described in greater detail.

Figure 11. Social vulnerability: Indicators chosen for this assessment

Social Indicator	*Data source*	*Section of technical document*
Older population	American Community Survey	5.1.1
Young children	American Community Survey	5.1.2
Poverty	American Community Survey	5.1.3
Limited English proficiency	American Community Survey	5.1.4
People of Color	American Community Survey	5.1.5
Disability	American Community Survey	5.1.6
No Vehicle access	American Community Survey	5.1.7
Renters	American Community Survey	5.1.8
No Central Air conditioning	Minneapolis City Assessor	5.1.9

2. Analysis of landscape vulnerability to flooding

Minneapolis has been experiencing over 20% more intensive heavy precipitation days between 1981-2010 compared heavy precipitation days between 1951-1980 (http://glisa.umich.edu/climate/extreme-precipitation). The Great Lakes Integrated Sciences + Assessments institute projects that heavier rain events will continue to increase in frequency. Understanding the City's vulnerability to flooding in a future with more intense rainfall events requires an understanding of how the current stormwater drainage system in Minneapolis operates. The stormwater drainage system is a complex set of interrelated naturally-occurring and human-influenced factors.

The Climate Change Vulnerability Assessment mapped five factors contributing to the stormwater drainage system, and thus flooding, based upon consultations with City Staff at Minneapolis' Department of Public Works and data availability:

1. Surface Water Flow Accumulation
2. FEMA Floodplains
3. Elevation
4. Slope
5. Land Cover (represented by impervious surface and vegetation cover)

Slope was later removed from final consideration because its influence is minimal in Minneapolis and topographic features are better represented by the Elevation factor.

One critical component not included in the list of factors contributing to the stormwater drainage system is stormwater infrastructure. Stormwater infrastructure is complex and built by taking into account factors such as those listed above, as well as specific design capacities. The most relevant one for this assessment is the "storm event" capacity of the City's stormwater infrastructure. Current best practices in Minnesota dictate a 10-year storm event design capacity for stormwater infrastructure.[5] The greater the number of years of the event, the larger the event, but also the less likely that event is occur. A 2-year storm event would expect less rainfall in an hour than a 10 year event. A 2-year event is likely to happen every 2 years, as a 10-year event is likely to happen every 10 years. In the past the stormwater infrastructure in Minneapolis has been designed for 2-year (1.4"/hour) and 5-year (1.8"/hour) storm events. As per Figure 12, approximately 47% of City's stormwater infrastructure was built before 1960 for storm events only accounting for up to 5-year storm events.[6]

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[5] Minnesota Pollution Control Agency. (2000) *Stormwater Best Management Practices Manual*. Chapter 4: "Best Management Practices for Stormwater Systems." https://www.pca.state.mn.us/sites/default/files/swm-ch4.pdf

[6] http://www.minneapolismn.gov/ publicworks/stormwater/stormwaterlocal-surface

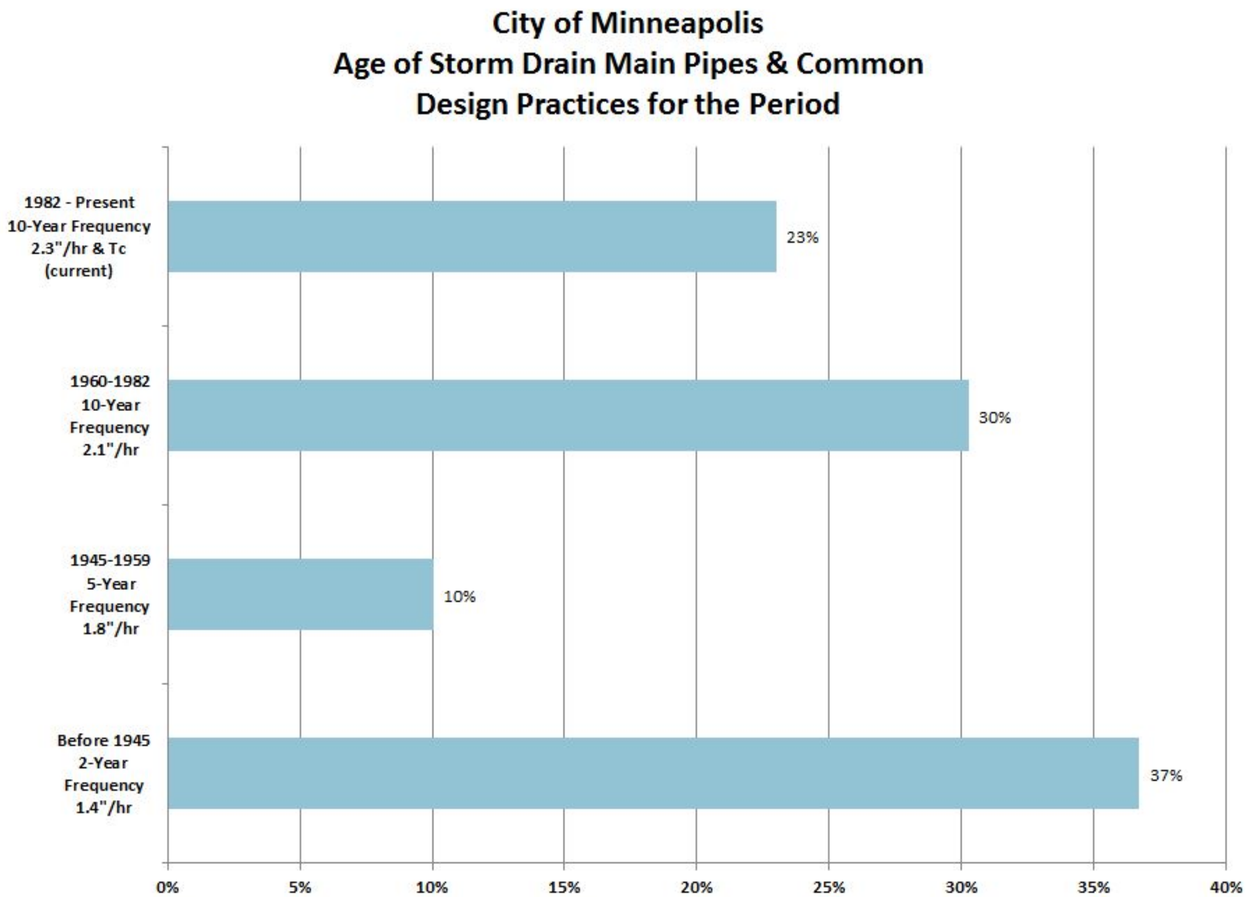

Figure 12. Age of storm drain main pipes & common design practices for the period

The incrementally-designed and -built nature of City's stormwater infrastructure makes it difficult to fully understand how water flows during rain events. To better understand the working of the stormwater infrastructure, and the stormwater drainage system as a whole, the Minneapolis Public Works Department is currently in the midst of a multiyear Hydraulics and Hydrology study. The analysis performed in their study will create a more comprehensive understanding of how the City's stormwater infrastructure functions in conjunction with the factors analyzed in this document. Because that study is only approximately half-way done, the climate change vulnerability assessment and this technical document focused on the five factors for which data was available.

2.1. Surface water flow accumulation analysis (Digital Elevation Model)

2.1.1. Data details

Measure: Elevation grid of Minneapolis; at least one-half mile buffer past city boundaries
Source: Digital Elevation Model provided by the City of Minneapolis
Date: unknown
Level of granularity: one-meter raster grid

2.1.2 Map creation

A map of surface water flow accumulation in Minneapolis was created using a Digital Elevation Model raster layer provided by the City of Minneapolis (elev_29ftharn). Cell Size was changed to 10 feet (Environmental Settings/ Raster Analysis) based upon recommendations from City staff due to computer processing capacities and the granularity of the DEM.
The Fill tool (in the Spatial Analyst toolset) was run on elev_29ftharn to fill in any areas of internal drainage. When running this tool an optional Z Limit depth of two-feet was chosen based on two factors:

1. Recommendation from City staff to choose a Z Depth between 0.5 and 3.0 feet, and
2. Due to computer processing capacities incapable of running the analysis at any depth shallower than two-feet.

The new raster created from this step is called Fill2_elev_294.
The Flow Direction tool (in the Spatial Analyst toolset) was run on the Fill_elev_294 to create the new raster called FlowDir_Fill2.
The Sink tool (in the Spatial Analyst toolset) was run on the Fill_elev_294 raster. The sink tool produces visualizations depicting depressions deeper than the specified Z Limit of two-feet used in the Fill tool. This new raster is called Sink_FlowDir1.
The Flow Accumulation tool (in the Spatial Analyst toolset) was run on the FlowDir_Fill2 to create another new raster called FlowAcc_Flow1 (also names "Accumulation Cell Count").
The Classify tool was lastly utilized to group and differentiate the intensity of flow accumulation. The raster classification was set to exclude values 0 to 20240 on recommendation from City staff in order to remove the lowest accumulation pixels from the classification display. The raster was then classified by 9 quantiles grouped as such: (1) 20,241 - 21,100, (2) 21,101 - 26,350, (3) 26,351 - 36,900, (4) 36,901 - 47,450, (5) 47,451 - 63,250, (6) 63,251 - 79,100, (7) 79,101 - 116,000, (8) 116,001 - 231,950, (9)* 231,951 - 1,344,250. This final raster is called FlowAcc_Flow1 and is complemented by the previous new raster Sink_FlowDir1.

*The ninth quantile group has a markedly larger range for two reasons. The first reason is that areas accumulating enough points for the ninth quantile are fed by the eight smaller quantile ranges, which creates a much larger accumulation score. The second reason is that the analysis had to account for the Mississippi River. Because the River is the lowest part of the City in most areas, most water eventually drains to it due to the scores it receives for its large difference in elevation, which creates a very high accumulation score. The vast majority of areas in the ninth quantile are in the Mississippi River.

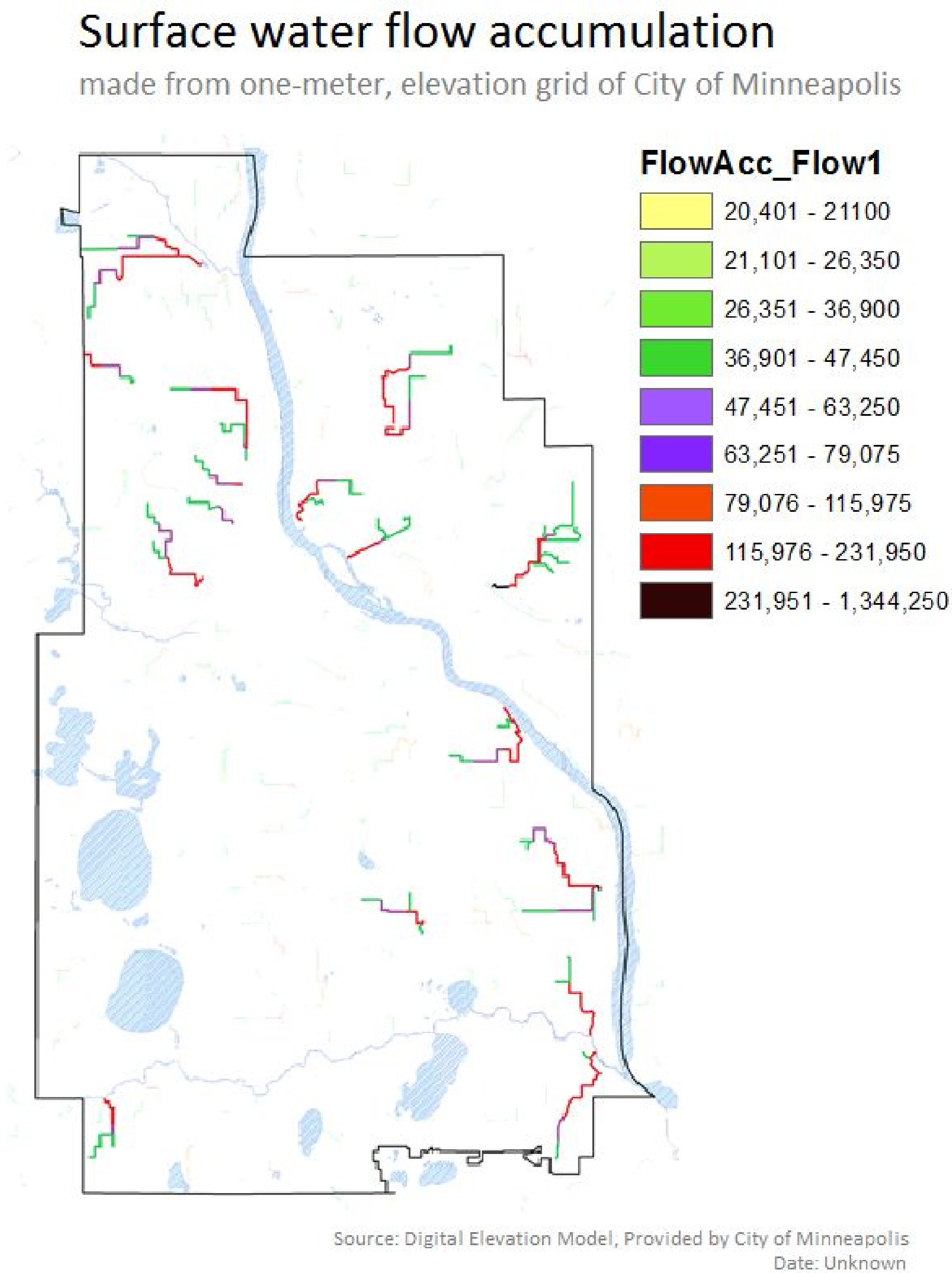

Figure 13. Map of surface water flow accumulation*
This map features 9 quantiles displaying water accumulation based upon a digital elevation model

from the City of Minneapolis Public Works Department

*This map has been rendered for improved visualization purposes

2.2. Additional variables considered

Although not central to our analysis of flooding, additional variables were considered and mapped because of their importance to understanding the movement of water in an extreme flood event.

2.2.1. Floodplains

2.2.1.1. Data details

Measure: Land area within 100-year or 500-year floodplains.
Source: Federal Emergency Management Agency. URL:
https://gisdata.mn.gov/dataset/water-dnr-fema-dfirm
Date: January 2006
Level of granularity: County (clipped to Minneapolis city boundaries before analysis)

2.2.1.2. Map creation

FEMA Floodplain data was gathered from the Minnesota Geospatial Commons, which has compiled all unmodernized flood hazard zones delineated by FEMA for Digital Flood Rate Insurance Maps (DFIRM) for the state. In February 2016, DFIRM panels for Minnesota were updated to include Hennepin County and thus the city of Minneapolis, rendering the shapefile usable for this study. Land within 100-year floodplains has a one-percent annual risk of flooding. Land within 500-year floodplains has a 0.2-percent annual risk of flooding.

To create the map, the statewide floodplain shapefile (**flood_hazard_zones_unmodernized**) was clipped to the boundaries of the City of Minneapolis plus its adjacent water bodies (**CityBoundary_Water_Merge**). The layer created from this step is called **flood_hazard_zones_clipMpls**. 100 and 500-year floodplains were mapped via the existing attribute designations within the shapefile.

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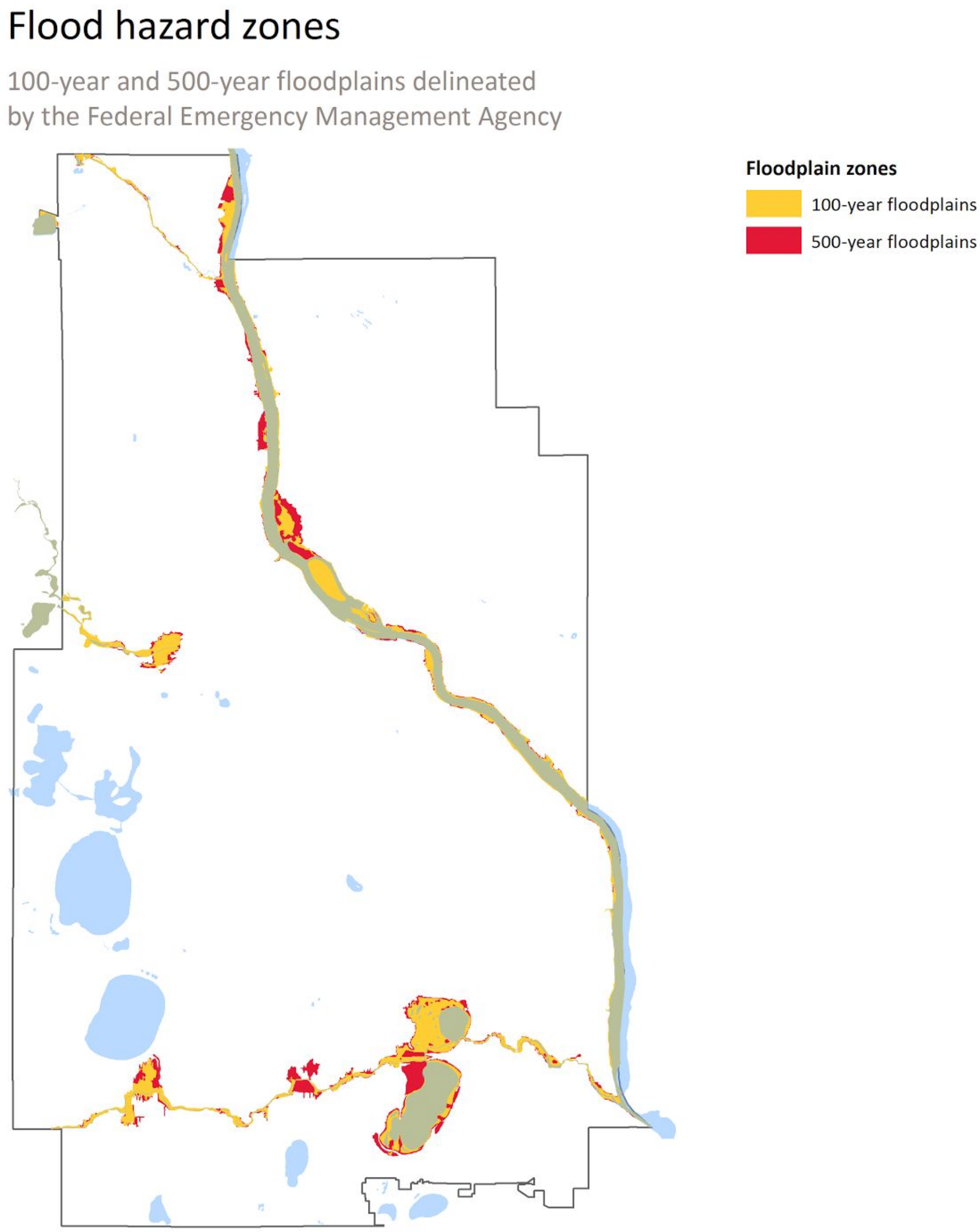

Figure 14. Map of flood hazard zones

This map shows 100-year and 500-year floodplains delineated by the Federal Emergency Management Agency.

2.2.2. Elevation

2.2.2.1. Data details

Measure: Elevation above sea level
Source: City of Minneapolis Open Data
Date: Unknown
Level of granularity: 2-foot contour lines

2.2.2.2. Map creation

Elevation was mapped using a 2-foot elevation contours layer from Minneapolis Open Data (Elevation_Contours_2_Foot).[7] The map categorizes contour layers in quintiles.

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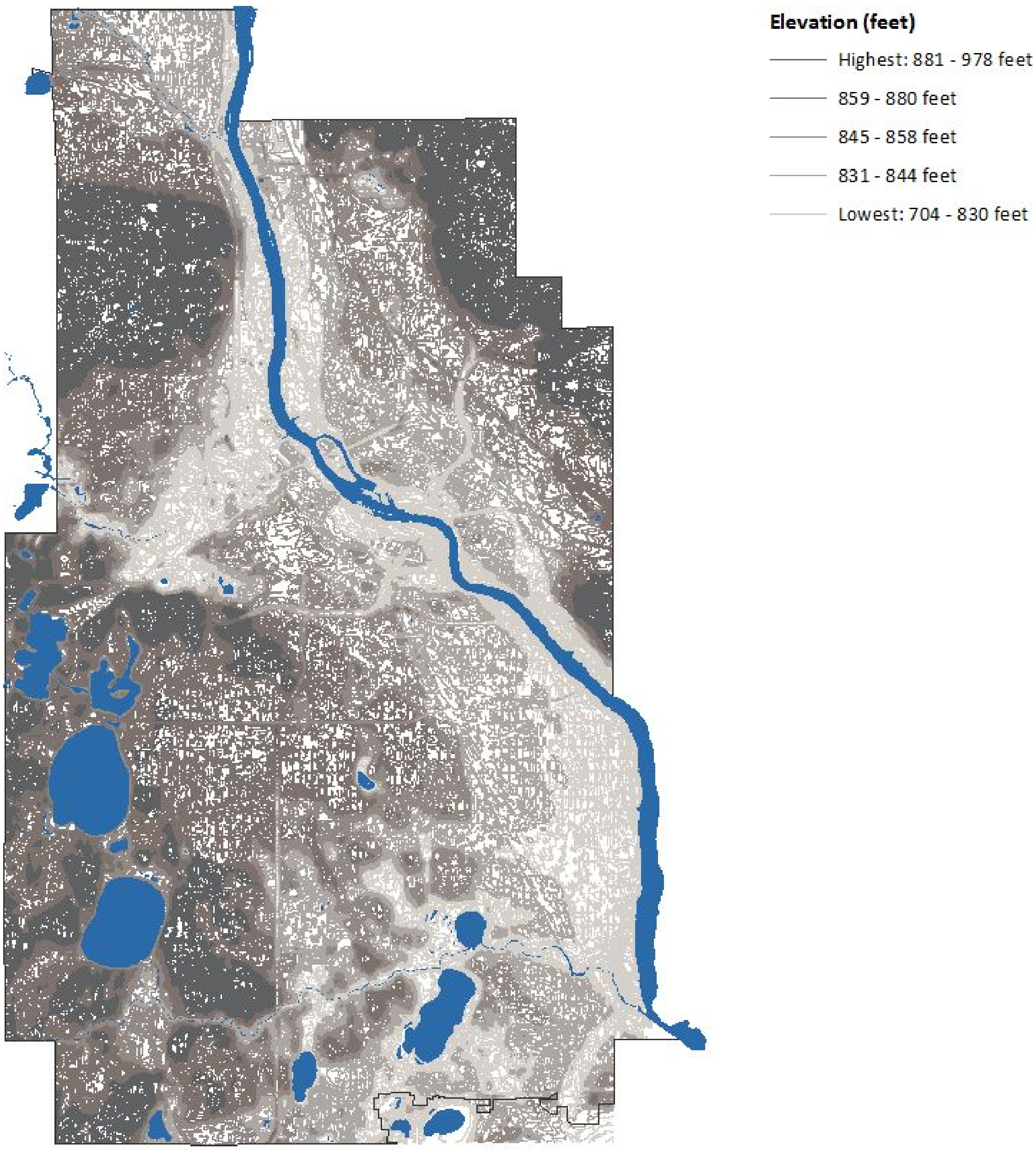
[7] URL: http://opendata.minneapolismn.gov/datasets/107ae837504447bab708d481fdd52175_0

Elevation

2-foot elevation contours



Source: 2-foot elevation contours
provided by the City of Minneapolis.
Elevation contours are grouped into quintiles.

Figure 15. Map of elevation in Minneapolis

This map shows elevation in Minneapolis, measured in two-foot elevation contours.

2.2.3. Slope

2.2.3.1. Data details

Measure: Slope
Source: Digital Elevation Model provided by the City of Minneapolis
Date: Unknown
Level of granularity: 3 feet

2.2.3.2. Map creation

A map of slope in Minneapolis was created using a Digital Elevation Model raster layer provided by the City of Minneapolis (DEM_3FT). First, the Slope tool (in the Spatial Analyst toolset) was run on DEM_3FT. The new raster created from this step is called DEM_slp. Next, the Reclass tool was used to classify DEM_slp into slope groups. The new raster created from this step is called DEM_slprc. The groups used were: (1) Less than 12 percent slope, (2) 12-18 percent slope, and (3) More than 18 percent slope. This classification is based on development restrictions described in the Minneapolis Code of Ordinances (https://www2.municode.com/library/mn/minneapolis/codes/code_of_ordinances?nodeId=MICOOR_TIT20ZOCO_CH551OVDI_ARTVISHSHOVDI_551.500DESLBETW12EI18PE). Finally, the Extract by Mask tool (in the Spatial Analyst toolset) was used to clip DEM_slprc to the Minneapolis city boundaries. This final raster is called DEM_slprcex.

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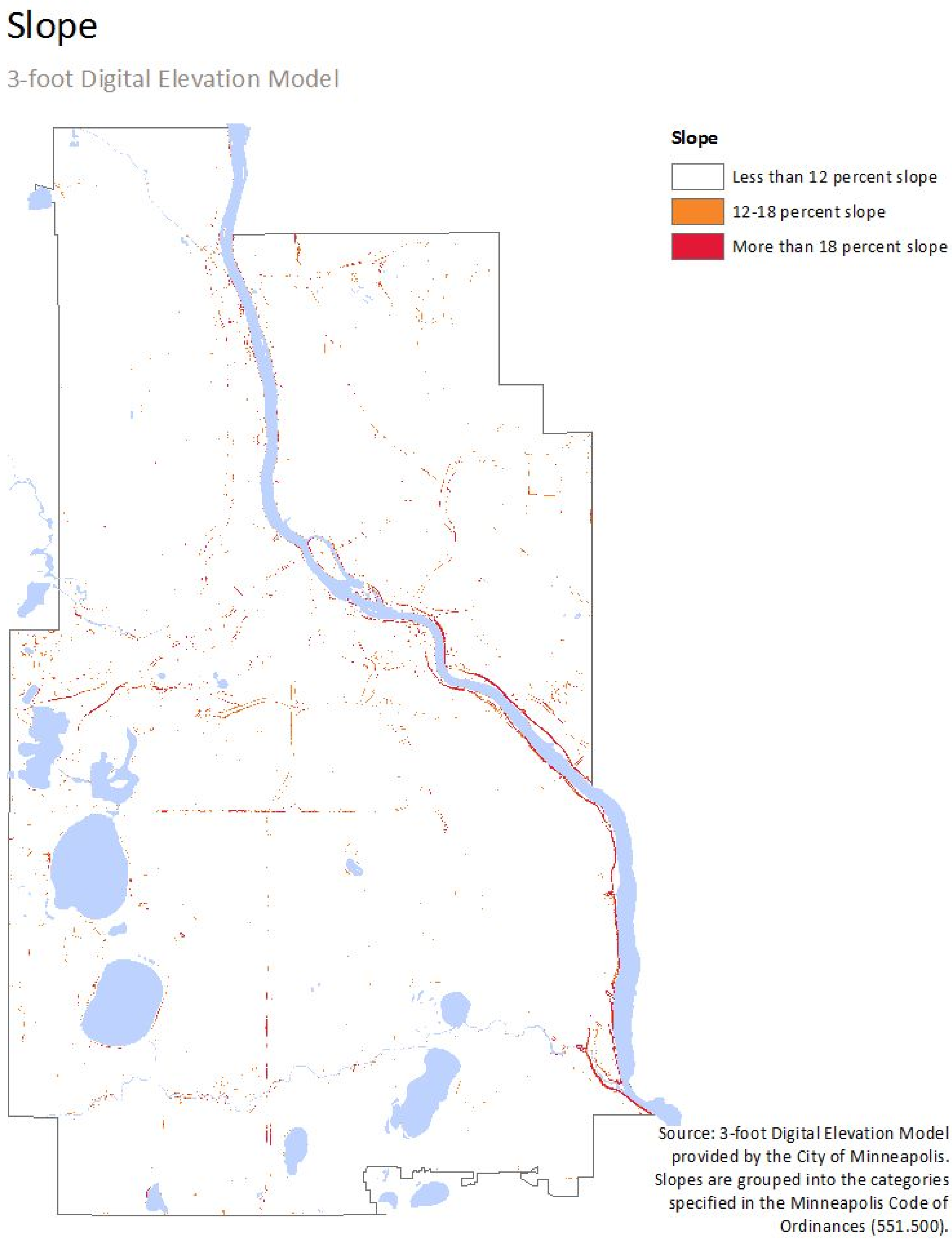

Figure 16. Map of slope in Minneapolis

This map shows slope in Minneapolis, calculated using a three-foot Digital Elevation Model.

2.2.5. Land Cover (Impervious surface and vegetation cover)

Although impervious surface and vegetation cover are analyzed in great detail in the Heat section below (Figures 26 and 28), the measure is also important for understanding flooding potential. Impervious surface and vegetation cover are indicators of runoff potential. When precipitation falls on impervious surfaces, such as roads, streets, sidewalks, and buildings, it is unable to infiltrate into the soil. Conversely, the greater portion of vegetation cover present, the more precipitation may infiltrate the soil, and thus, the less precipitation available as run-off on impervious surfaces. Instead, this precipitation flows overland along a negative elevation gradient until it reaches either a sewer inlet, a sufficiently permeable surface, or a ponding area. Areas with high amounts of impervious surface can contribute a substantial amount of water to lower-lying land or waterbodies. The opposite may be said for areas with high amounts of vegetation cover, as well as the added benefit of vegetative water filtration and groundwater recharge.

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3. Analysis of landscape vulnerability to heat

3.1 Urban heat island effect

An urban heat island (UHI) describes a city or built area that is significantly warmer than its surrounding rural environment. Smoliak et al. note that UHI effects in cities around the world are the result of “the systematic manipulation and replacement of natural environments with built environments”[8]. In urban areas like Minneapolis, the UHI effect is likely to exacerbate the hazardous impacts of projected increases in the number of hot days associated with climate change.

Urban heat island effect data was shared by the Department of Soil, Water, and Climate at the University of Minnesota[9]. This data represents temperature measurements taken at 15-minute intervals from 160-180 temperature sensor stations throughout the Twin Cities metropolitan area. A shapefile with the locations of these temperature sensors was also shared.[10] The temperatures on land between temperature sensors were interpolated with impervious surface cover (“cokriged”) to create a 1-kilometer grid. Reference rural temperatures were gathered from nine rural airports and averaged. UHI was calculated by subtracting reference rural temperatures from urban temperatures. The data shared by Dr. Snyder is published in the following journal article: *Brian V. Smoliak, Peter K. Snyder, Tracy E. Twine, Phillip M. Mykleby, and William F. Hertel. 2015. Dense Network Observations of the Twin Cities Canopy-Layer Urban Heat Island. Journal of Applied Meteorology and Climatology 54: 1899-1917.*

The data strongly indicates that Minneapolis has a much stronger UHI compared to the metropolitan area. In addition, the UHI is remarkably consistent across Minneapolis. According to Philip Mykleby, a researcher in the Department of Soil, Water, and Climate at the University of Minneapolis, the “warmest stations are almost exclusively in or near downtown Minneapolis.”[11] Because impervious surface is used to interpolate UHI in the co-kriging algorithm, impervious surface is very strongly correlated with the UHI data. The amount of vegetation, measured in this analysis with the Normalized Difference Vegetation Index (NDVI), is also strongly correlated with Urban Heat Island. Both impervious surface and NDVI are indicated in the Smoliak et. al paper as being highly correlated with UHI (with impervious surface having the stronger correlation). Additional contributors indicated by Mykleby, but not included in our analysis, include:

- Waste heat produced by machinery such as air conditioners and automobiles

[8] Brian V. Smoliak, Peter K. Snyder, Tracy E. Twine, Phillip M. Mykleby, and William F. Hertel. 2015. Dense Network Observations of the Twin Cities Canopy-Layer Urban Heat Island. Journal of Applied Meteorology and Climatology 54: 1899-1917

[9] Department of Soil, Water, and Climate, University of Minnesota, 439 Borlaug Hall, 1991 Upper Buford Circle, St. Paul, MN 55108. E-mail: pksnyder@umn.edu

[10] The precision of the point data was changed slightly in order to protect the anonymity of volunteers.

[11] Email communication, March 22, 2016.

- Meteorological factors
    - Nighttime UHI tends to be higher on clear, calm nights, when heat radiates away quickly in rural areas, and calm winds reduce mixing.
    - During the winter, after a snowfall, daytime UHI values tend to be slightly higher, because snow is plowed in urban areas more than in rural areas, which changes the albedo of the urban area compared with the rural areas.[12]

3.1.1. Data details

Measure: Temperature difference as compared to rural reference area, in degrees Fahrenheit
Source: University of Minnesota
Date: Five time periods in Summer 2012 (detailed below)
Level of granularity: One-kilometer raster grid

Urban Heat Island effect data was shared as five separate NETCDF files for five different time periods, detailed in the table below. Data from the summer of 2012 was selected because it was the first year in which a complete data set was collected, and because it was one of the hottest summers on recent record . Both July 4 and July 6 were examined because of the significant difference in the days' daytime and nighttime UHI effect.

Figure 17. 2012 Notes accompanying urban heat island data

Time period	**Notes**	**File name**
June, July, and August 2012 (average)	Summer 2012 was one of the hottest summers on record for the Twin Cities metropolitan area.	JJA_2012_UHI
July 4, 2012 (average)	July 4, 2012 can be considered a “normal” hot summer day in 2012. The high for that day was 100˚F. July 4 is a more ideal day to look at a heat event.)	Jul4_2012
July 4, 2012 (9-10pm)	9-10pm was the hour with the maximum UHI effect on July 4, 2012.	Jul4_9_10PM_2012
July 6, 2012 (average)	July 6, 2012 was technically the hottest day of the year - the high for that day was 102˚F. However, a storm came through at about 6-7pm on that day. This storm substantially reduced the temperature and humidity.	Jul6_2012

[12] Email communication, March 22, 2016.

July 6, 2012 (3-4pm)	Because of the (hour with the maximum UHI effect on that day)	Jul6_3_4PM_2012

3.1.2. Map creation

All five NETCDF files were batch imported into ArcGIS using the “Make NetCDF Raster Layer” tool:

1. JJA_2012_UHI → UHI_Layer1
2. Jul4_9_10PM_2012 → UHI_Layer2
3. Jul4_2012 → UHI_Layer3
4. Jul6_3_4PM_2012 → UHI_Layer4
5. Jul6_2012 → UHI_Layer5

The five files were then exported as final raster layers:

1. UHI_Layer1 → UHI_JJA
2. UHI_Layer2 → UHI_Jul4_9_10
3. UHI_Layer3 → UHI_Jul4
4. UHI_Layer4 → UHI_Jul6_3_4
5. UHI_Layer5 → UHI_Jul6

Next, all five layers were clipped to the seven-county metropolitan region to create the final layers:

1. UHI_JJA → **UHI_JJA_clip**
2. UHI_Jul4_9_10 → **UHIJ4_910clip**
3. UHI_Jul4 → **UHI_Jul4_clip**
4. UHI_Jul6_3_4 → **UHIJ6_3_4clip**
5. UHI_Jul6 → **UHI_J6_clip**

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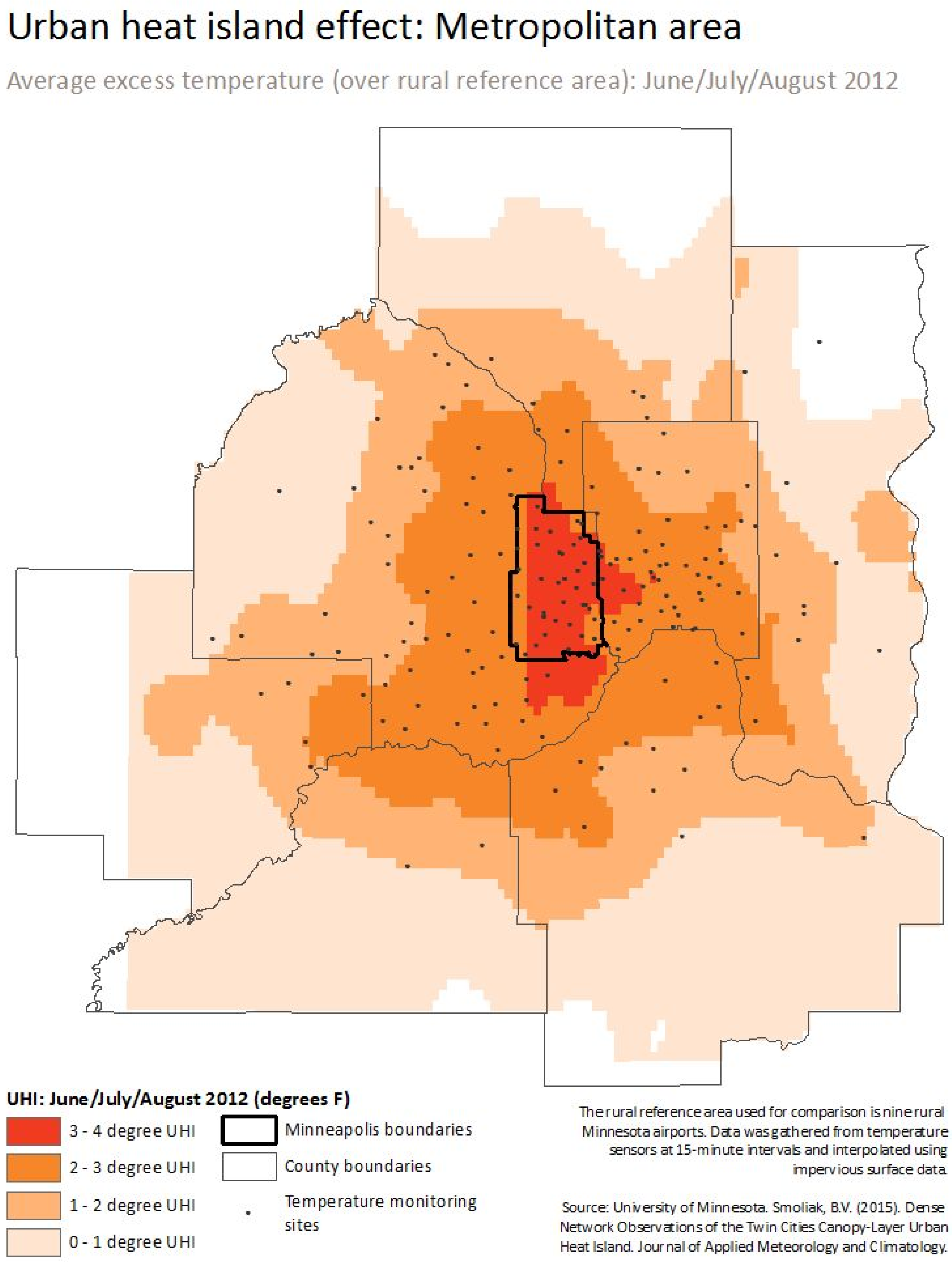

Figure 18. Average urban heat island effect Minneapolis-St. Paul Metropolitan area
(June-August 2012)

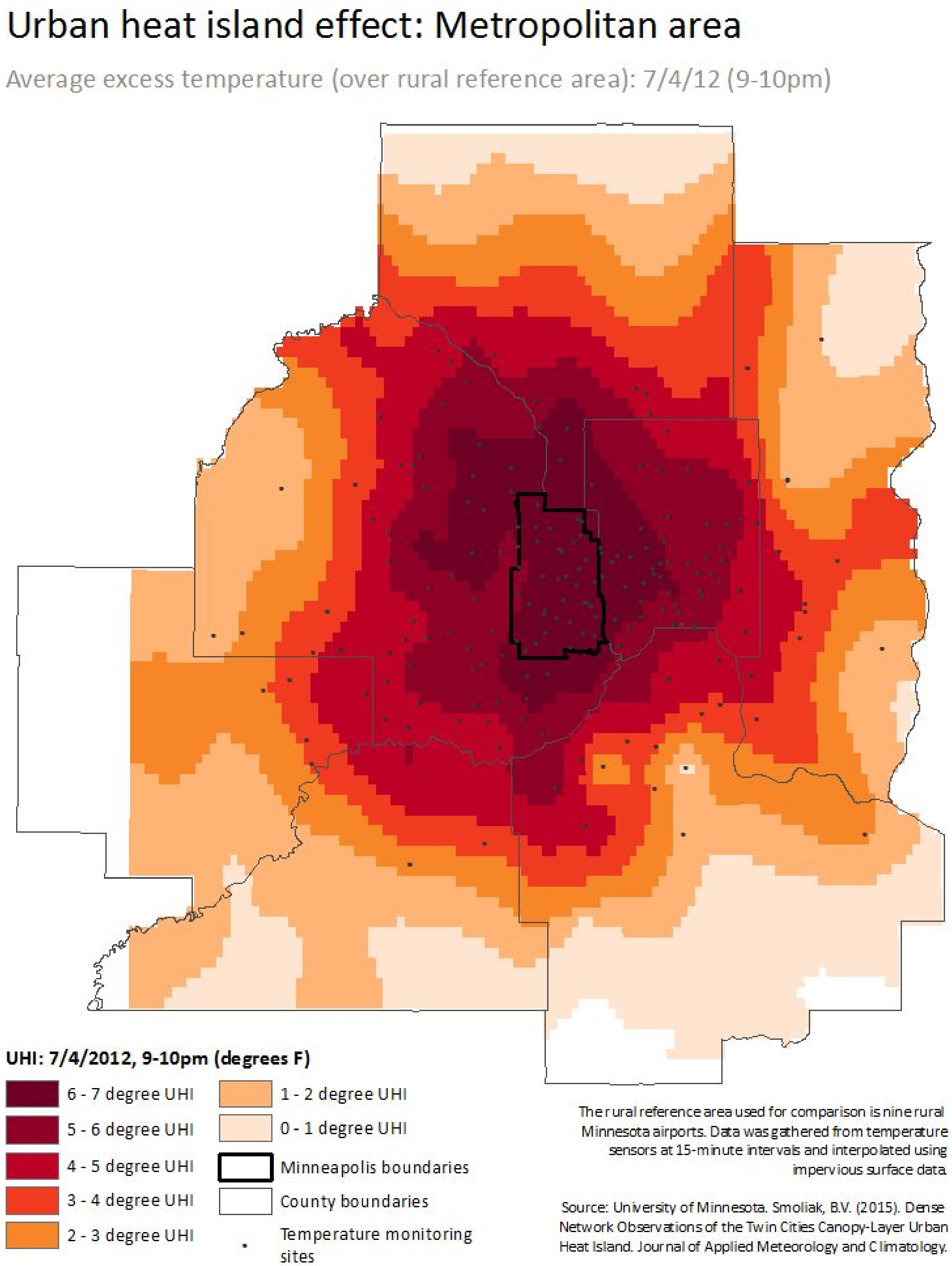

Figure 19. Average urban heat island effect Minneapolis-St. Paul Metropolitan area
July 4, 2012; 9-10pm

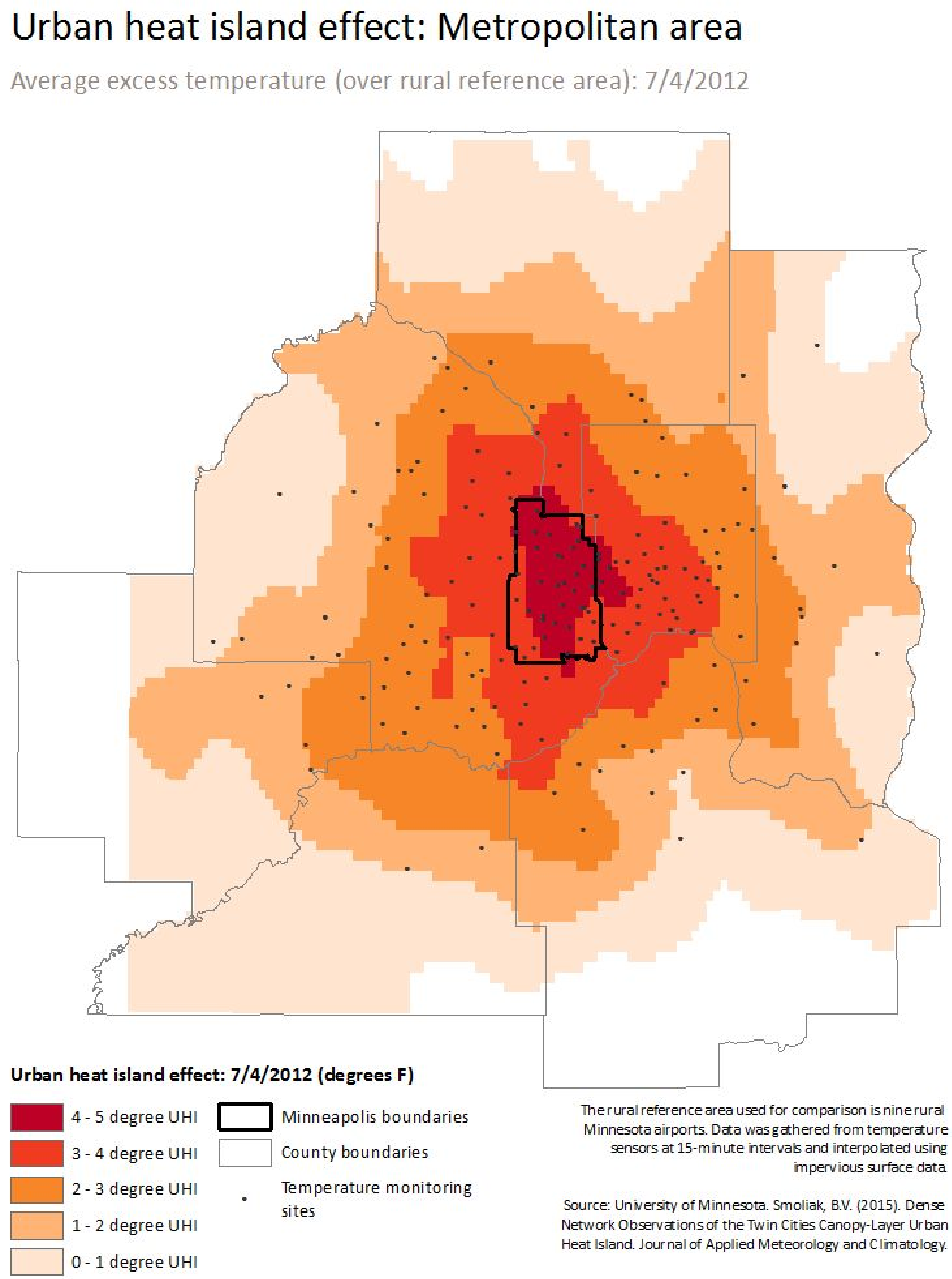

Figure 20. Average urban heat island effect Minneapolis-St. Paul Metropolitan area
July 4, 2012

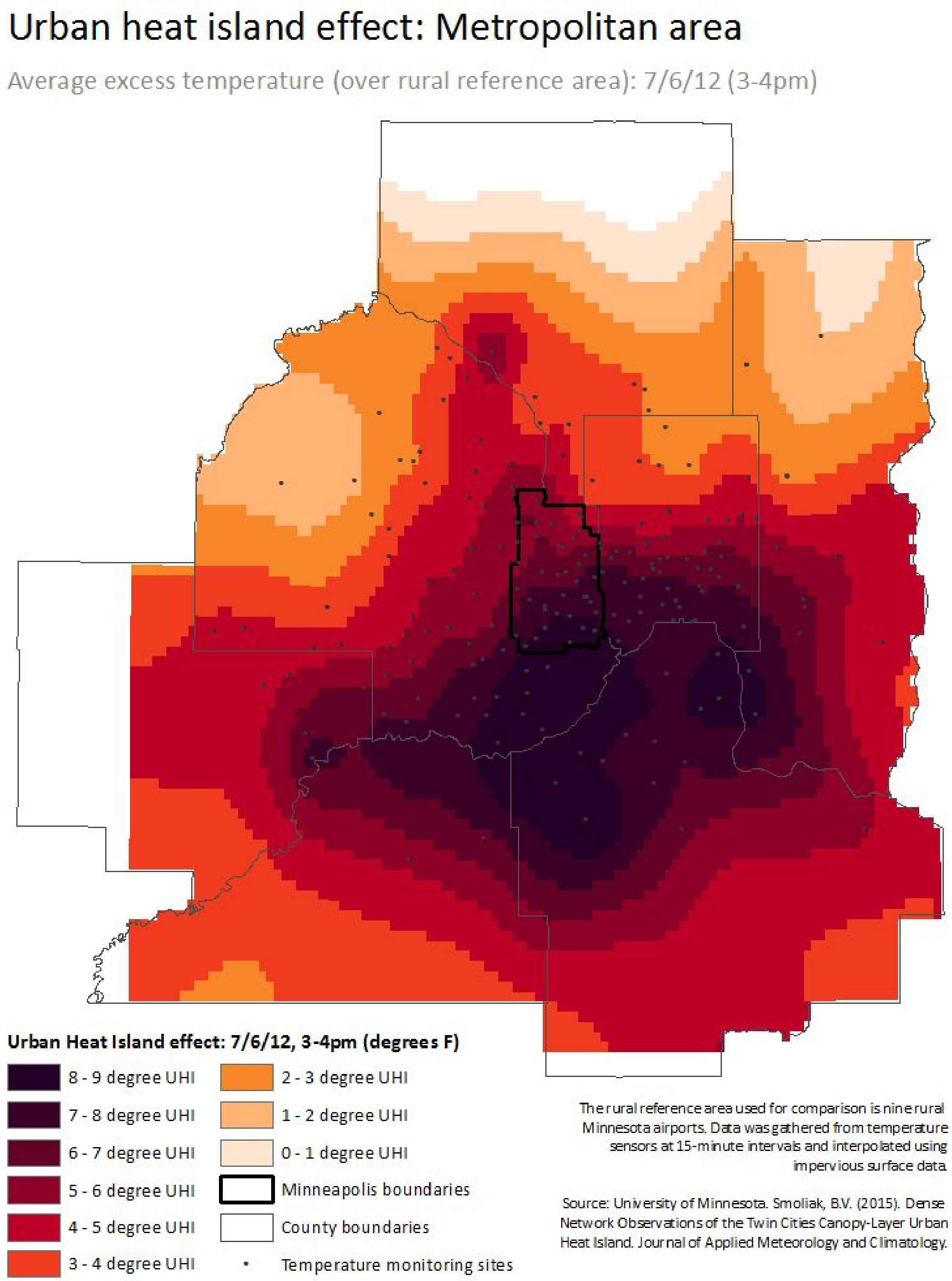

Figure 21. Average urban heat island effect Minneapolis-St. Paul Metropolitan area
July 6, 2012; 3-4pm

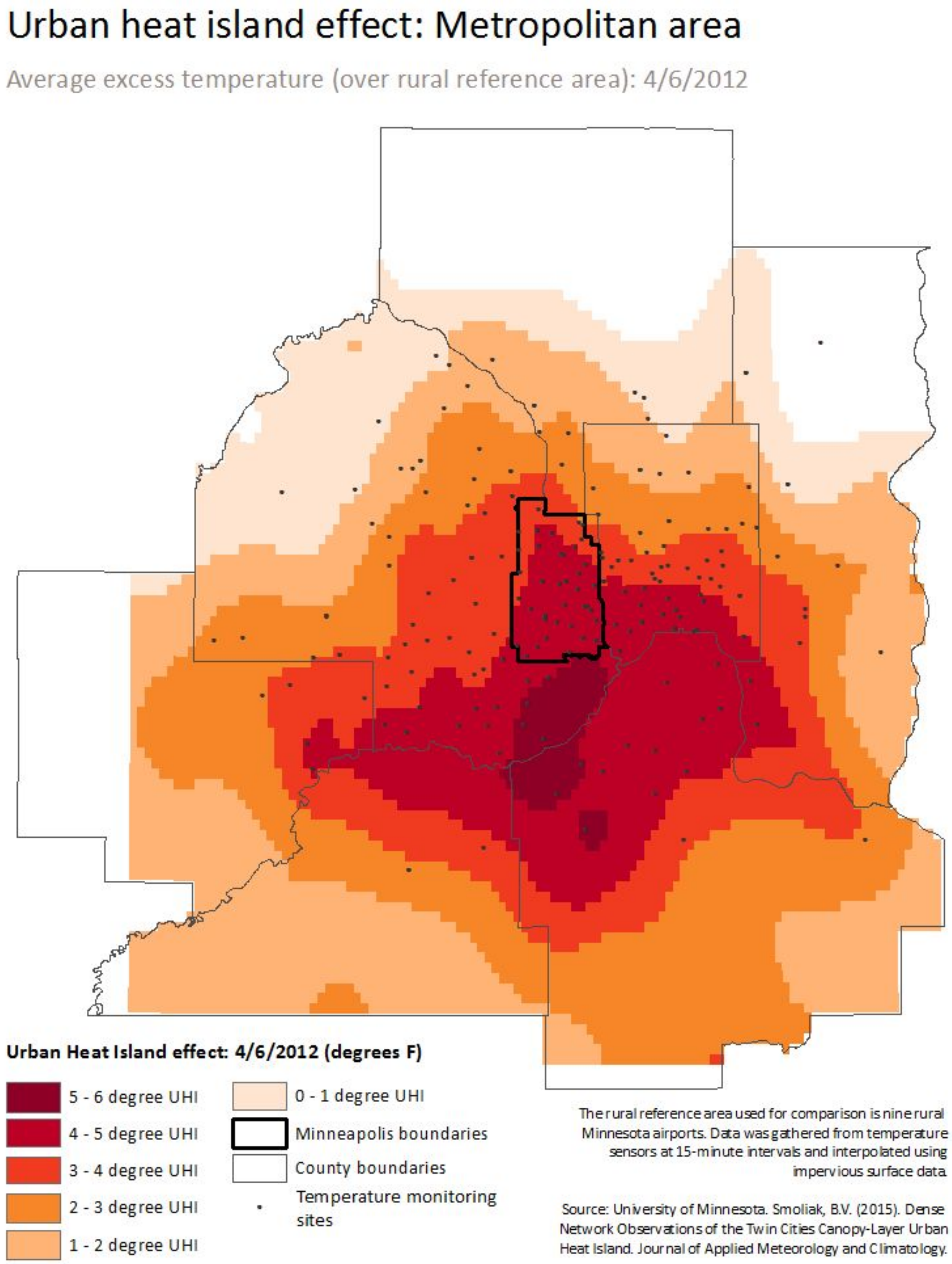

Figure 22. Average urban heat island effect Minneapolis-St. Paul Metropolitan area
April 6, 2012

3.2. Impervious land cover

3.2.1. Data details

Measure: Land with 1%-100% impervious surface cover
Source: Remote Sensing and Geospatial Analysis Lab at the University of Minnesota. URL:
http://portal.gis.umn.edu/map_data_metadata/LandCover_MN2013.html
Date: 2013
Level of granularity: 15-meter raster grid

Impervious surface cover is an indicator of susceptibility to the urban heat island effect. Impervious surfaces, such as roads, streets, sidewalks, and buildings, absorb and retain the sun's heat. As temperatures fall in the evening, this absorbed heat is released, increasing evening temperatures.

3.2.2. Map creation: Initial data processing

Impervious land cover data was gathered from the Remote Sensing and Geospatial Analysis Lab at the University of Minnesota. The dataset was the Minnesota Land Cover Classification and Impervious Surface Area by Landsat and Lidar (2013 update - Version 1). URL: http://portal.gis.umn.edu/ The resolution is a 15-meter by 15-meter grid.

First, the IMG file (**MN_LandCover2013v1.img**) downloaded from the URL above was added from the zip file to ArcMap.

3.2.2.1. Creation of visuals for PowerPoint

MN_LandCover2013v1.img was then clipped to the seven-county metropolitan area and to the Minneapolis city boundaries using the Extract by Mask tool. This image was for purely visual purposes, for display in the final PowerPoint presentation. The percent impervious surface was grouped into categories recommended in the metadata: 1 - 10, 11- 25, 26 - 40, 41 - 60, 61 - 80, and 81 - 100 percent impervious.

Extract by Mask specifications (seven-county metropolitan area):

- Input raster: MN_LandCover2013v1.img
- Input raster or feature mask data: Counties_MetroArea
- Output raster: **MN_LandCover2013v1_SevenCounties**

Extract by Mask specifications (Minneapolis city boundaries):

- Input raster: MN_LandCover2013v1.img
- Input raster or feature mask data: MplsCityBoundary
- Output raster: **MN_LandCover2013v1_ClipMpls**

Four additional layers were then created for inclusion in the PowerPoint. The “impervious surface” grid cells (those with a value of 1-100) were extracted from MNLC13_ExClip and from MN_LandCover2013v1_SevenCounties using the Extract by Attributes tool (in the Spatial Analyst toolset). Then, the “pervious surface” grid cells (those with a value of 101-110) were extracted from MNLC13_ExClip and from MN_LandCover2013v1_SevenCounties using the Extract by Attributes tool. The resulting layers from this process are:

- **MN_LandCover2013v1_ClipMpls_ExAttImpervious** (impervious surface clipped to Minneapolis boundaries)
- **MN_LandCover2013v1_ClipMpls_ExAttPervious** (pervious surface clipped to Minneapolis boundaries)
- **MN_LandCover2013v1_SevenCounties_ExAttImpervious** (impervious surface clipped to seven-county boundaries)
- **MN_LandCover2013v1_SevenCounties_ExAttPervious** (pervious surface clipped to seven-county boundaries)

3.2.2.2. Initial data processing for analysis

Next, in the image attribute table, records with Value<111 were selected from MN_LandCover2013v1.img and exported to a new raster layer called **MNLC13_Ex**.

MNLC13_Ex was then clipped to the Minneapolis city boundaries using the Extract by Mask tool.

Extract by Mask specifications:

- Input raster: MNLC13_Ex
- Input raster or feature mask data: MplsCityBoundary
- Output raster: MNLC13_ExClip

In the attribute table, records with values from 101-110 represent other land cover types not categorized as impervious surface. These land cover types include Emergent Wetlands, Forested and Shrub Wetlands, Open Water, Coniferous Forest, Deciduous Forest, Managed Grass and Natural Grass, and Row Crops. For purposes of this analysis, these land cover types were coded as a 1 (1% impervious surface) by using the Reclassify by Table tool.

Reclassify by Table specifications:

- Input raster: MNLC13_ExClip
- Input remap table: **MNLC13_ReclassTable.txt**
- From value field: VF
- To value field: VT
- Output value field: VA
- Output raster: **MNLC13_ExClipRec**

Land cover

Impervious and non-impervious surface cover

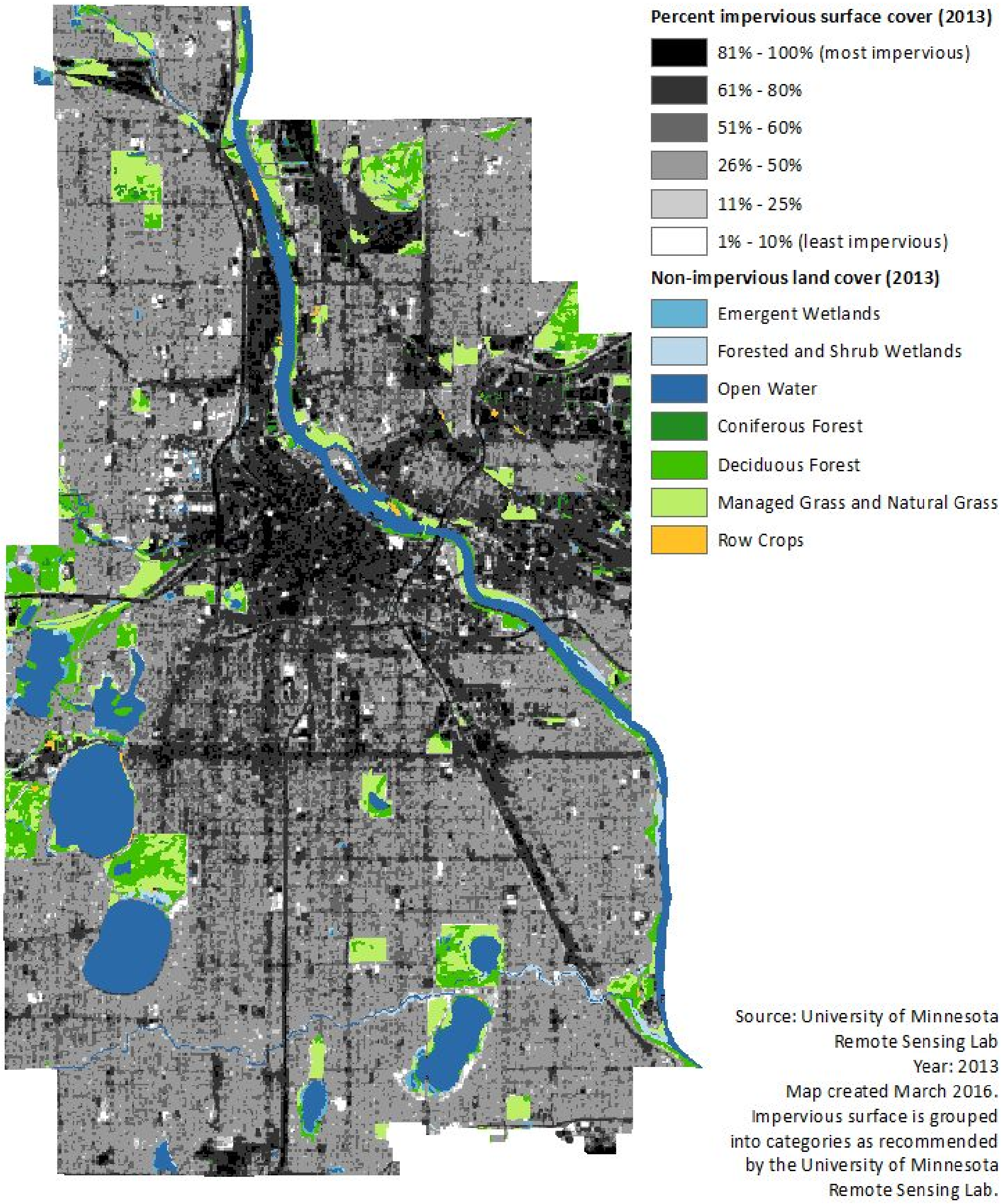

Figure 23. Land cover - Impervious and non-impervious surface cover
City of Minneapolis

Land cover

Impervious and non-impervious surface cover

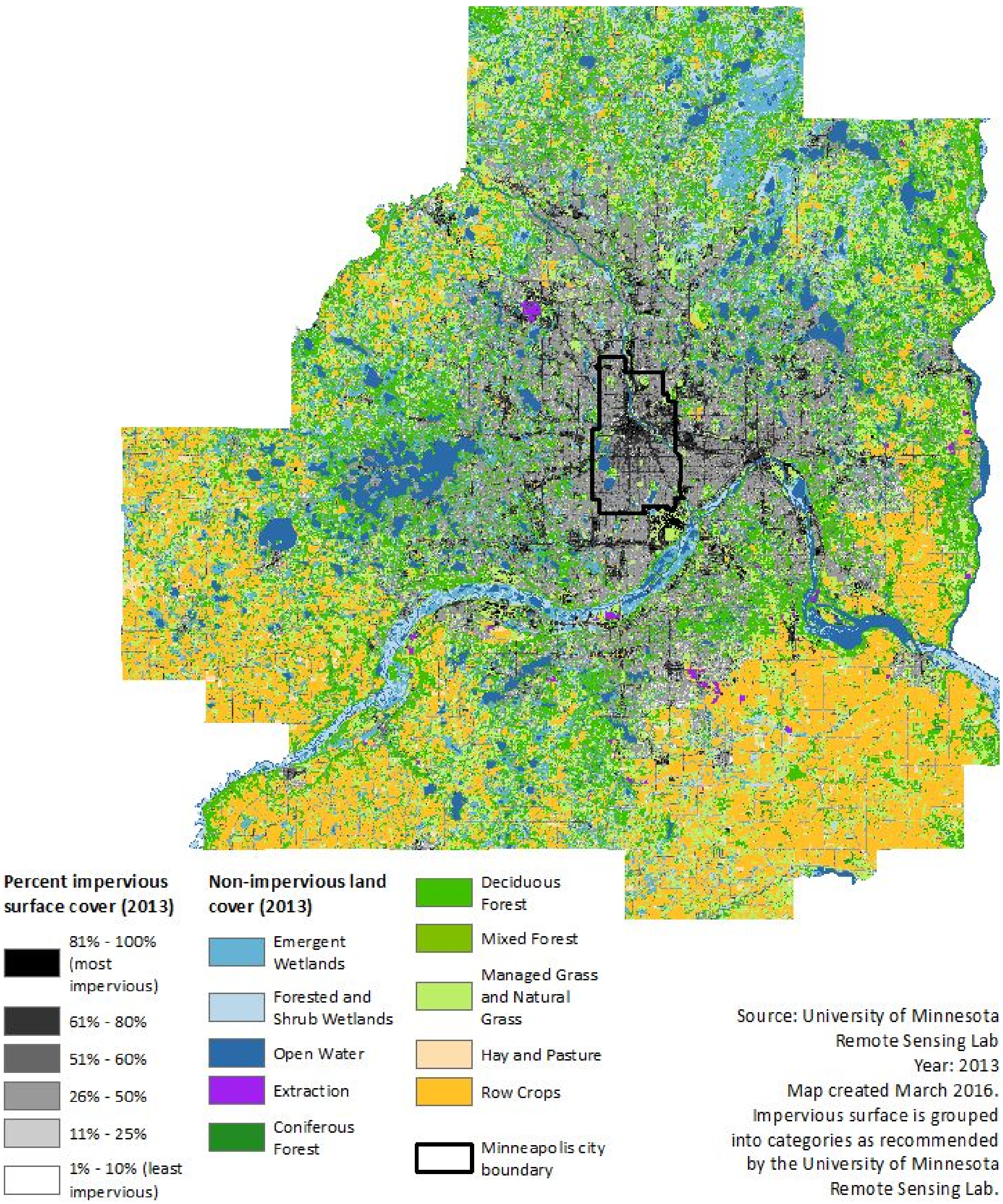

Figure 24. Land cover - Impervious and non-impervious surface cover
Minneapolis-St. Paul metropolitan area

3.2.3. Map creation: Aggregating impervious surface by Census tract

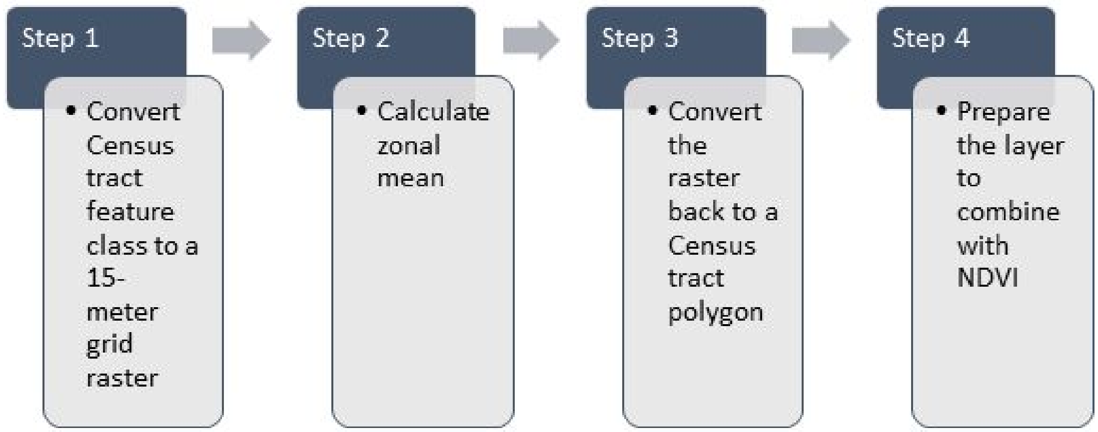

Figure 25. Process diagram for aggregating impervious surface by census tract

For our analysis, our group wanted to be able to rank Census tracts by overall percent of impervious surface. To accomplish this, the Zonal Statistics tool was used to calculate the mean percent of impervious surface cover (by pixel) across each Census tract.

3.2.3.1. Preliminary step 1: Convert Census tract feature class to a 15-meter grid raster

In order to calculate Zonal Statistics, the Census tract feature class (MplsTracts2010, a vector polygon file) had to first be converted to a 15-meter grid raster using the Polygon to Raster tool, to create the new raster MTrcts2010_15m.

Polygon to Raster specifications:

- Input Features: MplsTracts2010
- Value field: GEOID10
- Output Raster Dataset: **MTrcts2010_15m**
- Cellsize: 15

Note: It’s important to check and make sure all of the tracts came through.

3.2.3.2. Calculate zonal mean

Once the preliminary step was completed, then Zonal Statistics could be run to calculate the mean percent impervious surface by Census tract.

Zonal Statistics specifications:

- Input raster or feature zone data: MTrcts2010_15m
- Zone field: GEOID10
- Input value raster: MNLC13_ExClipRec
- Output raster: **MNLC13_ZMean**
- Statistics type: mean

3.2.3.3. Convert the raster back to a Census tract polygon

We then wanted to convert our layer from a raster back to a Census tract polygon. There are two steps in this process. First, MNLC13_ZMean had to be converted from a floating point raster (one with infinite decimal points) to an integer raster. The Raster Calculator tool was used to accomplish this.

Raster Calculator specifications:

- Formula: Int("MNLC13_ZMean" * 10000)
    - Note: MNLC13_ZMean was multiplied by 10000 to preserve the decimal points.
- Output raster: **MNLC13_ZMean_int**

Note: Using the “Int” function in the Raster Calculator truncates any decimal points - it does not round. This slight degree of error is minimized by multiplying by a large number, as was done above.

The raster MNLC13_ZMean_int was then converted to a polygon using the Raster to Polygon tool.

Raster to Polygon specifications:

- Input raster: MNLC13_ZMean_int
- Field: VALUE
- Output polygon features: **MNLC13_ZMean_int_tract**
- Leave “Simplify polygons” checked

Converting a raster to a polygon often incidentally creates tiny extra unwanted polygons. In our case, six extra polygons were created. The Eliminate tool was used to absorb these smaller polygons into larger nearby ones. Before running the Eliminate tool, the six tiny polygons were selected in the attribute table.

Eliminate specifications:

- Input layer: MNLC13_ZMean_int_tract
- Output feature class: **MNLC13_ZMean_int_tract_elim**

Finally, because MNLC13_ZMean was multiplied by 10000 to create MNLC13_ZMean_int, the values must be converted back to their original state. To do this, a new field was created in MNLC13_ZMean_int_elim. The new field (double) is called PctImp_Mean. To convert the values, Field Calculator was used. Equation: PctImp_Mean = [gridcode] /10000 .

MNLC13_ZMean_int_tract_elim was saved as two layer files for display:
- MNLC13_ZMean_int_tract_elim_RedToGreen (red is most vulnerable)
- MNLC13_ZMean_int_tract_elim_OrangeToBlue (orange is most vulnerable)

3.2.3.4. Prepare the layer to combine with NDVI

First, the mean and standard deviation for the entire PctImp_Mean field were gathered. The mean was found to be 48.818759 and the median was found to be 10.221927.

Second, a new field (Double) called Z_Score was created. Using the Field Calculator, the following equation was entered: (([PctImp_Mean]-48.818759)/(10.221927)).

Third, a new field (Text, 50 characters) called STD_DEV was created. Using the Select by Attributes and Field Calculator functions, the following values were coded:

Select by Attributes	Field Calculator
Z_Score <-2	">2 SD below mean"
Z_Score >= -2 AND Z_Score <-1	"1-2 SD below mean"
Z_Score >= -1 AND Z_Score <0	"<1 SD below mean"
Z_Score >= 0 AND Z_Score <1	"<1 SD above mean"
Z_Score >= 1 AND Z_Score <2	"1-2 SD above mean"
Z_Score >= 2	">2 SD above mean"

Fourth, a new field (Short integer) called “RasterValue” was created. Using the Select by Attributes and Field Calculator functions, the following values were coded:

Select by Attributes	Field Calculator
STD_DEV = ">2 SD below mean"	1
STD_DEV = "1-2 SD below mean"	2
STD_DEV = "<1 SD below mean"	3
STD_DEV = "<1 SD above mean"	4
STD_DEV = "1-2 SD above mean"	5
STD_DEV = ">2 SD above mean"	6

Next, the impervious land cover layer resolution (15-meter grid) had to be rescaled to match the NDVI layer resolution (30-meter grid). This was accomplished using the Aggregate tool.

Aggregate specifications:

- Input raster: MNLC13_ExClipRec
- Output raster: **MNLC13_ExClipRecAgg**
- Cell factor: 2
- Aggregation technique: Mean
- Uncheck “Expand extent if needed”

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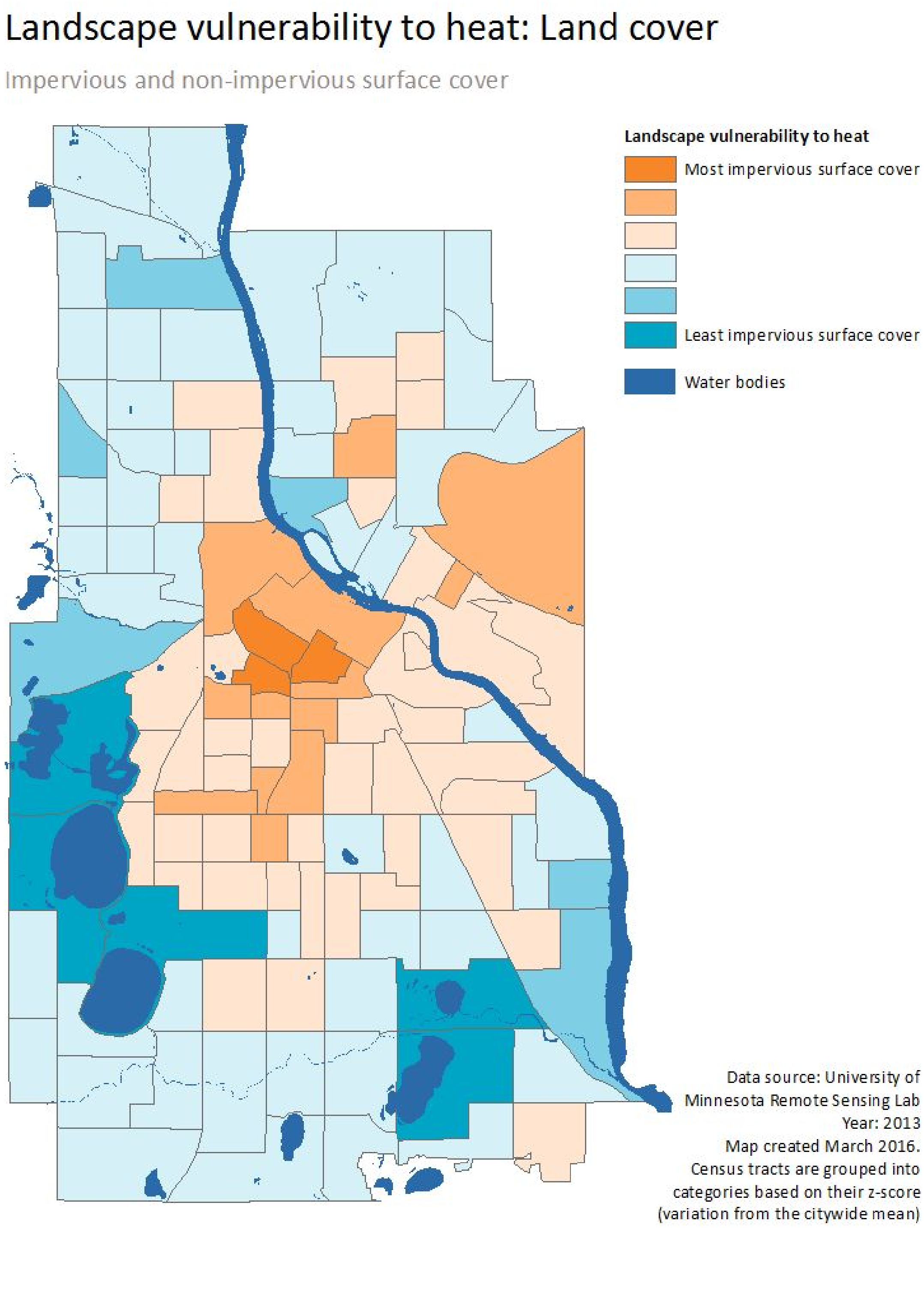

Figure 26. Landscape vulnerability to heat: Land cover

Grouped at census tract level by z-score

3.3. Normalized Difference Vegetation Index (NDVI)

3.3.1. Data details

Measure: Land with green surface cover
Source: United States Geological Survey. URL: http://earthexplorer.usgs.gov/
Date: 12/27/2015
Level of granularity: 30-meter raster grid (aerial photo)

Healthy vegetation reduces the urban heat island effect by providing shade and cooling through evapotranspiration. The Normalized Difference Vegetation Index is a measure of "greenness." The equation used to calculate NDVI is near-infrared radiation minus visible radiation divided by near-infrared radiation plus visible radiation. NDVI is calculated with the following equation: (NIR - Red) / (NIR + Red), where NIR = Near Infrared. The values range from -1 (least green) to 1 (most green). Areas with a higher NDVI have more cooling potential than areas with low NDVI.

3.3.2. Map creation: Initial data processing

In order to create the NDVI map, a Landsat 8 aerial image was downloaded from the United States Geological Survey Earth Explorer and then processed into an NDVI image within ArcMap. The image resolution is a 30-meter by 30-meter raster grid.

Downloading the Landsat 8 image from USGS
After navigating to the United States Geological Survey Earth Explorer (http://earthexplorer.usgs.gov), an account was created by clicking the button in the upper right corner of the screen. It is essential to log in to that account before progressing any further.

Next, the area of interest was selected by navigating to the Search Criteria tab, clicking Path/Row and then clicking Polygon. A polygon shape was created by clicking on the map to indicate the corners of the area of interest. The polygon was made slightly larger than necessary because it is easy to clip it in ArcGIS later.

Next, the Data Sets tab (next to the Search Criteria tab) was selected, and the box next to *L8 OLI/TIRS* was selected.

Next, the Results tab (near the Search Criteria and Data Sets tabs) was selected. An image was chosen that completely covered the area of interest. A helpful hint is to use the "Show Footprint" button (it looks like a footprint) to easily view the areal extent of each image. For this analysis, the image with Landsat Scene Identifier LC80270292015201LGN00 was used. The acquisition date of this image was 07/20/2015.

Once the image was chosen, the “Download Options” button was clicked (it looks like a hard disk with a green downward arrow above it). Then the word Download was clicked, next to the option “Level 1 GeoTIFF Data Product.” A tar.gz file began to download, and it took a while.

Once the tar.gz file was downloaded, the file was extracted into the desired target folder using 7-Zip. The result was a .tar file. That .tar file was extracted again to the same folder (it is double-compressed), and a series of new TIFF files appeared in the folder.

Processing the image in ArcMap
All of the TIFF files extracted in the steps above were added to a new ArcMap document.

Using the Composite Bands tool, all of the TIFF files with a number at the end (e.g. “B1”) were added together. The output raster was saved as **Landsat8_072015**.

The symbology of the new layer was changed as follows:

- Red: Band_5
- Green: Band_4
- Blue: Band_3

Next the image was processed into an NDVI layer. The first step was to click Windows → Image Analysis. Then, the “Image Analysis Options” button in the top left corner of the Image Analysis pane was selected. In the NDVI tab, the “Use Wavelength” box was checked and the “Scientific Output” box was unchecked. The Red Band value was changed to 4 and the Infrared Band value was changed to 5.

In the Image Analysis toolbar, the composite image was selected at the top (in our case, Landsat8_072015) then the NDVI button was clicked to calculate NDVI scores (the button looks like a leaf). This layer is only temporary.

Once NDVI was calculated, the image was exported as a new .img file. The .img NDVI file in this analysis was named **Landsat8_072015_NDVI**. NDVI ranges from -1 (least vegetation) to 1 (most vegetation).

The process above created an NDVI layer for the entire aerial image. For this analysis, an NDVI layer specific to Minneapolis was needed. To create this, the composite raster was clipped to the Minneapolis city boundaries using the Extract by Mask tool (in the Spatial Analyst toolset).

Extract by Mask specifications:

- Input raster: Landsat8_072015
- Input raster or feature mask data: MplsCityBoundary
- Output raster: **Landsat8_072015_Mpls**

The NDVI calculation was then run on this extract using the process above. The new Minneapolis NDVI layer was saved as **Landsat8_072015_Mpls_NDVI**.

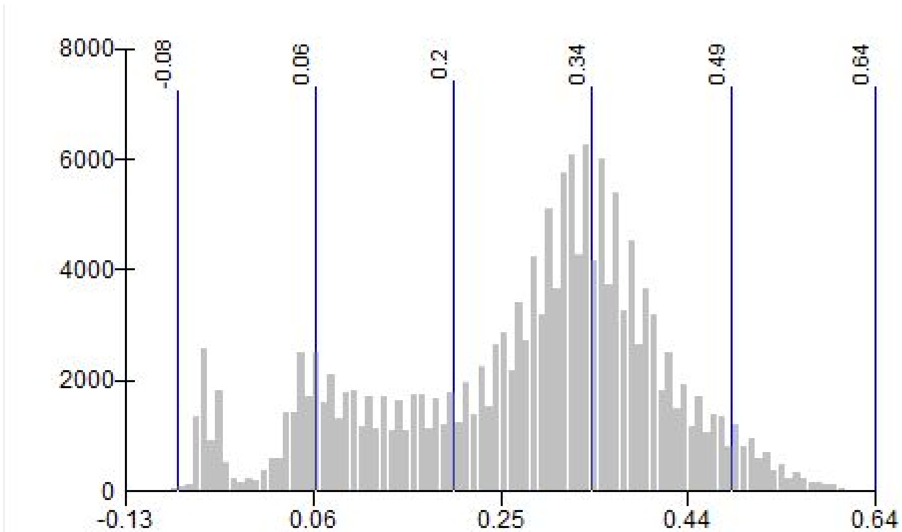

Figure 27. Distribution of NDVI in Minneapolis (by 15-meter grid cell)

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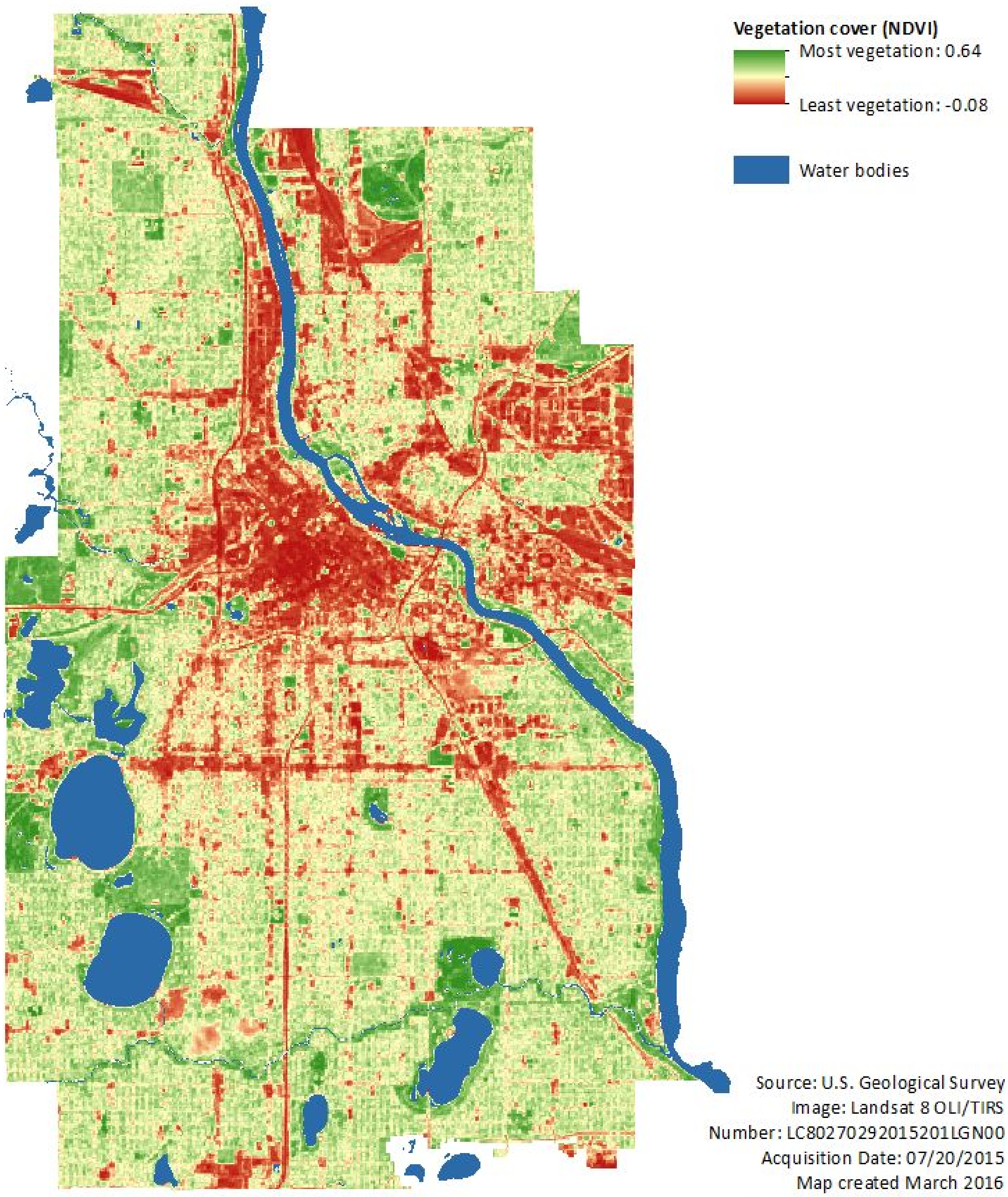
Vegetation cover

Normalized Difference Vegetation Index (NDVI)



Source: U.S. Geological Survey
Image: Landsat 8 OLI/TIRS
Number: LC80270292015201LGN00
Acquisition Date: 07/20/2015
Map created March 2016
NDVI scores range from -1 to 1.

Figure 28. Vegetation cover
Normalized difference vegetation index (NDVI)

3.3.2.1. Creation of visuals for PowerPoint

Landsat8_072015_NDVI was then clipped to the seven-county metropolitan area. This image was for purely visual purposes, for display in the final PowerPoint presentation.

Extract by Mask specifications (seven-county metropolitan area):

- Input raster: Landsat8_072015_NDVI
- Input raster or feature mask data: Counties_MetroArea
- Output raster: **Landsat8_072015_NDVI_SevenCounties**

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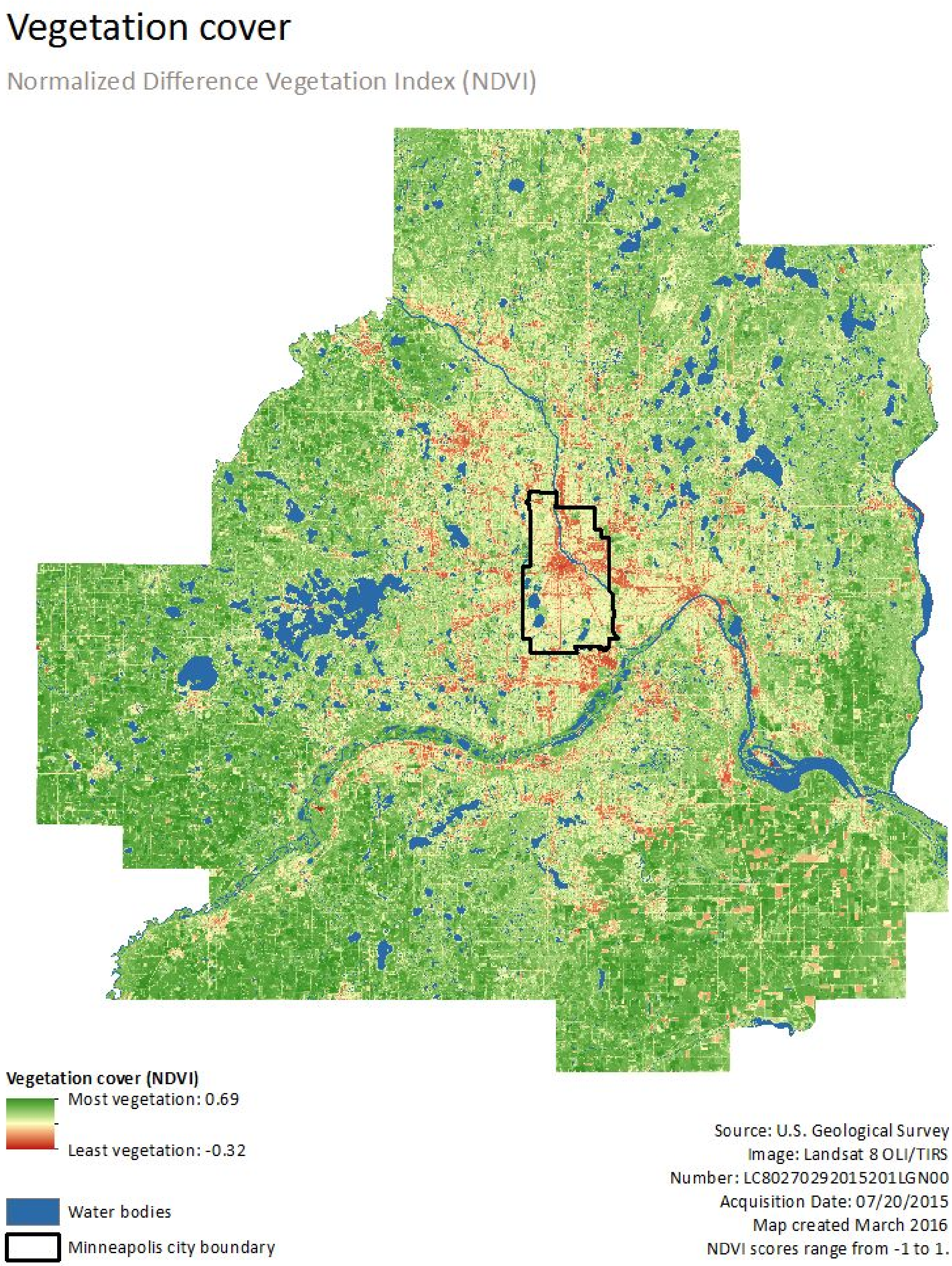

Figure 29. Vegetation cover

Normalized difference vegetation index (NDVI); Minneapolis-St. Paul metropolitan area

3.3.3. Map creation: Aggregating NDVI by Census tract

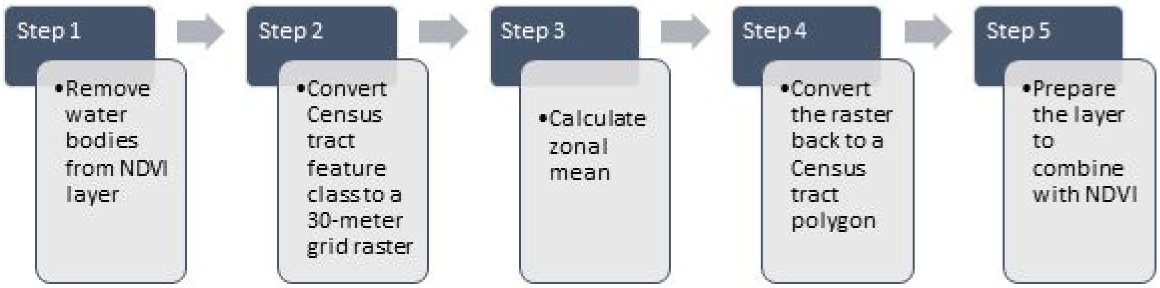

Figure 30. Process diagram for aggregating NDVI by census tract

For our analysis, our group wanted to be able to rank Census tracts by overall NDVI. To accomplish this, the Zonal Statistics tool was used to calculate the mean NDVI value (by pixel) across each Census tract.

3.3.3.1. Preliminary step 1: Remove water bodies from NDVI layer

In the NDVI, water bodies show up as no vegetation, which in our analysis would liken them to parking lots. There is evidence that water bodies mitigate the urban heat island effect, so to control for this factor, water bodies were removed from the NDVI layer prior to calculating zonal statistics.

To accomplish this, the layer of Minneapolis water bodies (Water) was erased from the Minneapolis city boundaries (MplsCityBoundary) using the Erase tool.

Erase specifications:

- Input features: MplsCityBoundary
- Erase features: Water
- Output feature class: **MplsCityBoundary_WaterErase**

Then the water bodies were removed from the NDVI layer using the Extract by Mask tool, by using MplsCityBoundary_WaterErase as a mask.

Extract by Mask specifications:

- Input raster: Landsat8_072015_Mpls_NDVI
- Input raster or feature mask data: MplsCityBoundary_WaterErase
- Output raster: **L8Jul15MplsNDVI_WaterErase**

3.3.3.2. Preliminary step 2: Convert Census tract feature class to a 30-meter grid raster

In order to calculate Zonal Statistics, the Census tract feature class (MplsTracts2010, a vector polygon file) had to first be converted to a 30-meter grid raster using the Polygon to Raster tool, to create the new raster MTrcts2010_30m.

Polygon to Raster specifications:

- Input Features: **Mpls_Tracts_2010**
- Value field: GEOID10
- Output Raster Dataset: **MTrcts2010_30m**
- Cellsize: 30

Note: It's important to check and make sure all of the tracts came through.

3.3.3.3. Calculate zonal mean

Once the two preliminary steps were completed, then Zonal Statistics could be finally be run to calculate the mean NDVI by Census tract.

Zonal Statistics specifications:

- Input raster or feature zone data: MTrcts2010_30m
- Zone field: GEOID10
- Input value raster: L8Jul15MplsNDVI_WaterErase
- Output raster: **L8NDVI_ZMean**
- Statistics type: mean

3.3.3.4. Convert the raster back to a Census tract polygon

We then wanted to convert our layer from a raster back to a Census tract polygon. There are two steps in this process. First, L8NDVI_ZMean had to be converted from a floating point raster (one with infinite decimal points) to an integer raster. The Raster Calculator tool was used to accomplish this.

Raster Calculator specifications:

- Formula: Int("L8NDVI_ZMean" * 1000000)
    - Note: L8NDVI_ZMean was multiplied by 1000000 to preserve the decimal points.
- Output raster: **L8NDVI_ZM_int**

Note: Using the "Int" function in the Raster Calculator truncates any decimal points - it does not round. This slight degree of error is minimized by multiplying by a large number, as was done above.

The raster NDVI_ZM_int was then converted to a polygon using the Raster to Polygon tool.

Raster to Polygon specifications:
- Input raster: L8NDVI_ZM_int
- Field: VALUE
- Output polygon features: **L8NDVI_ZM_int_tract**
- Leave “Simplify polygons” checked

Converting a raster to a polygon often incidentally creates tiny extra unwanted polygons. In our case, five extra polygons were created. The Eliminate tool was used to absorb these smaller polygons into larger nearby ones. Before running the Eliminate tool, the five tiny polygons were selected in the attribute table.

Eliminate specifications:
- Input layer: L8NDVI_ZM_int_tract
- Output feature class: **L8NDVI_ZM_int_tract_elim**

Finally, because L8NDVI_ZMean was multiplied by 1000000 to create L8NDVI_ZM_int, the values must be converted back to their original state. To do this, a new field was created in L8NDVI_ZM_int_tract_elim. The new field (double) is called NDVI_Mean. To convert the values, Field Calculator was used. Equation: NDVI_Mean = [gridcode] /1000000 .

3.3.3.5. Prepare the layer to combine with impervious land cover

First, the mean and standard deviation for the entire NDVI_Mean field were gathered. The mean was found to be 0.282006 and the median was found to be 0.063208.

Second, a new field (Double) was created called Z_Score was created. Using the Field Calculator, the following equation was entered: (([NDVI_Mean]-0.282006)/(0.063208)).

Third, a new field (Text, 50 characters) called STD_DEV was created. Using the Select by Attributes and Field Calculator functions, the following values were coded:

Select by Attributes	**Field Calculator**
Z_Score <-2	">2 SD below mean"
Z_Score >= -2 AND Z_Score <-1	"1-2 SD below mean"
Z_Score >= -1 AND Z_Score <0	"<1 SD below mean"
Z_Score >= 0 AND Z_Score <1	"<1 SD above mean"
Z_Score >= 1 AND Z_Score <2	"1-2 SD above mean"
Z_Score >= 2	">2 SD above mean"

Fourth, a new field (Short integer) called “RasterValue” was created. Using the Select by Attributes and Field Calculator functions, the following values were coded:

Select by Attributes	Field Calculator
STD_DEV = ">2 SD below mean"	6
STD_DEV = "1-2 SD below mean"	5
STD_DEV = "<1 SD below mean"	4
STD_DEV = "<1 SD above mean"	3
STD_DEV = "1-2 SD above mean"	2

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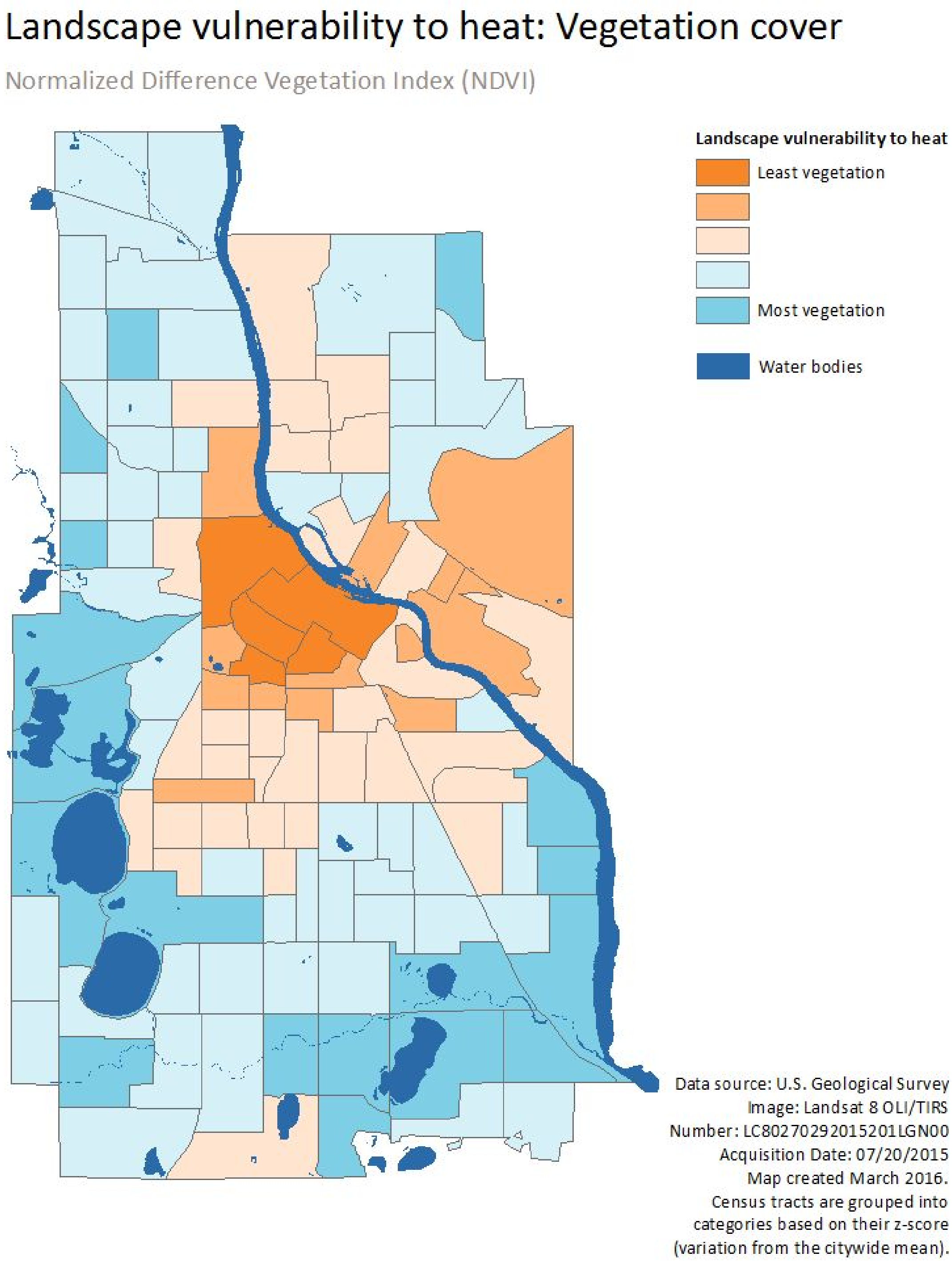

Figure 31. Landscape vulnerability to heat: Vegetation cover
Normalized difference vegetation index (NDVI) grouped at census tract level

3.4. Combining NDVI and Impervious Surface

3.4.1. Map creation: 30-meter raster

NDVI values are on a scale from -1 to 1. We added 1 to the NDVI layer L8Jul15MplsNDVI_WaterErase using the Raster Calculator tool in order to convert all of the values to positive numbers.

Raster Calculator specifications:
- Equation: “L8Jul15MplsNDVI_WaterErase”+1
- Output raster: **L8Jul15MplsNDVI_WE_Pos**

For the NDVI variable, higher values represent “good” and lower values represent “bad”. For the impervious surface variable, higher values represent “bad” and lower values represent “good.” To reconcile these oppositely oriented scales, we subtracted L8Jul15MplsNDVI_WE_Pos from 2 using the Raster Calculator tool.

Raster Calculator specifications:
- Equation: 2-"L8Jul15MplsNDVI_WE_Pos"
- Output raster: **L8Jul15MplsNDVI_WE_PosFlip**

The NDVI and impervious surface layers are expressed in very different scales. It was essential to normalize both measures before attempting to combine them together. This was accomplished by calculating the *z score* for each raster grid using the Raster Calculator tool. Z scores express the values in a dataset along a standardized scale that relates to the standard deviation of value range; in any z score calculation, one standard deviation is equal to 1. The equation for calculating z score values is as follows:

$$\text{Z score} = (X - \mu)/\sigma\,,$$

where X is the given value for that Census tract, μ is the mean citywide value, and σ is the standard deviation for the range of values.

The mean and standard deviation statistics for the L8Jul15MplsNDVI_WE_PosFlip and MNLC13_ExClipRecAgg raster layers was found by selecting “Properties” and selecting the Source tab.

	Mean (μ)	Standard Deviation (σ)
L8Jul15MplsNDVI_WE_PosFlip	0.7091103573739974	0.1245811026573535
MNLC13_ExClipRecAgg	44.97458687704984	22.65983991808896

Using the Raster Calculator tool, both raster layers were transformed into their z score values.

Raster Calculator specifications for the L8Jul15MplsNDVI_WE_PosFlip layer:

- Equation: (“L8Jul15MplsNDVI_WE_PosFlip”-0.709110357373997)/0.1245811026573535
- Output raster: **NDVI_posflip_zscore**

Raster Calculator specifications for the MNLC13_ExClipRecAgg layer:

- Equation: (“MNLC13_ExClipRecAgg”- 44.97458687704984)/22.65983991808896
- Output raster: **MNLC13_Impervious_Zscore**

Finally, to combine the NDVI and Impervious Surface variables, the two resulting layers were added together using the Raster Calculator tool.

Raster Calculator specifications:

- Equation: NDVI_posflip_zscore + MNLC13_Impervious_Zscore
- Output raster: **Combined_NDVI_Impervious_zscores**

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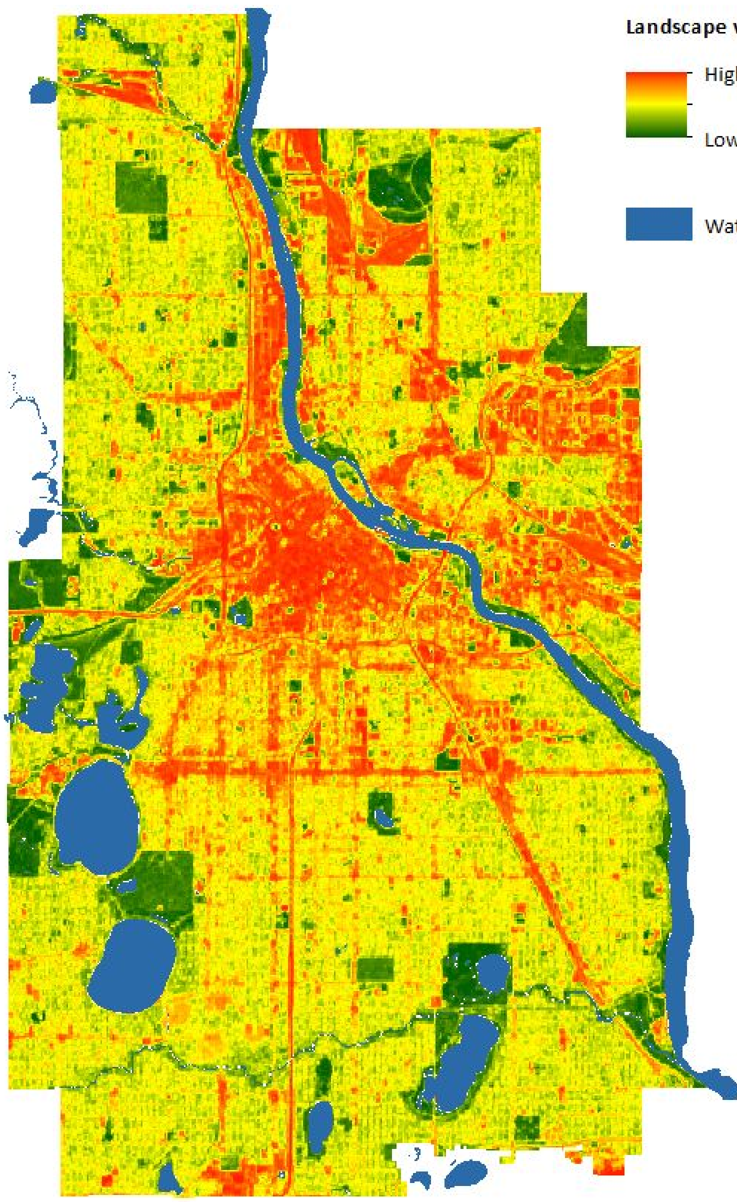
Landscape vulnerability to heat: Impervious cover + vegetation

Combined effect of land cover and vegetation



Landscape vulnerability to heat

Highest landscape vulnerability to heat

Lowest landscape vulnerability to heat

Water bodies

Data sources: University of Minnesota Remote Sensing Lab, U.S. Geological Survey
Map created March 2016.
Census tracts are grouped into categories based on their z-score (variation from the citywide mean).

Figure 32. Landscape vulnerability to heat: Impervious cover + vegetation
Combined effect of land cover and vegetation

3.4.2. Map creation: Aggregating to Census tracts

In order to combine the NDVI and impervious surface variables by Census tract, the combined NDVI and Impervious land cover 30-m raster layer (Combined_NDVI_Impervious_zscores) was averaged by Census tract using the Zonal Statistics method.

Zonal Statistics specifications:

- Input raster or feature zone data: MTrcts2010_30m
- Zone field: GEOID10
- Input value raster: Combined_NDVI_Impervious_zscores
- Output raster: **LCNDVI_zCombine_zonaltracts**
- Statistics type: mean

We then wanted to convert our layer from a raster back to a Census tract polygon. First, LCNDVI_zCombine_zonaltracts had to be converted from a floating point raster (one with infinite decimal points) to an integer raster. The Raster Calculator tool was used to accomplish this.

Raster Calculator specifications:

- Formula: Int("LCNDVI_zCombine_zonaltracts" * 100000)
- Output raster: **LCNDVI_int_z**

Note: Using the "Int" function in the Raster Calculator truncates any decimal points - it does not round. This slight degree of error is minimized by multiplying by a large number, as was done above.

The raster LCNDVI_int_z was then converted to a polygon using the Raster to Polygon tool.

Raster to Polygon specifications:

- Input raster: LCNDVI_int_z
- Field: VALUE
- Output polygon features: **LCNDVI_int_z_tract**
- Leave "Simplify polygons" checked

Converting a raster to a polygon often incidentally creates tiny extra unwanted polygons. In our case, five extra polygons were created. The Eliminate tool was used to absorb these smaller polygons into larger nearby ones. Before running the Eliminate tool, the five tiny polygons were selected in the attribute table.

Eliminate specifications:

- Input layer: LCNDVI_int_z_tract
- Output feature class: **LCNDVI_int_z_tract_elim**

Finally, because LCNDVI_zCombine_zonaltracts was multiplied by 100000 to create LCNDVI_int_z, the values must be converted back to their original state. To do this, a new field was created in LCNDVI_int_z_tract_elim. The new field (double) is called LCNDVI_Mean. To convert the values, Field Calculator was used. Equation: NDVI_Mean = [gridcode] /100000 .

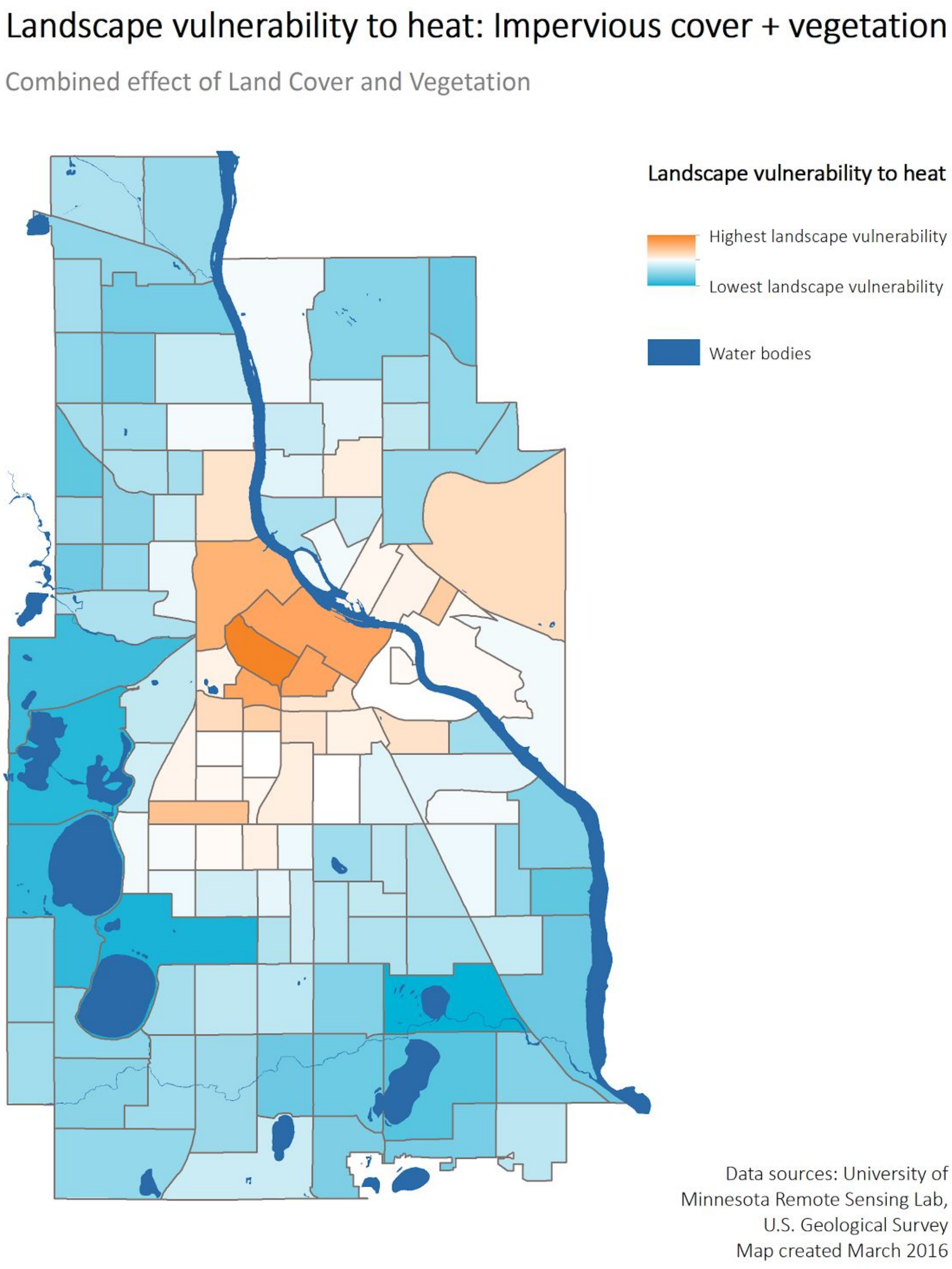


Figure 33. Landscape vulnerability to heat: Impervious cover + vegetation
Combined effect of land cover and vegetation grouped at census tract level

4. Health outcomes data

Increasing frequency and intensity of heat events will have health consequences for people in Minneapolis. Extended hot weather can exacerbate existing health conditions and increase risk of illness or death. From the Human Health segment of the National Climate Assessment:

Extreme heat events have long threatened public health in the United States. Many cities, including St. Louis, Philadelphia, Chicago, and Cincinnati, have suffered dramatic increases in death rates during heat waves. Deaths result from heat stroke and related conditions, but also from cardiovascular disease, respiratory disease, and cerebrovascular disease.[13]

One way to begin to understand health vulnerability in the face of climate change is to look at existing spatial patterns of hospital admissions for heat-related illness, heart attacks and asthma in Minneapolis. This section presents three maps to this effect. These three health maps were not included in the cumulative vulnerability assessment because they represent vulnerability outcomes rather than the conditions that contribute to vulnerability. These measures are also not compatible with other social variables in the assessment because the data is not sufficiently granular to captures detailed patterns at the sub-city level. Nevertheless, the link between forecasted increases in heat events and human health consequences is a critical concern for the City, and should be addressed through reductions in landscape vulnerability to heat as well as efforts to reduce social vulnerability to climate change as discussed in Section 5 of this report.

4.1. Heat-related emergency department visits

4.1.1. Data details

Measure: Age-adjusted rate of heat-related emergency department visits per 100,000 people
Source: Minnesota Department of Health. URL: https://apps.health.state.mn.us/mndata/heat_ed
Date: 2009-2013 annual average
Level of granularity: Zip code

The rate of emergency department visits directly attributed to heat-related illness is a measure of vulnerability to heat. The data represents the Zip codes where people live who visit the emergency department for heat-related reasons.

[13] Luber, G., K. Knowlton, J. Balbus, H. Frumkin, M. Hayden, J. Hess, M. McGeehin, N. Sheats, L. Backer, C. B. Beard, K., L. Ebi, E. Maibach, R. S. Ostfeld, C. Wiedinmyer, E. Zielinski-Gutiérrez, and L. Ziska, 2014: Ch. 9: Human Health. *Climate Change Impacts in the United States: The Third National Climate Assessment*, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 220-256. doi:10.7930/J0PN93H5.

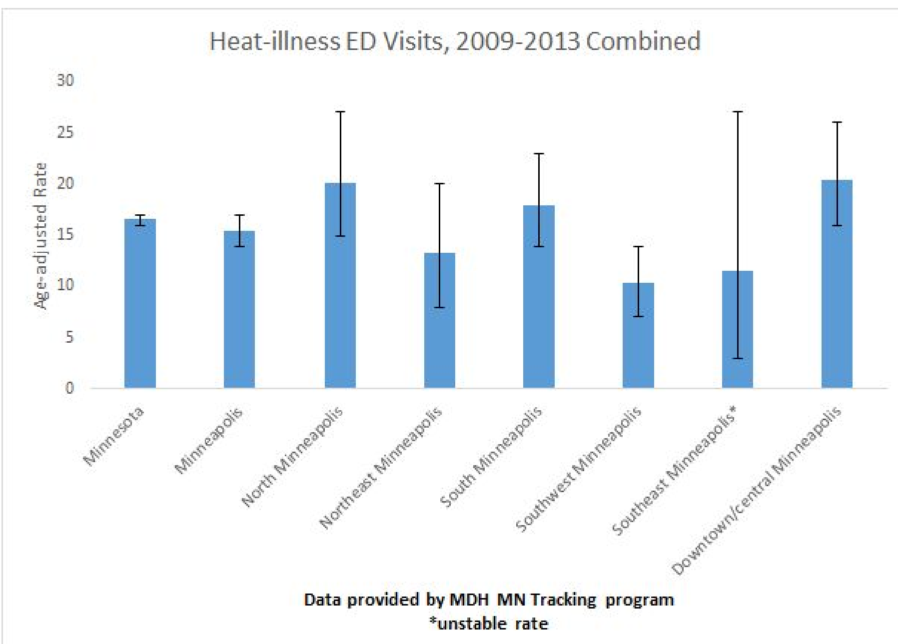
4.1.2. Map creation

Heat-related emergency department visit data was received directly from the Minnesota Health Department Minnesota Tracking Program by zip code for 2009-2013. The spreadsheet we received included the age-adjusted rate of visits per 100,000 people, 95-percent confidence intervals, whether the rate differed significantly from the Minnesota rate, whether the rate was unstable, the count of heat-related emergency department visits, and the five-year average annual population. Heat-related emergency department visit data is available to the public at https://apps.health.state.mn.us/mndata/heat_ed. Additional information is available at https://apps.health.state.mn.us/mndata/heat_metadata.

In the spreadsheet, the Minnesota Health Department aggregated Minneapolis zip codes into the following regions based on data by the City of Minneapolis:

- North Minneapolis: 55411, 55412
- Northeast Minneapolis: 55413, 55418
- South Minneapolis: 55406, 55407, 55417, 55450
- Southwest Minneapolis: 55408, 55409, 55419, 55410
- Southeast Minneapolis:[14] 55414, 55455
- Downtown/central Minneapolis: 55401, 55402, 55403, 55404, 55405, 55415, 55454

The following bar graph provided by MDH indicates the margins of error associated with the estimates:



[14] The Southeast Minneapolis estimate is considered unstable because the numerator is less than 20 counts.

Figure 34. Margins of error associated with estimates

Additional Data Notes from the spreadsheet include the following:

- Heat-related Illness Emergency Department Visits are identified as any primary or secondary diagnoses that include the ICD-9-CM codes: 992.0-992.9, E900.0, and E900.9. ED visits include both patients treated and released from the ED as well as those that enter the ED and are admitted to the hospital.
- Data Sources: Minnesota hospitals report data on inpatient admissions/ED visits on a voluntary basis to the Minnesota Hospital Association (MHA). In 2010, 99.3% of all hospitals in the state reported hospital discharge data to the MHA, representing 99.4% of all licensed beds in the state. Denominator data came from US Census on Factfinder site.
- Exclusions: Data does not include data from federal and sovereign hospitals (e.g., Veteran's Administration and Indian Health Service), thus rates for counties in which residents are likely to visit hospitals that do not submit data to the Minnesota Hospital Association (e.g., Veteran's Administration or Indian Health Services hospitals) may be artificially low. Minnesota residents discharged from Wisconsin hospitals are not included, so hospitalization and ED visit rates for counties in which residents are likely to receive care from Wisconsin may be underestimated.
- Inclusions: Minnesota residents who are discharged from a hospital in Minnesota. After 2005, it also includes Minnesotans discharged from the bordering states of North Dakota, South Dakota, or Iowa.
- Data in the reports represent the number of heat-related ED visits (events) and not the number of individual people. Multiple ED visits by the same patient cannot be identified, and are not excluded.

The spreadsheet was joined to a shapefile of Minneapolis zip codes using the Join tool (**MDH_HeatRelatedIllness_AllZips_New**). The zip codes were then dissolved on the following fields using the Dissolve tool: GeographicArea, AgeAdjRate, ConfInt95, LowerCI, UpperCI, LowerCIbar, UpperCIbar, SigDiffMN, Unstable, CntHRI_EDvisits, AvgAnnPop5yr, Years (**MDH_HeatRelatedIllness_AllZips_Diss_New**). This shapefile was then clipped to the Minneapolis city boundaries for the final map (**MDH_HeatRelatedIllness_AllZips_Diss_New_Clip**).

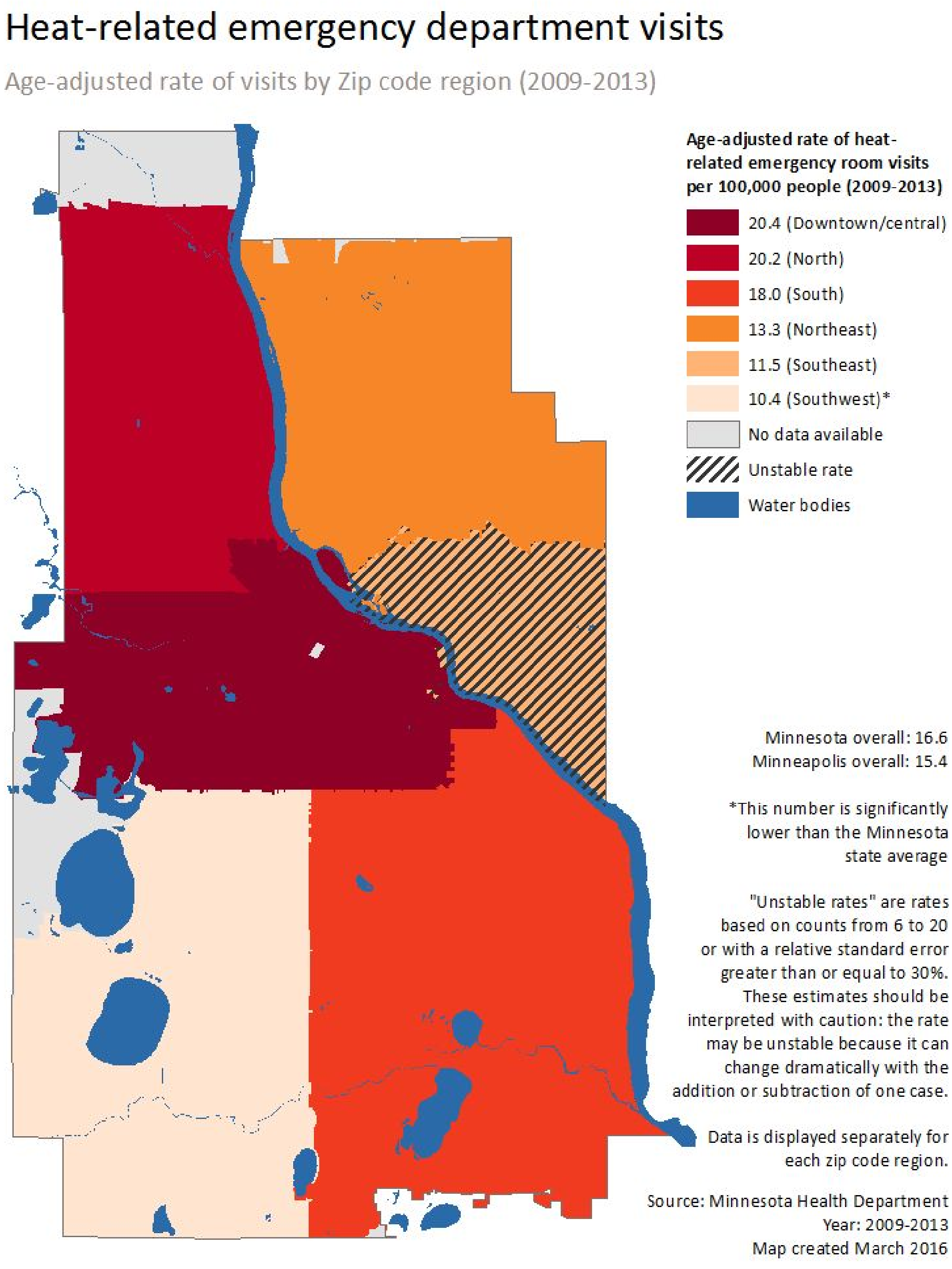


Figure 35. Health-related emergency department visits
Age-adjusted rate of visits by Zip code region (2009-2013)

4.2. Asthma emergency department visits

4.2.1. Data details

Measure: Age-adjusted rate of asthma emergency department visits per 10,000 people
Source: Minnesota Department of Health. URL:
https://apps.health.state.mn.us/mndata/asthma_staticmaps
Date: 2009-2013 annual average
Level of granularity: Zip code

Asthma is an underlying condition that can make people more susceptible to extreme heat events.[15][16] The rate of emergency department visits directly attributed to asthma is a measure of vulnerability to extreme heat events such as those expected to occur more frequently due to climate change. The data represents the Zip codes where people live who visit the emergency department for asthma reasons.

4.2.2. Map creation

Asthma emergency department visit data was downloaded from the Minnesota Health Department website by zip code for 2009-2013. The downloaded spreadsheet included the age-adjusted rate of visits per 10,000 people for residents of all ages (overall), for residents between 0-17 years of age, and for residents age 18 or older. Some data is marked as unstable, which means the rates are based on counts from 6 to 20 or with a relative standard error greater than or equal to 30%. Unstable rates should be interpreted with caution: the rate may be unstable because it can change dramatically with the addition or subtraction of one case. Some data is not shown, because rates are not calculated when the number of counts is less than or equal to 5, or when the population estimates for that area were not available. Additional information is available at https://apps.health.state.mn.us/mndata/asthma_metadata.

To create the map, the downloaded spreadsheet (AsthmaEDVisits) was saved as a new file (AsthmaEDVisits_GIS). The fields “0-17” and “18+” were removed. A new field called “AllAgesNotes” was created to mark data in “All_ages” classified as either unstable (U) or not shown (NA).

The spreadsheet AsthmaEDVisits_GIS was then joined to a shapefile of Minneapolis zip codes using the Join tool (**MDH_AsthmaED_ZipCode_0913**).

[15] Lin, Shao; Luo, Ming; Walker, Randi J.; Liu, Xiu; Hwang, Syni-An; Chinery, Robert. “Extreme High Temperatures and Hospital Admissions for Respiratory and Cardiovascular Diseases”. *Epidemiology* 2013; 20, 5: 738-746.
[16] Zhiwei Xu, Cunrui Huang, Wenbiao Hu, Lyle R Turner, Hong Su, Shilu Tong. “Extreme temperatures and emergency department admissions for childhood asthma in Brisbane, Australia.” *Occup Environ Med* 2013;70:730-735

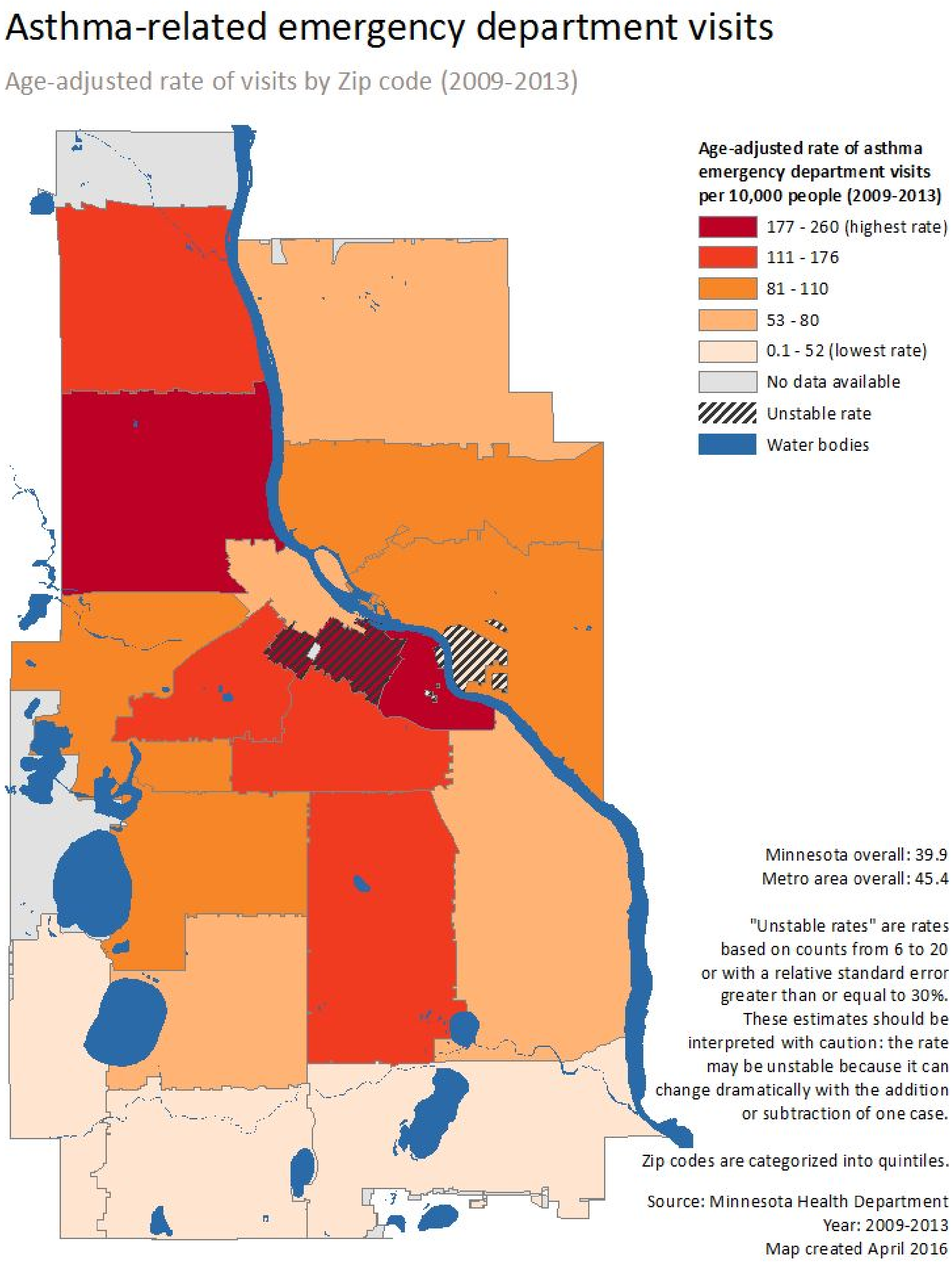


Figure 36. Asthma-related emergency department visits
Age-adjusted rate of visits by Zip code (2009-2013)

4.3. Heart attack hospitalizations

4.3.1. Data details

Measure: Age-adjusted rate of heart attack hospitalizations per 10,000 people (adults 35 years and older)
Source: Minnesota Hospital Association (hospitalizations), American Community Survey (average annual population), via the Minnesota Department of Health. URL:
https://apps.health.state.mn.us/mndata/asthma_staticmaps
Date: 2009-2013 annual average
Level of granularity: Zip code

The rate of hospitalizations directly attributed to heart attacks is a measure of vulnerability to ____. The data represents the Zip codes where people live who are hospitalized for heart attacks (acute myocardial infarctions).

4.3.2. Map creation

Heart attack hospitalization data was received directly from the Minnesota Health Department Minnesota Tracking Program by zip code for 2009-2013. The spreadsheet we received included the age-adjusted rate of visits per 10,000 people, 95-percent confidence intervals, the count of heart attack hospitalizations, the average annual zip code population (using American Community Survey data), whether the rate was unstable, and whether the rate was suppressed. Additional information is available at https://apps.health.state.mn.us/mndata/heart_metadata.

Data marked as unstable means the rates are based on counts from 6 to 20 or with a relative standard error greater than or equal to 30%. Unstable rates should be interpreted with caution: the rate may be unstable because it can change dramatically with the addition or subtraction of one case. Some data is not shown, because rates are not calculated when the number of counts is less than or equal to 5, or when the population estimates for that area were not available. To protect privacy, hospitalization counts between 1 and 5 are suppressed if the underlying population is less than 100,000 people.

To create the map, the original spreadsheet (Minneapolis_HIA) was saved as a new file (Minneapolis_HIA_GIS). All data from the tab AMIZIPCode2009-2013 was copied to a new tab called AMI_GISready. In this new tab, the field name "Count" was changed to the field name "HeartAttackCount", and rows 1, 3, and 4 (the title, the Minnesota-wide data, and the 7-County Metro Area data) were deleted.

The tab AMI_GISready was then joined to a shapefile of Minneapolis zip codes using the Join tool. The joined data was exported to create a new shapefile (**MDH_HeartAttackHosp_ZipCode_0913**). Next, the "Suppressed" zip codes were exported to a new shapefile

(**MDH_HeartAttackHosp_ZipCode_0913_Suppressed**) and removed from MDH_HeartAttackHosp_ZipCode_0913.

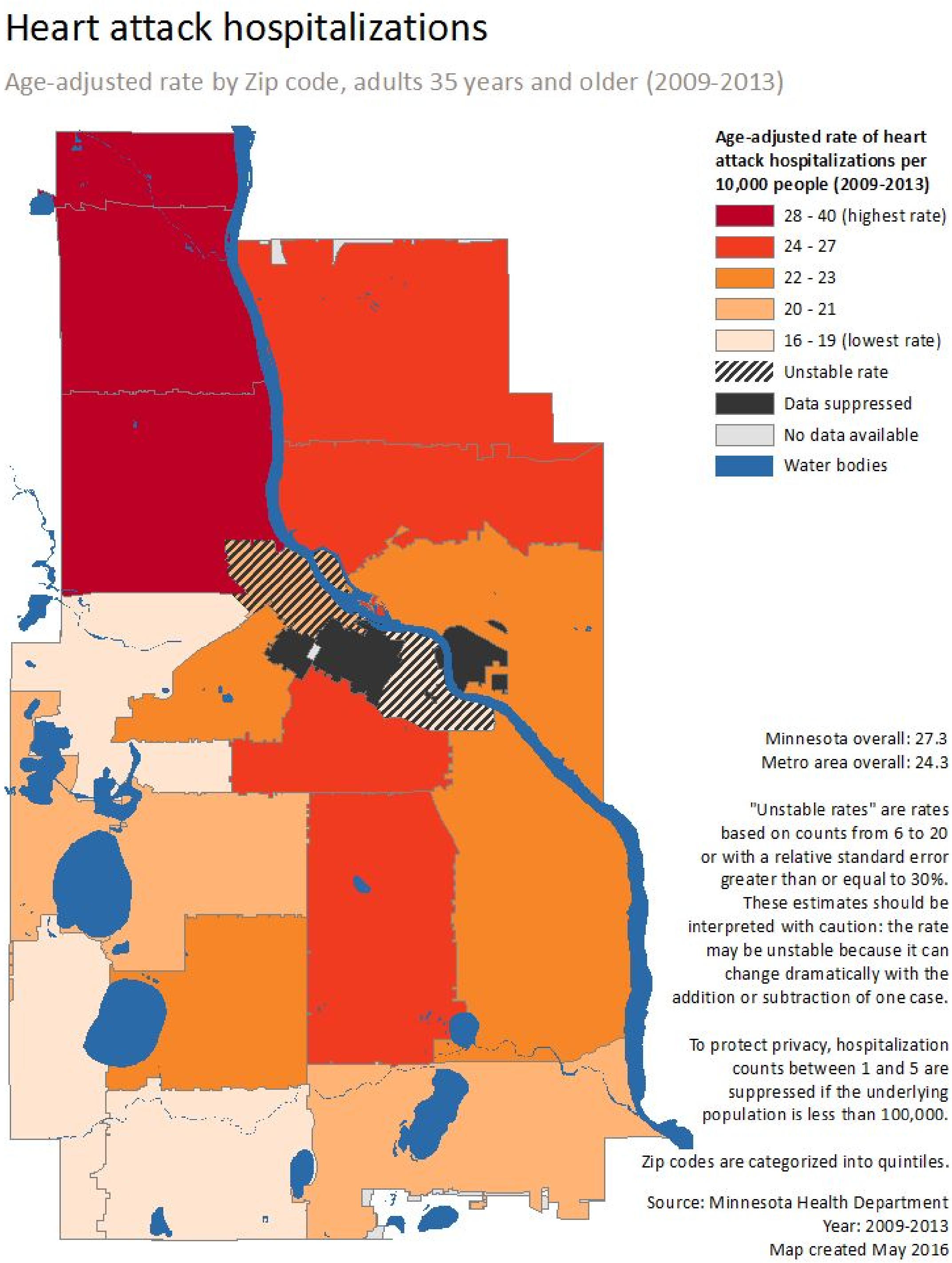


Figure 37. Heart attack hospitalizations
Age-adjusted rate by Zip code, adults 35 years and older (2009-2013)

5. Social vulnerability index: data source and rationale

5.1 Data sources

The following are the indicators selected to represent social vulnerability to climate change, with an explanation of the data source and the rationale behind the indicator selection.

5.1.1 Elderly population

Percent of population aged 65 years or older
Source: American Community Survey, Table DP05
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

Elderly populations tend to be characterized by more mobility constraints and greater biological susceptibility to extreme environmental conditions, which induce vulnerability the context of both extreme heat and flooding conditions[17]. They are also more likely to lack the economic resources to be resilient to natural disaster impacts[18].

Limitations: Assuming all elderly individuals have the same vulnerability to natural hazards disregards the complexity and heterogeneity that exists among populations of older age. Ngo[19] observes this complexity and reminds us that "within the elderly population, the young old, aged, oldest old, and frail elderly demonstrate a broad diversity in health, level of function, and social standing."

5.1.2 Young children

Percent of population aged 5 years or younger
Source: American Community Survey, Table DP05
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

At the younger extreme of the age spectrum, greater vulnerability exists because of the limitations on "movement out of harm's way"[20]. The vulnerability of young children stems from their dependence on

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[17] Cutter et. al. "Social Vulnerability to Environmental Hazards." *Social Science Quarterly*, Volume 84, Number 2, June 2003.
[18] Morrow, Betty Hearn. **Identifying and Mapping Community Vulnerability.** Disasters, 1999, Vol.23(1), pp.1-18
[19] Ngo, E. (2001). "When Disasters and Age Collide: Reviewing Vulnerability of the Elderly." *Nat. Hazards Rev.*, 10.1061/(ASCE)1527-6988(2001)2:2(80), 80-89.
[20] Cutter et. al. "Social Vulnerability to Environmental Hazards." *Social Science Quarterly*, Volume 84, Number 2, June 2003.

others for their wellbeing and livelihood[21], as well as their limited physical and mental ability to respond effectively to emergency situations. Very young children represent these vulnerabilities to a greater degree than older children, and are especially vulnerable to extreme heat[22]. Also, like older adults, young children have greater biological susceptibility to extreme environmental conditions, specifically extreme heat because they are not as efficient at regulating their body temperature.

Limitations: The vulnerability of very young children is not only dependent upon biological factors related to age, but is also situational in nature and dependent upon a child's environment and family support[23]. This assessment assumes that young children are themselves vulnerable, but Morrow and Cutter et. al also highlight that children can be a causal factor of vulnerability in households with limited resources, such as single-parent households, wherein the financial strain of raising a child in already compromised circumstances can impact resilience to a disaster.

5.1.3 Poverty

Percent of population living at or below the Federal poverty level
Source: American Community Survey, Table S1701
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

Living in poverty might be characterized by having fewer resources at one's disposal, in general and in times of crisis. Cutter et. al describe the effect of socioeconomic status as "the ability to absorb losses and enhance resilience to hazard impacts". Poverty as an indicator represents a lack of the inherent resilience that comes with wealth and socioeconomic status. Poverty has been associated with overall higher rates of poor quality housing, more limited ability to respond to emergency warnings or make preparations in advance of impending hazards, greater dependence on social assistance, and greater difficulties in recovering livelihoods following a natural hazard event[24]. These and other associated factors combine to create the link between poverty and vulnerability.

Limitations: While the poverty - vulnerability link is strong and may seem self-evident, Cannon warns that the two should not be seen as synonymous and that implying causality between poverty and vulnerability discounts the capacities that exist to create a greater resilience to natural hazards despite poverty.[25]

5.1.4 Limited English

Percent of population (5 years or older) who speak English "less than well"

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[21] Cannon, Terry (2008) : Reducing people's vulnerability to natural hazards communities and resilience, Research paper / UNU-WIDER, No. 2008.34, ISBN 978-92-9230-080-7
[22] McGeehin, M., & Mirabelli, M. (2001). The potential impacts of climate variability and change on temperature-related morbidity and mortality in the United States. Environmental Health Perspectives, 109, 185–189
[23] Morrow, Betty Hearn. "Identifying and mapping community vulnerability."*Disasters* 23.1 (1999): 1-18.
[24] Morrow, Betty Hearn. "Identifying and mapping community vulnerability."*Disasters* 23.1 (1999): 1-18.
[25] Cannon, Terry (2008) : Reducing people's vulnerability to natural hazards communities and resilience, Research paper / UNU-WIDER, No. 2008.34, ISBN 978-92-9230-080-7

Source: American Community Survey, Table S1601
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

Persons who lack fluency in the dominant language will struggle to find adequate information or respond appropriately when important information is disseminated in the dominant language. Phillips and Morrow[26] cite an example of a warning broadcast about an impending tornado in Texas which was broadcast on the English-language television station, but could not be broadcast on the Spanish-language channel, resulting in significant loss of life. When it comes to responding to extreme weather conditions such as those predicted by climate change forecasts, systematic language-related barriers stack the deck against those with limited English proficiency.

Limitations: The ACS classification of those who speak English "less than very well" is overly general, and may not fully capture the range of limited English capacity that contributes to risk in the face of climate change. Furthermore, the ACS, based on sampling, is of questionable value when it comes to accurately capturing the population with limited capacities to participate in a verbal or written survey because of language limitations.

5.1.5 People of color

Percent of the population not identifying as White, Not Hispanic
Source: American Community Survey, Table DP05
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

Race is recognized as a vulnerability variable because many studies corroborate that persons of color fare significantly worse in the face of natural hazards. This outcome may be due to patterns of historic discrimination leading to differences in socioeconomic status and geographic location, significantly divergent health risks and outcomes (especially related to chronic disease), or differing cultural norms and expectations (Mays et al., 2007[27]; Cutter et. al 2003; Phillips and Morrow 2007). Race becomes a significant factor for vulnerability " through the lack of access to resources, cultural differences, and the social, economic, and political marginalization that is often associated with racial disparities" (Cutter et. al 2003).

Limitations: In many ways, it is uncomfortable to ascribe vulnerability causality to race. A discerning view would see race as the canvas upon which socioeconomic and health disparities have played out throughout history, creating differences in access, mobility and life chances that express themselves through greater levels of vulnerability. Defining race in this assessment as *all* persons of color, or those who are persons of color by virtue of the fact that they do not identify as "White, Not Hispanic,"

[26] Phillips, Brenda D., and Betty Hearn Morrow. "Social science research needs: Focus on vulnerable populations, forecasting, and warnings." *Natural Hazards Review* 8.3 (2007): 61-68.
[27] Mays VM, Cochran SD, Barnes NW. Race, race-based discrimination, and health outcomes among African Americans. Annu. Rev. Psychol., 2007

creates a treatment of race that fails to honor significant differences, cultural and demographic, that exist between different non-white communities. Nonetheless, this assessment takes the view that it is important to recognize the reality that vulnerability *does* play out in the arena of race, especially in light of the fact that the Twin Cities Metro Area is forecast to see significant growth in populations of color over the coming decades.[28]

5.1.6 Disability

Percent of civilian noninstitutionalized population who report a disability
Source: American Community Survey, Table S1810
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

The implications of having a disability are "[p]hysical and mental limitations" which can "affect disaster response" (Morrow). Vulnerability arises when disabled individuals cannot react to emergency situations with adequate expediency, or they depend heavily upon assistance from others to remove themselves from compromising situations.

Limitations: In this study, no attempt was made to distinguish between types of disabilities, or determine the impact of the reported disability on an individual's response to hazards.

5.1.7 Vehicle access

Percent of households with no vehicle
Source: American Community Survey, Table B08201
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

The implications of vehicle access is the capacity to remove one's self swiftly from a dangerous situation. Households with no vehicle have more limited mobility in a time of crisis, and are thus more vulnerable to extreme weather threats associated with climate change.

Limitations: Access to a vehicle represents an indirect factor of vulnerability, and not an inherent characteristic. Vehicle access or ownership is a more fluid characteristic than age, disability or other intrinsic variables.

5.1.8 Renters

Percent of households who are renters
Source: American Community Survey, Table B25003
Date: 2010-14 5-year Estimates
Level of granularity: Census tract

[28] Twin Cities Metropolitan Council's *Thrive2040* plan

Renters have less agency over their housing conditions and location than homeowners, and as such are more vulnerability to natural hazards. Renting can be an indication of limited resources, and Cutter intimates that households rent “because they are either transient or do not have the financial resources for home ownership” (2003).

Limitations: Renters’ vulnerability can often come *after* the impact of a natural disaster or major weather event, where renters tend to have fewer resources to put toward recovery and fewer financial options made available to them. Rentership represents an indirect factor of vulnerability, and not an inherent characteristic.

5.1.9 Air conditioning

Average percent of residential parcel units with central air conditioning
Source: Minneapolis City Assessor’s Office
Date: Spring 2016
Level of granularity: Parcel level (later summarized to Census tract)

Lack of central air conditioning is an indicator of household inability to cool living spaces. During periods of high temperatures, residents without central air conditioning may be less able to access cooler temperatures, resulting in a greater degree of vulnerability. The ability to cool down can reduce risk of heat-related illness in the case of extreme or prolonged heat[29].

The City of Minneapolis tracks units with central air conditioning by parcel, expressing this as a percentage of units within a parcel that have central air. While the City tracks this across all different types of land use, this analysis eliminated Commercial and Industrial parcels in favor of representing a social vulnerability characteristic within the home.

Limitations: This data does not include households with window air conditioning. This data also does not account for alternate ways of accessing cooler temperatures (such as staying at the home of a friend or relative with air conditioning).

5.2 Data preparation and map creation

All social vulnerability indicator maps were developed using a similar procedure. First, data tables were downloaded from their original sources and cleaned; then, data was joined to spatial boundaries; finally, Census tracts were scored based on their standard deviation from the citywide mean. This process is outlined here.

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[29] Center for Disease Control. “Extreme Heat Prevention Guide Part 1”. *Emergency Preparedness and Response.* <http://emergency.cdc.gov/disasters/extremeheat/heat_guide.asp.>, Last Updated September 22, 2015.

5.2.1 Data details

Eight of the nine population variables are derived from American Community Survey (ACS) 2010-14 5-Year Estimates data at the Census tract level. The following ACS tables were downloaded from American FactFinder to represent the selected variables:

Figure 38. Social vulnerability variables selected from American Community Survey (2010-2014)

Variable	ACS Table	Table Attribute Code	Attribute Used for Analysis
Poverty	S1701	HC03_EST_VC01	Percent below poverty level; Estimate; Population for whom poverty status is determined
People of Color	DP05	HC03_VC94	100 - (Percent; Total population Not Hispanic or Latino White alone)
Disability	S1810	HC03_EST_VC01	Percent with a disability; Estimate; Total civilian noninstitutionalized population
Limited English proficiency	S1601	HC03_EST_VC01	Percent of specified language speakers - Speak English less than "very well"; Estimate; Population 5 years and over
Older population	DP05	HC03_VC29	Percent; SEX AND AGE - 65 years and over
Young children	DP05	HC03_VC08	Percent; SEX AND AGE - Under 5 years
Renters	B25003	HD01_VD03	(Estimate; Total: - Renter occupied)/(Estimate; Total:)
No Vehicle access	B08201	HD01_VD03	(Estimate; Total: - No vehicle available)/(Estimate; Total:)

As the table indicates, data sources expressed as a number were recalculated to reflect a percentage value by Census tract.

Census tracts were selected as the spatial level of analysis because of their comparable size to Minneapolis neighborhoods and because ACS data is likely to have greater error associated with it at smaller geographies like Census block groups and blocks. Unlike U.S. Census data that reflects full population counts, ACS data is derived via sampling estimates and is necessarily associated with a margin of error.

At the Census tract level, margins of error can be more significant than at larger geographies. It is not uncommon for ACS data at the Census tract level to be used without much consideration given to the margin of error propensity. Our team did conduct an assessment of error significance and estimate reliability using the guidelines established by the Esri Data Team[30]. This assessment of ACS data reliability ultimately did not factor into the assessment process. Nonetheless, the procedure follows these steps:

1) Derive Standard Error (SE) from the margin of error statistic for each Census Tract by dividing the Margin of Error (MOE) by 1.645, which aligns with the 90 percent confidence interval used by the ACS.
2) Calculate the Coefficient of Variation (CV): $(SE \div Estimate\ Value)\ x\ 100$
3) Define reliability using the following scale:
    - CV $\leq$ 12 $\rightarrow$ Highly Reliable (color code = green)
    - CV $>$ 12 and < 40 $\rightarrow$ Medium Reliability (color code = yellow)
    - CV $\geq$ 40 $\rightarrow$ Low reliability (color code = red)

Full results of this analysis are included in the "Complete ACS Workbook", an Excel document appendix to this technical methodology document. Reliability results are color coded and labeled in each distinct variable worksheet.

5.2.2 Map creation: ACS data

Once cleaned, social vulnerability data tables were given a spatial association through an ArcMap table join, between ACS-derived data tables and Census tract spatial boundaries acquired from Census.gov via the TIGER/Line shapefile download portal [http://www.census.gov/geo/maps-data/data/tiger-line.html]. The join was based on the unique Census tract ID number provided by both datasets (field "GEOID10" in the spatial boundary shapefiles).

During the development of spatial datasets for the social vulnerability indicators, the key "measure" of each variable, or the percentage of the tract population associated with each indicator definition, was given a specific field name as outlined here:

Shapefile Name	**Measure description**	**Measure Field name**
Disability	*Pct that report having a disability*	PctDisab
YoungPop_Under5	*Pct of the population under 5 years of age*	PctUnder5
PeopleofColor	*Pct of the population not identifying as White, Not Hispanic*	PctNonWht

30 This resource explains the procedure: http://www.esri.com/~/media/Files/Pdfs/library/whitepapers/pdfs/the-american-community-survey.pdf#page=6

LimitedEnglish	*Pct of population (5 yrs or older) who speak English "less than well"*	PctEngLess
Elderpop_Over65	*Pct of population aged 65 years or older*	Pct65up
Poverty	*Pct of population living at or below the Federal poverty level*	PctBelow
NoVehicle	*Pct of households with no vehicle*	PctNoVeh
RenterPop	*Pct of households who are renters*	PctRenter
ACParcels_SpatialJoin	*Avg percentage of parcel (units) that contain central air conditioning*	Avg_AC_Valu e

Choropleth map displays of individual variable vulnerability were generated for each population indicator. Rather than displaying values based on percentage quantiles, which would have necessitated determining meaningful cutoff points for each indicator, the data display scheme was based on standard deviation from the citywide mean for each indicator. To develop a common display between all maps, Census tract values were converted first to *z-scores* via the following formula:

$$\text{Z score} = (X - \mu)/\sigma ,$$

where X is the given value for that Census tract, μ is the mean citywide value, and σ is the standard deviation for the range of values.

Z-scoring has the effect of transforming a standard deviation range into a standardized format where one standard deviation is equal to 1, two standard deviations is equal to 2, and so forth for any data range. Transforming a value into a z-score essentially converts the value into its relative standard deviation position in the dataset, such that if the value were one standard deviation below the mean its z-score value would be -1, for example.

So transformed, every social vulnerability variable dataset was displayed using an identical categorical expression based on the following data query and classification in ArcMap:

Attribute Table Query	**Classification**
Z_Score < -2	">2 SD below mean"
Z_Score >= -2 AND Z_Score <-1	"1-2 SD below mean"
Z_Score >= -1 AND Z_Score <0	"<1 SD below mean"

Z_Score >= 0 AND Z_Score <1	"<1 SD above mean"
Z_Score >= 1 AND Z_Score <2	"1-2 SD above mean"
Z_Score >= 2	">2 SD above mean"

The classification and color scheme based upon it for the population maps is thus removed from indicating the actual values, but instead refers to standard deviation classifications and hence shows a variable scale that is relative only to itself and in the context of Minneapolis. In order to aid the viewer in applying real context to each map, the range of actual values for each standard deviation range was provided in each map legend.

An orange-white-blue color gradient was selected that would divorce the population variable maps from conventional normative concepts of a "good to bad" scale often connoted by particular coloration like a green-to-red scale. On all maps, orange is associated with higher z-scores and hence connotes a location of higher vulnerability; blue is associated with lower scores and hence lesser vulnerability. Light or whiter colors represent "middle" values closest to the mean. Maps are displayed at a 1:85,000 scale in a standard 8 ½" x11" layout. Every population variable was mapped individually to provide a sense of the relative importance of each indicator, by Census tract.

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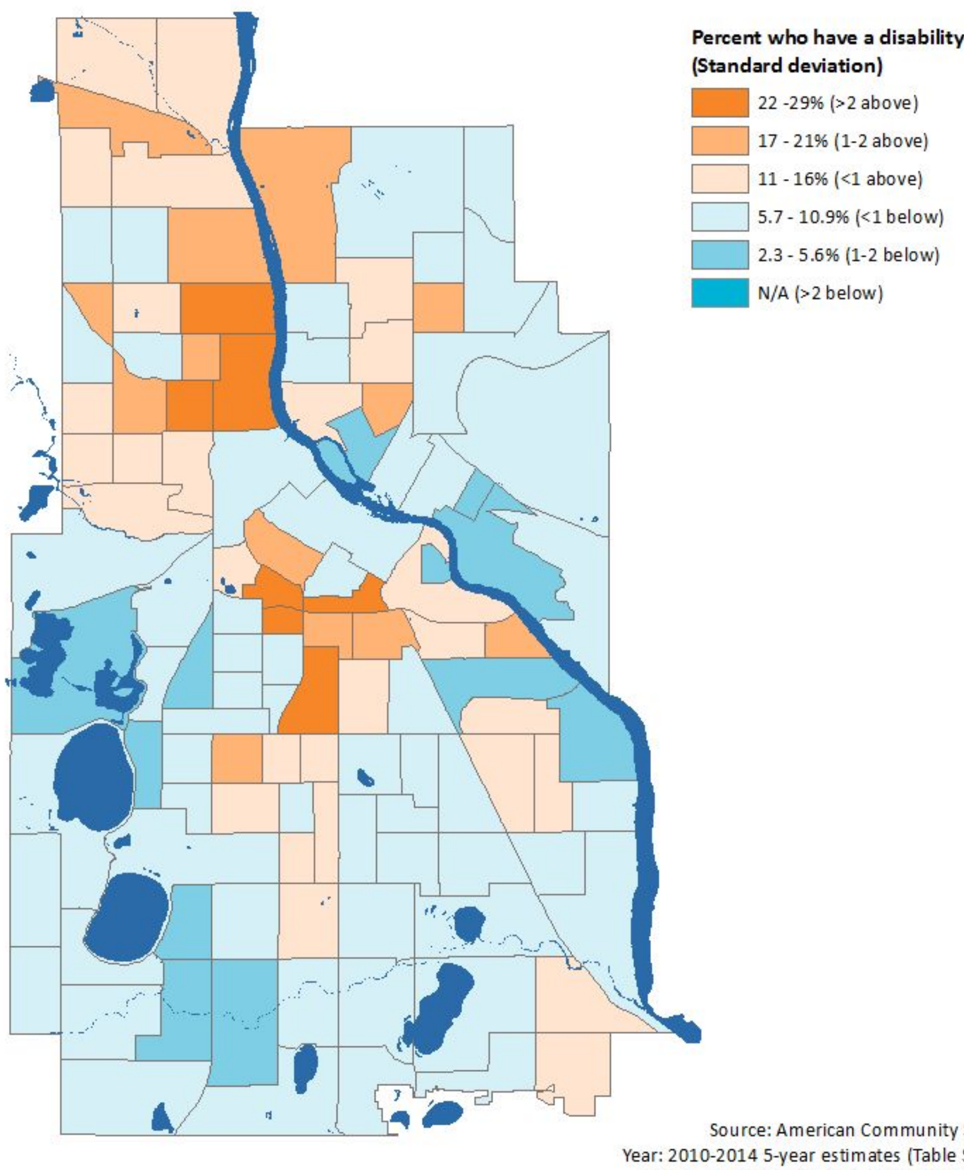
Social vulnerability to climate change: Disability

Percent of total civilian non-institutionalized population with any disability



Source: American Community Survey
Year: 2010-2014 5-year estimates (Table S1810)
Census tracts classified by standard deviation
(variation from the citywide mean)

Figure 39. Disability map

This maps shows the percentage of the population with a disability, by Census tract. Vulnerability arises when disabled individuals cannot react to emergency situations with adequate expediency, or they depend heavily upon assistance from others to remove themselves from compromising situations.

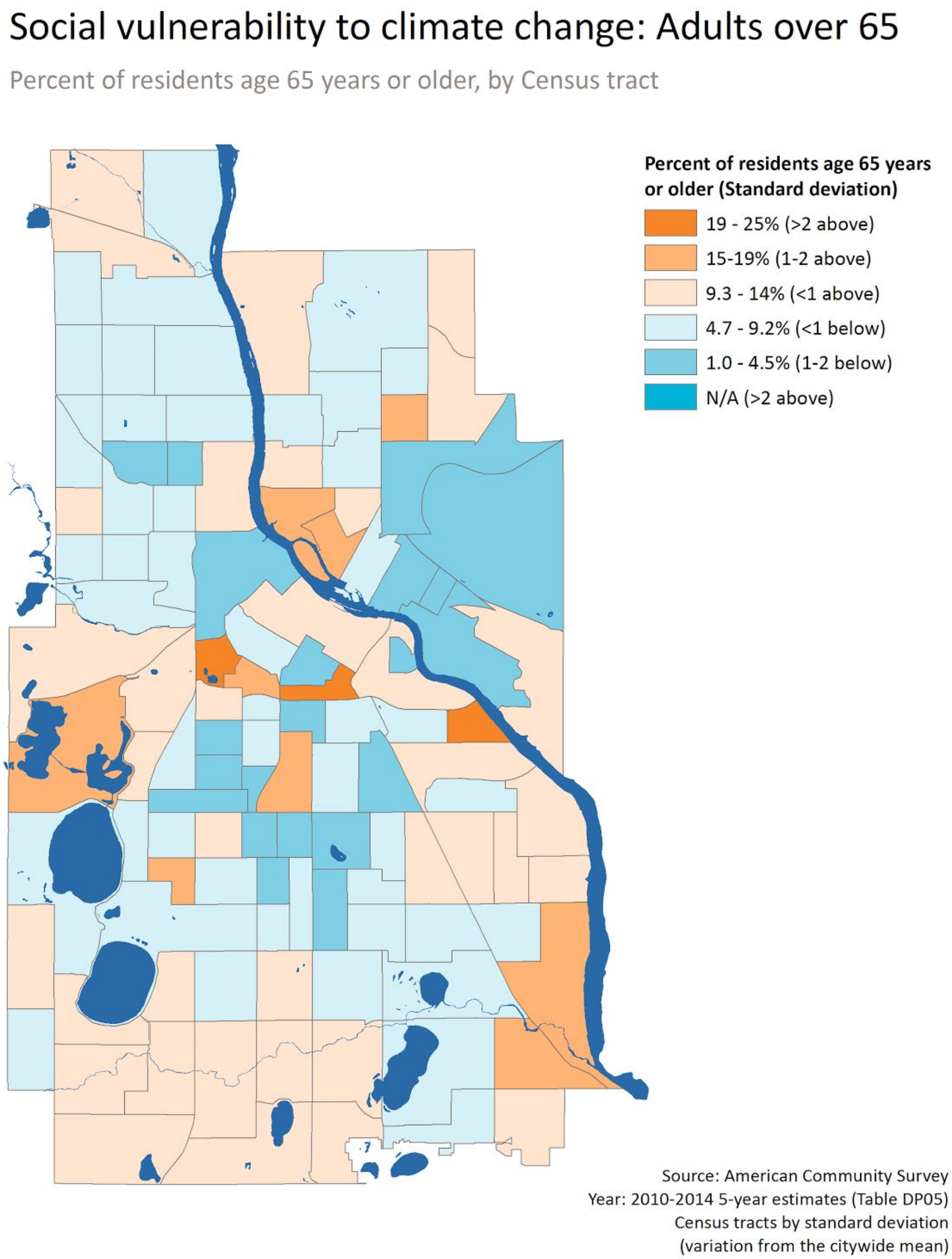


Figure 40. Elderly population map

This map shows the percentage of the population over the age of 65, by Census tract. Elderly populations tend to be characterized by more mobility constraints and greater biological susceptibility to extreme environmental conditions.

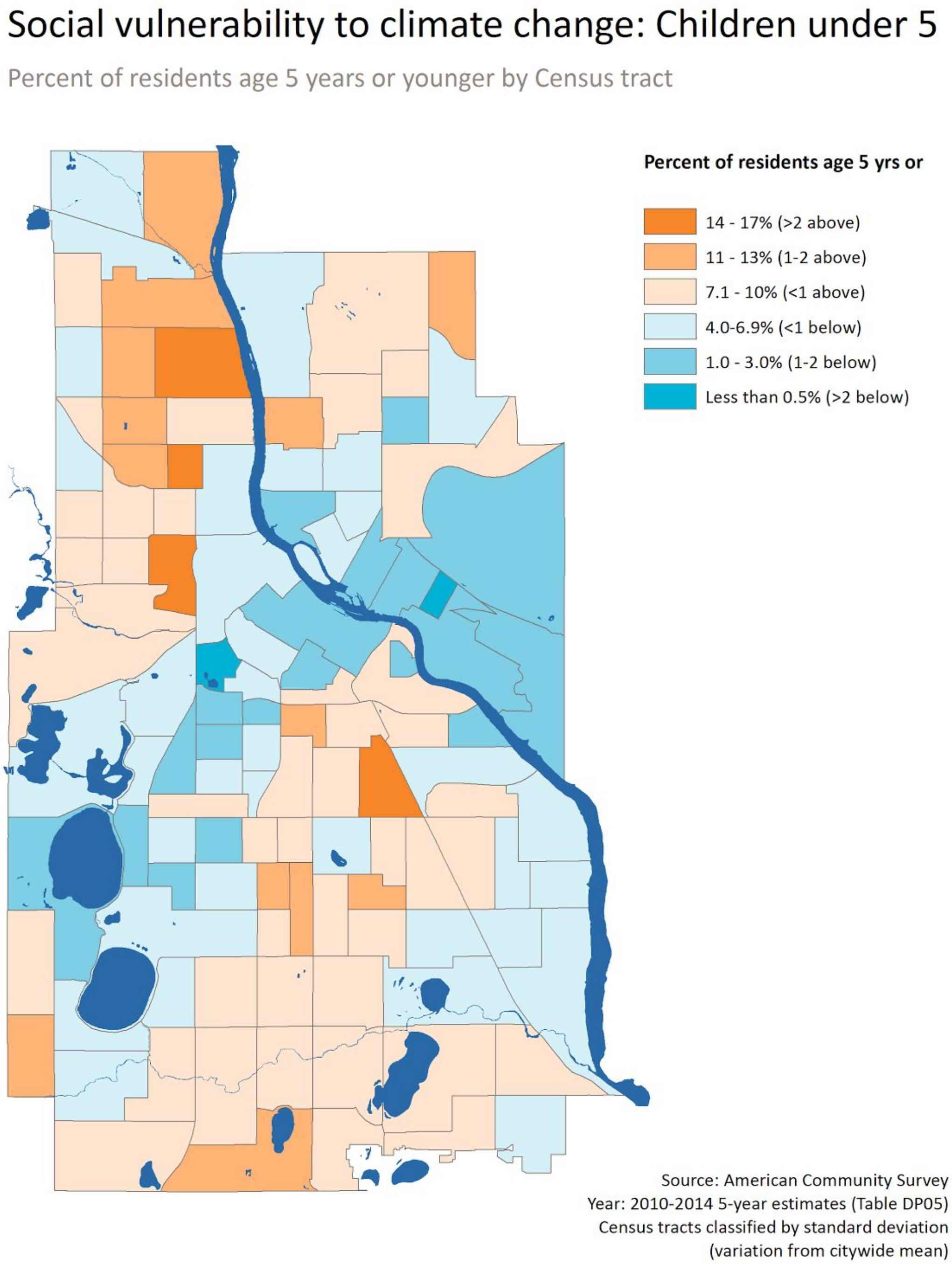


Figure 41. Young population map

This map shows the percentage of the population aged 5 and under, by Census tract. The vulnerability of young children stems from their dependence on others for their safety and health.

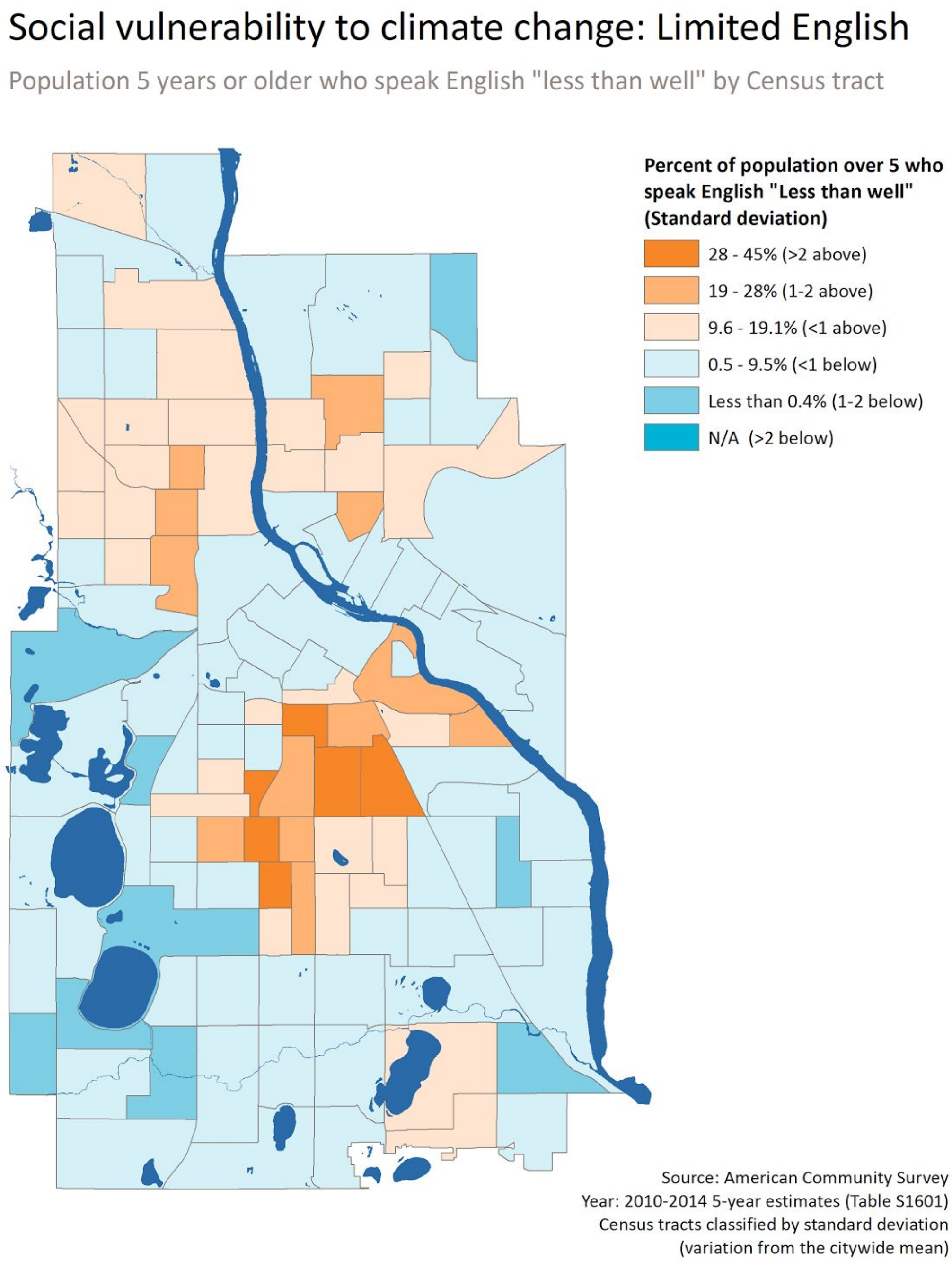


Figure 42. Limited English proficiency map

This map shows the percentage of the population that speaks English "less than well", by Census tract. Persons who lack fluency in the dominant language will struggle to find adequate information or respond appropriately when important information is disseminated in the dominant language.

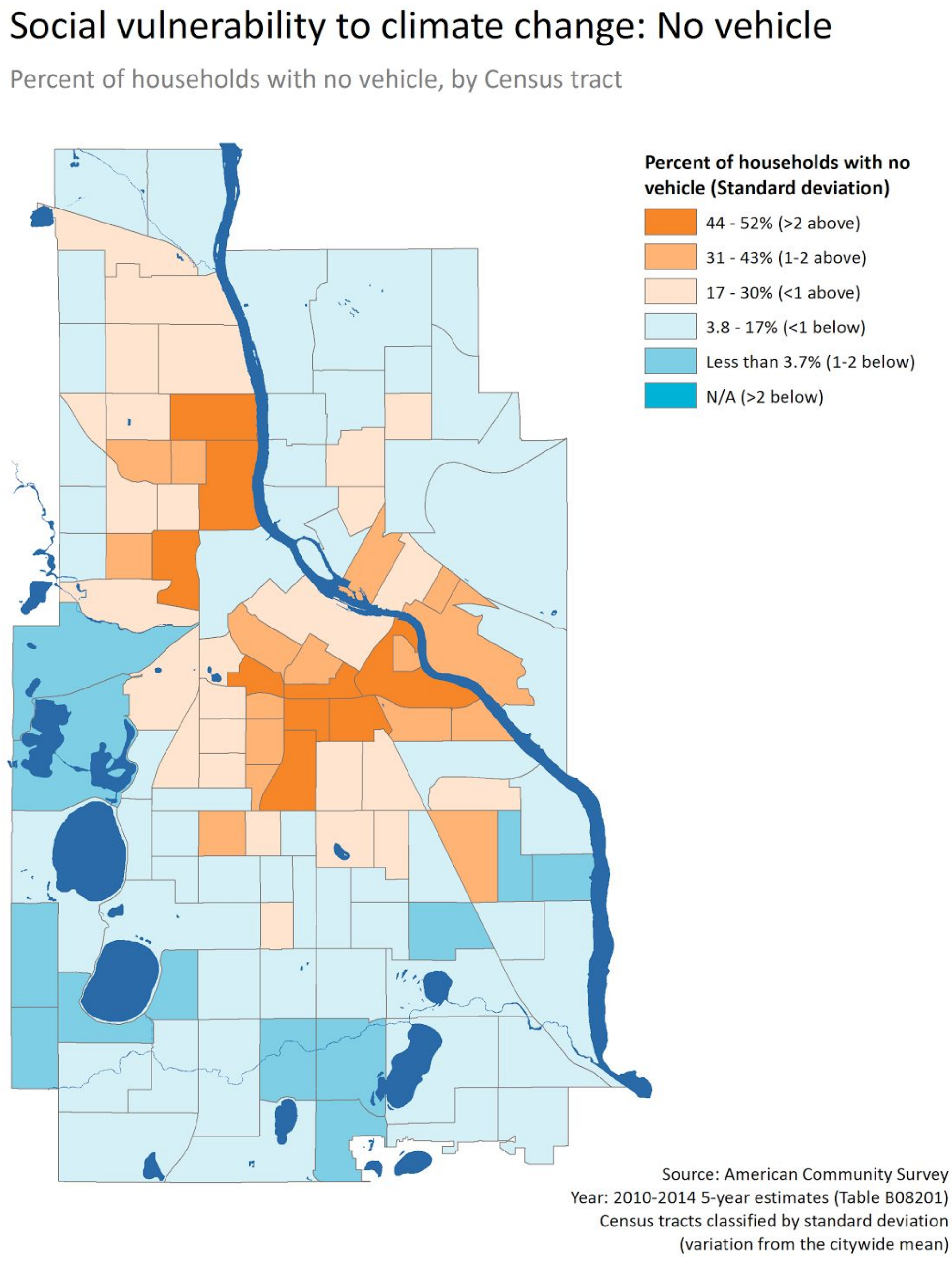


Figure 43. No Vehicle map

This map shows the percentage of households with no vehicle, by Census tract. Households with no vehicle have more limited mobility in a time of crisis, and are thus more vulnerable to extreme weather threats associated with climate change.

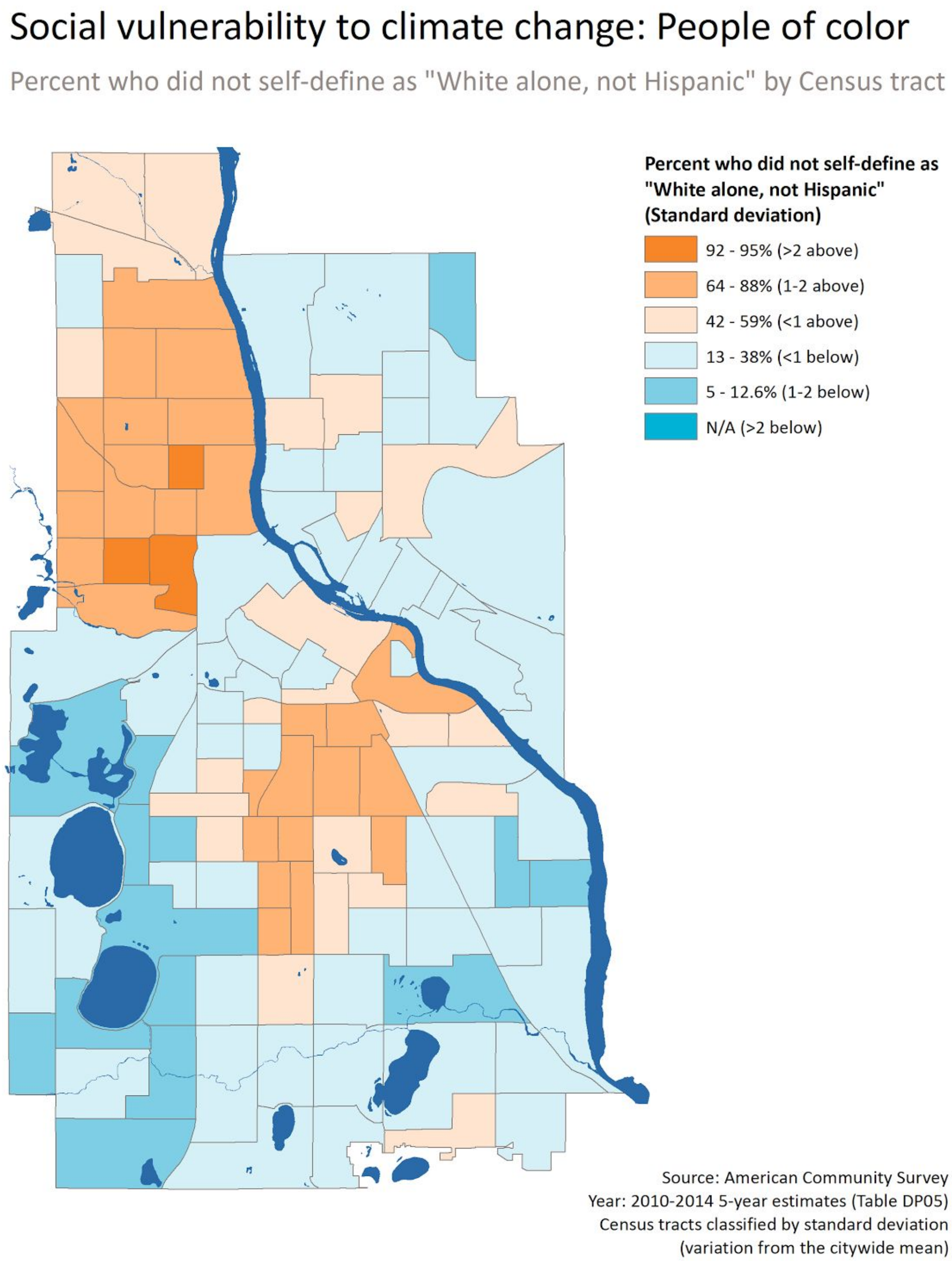
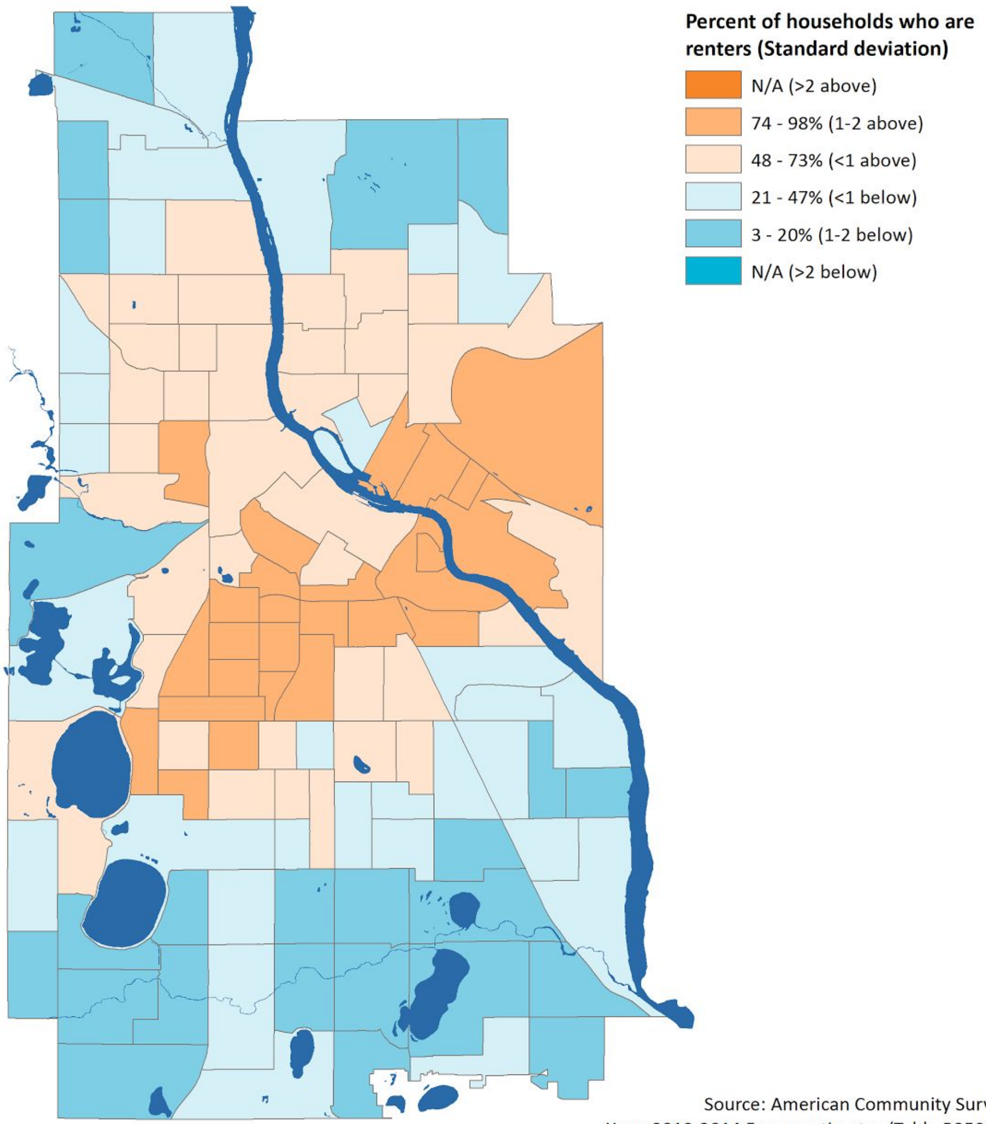


Figure 44. People of color map

This map shows percentage of the population who are people of color, by Census tract. Race is recognized as a vulnerability variable because many studies corroborate that persons of color fare significantly worse in the face of natural hazards.

Social vulnerability to climate change: Renters

Percent of households who are renters by Census tract



Source: American Community Survey
Year: 2010-2014 5-year estimates (Table B25003)
Census tracts classified by standard deviation
(variation from the citywide mean)

Figure 45. Renters map

This map shows the percent of the population that rents (as opposed to owns) their place of residence, by Census tract. Renters have less agency over their housing conditions and location than homeowners, and as such are more vulnerability to natural hazards.

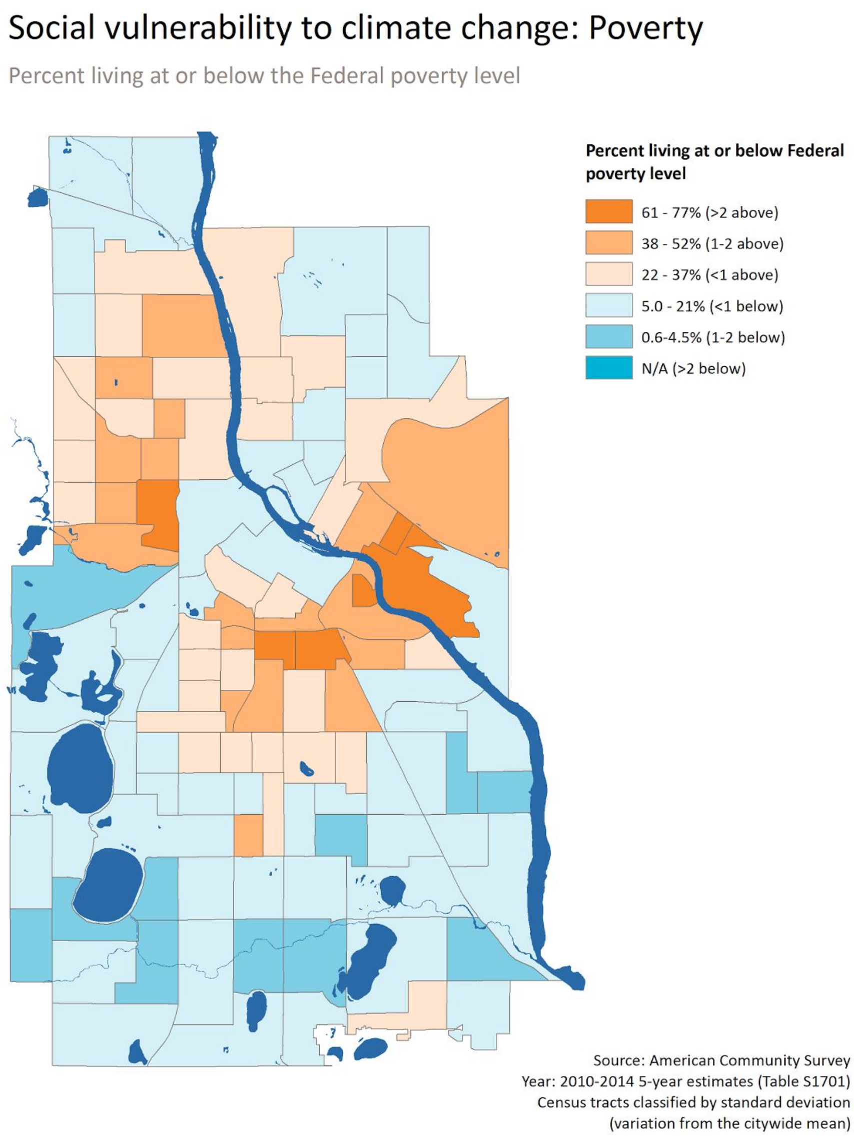


Figure 46. Poverty map

This map shows the percent of the population that live below the Federal poverty line, by Census tract. Living in poverty might be characterized by having fewer resources at one's disposal, in general and in times of crisis. Poverty as an indicator represents a lack of the inherent resilience that comes with wealth and socioeconomic status.

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5.2.3 Map Creation: Air conditioning

Data regarding air conditioning is not available from the U.S. Census Bureau at the Census Tract level, and thus the procedure for mapping air conditioning was modified for this assessment. Data indicating the presence of *central air conditioning* is collected by the Minneapolis City Assessor, on a property by property basis. A special data request was fulfilled by the City assessor's office, in which air conditioning data was displayed by property ID, address, and a value indicating the percentage extent of central AC on the property as delineated by the value field "AC_CD". Under the AC_CD field, a value of 1 indicates that 100 percent of the units on the property have central AC, whereas a value of 0.25 indicates that 25 percent of the units on the property have access to central AC. If the parcel contains one dwelling unit and that unit has AC, it would retain a value of 1.

The assessor data provided includes a "SHORT_DESC" (short description) category describing the type of building loosely based on land use category. Building types "Commercial" and "Industrial" building types were removed from the dataset via Excel's "Filter" function, to focus the study analysis on access to air conditioning in residential buildings only.

The filtered assessor data was joined to Hennepin County parcel data, available from OpenData Hennepin County[31] using the "Join" function in ArcGIS in order to create a spatial orientation for the AC data. The corresponding shapefile is named *Air_Conditioning_ResidentialOnly*. A new field titled "AC_Value" was created to capture the "AC_CD" value for each parcel (using Field Calculator and creating an equivalency between "AC_CD" and the new "AC_Value" field), preparing the data for a Spatial Join.

Of the 125,926 parcels in Minneapolis included in the residential filtered dataset, 62,891 did not join from assessor data. The Assessor's office confirmed that parcels not included in their original dataset provided upon request should be assumed to have no central air conditioning, hence the reason they were not included. The 62,891 non-joining parcels had a "NULL" value in their "AC_CD" field but were reclassified using the Field Calculator to have a "0" value, meaning that these parcels could be assumed to have no air conditioning for any units contained therein.

A Spatial Join was used to aggregate the air conditioning data up to the Census tract level, using Average as the aggregation type. The resulting shapefile is *ACParcels_SpatialJoin*. The resulting feature class contains the field "Avg_AC_Value" which represents the average (by Census tract) of percentage of parcel (units) that contain central air conditioning. Because the variable in question is the percentage of parcels that *do not* have central air conditioning, a new field entitled *Avg_wo_AC* was calculated as the binary opposite equivalent, or percentage *without* central air conditioning. Using the field calculator, the equation is *Avg_wo_AC* = 1 - Avg_AC_Value. From this *Avg_wo_AC* field, z-scores were developed and Census tracts were then classified on a 1-6 scale in the same manner as all other social vulnerability variables.

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[31] [http://gis.hennepin.opendata.arcgis.com/datasets/7975aabf6e1e42998a40a4b085ffefdf_1]

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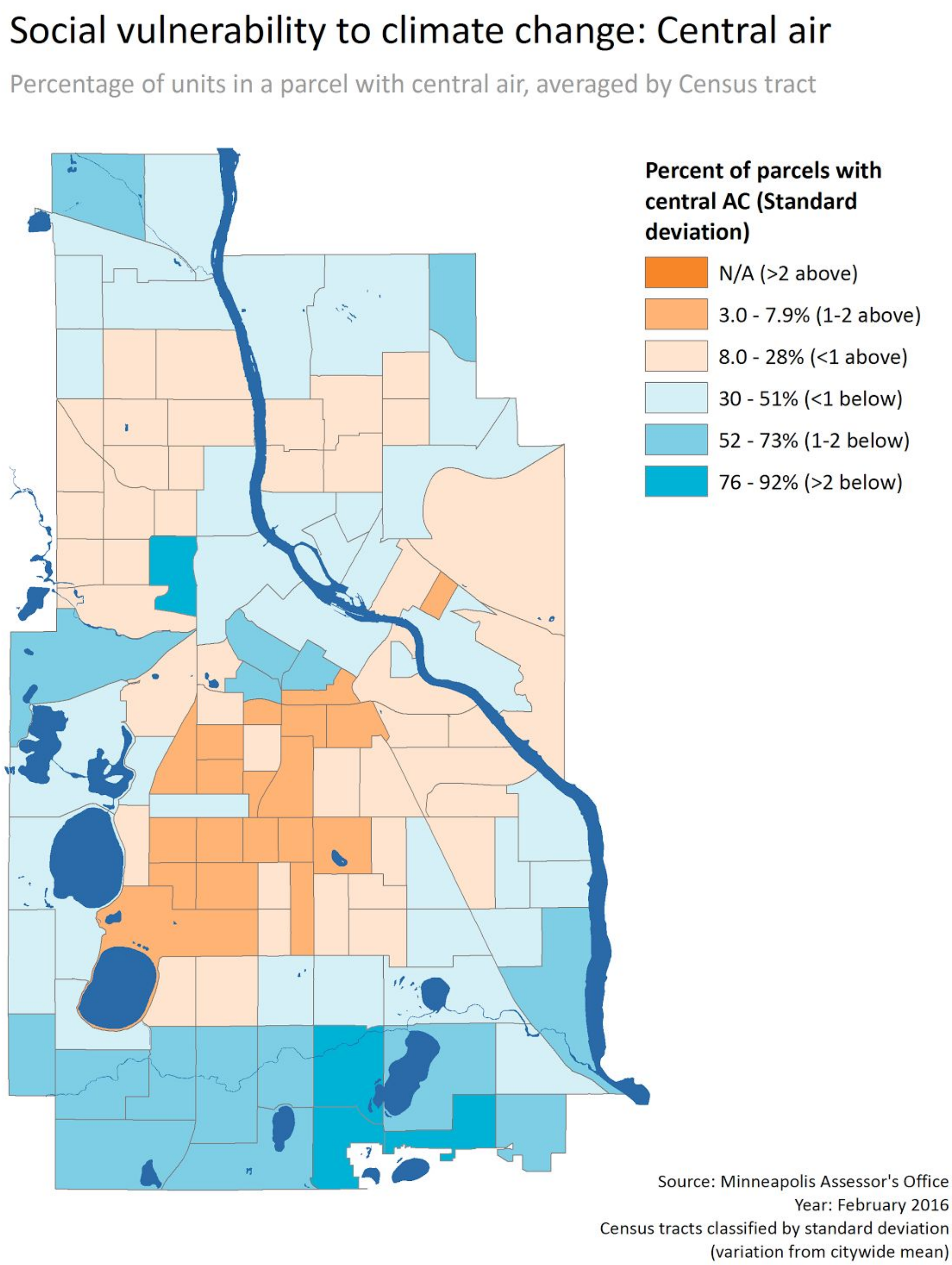

Figure 47. Lacking air conditioning map

This map shows the mean percentage of parcels with no central air, summarized by Census tract. During periods of high temperatures, residents without central air conditioning may be less able to access cooler temperatures, resulting in a greater degree of vulnerability.

5.3.1 Aggregate score method

This method assigns a score value to Census tracts and then adds the scores together from all nine variables to create an aggregate score for each Census tract, which is then displayed on a map. It does not take variable correlation into account directly. A sensitivity analysis on the nine variables confirmed that removal of any one variable from the final cumulative score has a negligible effect on the top scoring Census tracts.

5.3.1.1 Assigning “vulnerability scores”

To achieve an aggregate vulnerability map, a vulnerability scoring scale was applied to each population variable using the Select by Attributes and Field Calculator functions, scoring each Census tract on a 1 - 6 scale depending on standard deviation classification:

Std Dev Classification	**Score**
">2 SD below mean"	1
"1-2 SD below mean"	2
"<1 SD below mean"	3
"<1 SD above mean"	4
"1-2 SD above mean"	5
">2 SD above mean"	6

The scoring system reflects a vulnerability scale, such that a 1 indicates the lowest relative vulnerablity and 6 indicates highest relative vulnerability. The following table reviews the fields that were created in common for every indicator shapefile before the final step of aggregating them together into a final index score:

Z_score	The “standardized” value reflecting standard deviation score for each Census tract. Z-score calculated as $(X - \mu)/\sigma$).
STD_DEV	Delineates the standard deviation classification in relation to the mean, based on z-score
RasterValue	A vulnerability score that is based on z-score value

5.3.1.2 Polygon To raster and aggregating indicators

Once given a score under the RasterValue field, every variable was transformed into a raster dataset using the “Polygon to Raster” tool, retaining RasterValue as the value field.

Social indicator	Polygon shapefile name	Raster name
Poverty	Poverty	PovertyR
People of Color	PeopleOfColor	RaceR
Disability	Disability	DisabilityR
Limited English proficiency	LimitedEnglish	LimEngR
Older population	Elderpop_Over65	ElderPopR
Young children	YoungPop_Under5	YoungPopR
Renters	RenterPop	RenterR
No Vehicle access	NoVehicle	NoVehicleR
No Central AC	Air_Conditioning	AirCondR

All nine variable rasters were added together using Raster Calculator, creating an aggregate map of vulnerability. The cumulative raster layer (a raster file entitled *RasterPop9*) contains aggregate Census tract scores from all nine social indicators, with scores ranging from 23 to 46. The resulting map is shown here:

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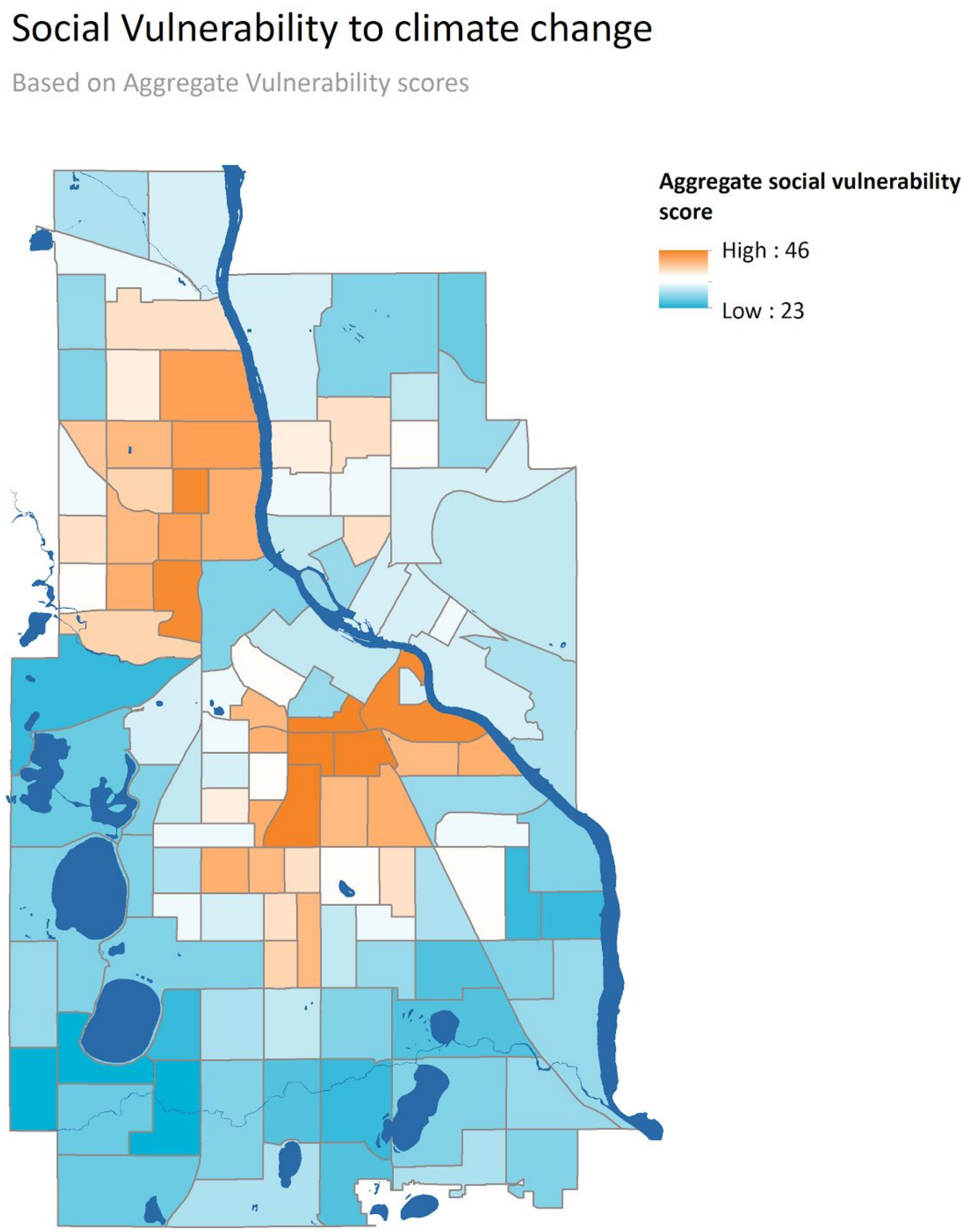

Figure 48. Social Vulnerability map: Aggregate method
This map shows the outcome of adding the scores from the nine social vulnerability indicators together to create an aggregate social vulnerability score. The darker orange hues indicate the highest-scoring places in Minneapolis with respect to social vulnerability.

5.3.2 Principal Component Analysis method

When using a multidimensional index to measure an attribute, as in the case in this assessment with social vulnerability, an aggregate variable approach can be confounded by strong pairwise variable correlations. When variables are simply added together to create a total composite score, there is no accounting for the mutual explanatory value of highly correlated variables and the result may be overemphasis on the impact of singular values. The correlation matrix below shows the strength of the associations between the z-scores of each variable pairing in the social vulnerability index, with 1 being a perfect positive correlation, -1 being a perfect negative correlation, and 0 meaning no variable relationship at all. There are several pairwise variable combinations that have high correlations of 0.6000 or greater.

	Disability	Under Five	Race	Limited English	Elderly	Poverty	No Vehicle	Renters	No AC
Disability	1								
Under Five	0.162095	1							
Race	0.574056	0.49962	1						
Lim. English	0.423491	0.37881	0.77497	1					
Elderly	0.148152	-0.2472	-0.3875	-0.3449	1				
Poverty	0.427983	0.12067	0.68627	0.62268	-0.4034	1			
No Vehicle	0.689024	-0.0082	0.57687	0.53603	-0.0807	0.79216	1		
Renters	0.404412	-0.2661	0.41981	0.47743	-0.2397	0.75043	0.7992	1	
No AC	0.192553	-0.0939	0.39381	0.43592	-0.3356	0.42807	0.3676	0.58717	1

Figure 49. A correlation matrix for the nine social variables shows that many of the variable pairs approach high correlations (> 0.6).

The high correlations between certain variable pairs in this index calls into question the validity of an summed aggregation score methodology. An alternative methodology known as principal component analysis (PCA) transforms an index of variables into distinct, uncorrelated elements that collectively explain the variation of the dataset. The result of a PCA analysis is a "compressed" index that summarizes the critical variance in the dataset and removes problematic variable correlation.

The free statistical program R was used to conduct PCA. The data input was a single Excel spreadsheet of the z-score values for each of the nine variables by Census tract. For the complete z-score input table and a workbook of the PCA analysis output, refer to the Excel document entitled "PCA_zscores_workbook" in the associated data accompanying this report.

The following R code was used to run the analysis, using the "prcomp" function:

```
mydata <-read.csv("Nine_Variables.csv",header=TRUE,row.names=1)
mydata.pca <- prcomp(mydata, retx=TRUE, center=TRUE,scale.=TRUE)

loadings <- mydata.pca$rotation
rownames(loadings) <- colnames(mydata)
#This gives the factor loadings

scores <- mydata.pca$x
#This gives the principal component scores

summary(mydata.pca)
#Gives the relative importance of each component

screeplot(mydata.pca, type="lines",col=3)
#Creates a screeplot for the data, showing variance by component
```

A scree plot and the PCA component summary indicate that it is appropriate to keep just the first three components from the PCA analysis, as they together explain 82 percent of the variation. Authors of comparable city vulnerability assessments indicate that it is best to select as many components as explain at least 70 percent of the variation[32].

	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**
Standard deviation	2.1118	1.269	1.1366	0.77814	0.60638	0.53181	0.43274	0.33151	0.29131
Proportion of Variance	0.4955	0.1789	0.1436	0.06728	0.04086	0.03142	0.02081	0.01221	0.00943
Cumulative Proportion	0.4955	0.6744	0.818	0.88527	0.92613	0.95755	0.97836	0.99057	1.00000

A summary of the PCA component outcomes, including (on the bottom row) the percent of the dataset variation explained by each principal component. Going out to the 3rd component (PC3) hits the 70 percent threshold.

[32] Based on a correspondence with Matt Wolff of the San Francisco department of Health, April 7th, 2016.

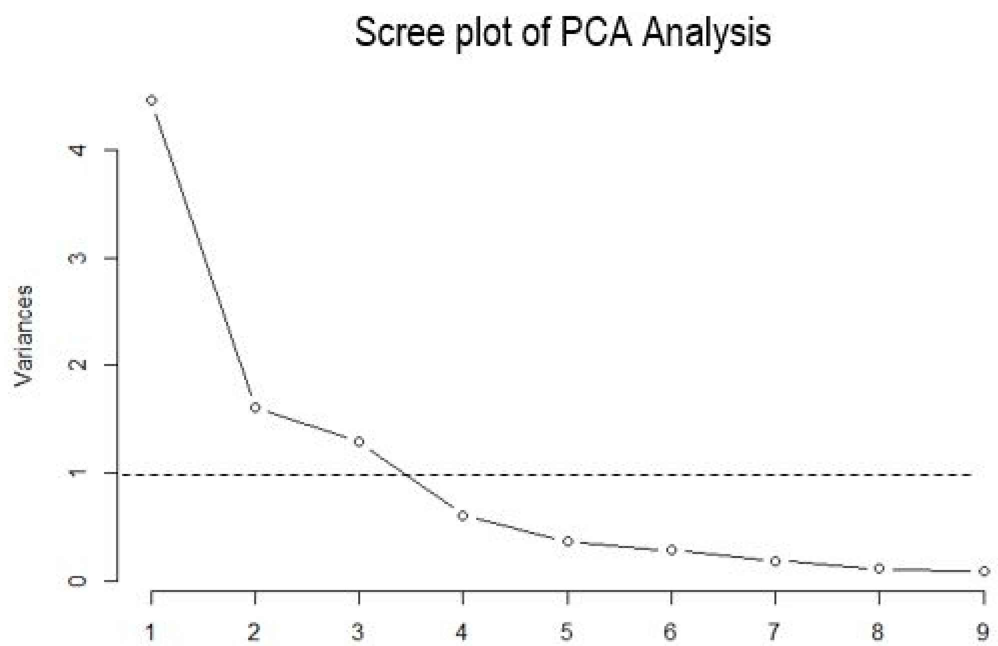

Figure 50. A “scree” plot depicts the diminishing variance explained by the set of principal components. Here, the cutoff point for retaining components is an eigenvalue of 1.

Summing the first three component scores and mapping the resulting total scores by Census tract produces the map shown in 5.3.2.1 below.

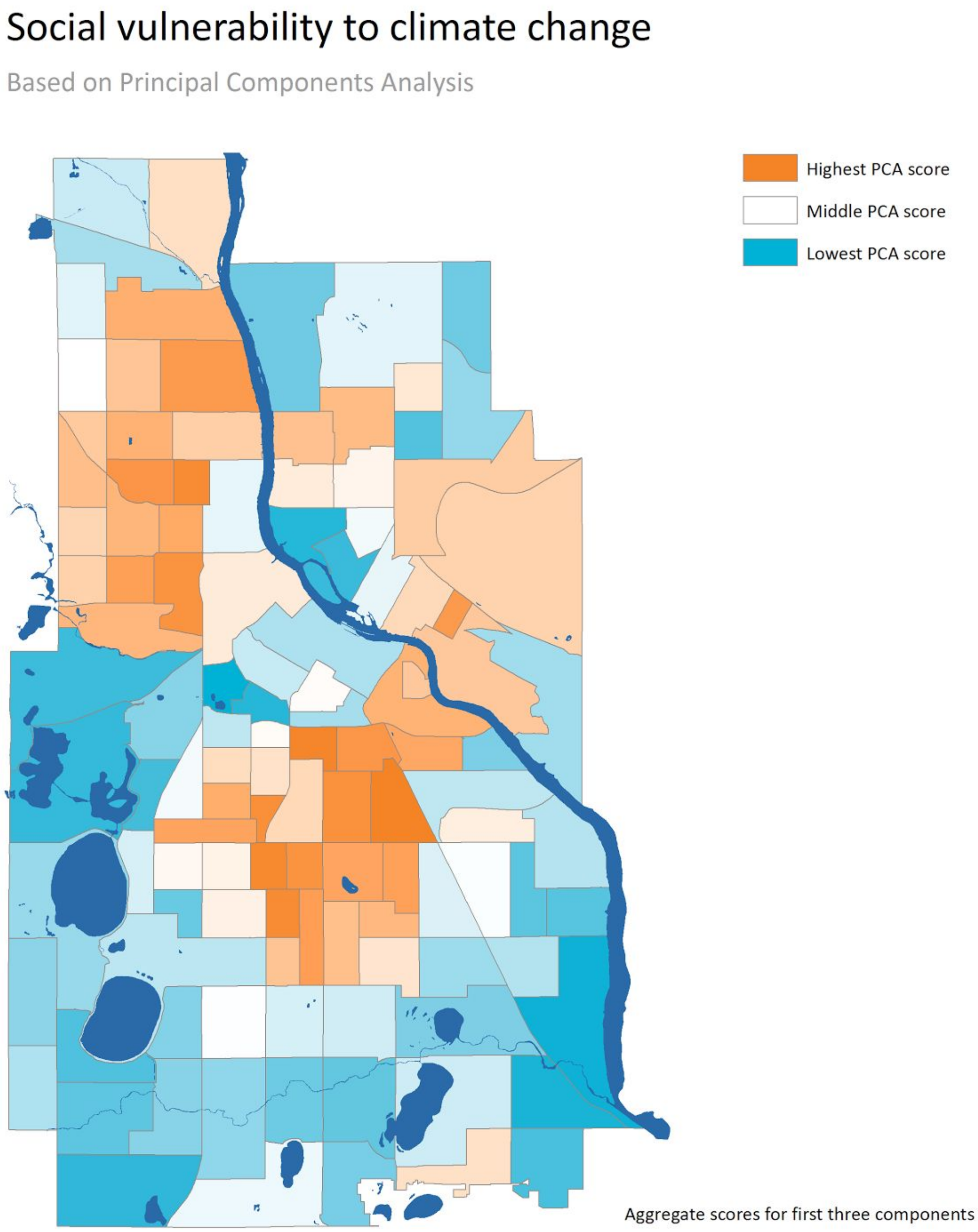

Figure 52. Social vulnerability map: PCA method
This map depicts the outcome of a principal component analysis for the nine factors of social vulnerability, retaining and adding the first three components. The highest scoring (darkest orange) places are those places that are the most socially vulnerable.

Comparing the Aggregate Score Method and Principal Component Method vulnerability maps shows that although the maps are not identical, they produce similar indications of high social vulnerability trends across Minneapolis.

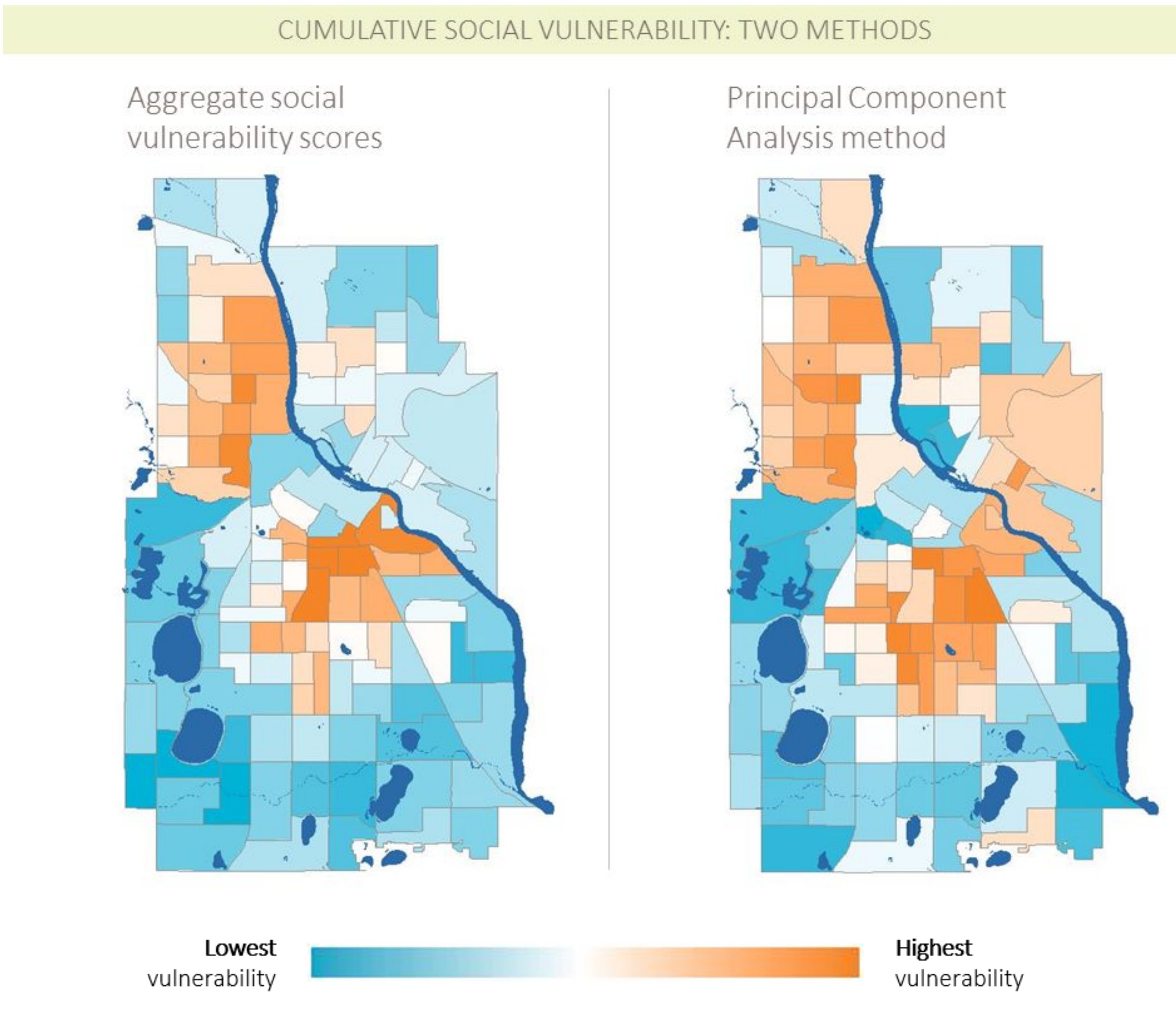

Figure 53. Comparing social vulnerability mapping methods

This side-by-side display of the outcomes of both social vulnerability mapping methods allows for a visual comparison. Both methods give a similar overall spatial indication of higher social vulnerability, but there are some key differences (particularly in North and Southeast Minneapolis) that are apparent. There is precedent for adopting the PCA method in vulnerability assessments to account, but the recommendation for public-facing communications is the aggregate method because it is more straightforward in its methodology.

5.3.3 Social vulnerability methodology recommendation

The rationale behind attempting two different methodologies to measure and display social vulnerability arises from concerns regarding the high correlation between social vulnerability indicators. Aggregating a cumulative vulnerability score without accounting for correlation risks conflating or overstating variable impact. The benefit of a Principal Component Analysis is that it accounts for and removes correlation from the analysis when scoring index values; the drawbacks are that it is overly complicated to perform, and produces a resulting valuation system with no tangible connection to the original index variables. Because the resulting score system is heavily transformed, sharing PCA results with the public presents a challenge.

This study recommends that PCA analysis results be retained for use only by City of Minneapolis staff. For analysis purposes, it may be important to consider the cumulative effect of the social vulnerability matrix without the impact of variable correlation. However, because the concept of aggregate or additive variables is simpler to comprehend and visualize, this study recommends adopting the Aggregate Method results for communication with the public. The ability to understand the component indicators and interpret their combined impact is an important feature of this methodology.

Both methods require the same methodology up until the point of generating z-scores by Census tract, but after that point they diverge. This graphic outlines the basic steps of each analysis as an overview:

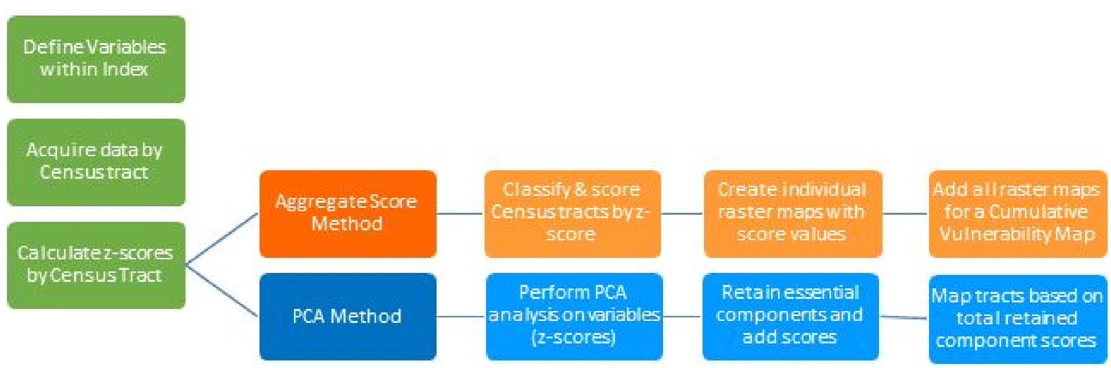

Figure 54. Overview outline for z-score analysis

6. Cumulative Landscape and Social Vulnerability Map

A key anticipated outcome of this assessment was the creation of a cumulative vulnerability map combining landscape and social vulnerability in the City of Minneapolis. Because our flooding analysis became a more qualitative component of this assessment, flooding vulnerability was not included as a component of this final map. The cumulative climate change vulnerability map is therefore composed of the combined impacts from landscape vulnerability to heat and social vulnerability.

In figure 55, the map on the left illustrates landscape vulnerability to heat by Census tract. High vulnerability tracts in this map (displayed in orange) are defined as those with the lowest vegetation cover and the highest impervious surface cover. The middle map displays aggregate social vulnerability by Census tract. Here, the map produced by the aggregate method was chosen over the principal components analysis method map because of its simpler scoring methodology and more direct relationship to its index components. The final map on the right shows the combined impact of both landscape vulnerability and social vulnerability, although the two input maps were modified and rescored to account for their different scales before they were added together to produce the overall place vulnerability map. This modification and rescoring process is described fully in section 6.1.

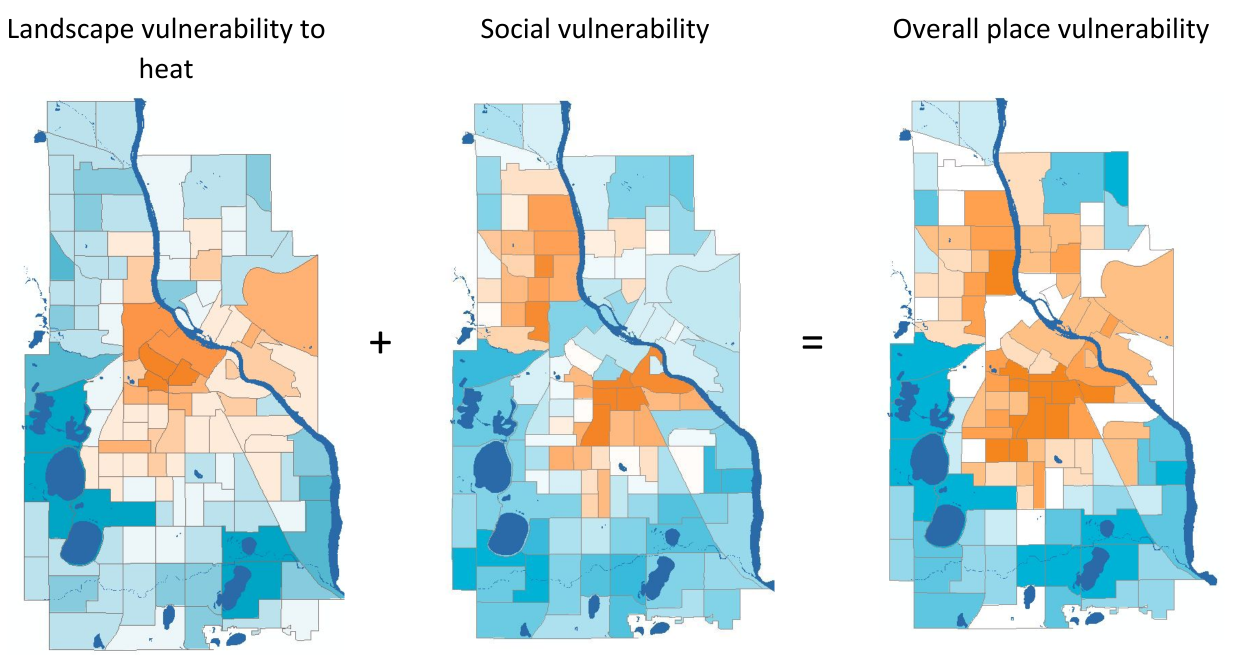

Figure 55. Overall place vulnerability is derived from the social and heat vulnerability assessment scores. The overall place vulnerability map adopts an 8-point scoring scale, with the highest-scoring tracts shown in darkest orange. These highest-scoring Census tracts represent places in Minneapolis

that are the most vulnerable to climate change when both heat and social factors are considered. These places may be considered priority places for climate change adaptation or resilience measures.

6.1 Using the Reclassify tool to rescore

The heat and social vulnerability maps each have a different range of vulnerability scores due to variation in each dataset. These differences must be accounted for when combining the two maps.To harmonize the different scales in each dataset, the vulnerability values were grouped into quintiles and then the harmonized scores were added together.

The Reclassify tool under Spatial Analyst toolbox in ArcMap was used to group the data from both the heat and social cumulative vulnerability rasters into quintiles. The Census tracts in the lowest quintile were given a reclassified value of “1”, the tracts in the second quintile a value of “2”, and so on. The method simplifies the data to harmonize the ranges of both variables. However, the tradeoff is a loss of some of the nuance of the vulnerability scoring system. The major benefit of this approach is that it allows two very different scoring scales to be realigned so they can be added together in a meaningful way.

Input Raster	**Reclass field**	**Classify...**	**Output Raster**
LCNDVI_zCombine_zonaltracts	Value	Quintiles (5)	*Quint_LCNDVI*
RasterPop9	Value	Quintiles (5)	*Quint_RasterPop9*

6.2 Using raster calculator to combine maps

Once the newly reclassified raster layers based on quintile scores were created, the Raster Calculator tool was used to add the two raster layers (*Quint_LCNDVI* and *Quint_RasterPop9*) together. The resulting raster layer (*Pop_Heat_QuintAdd*) represents the aggregate impact of heat and social vulnerability, by Census tract, with scores ranging from 2 to 10. A Census tract that scored in the highest quintile for both landscape vulnerability to heat and social vulnerability would have been given the highest cumulative vulnerability value of “10” under this method, and would be visually construed as a tract with the “Highest Vulnerability” in dark orange.

The resulting Total Vulnerability map is shown here below. The map can be interpreted as distinguishing the areas in Minneapolis that are both (a) locations where highly vulnerable populations are present in greater proportion than the average and (b) locations where impervious surface cover and a lack of vegetative cover are most likely to contribute to the urban heat island effect.

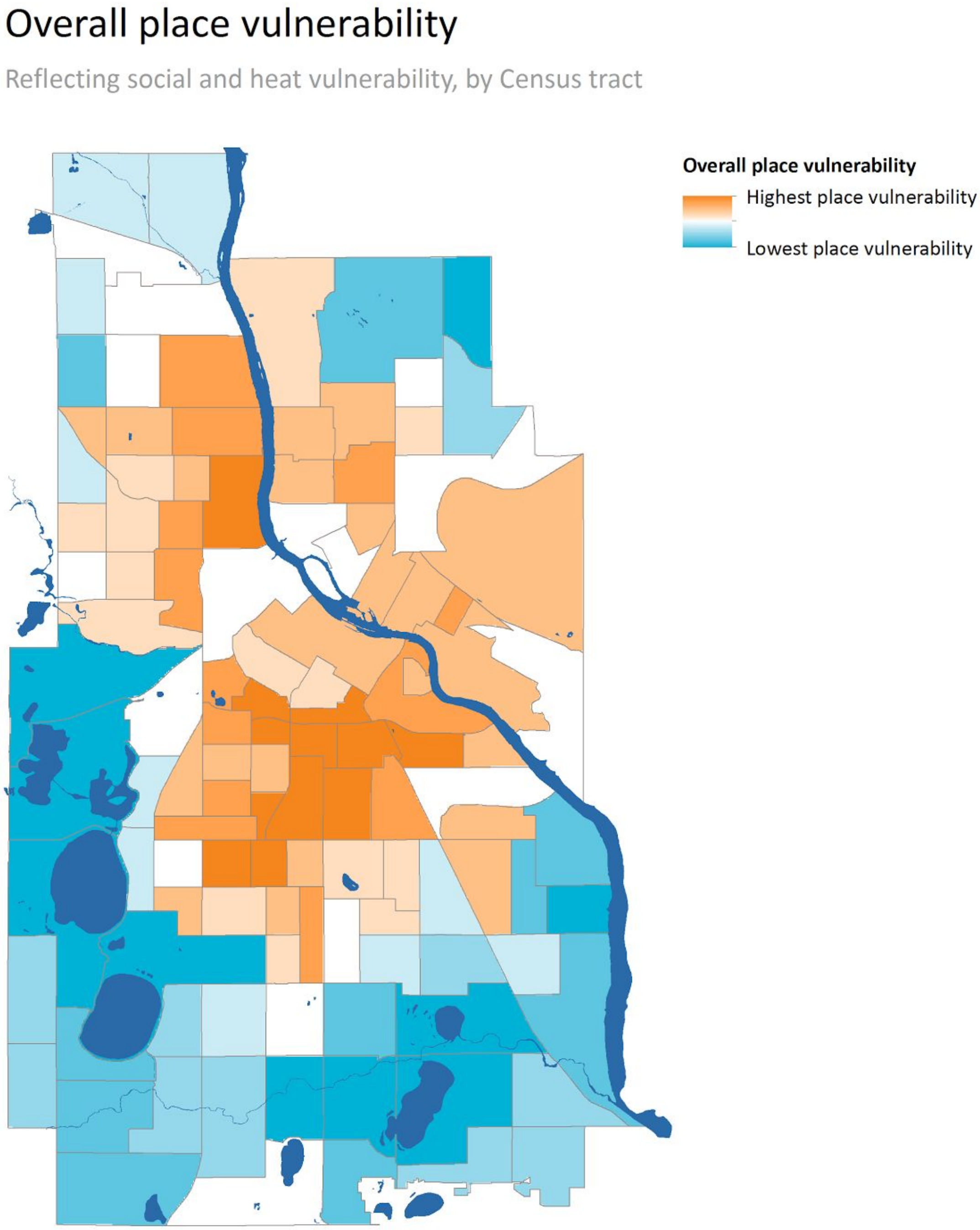

Figure 56.Overall place vulnerability map

6.3 Limitations of this approach

While a cumulative climate change vulnerability map can serve as a guide for citywide climate change adaptation policy, there are some inherent limitations to this approach that must be considered.

6.3.1 Limitation 1: A loss of granularity and nuance in the final map

While collapsing data into quintiles before adding the heat and social vulnerability effects together harmonizes the different ranges of each dataset, it results in an unavoidable loss of detail in the final combined map. The unavoidable result is that information that was once more nuanced is now merged into categories for an overall loss in explanatory value. Specifically, the score range that comprises the upper quintile for both datasets is wider than that of the lower quintiles, which means that variation in the highest scoring (most vulnerable) tracts is obscured. When selecting priority areas for climate adaptation action, particularly in the context of limited program resources, variation among high-vulnerability tracts is essential information.

6.3.2 Limitation 2: The “apples and oranges” problem

While the components of the Total Vulnerability map both help to explain aspects of vulnerability to climate change in Minneapolis, it is useful to pause and consider whether these discrete vulnerability measures can truly be combined into one measure.

The Cumulative Social Vulnerability map is a depiction of areas in the City where populations most susceptible to hazards associated with climate change tend to live in greater proportion. Vulnerability is here defined as the pronounced presence of populations that score high on the index of social variables, and it refers to areas where people live.

The Heat Vulnerability map is a depiction of areas in the City where impervious cover is highest and vegetative cover is lowest, thereby signifying areas that are high contributors to the urban heat island effect. Here, vulnerability is defined as areas in Minneapolis with the greatest “deficit” in heat-mitigating land cover, and refers to areas of high opportunity to prepare for the projected increases in extreme heat associated with climate change.

Given these different conceptions of vulnerability, what does it mean to combine heat and social vulnerability maps together into a Total Vulnerability map? At best this combined map is an approximation of areas of Minneapolis that, for a myriad of reasons, may be priority focus locations for climate change adaptation policy. However, by combining the maps it is difficult to discern what tools or adaptive approaches will be most effective.

At the city scale, wherever adaptation policies are designed to be highly targeted and outcome-driven, there may be merit in considering the discrete components of spatial vulnerability rather than the total sum of all vulnerability.

6.3.3 Recommendation

The loss of explanatory value in the Total Vulnerability map, combined with the "apples and oranges" problem, leads to the conclusion that it may be wise to keep the heat and social vulnerability maps as separate entities when it comes to their usefulness as guiding documents for determining priority areas and adaptation policy solutions.

7. Study Datasets and Deliverables

All of the data described in this technical document will be made available to the City of Minneapolis, and can serve as a basis for replicating, modifying or expanding this analysis in the future. The following sections describe the data components and final deliverables of this assessment. All documents for the City of Minneapolis are contained in folder entitled "Minneapolis Climate Vulnerability Assessment", which will be distributed via flash drive and shared through a Google Drive account.

7.1 Data workbooks

Any non-spatial datasets that were used or modified during the course of this assessment can be found in the "Data" folder (Minneapolis Climate Vulnerability Assessment\Final Deliverables\Data).

The "Social" folder contains the following contents:

- *Complete ACS Workbook.xls*: Contains a codebook explaining the derivation of data from the American Community Survey, calculations that were completed to derive vulnerability variables, and a Margin of Error analysis (was not used in the final analysis).
- *PCA_zscores_workbook.xls*: A spreadsheet workbook of the results of Principal Components Analysis.
- *Raster Value Master Table.xls*: The z score classification scores for all nine social variables in one Excel table.
- *Social vulnerability sensitivity analysis.xls*: An initial assessment scheme designed to test the relative sensitivity of each individual social measure by systematically removing it from the overall score and analyzing the effect on the top ten most vulnerable Census tracts.
- *AC 2016*: Contains the original data from the Minneapolis City Assessor's office as well as parcel data filtered for only residential parcels.
- *PCA*: An R code file that was used to conduct PCA analysis.
- "Images" folder: contains images of charts and schematics used in the final report associated with social vulnerability.

The "Heat" folder contains:

- Minneapolis Department of Health data associated with heart attack hospitalizations by zip code
- UHI data (NETCDF files) from the UMN Department of Soil, Water and Climate

The “Flooding” folder contains:

- *Storm Drain Pipe Age* - An Excel table and chart from the City of Minneapolis

7.2 GIS data

All GIS-related files and data, as well as final maps, can be found in the folder entitled “Maps” (Minneapolis Climate Vulnerability Assessment\Final Deliverables\GIS). This folder contains subfolders with the following organization:

- “AllData” - All map layers that were created or used in this assessment can be found in this folder. Shapefiles and raster layers are further categorized by whether they related to Social, Heat or Flooding vulnerability. There is a fourth classification for “Additional Data,” which includes generic layers including water bodies and relevant Minneapolis boundaries.
- “FinalData” - Any map layers that were used to create maps showcased in the Technical Document or the project presentation are saved specifically in this folder. Shapefiles and raster layers are further categorized by whether they related to Social, Heat or Flooding vulnerability.
    - This folder also contains a subfolder entitled “LayerFiles” where all final map layers are saved with their associated color and classification schemes.
- “Maps” - In this folder, all final maps are saved as PDFs and PNG documents. This is also where the ArcMap (.mxd) working files are saved. *Data in the .mxd files may need to be re-linked if the filepath is broken. All data can be sourced from within the* “AllData” or “FinalData” folder.

7.3 Powerpoint presentation

The project team prepared two Powerpoint presentations for delivery to Minneapolis staff and committees. There is both a longer and a shorter version of this powerpoint found within the folder entitled “PPTs” (Minneapolis Climate Vulnerability Assessment\Final Deliverables\PPTs).