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Sacramento Urban Development
Quantifying and Mapping Urban Heat to Support Urban Planning Initiatives in Sacramento, California

DEVELOP Technical Report

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1. Abstract
The combined effects of increasing urbanization and climate change have exacerbated the urban heat island (UHI) effect and heat-related risks for city dwellers. Vulnerability to heat-related illnesses is further compounded by risk factors such as demographics, socioeconomic status, and pre-existing health conditions. The City of Sacramento, as California's fastest growing city in terms of population, is particularly invested in combatting the UHI effect. The team collaborated with the City of Sacramento and urban planning firm, Dyett and Bhatia, on three main goals: assessing urban heat at the neighborhood scale; identifying priority areas for cooling interventions; and assessing heat risk to the population. This project utilized NASA Earth observation products to identify hotspots within the community areas of Sacramento and create maps of urban heat, the heat-mitigation index, and heat risk of the study period from 2016-2020. The Surface Reflectance product were used from Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) and ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) thermal infrared sensor. Additionally, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Urban cooling model was used to assess the impact of increased tree canopy scenarios. Urban hotspots were identified in central Sacramento and along major transportation corridors such as Stockton Boulevard, while highest risk areas were identified in the community areas of Fruitridge/Broadway and North Sacramento. This project identified these high-opportunity areas for heat mitigation to inform the City of Sacramento's General Plan. This will inform the partners' plans to reduce citizen risk by addressing urban heat islands.

Key Terms
InVEST urban cooling model, Landsat 8 TIRS, ArcGIS Pro, ECOSTRESS, ecosystem services, heat mitigation

2. Introduction
2.1 Background Information
The City of Sacramento, California is in the process of updating the City's General Plan, which is a policy guide for future development and preservation of resources within the City. As one component of broader sustainability goals, the City hopes to alleviate the urban heat island effect (UHI), which will likely be exacerbated by warmer temperatures in coming decades. Heat islands are urbanized areas that experience higher temperatures compared to surrounding areas due to impervious materials, such as asphalt, that absorb and reemit solar heat more than natural vegetation (US EPA, 2014). In the Sacramento Valley, daily temperatures are predicted to rise 10° F, and the total number of days above 104° F is predicted to be above 40 days a year by 2100 (Kerlin, 2019).

According to the Centers for Disease Control (CDC), in the United States, extreme heat was the leading cause of weather-related deaths from 2000– 2009, with 7,800 deaths from 1999- 2009 (*Extreme Heat—NIHHIS*, 2017). Exposure to high frequencies of extreme heat events can significantly impact public health and can be directly linked to heat-related illnesses including heat cramps, heat exhaustion, and heat stroke (Communitywide CAP, 2017). Increases in temperature create barriers for health equity because vulnerable communities often carry a disproportionate burden of climate effects (Sacramento County, 2017). These communities—which include low-income individuals, those with preexisting health conditions, young children, the elderly, the homeless, some tribal nations, and socially and linguistically isolated peoples—often reside in neighborhoods with less infrastructure for urban cooling and are less likely to have access to transportation that provides an escape to cooler areas (Sacramento County, 2017). They are also more likely to live in housing that lacks air-conditioning or forgo air-conditioning to reduce electric bills (Cooley et al., 2012). Neighborhoods situated in urban heat islands have more instances of chronic illness, creating a social and climate justice dilemma (Kerlin, 2019).

A variety of factors influence perceived temperature including radiation, relative humidity, and wind speed (Steadman, 1984). *In situ* measurements of these metrics are limited by their scale and resolution. In contrast, remotely-sensed data allow researchers to directly assess temperature across any sized area at the meter scale. Remote sensing has been used to assess and model urban heat island effects and locate urban hotspots using land surface temperature (LST) as a proxy for apparent temperature (Wang et al., 2016). This study used the Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Spectrometer (TIRS) and the International Space Station (ISS) Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) to study daytime and nighttime LST, as similarly used for heat studies in other cities (Wang et al., 2016; Hulley et al., 2019). Previous studies have also found that minimum temperatures during heatwaves are greater predictors of health outcomes than maximum temperatures (Hajat et al., 2002; Schwartz, 2005; Zhang, et al. 2012). Therefore, capturing nighttime temperatures is critical to understanding heat retention in cities and addressing the impacts of urban heat.

The City of Sacramento is equipped with an array of tools to affect change in the built environment; however, the City does not currently incorporate remote sensing data into its decision process. A spatial analysis of temperature disparities during peak summer months (May through September) will help the City's planning team understand the implications of these interventions and prioritize areas of the City that are home to a high proportion of vulnerable populations or are most likely to experience rapid growth. The results of the team's work will be incorporated into the City of Sacramento General Plan and Climate Action and Adaptation Plan in the form of specific policies and standards, including interventions such as cool paving or tree canopy coverage in transit priority areas to help the City adapt to increasing urban heat.

2.2 Study Area
The City of Sacramento in California was the study area for this project. Per the partners' request, the study area was aggregated from the official City limits as well as two 'Special Study Areas' (Natomas Study Area and a section of the Fruitridge/Broadway neighborhood) which are currently unincorporated but may be annexed by the City in the future (City of Sacramento, 2015). The study area was subdivided into 11 neighborhoods (Figure 1). The study period included summer months of May through September from 2016 to 2020. Sacramento only experienced a 1.1 percent change in population between 2019 and 2020 (California

Department of Finance, 2020). However, the City is California's fastest growing large city in terms of population and is dedicated to promoting sustainable, equitable, and inclusive change.

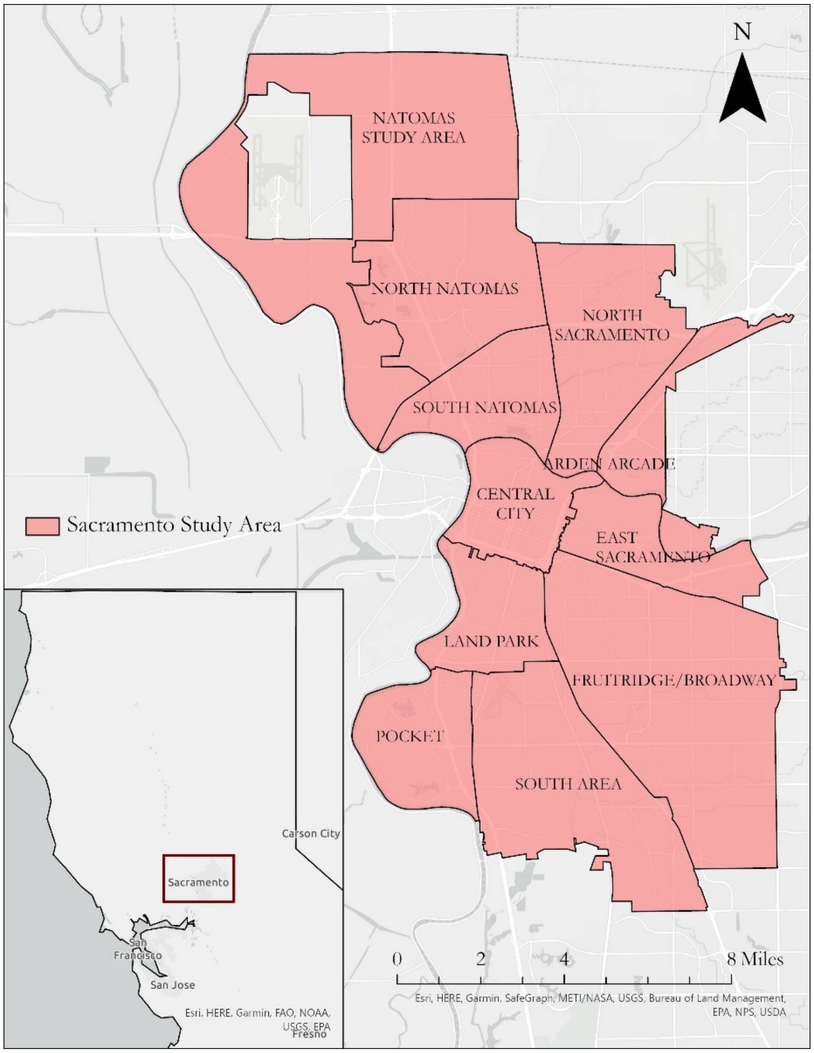

Figure 1. Study area of the City of Sacramento, California.

2.3 Project Partners & Objectives

The City of Sacramento has hired the urban planning firm, Dyett & Bhatia, to assist with updating the General Plan for 2040. Previous reports have established that the City suffers from an urban heat island problem that disproportionally affects vulnerable populations, such as the elderly, the poor, and people with pre-existing conditions – vulnerabilities that frequently coincide with one another (Cooley et al., 2012; Jiang et al., 2020; Sacramento County, 2017; Sacramento Department of Public Works, 2018). These studies lack information on the sources of heat at a very fine scale. To complement existing data, City management needs high resolution data on urban hot spots and how effectively and equitably the UHI is currently being mitigated across communities. By using NASA Earth observations, the team shows surface temperature patterns at 30m and 70m resolutions for daytime and nighttime temperatures respectively, in contrast to the 2km resolution of the City's previous analyses. Analyses of social vulnerability to extreme heat in California have typically used cumulative indexes of vulnerability metrics and were conducted at the county scale (Cooley et al., 2012; Sacramento County, 2017). In this study, the team examines social vulnerability to heat among 11 distinct metrics informed by literature and previous heat risk studies (Sacramento County, 2017; USGCRP 2016): age above 65, age above 65 and living alone, age below 11, cardiovascular disease, asthma, race/ethnicity, housing burden, homelessness, linguistic isolation, poverty, and unemployment. This is the first heat risk index that the team is aware of that includes homelessness in Sacramento. The inclusion of race/ethnicity is also an improvement over some existing indexes. The team combined these vulnerability metrics with heat exposure to create a heat risk index for the study area. Finally, the team applied the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) urban cooling model (*InVEST | Natural Capital Project*) to illustrate high-value opportunities for further UHI heat mitigation. Insights from this study will guide sustainable and equitable development goals set forth in the Sacramento General Plan for 2040.

3. Methodology

3.1 Data Acquisition

The team retrieved satellite imagery for summer days (1 May – 30 September) via two platforms (Table A1). Landsat 8 data for 2016-2020 were retrieved from Google Earth Engine. The LANDSAT/LC08/C01/T1_SR Landsat 8 Surface Reflectance Tier 1 image collection was retrieved and processed using a script developed by the NASA DEVELOP Spring 2020 AZ Philadelphia Health & Air Quality team and modified for this project. These images were used to calculate albedo and daytime LST. Nighttime LST was assessed using ECOSTRESS LST (ECO2LSTE.001) and cloud mask (ECO2CLD.001) level 2 data for 2018-2020, requested and downloaded from the NASA Application for Extracting and Exploring Analysis Ready Samples (AppEEARS).

Evapotranspiration (ET) data from ISS ECOSTRESS were also requested and retrieved through NASA AppEEARS. Level-3 Evapotranspiration (PT_JPL) products representing daily ET for summer days in 2018-2020 were downloaded and manually filtered. As thirty layers are needed for a stable mean, thirty-one of the clearest images were selected from the collection according to the following criteria: full coverage of the area of interest with no major data voids from cloud coverage as determined by the team, no linear artifacts, and reasonable ET values.

Socioeconomic and demographic data were accessed from three sources: the CalEnviroScreen 3.0 product was downloaded from the California Office of Environmental Health and Hazard Assessment (OEHHA); supplementary 2017 American Community Survey Five-Year Estimates was downloaded from the U.S. Census Bureau; and homelessness data (311 reports of homeless encampments) was provided by the City of Sacramento. Social vulnerability factors were grouped into two categories: heat sensitivity and socioeconomic factors. Heat sensitivity factors included children under age 11, 65 and older elderly community living alone, and those with asthma and cardiovascular disease. Risk-multiplying socioeconomic factors included race/ethnicity, homelessness, housing burden, linguistic isolation, poverty, and unemployment.

The team utilized a land use/land cover (LULC) dataset that was provided by Dyett and Bhatia in conjunction with the Multi-Resolution Land Characteristics Consortium (MRLC) USA National Land Cover Database (NLCD) 2016 United States Forest Service (USFS) Tree Canopy Cover (CONUS) to create a LULC input for the InVEST urban cooling model. Similarly, the team received a building cartography GIS layer from the City of Sacramento partners which was used to calculate building intensity. Humidity data for the InVEST urban cooling model heat reduction valuation was acquired from the Weather Atlas (Monthly Weather Forecast and Climate Sacramento, CA, 2020). The average humidity was calculated from the reported average humidity values in May through September for Sacramento, CA.

3.2 Data Processing

3.2.1 Land Surface Temperature (LST)

The team calculated daytime LST from the Landsat 8 Surface Reflectance Tier 1 Product using the NASA DEVELOP AZ Spring 2020 Philadelphia Health & Air Quality script in Google Earth Engine (GEE). Although Landsat 8 provides a Provisional Surface Temperature product, it is not yet available in GEE. For this reason, the team used the Surface Reflectance product to calculate LST in this project. The script first filtered the collection to include only images for summer, as defined by project partners (May 1 – September 30), then masked clouds and cloud shadows from images using the cloud and quality assurance bands of the dataset. The final filtered collection included 152 images. The script then calculated Normalized Difference Vegetation Index (NDVI) to calculate emissivity (E) (Shen et al., 2015), which was then used with the brightness (BT) band on Landsat 8 TIRS (band #10) to calculate LST (Equation 1).

$$\mathrm{LST} = \frac{\mathrm{BT}}{1+(0.0000115\times\left(\frac{\mathrm{BT}}{0.01438}\right)\times\log\left(\mathrm{E}\right))} \tag{1}$$

After calculating LST for each image, the team calculated the mean LST for each pixel for the entire collection to have a final LST image for the study period.

The team processed nighttime LST data from ECOSTRESS by first filtering the downloaded collection in RStudio (Version 1.3.1073) to include only nighttime images, defined as 23:00 – 04:00 Pacific time. We then masked clouds and cloud shadows from LST images using the ECOSTRESS cloud datasets. The final collection included 74 images while excluding images with erroneous data values that exceeded the possible temperature range for the study area. Just as for the daytime LST images, the team calculated mean LST of all images in the collection for a single mean nighttime LST image to represent the entire period.

3.2.2 UHI Identification / Urban Heat Maps

Mean LST for the study area was used to identify urban hotspots. To best depict the magnitude of the UHI effect in the study area, the team selected two reference sites to compare to the study area. The team created two reference sites of predominantly agricultural land cover adjacent to the City of Sacramento. One reference site is located south-southwest of the City and east of Dixon, while the other is south-southeast of Sacramento and south of Elk Grove (Figure 2). The team selected these reference sites according to the following criteria: outside of city limits, little urbanization, and similar elevation. Bodies of water and transportation corridors such as highways were excluded. The combined area of the selected reference site polygons closely matched that of the study area.

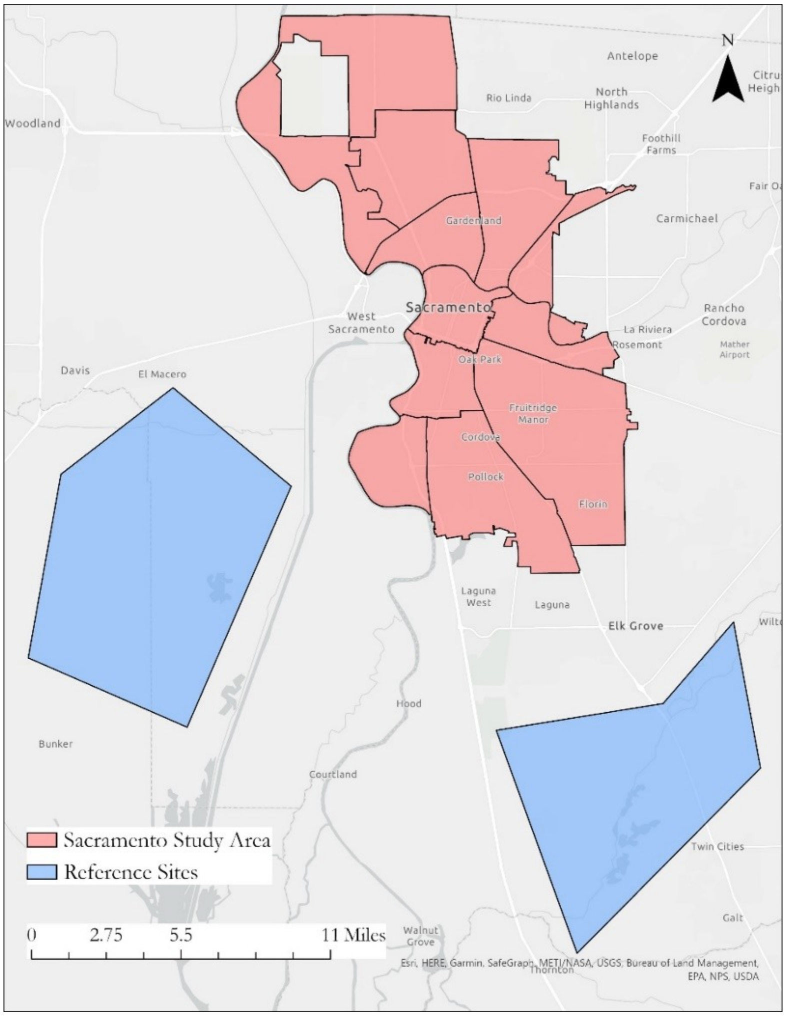

Figure 2. Study area of the City of Sacramento, California (pink) and the team's reference site locations (blue).

To calculate an UHI magnitude for the City relative to the reference sites, the team subtracted the mean LST of the daytime and nighttime reference sites (calculated using the Zonal Statistics as Table tool in ArcGIS Pro) from the mean daytime and nighttime LST images, respectively.

3.2.3. Evapotranspiration (ET)

The downloaded ET datasets were imported into Esri ArcGIS Pro and manually interpreted to discard any layer not matching the criteria highlighted in *Data Acquisition*. The average ET value for each cell was then calculated in ArcGIS Pro using the Cell Statistics tool. The units of ET required for the InVEST model were mm/day and were converted from W/m^2 using Equation 2.

$$1\ \text{mm/day} = 1\ \text{W m}^{-2} \times 0.0864\ \text{MJ day}^{-1}\ \text{W}^{-1} \times 0.408\ \text{mm day}^{-1}\ \text{m}^{2}\ \text{day}^{1}\ \text{MJ}^{-1} \quad (2)$$

3.2.4. Land Use/Land Cover (LULC)
Dyett and Bhatia provided a vector layer of categorized parcels within the city limits. However, the file did not include the North Natomas Special Study Area and had data voids where roads and water existed. The team created and categorized new polygons to fill in these gaps and joined them with the LULC layer. Finally, the team rasterized the vector layer with a 15ft cell size (~4.5m). This resolution was chosen because it was roughly ½ to ¾ width of some of the smallest parcels in the vector layer. The resolution of the LULC raster determines the resolution of all InVEST model output layers

It was necessary to add a "Background" LULC category to the attribute table of the raster. The 'Value' of this new category was automatically assigned a zero by ArcGIS Pro. The 'Background' category then needed to be added to the biophysical table, with its LULC code and all associated values set to 0 in order for the model to run. The model will reproject the input layers and a minimum bounding rectangle will be drawn around the area of interest. An error occurred where the reprojected LULC raster cells just outside the Area of Interest border were appearing with values of 127. Because there was no 127 LULC code in the biophysical table, this caused the model to fail. This was solved by setting the 'No Data' value to 127 when the raster is exported to a .tiff in ArcGIS Pro. At the time of writing, this was a known bug in several of the InVEST models and developers might address this in future releases.

3.2.5. Albedo
The InVEST urban cooling model requires a biophysical table with multiple corresponding values for each land use class. One of these values is albedo, which represents the proportion of solar radiation directly reflected by the LULC type (Sharp et al., 2020). The mean albedo was calculated using a previous Google Earth Engine script from the NASA DEVELOP AZ Spring 2020 Philadelphia Health & Air Quality project (Equation 3). Blue, Green, Red, NIR, SWIR1 and SWIR2 are bands 2, 3, 4, 5, 6, and 7, respectively, in Landsat 8 Surface Reflectance images and the coefficients are empirically derived weighting coefficients (Olmedo, Ortega-Farías, de la Fuente-Sáiz, Fonseca- Luego, & Fuentes-Peñailillo, 2016).

$$\text{albedo} = \text{Blue}\cdot 0.246+\text{Green}\cdot 0.146+\text{Red}\cdot 0.191+\text{NIR}\cdot 0.304+\text{SWIR1}\cdot 0.105+\text{SWIR2}\cdot 0.008 \quad (3)$$

Mean albedo for the City of Sacramento was then overlaid with a land cover dataset provided by the City. An average was then calculated for each land cover type using the Spatial Analyst Zonal Statistics as Table tool in ArcGIS Pro. Results were incorporated into the biophysical table as input for the InVEST urban cooling model.

3.2.6. Shade
Shade was another required value in the InVEST urban cooling model biophysical table input. Tree canopy cover was used as a proxy for shade. The team used the

ESRI USA NLCD Tree Canopy Cover 2016 layer (30m resolution) in ArcGIS Pro that was derived from the MRLC analytical version of this dataset in the calculation of shade. The team used the Spatial Analyst Zonal Statistics as Table tool to calculate the mean tree canopy cover per land cover type from the LULC vector layer. Results were then incorporated into the biophysical table as input for the InVEST urban cooling model.

3.2.7. Crop Evapotranspiration (Kc)

The InVEST model uses the crop evapotranspiration coefficients to predict the amount of evapotranspiration in a cell. However, since the evapotranspiration raster for the area of interest reflects actual evapotranspiration rather than potential evapotranspiration, the team assumed the actual evapotranspiration derived from ECOSTRESS had already integrated the crop coefficient into the calculation. Therefore, because the model requires a Kc value in the biophysical table, all Kc values were set to 1 as to not affect input ET. This results in the use of the original observed actual evapotranspiration within the model.

3.2.8 Building Intensity

Building Intensity is a product of the cumulative floor area of buildings on a certain land use category divided by the area of land of that category, which we estimated to the best of our ability. Our partners provided us with an incomplete cartographic layer of buildings in the city. The team performed a one-to-one spatial join of building polygons to the LULC vector, according to the where the building polygon center was located. To fill in the gaps of the dataset, the heights of buildings within each LULC category were examined, and reasonable representative heights were then assigned to any building within each LULC category that did not have height data. Then, building height was divided by a typical ceiling height for that building type (see Table B1) to produce an estimate of the number of floors in each building, rounded to the nearest whole number and any zeroes replaced with a 1. Building Intensity within each LULC category was then calculated according to Equation 4.

$$\text{Building intensity} = \sum \left(\text{Building Area} \times \text{Floors}\right) \div \text{Land Area} \tag{4}$$

3.2.9. Heat Risk

The CalEnviroScreen 3.0 shapefile product was clipped to the study area and invalid geometries were removed. The census tracts did not perfectly align with the study area shapefile (for example, inclusion of the river), so unaligned polygons and small slivers were edited to align with the study area polygons. For GEE to accept the shapefile, it was converted from multipart to singlepart. Small slivers and unaligned polygons were again checked to ensure alignment with the study area. Small slivers were removed and/or absorbed into adjacent polygons. Fields not relevant to the heat risk analysis, such as pollution metrics, were removed from the attribute table.

The team joined census tract data from the 2017 U.S. Census 5-Year Estimate 65 and older population data and instances of homeless encampments from the City of Sacramento’s 311 dataset to the CalEnviroScreen 3.0 shapefile. This shapefile was used to extract nighttime LST per census tract, which was then joined in the attribute table. This shapefile was then imported into GEE to calculate mean daytime temperature per census tract. Finally, the team exported the shapefile as a .csv for analysis further in Excel.

3.2.10 InVEST Input Data

Input layers into the InVEST urban cooling model include the LULC raster, the Area of Interest vector, the Evapotranspiration raster, and a biophysical table .csv that includes shade, Kc, albedo, and building intensity averages for each land use type (see section 3.2). The team used the biophysical table from the practice data folder (available for download on the Natural Capital Project website) of the InVEST urban cooling model user guide as a template.

Before using the InVEST urban cooling model, the team read the user manual and paid special attention to the formulas mentioned to thoroughly understand how each metric was being calculated. The team also audited the InVEST EdX MOOC before attempting to run the model and recommends doing so for future replication. To prepare the input layers, the team projected them into the same coordinate system and ensured the units of measurement were metric. All the supporting files for the area of interest vector had to be stored together, even though only the .shp was selected as the input in the model GUI; otherwise, the model would not run. Raster layers were all in .tiff format and all temperature values for InVEST inputs were in degrees Celsius. The team used the default values for Air Mixing Distance (2000m) and for Green Area Maximum Cooling Distance (400m), as this data was not available from the project partners.

3.3 Data Analysis

3.3.1 InVEST Urban Cooling

The team ran the InVEST urban cooling model under four different scenarios: current conditions and city-wide tree canopy cover increases of 10%, 20%, and 30%, as suggested by the City of Sacramento. The latter three scenarios increased shade cover proportionally for all but four of the land use categories. These four land use categories (‘vacant’, ‘open space/recreational’, ‘public’, and ‘schools’) are under more direct city jurisdiction and were therefore set at the City’s goal of 35% tree canopy cover for all scenarios, per the partners’ instruction. The model produces several outputs which were used for further analysis and comparison, including a cooling capacity raster, a heat mitigation index raster, and an estimated temperature raster. Temperature anomaly (T_{anom}) under current conditions and each of the three hypothetical scenarios was calculated by subtracting the mean LST of the reference sites from the modeled temperature output raster using the Raster Calculator function in ArcPro (Figures B1 – B4). Using the same tool, the team then subtracted the current condition temperature anomalies from those of the hypothetical scenarios’ temperature anomalies to produce a change in overall temperature anomaly (ΔT) (Equation 5). Areas with a decrease in temperature anomaly under this scenario would result in negative value, while those experiencing an increase in temperature anomaly would result in a positive value (Figures B5 – B7).

$$T_{anom} = \quad temp_{raster} - 34.58 \tag{5}$$

3.3.4 Heat Risk

The heat risk index was calculated in Excel following the methodology of California OEHHA's CalEnviroScreen. A detailed example of this calculation can be found in CalEnviroScreen 3.0 report. For each individual metric, the percentiles of the raw values were calculated and maintained relative to the City of Sacramento. The team retained enough significant figures to eliminate rank ties. A mean percentile value was calculated for vulnerability and exposure from each of their respective metrics. Vulnerability factors were evenly weighted, while exposure factors were weighed unevenly. The team chose to weigh daytime LST values half as heavily as the nighttime LST values following previous research that suggests that nighttime temperatures are greater predictors of heat-related health outcomes than daytime temperatures (Hajat et al. 2005; Schwartz et al. 2005; Zhang et al. 2012). The team used Equation 6 to calculate exposure, where $mDLST_i$ and $mNLST_i$ are the mean daytime and nighttime LST values, respectively, for census tract i:

$$\text{Exposure} = \frac{\left(\text{mDLST}_i \times 0.5\right) + \text{mNLST}_i}{1.5} \tag{6}$$

The values for vulnerability and exposure, termed component scores, were then scaled by the city maximum. A composite risk score was then calculated from these component scores using Equation 7:

$$\text{Risk} = \text{Exposure} \times \text{Vulnerability} \tag{7}$$

The team calculated the percentiles for these scores, which could then be visualized spatially by census tract. These final percentile risk index scores are used to identify neighborhoods in Sacramento with higher heat risk relative to each other.

4. Results & Discussion

4.1 Analysis of Results

4.1.1 UHI/Hotspot Identification

Sacramento is on average 7.3°F warmer than reference sites outside the City, with temperature differences ranging from as low as 40°F cooler to as high as 40°F warmer during daytime hours (Figure 3, Figure C1). During nighttime hours, the City ranged from 6°F cooler to 18°F warmer than the reference sites (Figure 3, Figure C2). Most of the areas that experienced high daytime UHI magnitude maintained higher temperatures at night, suggesting that these areas offer little relief from the heat for their residents. Urban hotspots were identified in the following communities: North Natomas, Central City, and eastern Fruitridge/Broadway. The greatest differences in temperature occurred in highly urbanized areas with little green space such as North Natomas. Areas that were cooler on average than the reference sites were green spaces with substantial tree cover and shade.

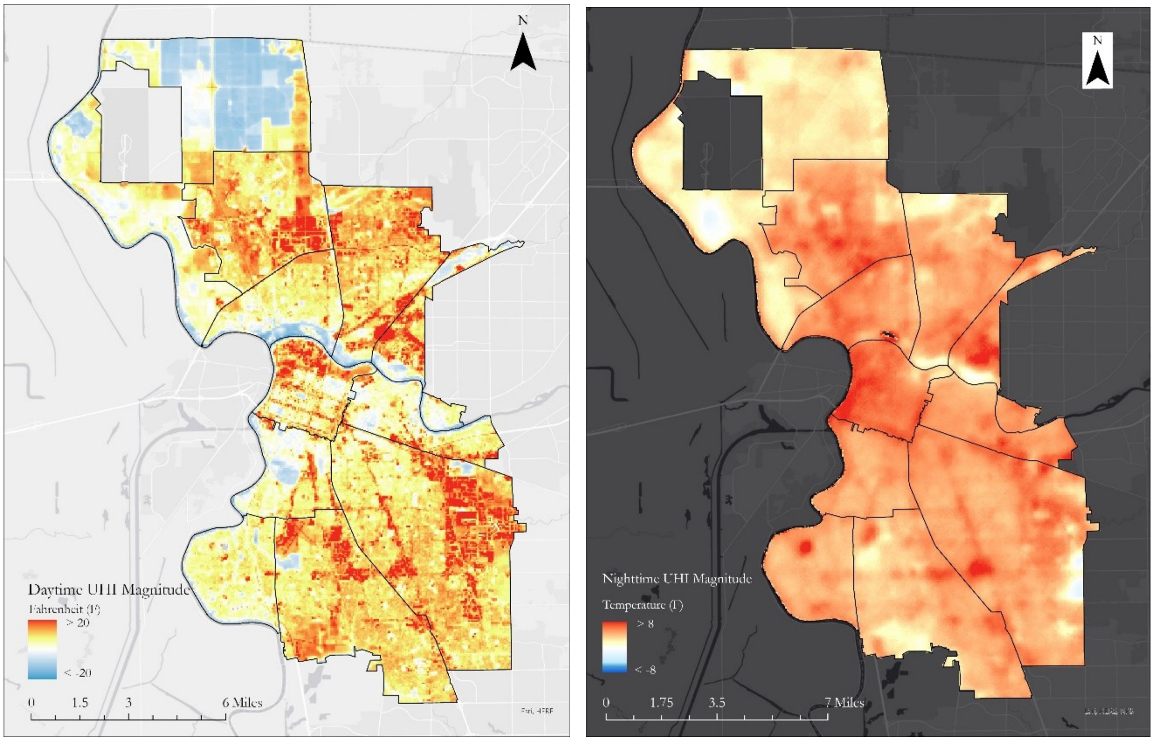

Figure 3. Daytime Urban Heat Island (UHI) Magnitude (left) and Nighttime Urban Heat Island (UHI) (right) for the City of Sacramento.

4.1.2 Heat Risk

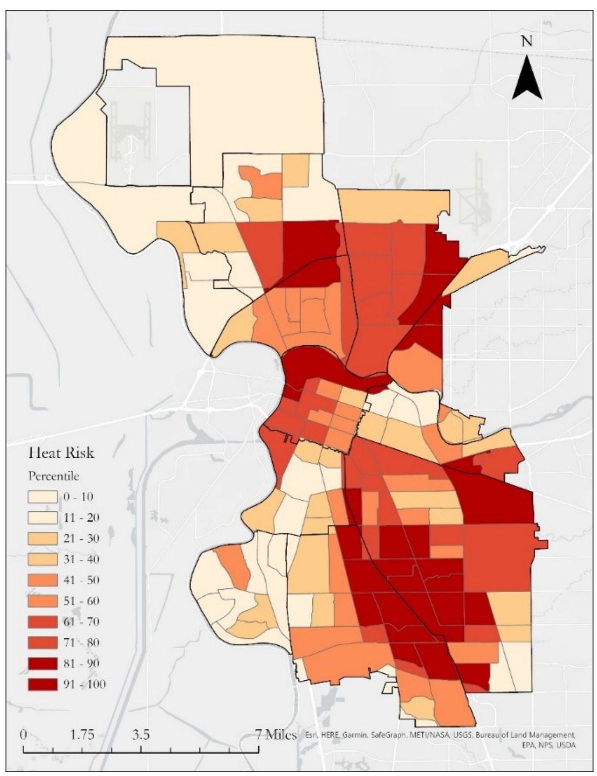

Figure 4. Heat Risk Percentile for the City of Sacramento

Heat exposure (Figure C3) and social vulnerability (Figure C4) did not always coincide in Sacramento. For example, the City Center experiences one of the highest UHI magnitudes but has a relatively low social vulnerability. In contrast, areas such as North Sacramento and the southern portion of South Area have relatively high social vulnerability scores but lower UHI magnitudes. Heat Risk incorporates both of these variables into a holistic perspective (Figure 4).

4.1.3 InVEST Urban Cooling Model

Cooling capacity is an intermediary output of the InVEST urban cooling model and is a product of shade, albedo, and evapotranspiration by land use type. It represents an area’s ability to counteract extreme heat. The darker red areas in the daytime cooling capacity map in Figure 5 represent areas that have low capacity to cool, typically experience higher temperatures, and are therefore opportunity areas for improvement. Large swaths of agricultural land, like in the northern most study area, can be misleadingly categorized as having low daytime cooling capacity due to their low shade and albedo values. Compare this area to the same location into the Daytime Heat Mitigation map (Figure 6); the area shifts from red, or low cooling capacity, to blue, or high meat mitigation. Discussed below is the importance of open green space in heat mitigation, which is not considered in the cooling capacity calculation.

The nighttime InVEST urban cooling model option considers only building intensity because buildings retain heat from the day and re-emit it at night. Residential areas are particularly red in the nighttime map in Figure 5, meaning low capacity for cooling. This is likely a function of the high number of housing units packed very tightly together on small parcels of land, more so than a function of their height.

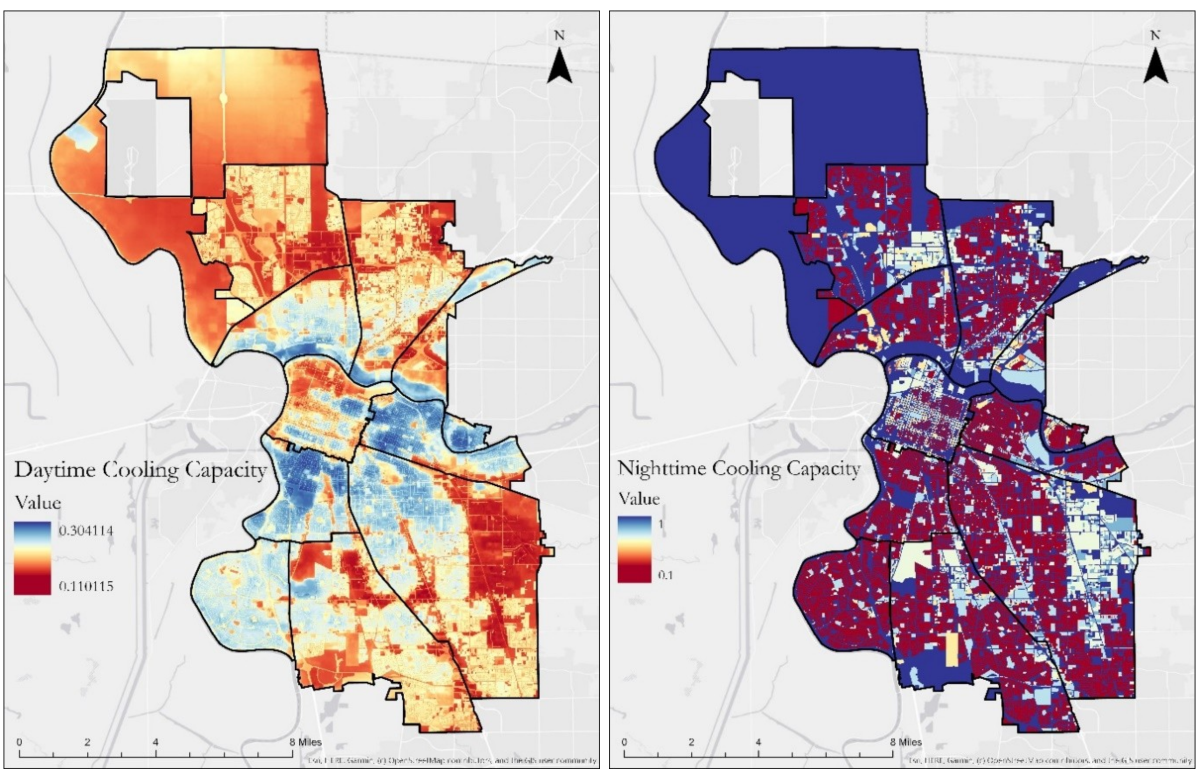

Figure 5. Daytime and Nighttime Cooling Capacity

The main InVEST urban cooling model output is a heat mitigation index raster. Heat mitigation is equal to cooling capacity unless pixels are given the green space designation in the biophysical table or are within the ‘Green Area Maximum Cooling Distance,’ as defined in the model GUI. Cells nearby a green space area over two hectares are given a distance-weighted average of heat mitigation (InVEST | Natural Capital Project). Dark red areas in the Daytime Heat Mitigation map (Figure 6) are places where there is low heat mitigation, higher temperatures, and therefore represent opportunities for the City to improve, while white/blue areas are where heat is being mitigated more effectively. Agricultural land in the northwest is deep blue and is providing cooling benefits to the residential areas along its border. Small sections in the western portions of the city, which represent parks, are also providing extra cooling benefits to the surrounding areas. Major transit corridors and many blocks appear dark red. These may be good locations for City investment in heat-mitigation strategies. These results demonstrate how important open green spaces are to urban heat mitigation.

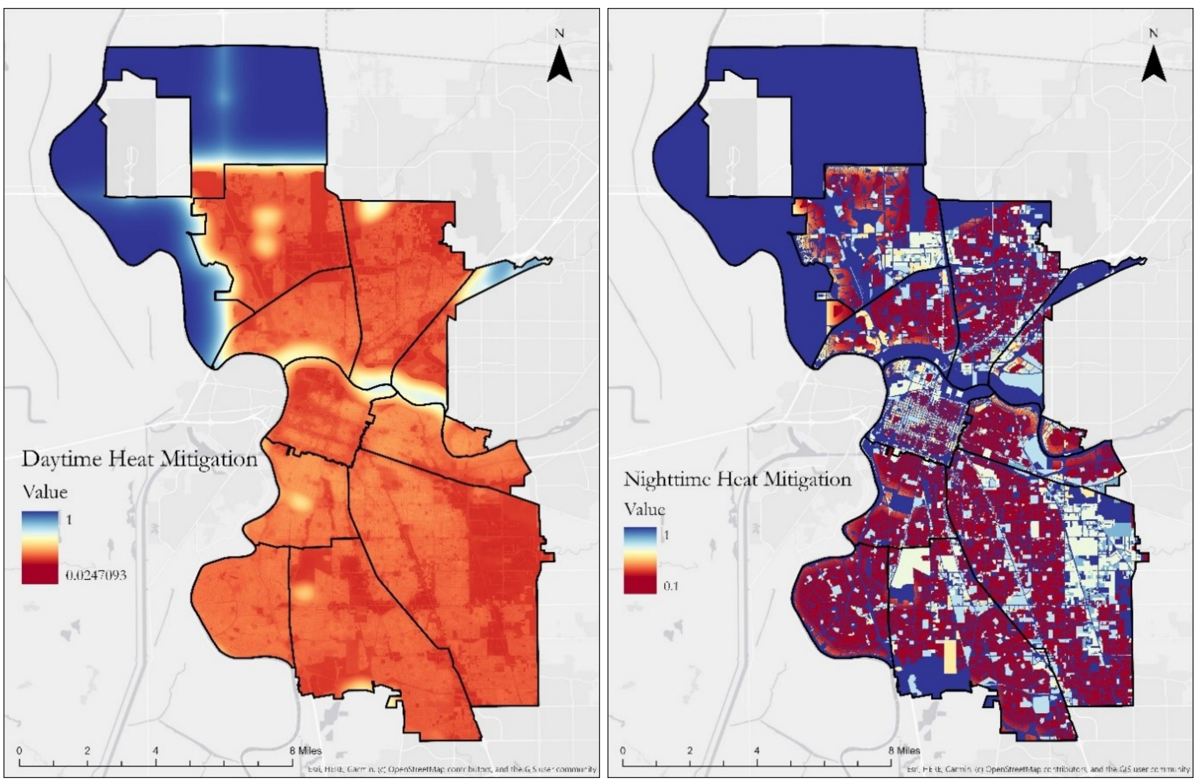

Figure 6. Daytime and Nighttime Heat Mitigation

The City of Sacramento was concerned with both social equity and cost efficiency in prioritizing heat mitigation investments. To serve both of these goals, the team averaged heat mitigation within census tracts using the ‘Zonal Statistics as Table’ tool in ArcPro, then joined the results with the Heat Risk map. Graphing Heat Risk against mean HMI in a scatter plot, census tracts in the top percentile were selected as priority areas (Figure C5). These 34 census tracts have low current capacity for extreme heat mitigation and very high-risk populations. The average

HMI is 0.19 and average daytime LST is 105.5ºF. Investment here would impact 166,371 citizens.

4.2 Uncertainties/ Limitations

Several assumptions were made throughout the project. Firstly, nighttime hours were defined as 11pm – 4am local time to represent the coolest part of the night and to maximize the number of images to ensure a stable mean. Additionally, the default cloud masks were applied for both Landsat and ECOSTRESS satellite imagery. Although the cloud mask can introduce error, the nighttime cloud mask can be particularly difficult to ensure accuracy as they are based on only temperature, not optical imagery. Daytime LST values were half-weighted in the heat risk analysis. While this is grounded in current literature that nighttime temperature is a greater risk for health-related outcomes, the end users and future studies may want to consider different weights.

The InVEST Urban cooling model is a new and imperfect tool. In part, this study serves as a test for how useful and accurate the model is. The model can be calibrated by manually adjusting coefficients in the model interface, but this requires ground-truthing, which was not possible within the ten-week project timeframe. Ground-truthing of its results may be needed if users would like to calibrate the model to better fit their circumstances. The team made partners aware of this option as a potential for future use. The InVEST Urban cooling model results are spatially explicit. However, the model averages shade, albedo, Kc, and building intensity for each LULC category. Therefore, the results are quite generalized and do not necessarily reflect conditions on the ground. Additionally, cooling capacity and heat mitigation are unitless values and therefore should not be interpreted as a percent of heat mitigated.

Additionally, the InVEST Urban cooling model expects temperature values to refer to air temperature, not surface temperature. Therefore, the intermediate air temperature outputs are not true air temperature. Using surface temperatures introduces more error into the model. While it is preferable to use a more precise estimate, the team did not have an estimate for Sacramento and therefore used the 2000m default value for air mixing distance. However, since the reference temperature and urban heat magnitude values are based on surface temperature (instead of air temperature as the model expects), then this value becomes much less important, rendering the intermediary output of temperatures after air mixing meaningless. The inputs to the model relied on some assumptions due to a lack of precise data. These included using generalized building heights and estimating floor numbers, using the default value for green area cooling distance, and calculating shade based only on tree canopy cover, which ignores building shade. Tree canopy cover was calculated using the lower resolution National Land Cover Dataset, which did not always correspond well with City-owned tree data.

4.3 Future Work

Along with investigating the uncertainties that were described above, further research into additional vulnerability datasets could be conducted to include a greater understanding of vulnerability and risk. The InVEST model also allows users to run additional valuations and scenarios that the team was not able to run due to the ten-week timeframe, but the partners can likely still utilize the model to continue their research for the update of the 2040 General Plan. These valuations consist of the percent work loss conversion into dollar value based on workforce size and salary, and the energy savings optional valuation, which measures the kilowatt hours consumed and the economic cost of cooling buildings under extreme urban heat.

5. Conclusions

This study shows that Sacramento citizens experience much hotter summer temperatures than nearby less developed areas in the Central Valley due to the urban heat island effect. Daytime LST is as much as 40ºF higher within the City. Extreme heat is unevenly distributed around the city. Local heat islands are located in the Central City, North Natomas, Arden Arcade, and Fruitridge/Broadway communities. Several areas of the city do not cool down significantly overnight, especially in the city center, exposing citizens to constant heat stress. Nighttime temperatures can be as much as 18ºF hotter than outside the city. While air temperature analyses more accurately assess how people experience heat, LST studies, such as this one, illustrate the sources of heat, which empowers end users to address the core causes of UHI.

Vulnerable communities are also unevenly distributed across the city. The team created a new heat risk index, relative to the City, that incorporates age, race, and homelessness, as well as other typical sensitivity and social indicators of vulnerability used in existing indexes. This is the first study in Sacramento to include a spatial representation of homelessness in the analysis. This work maps heat exposure and social vulnerability separately. However, the results illustrate the importance of considering both factors in conjunction when identifying targets for heat mitigation improvements since high exposure and high vulnerability do not always coincide. Failure to consider both together may result in inefficient allocation of resources.

The results of the InVEST model map heat mitigating ecosystem services in the City of Sacramento. The team has provided spatially explicit insight into where cooling capacity may be bolstered to alleviate the urban heat island effect. By cross referencing the heat mitigation index and the results of the heat risk analysis, the team identified 34 census tracts for priority intervention. The partners were particularly interested in considering the roll of urban greening as a heat mitigation strategy. By running the InVEST urban cooling model under 3 different scenarios of tree canopy cover, the team provided an estimate of how increasing shade alone can reduce city temperatures. These results also illustrated the ecosystem service value of open green space. Open green space provides minor refuge from urban heat as well as provides extra cooling benefits to the nearby built environment. The study also shows that transit corridors tend to be sources of urban heat and are not currently well mitigated in the City of Sacramento.

The partners may use these results to set goals for tree canopy cover and to create policies for new development going forward in their update to the City of Sacramento’s 2040 General Plan. This study also served as a feasibility test for using the InVEST urban cooling model. The lessons learned and the limitations thereof, discussed above, can be carried forward by the partners or other DEVELOP teams to support further studies.

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7. Glossary

Albedo – the fraction of light that is reflected by a surface
Cooling Capacity – a measure of a system's ability to remove heat
Earth observations – satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) – satellite mission that aims to measure how the terrestrial biosphere changes in response to environmental changes such as water availability
Evapotranspiration – the sum of evaporation of water from land and other surfaces and through transpiration by plants
Heat Mitigation Index – an index to estimate temperature reduction by vegetation
Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) – a suite of models used to map and value the goods and services from nature that benefit human life
Land Surface Temperature (LST) – the temperature of the surface of the Earth
Operational Land Imager (OLI) – sensor aboard the Landsat 8 satellite that measures visible, near-infrared, and shortwave infrared wavelengths
Thermal Infrared Sensor (TIRS) – sensor aboard the Landsat 8 satellite that measures both Earth's surface temperature and atmosphere temperature
Urban Hotspots – Areas of high urban air temperature
Urban Heat Island (UHI) effect – Heat islands are urbanized areas that experience higher temperatures compared to surrounding areas due to impervious materials, such as asphalt, that absorb and remit solar heat more than natural vegetation (US EPA, 2014)

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9. Appendices

Appendix A

Table A1
Platforms and sensors

Platform & Sensor	Parameters	Use
Landsat 8 OLI/TIRS	Surface reflectance to calculate albedo and daytime surface temperature	The thermal band and emissivity of the surface reflectance product and were used to calculate daytime land surface temperature and hotspots for 2016-2020. Surface reflectance was also used to calculate albedo for use in the InVEST model.
ISS ECOSTRESS	Nighttime land surface temperature images and cloud masks, Evapotranspiration	Nighttime measurements of land surface temperature were gathered from ECOSTRESS to enhance the partners' understanding of urban heat dissipation and consequent neighborhood-level health concerns. Evapotranspiration rates were gathered from ECOSTRESS for use in the InVEST model.

Appendix B

Table B
Generalized Building Values

Single Family	Typical Building Height (ft)	Estimated Ceiling Height (ft)
Multi-Family	25	9
Retail/Commercial	25	9
Industrial	20	15
Light Industrial	16	15
Office	16	15
Mobile Home	30	9
Mixed Use	10	15
Institution	30	15
School	16	15
Public	25	15
Vacant	25	15
Open Space/Recreation	16	15
Utilities	12.5	15

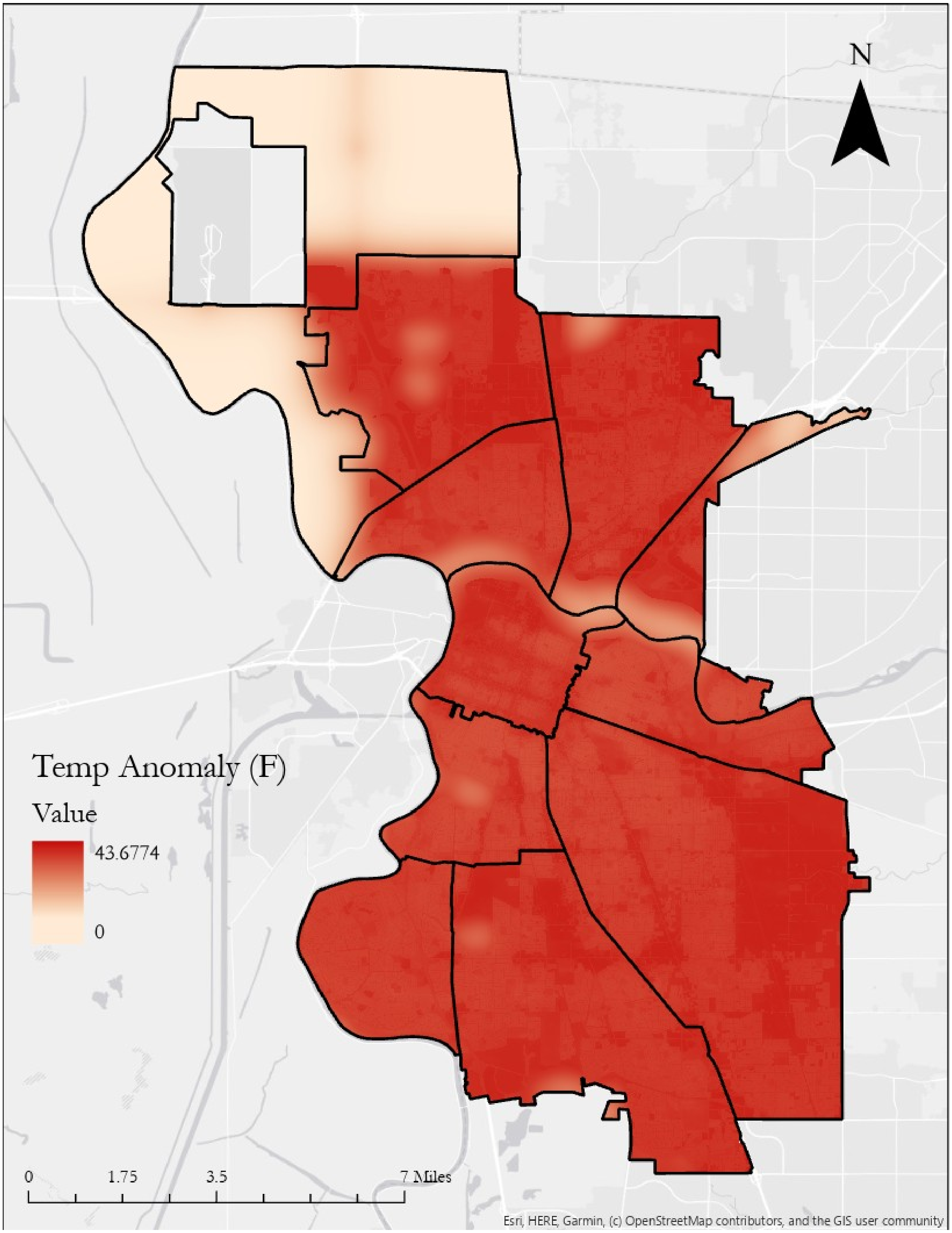

Figure B1. Temperature Anomaly with Current Conditions

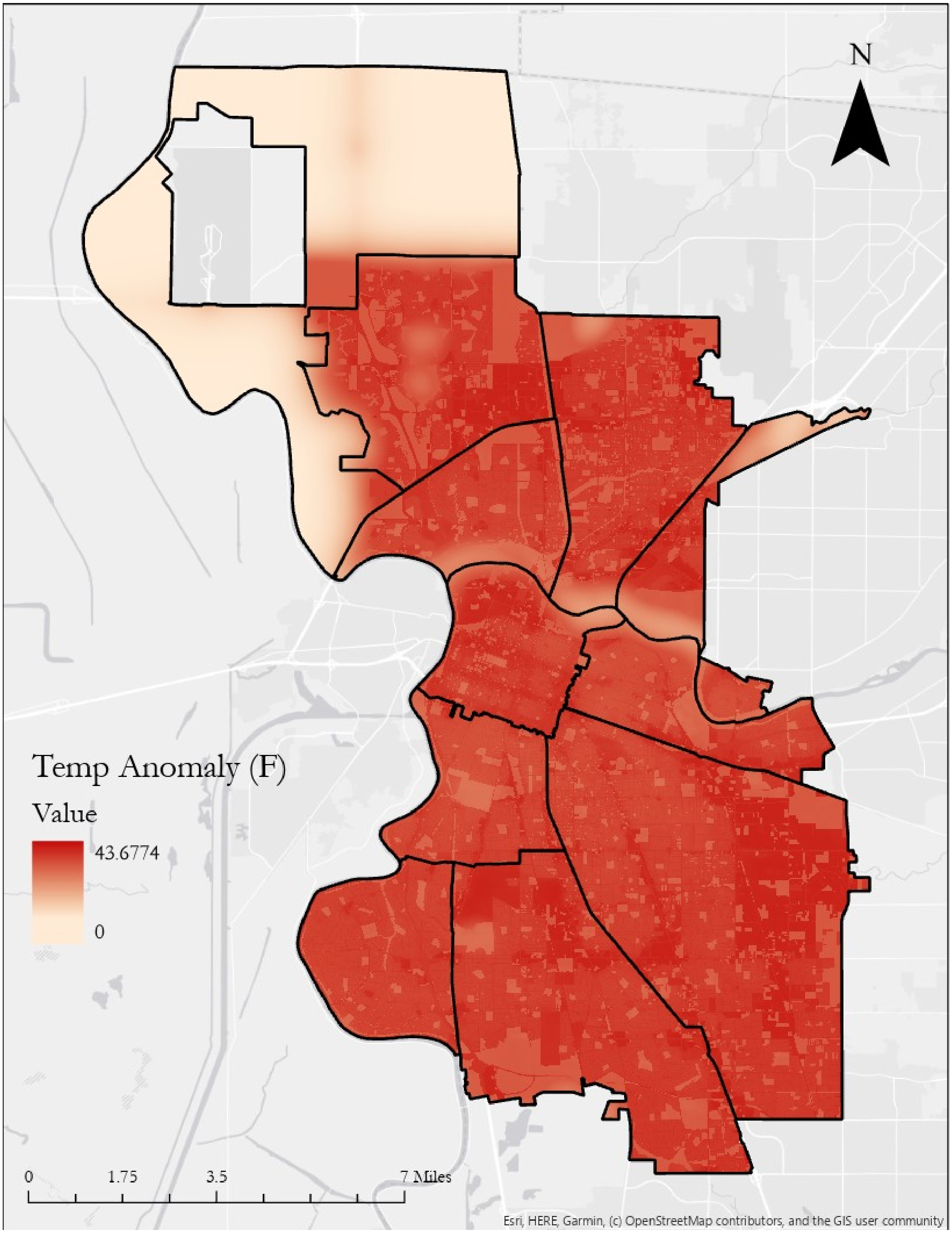

Figure B2. Temperature Anomaly with 10% Tree Canopy Increase

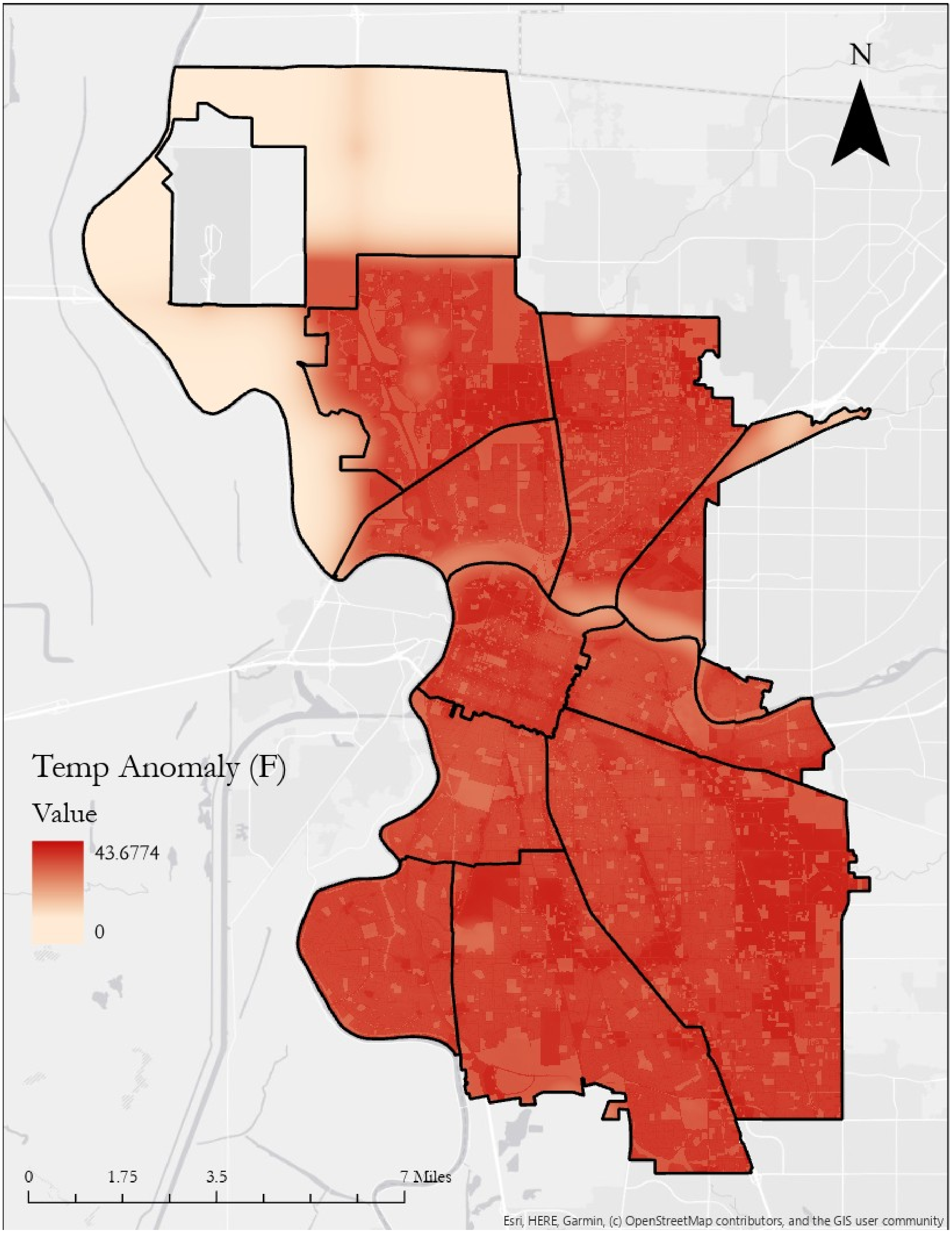

Figure B3. Temperature Anomaly with 20% Tree Canopy Increase

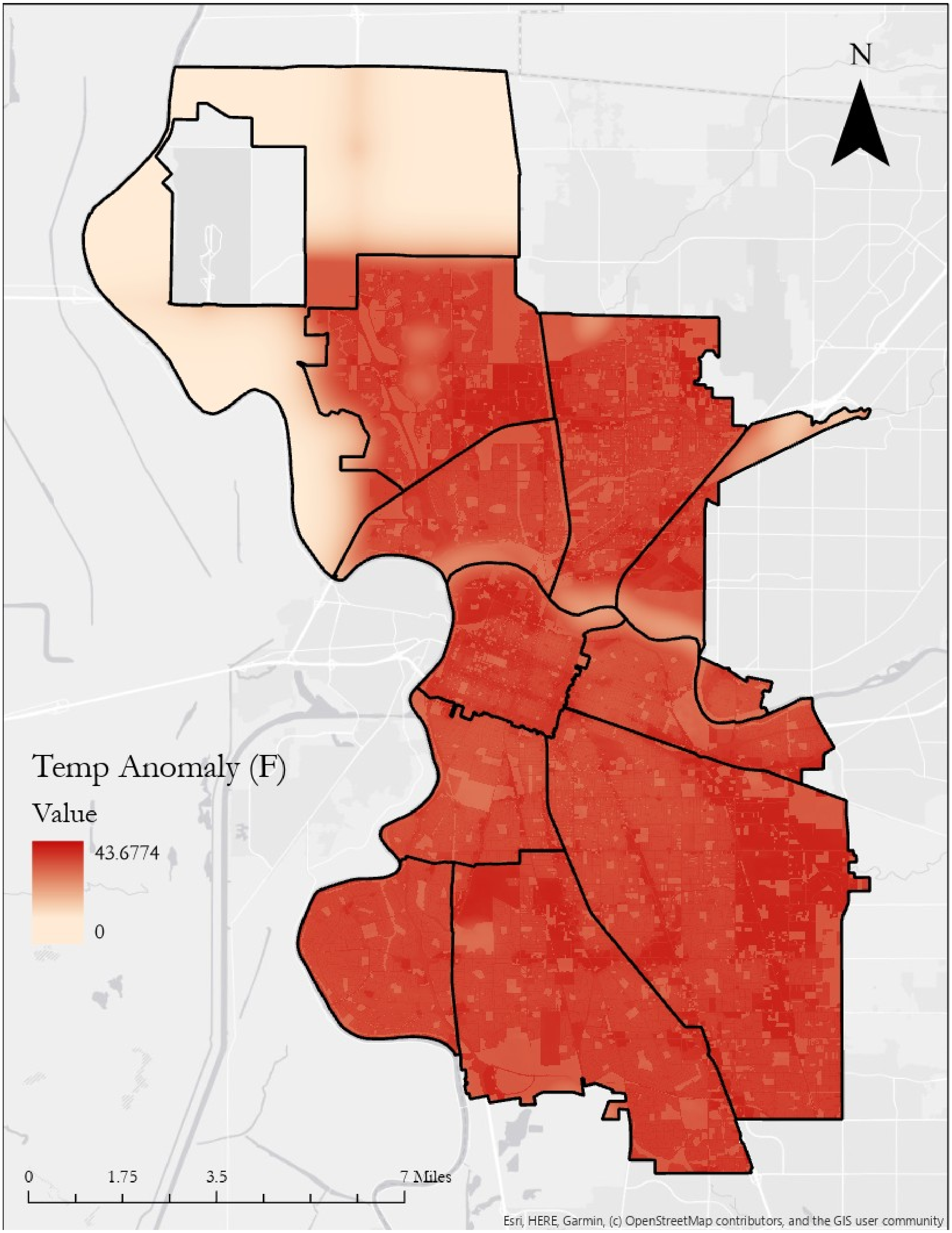

Figure B4. Temperature Anomaly with 30% Tree Canopy Increase

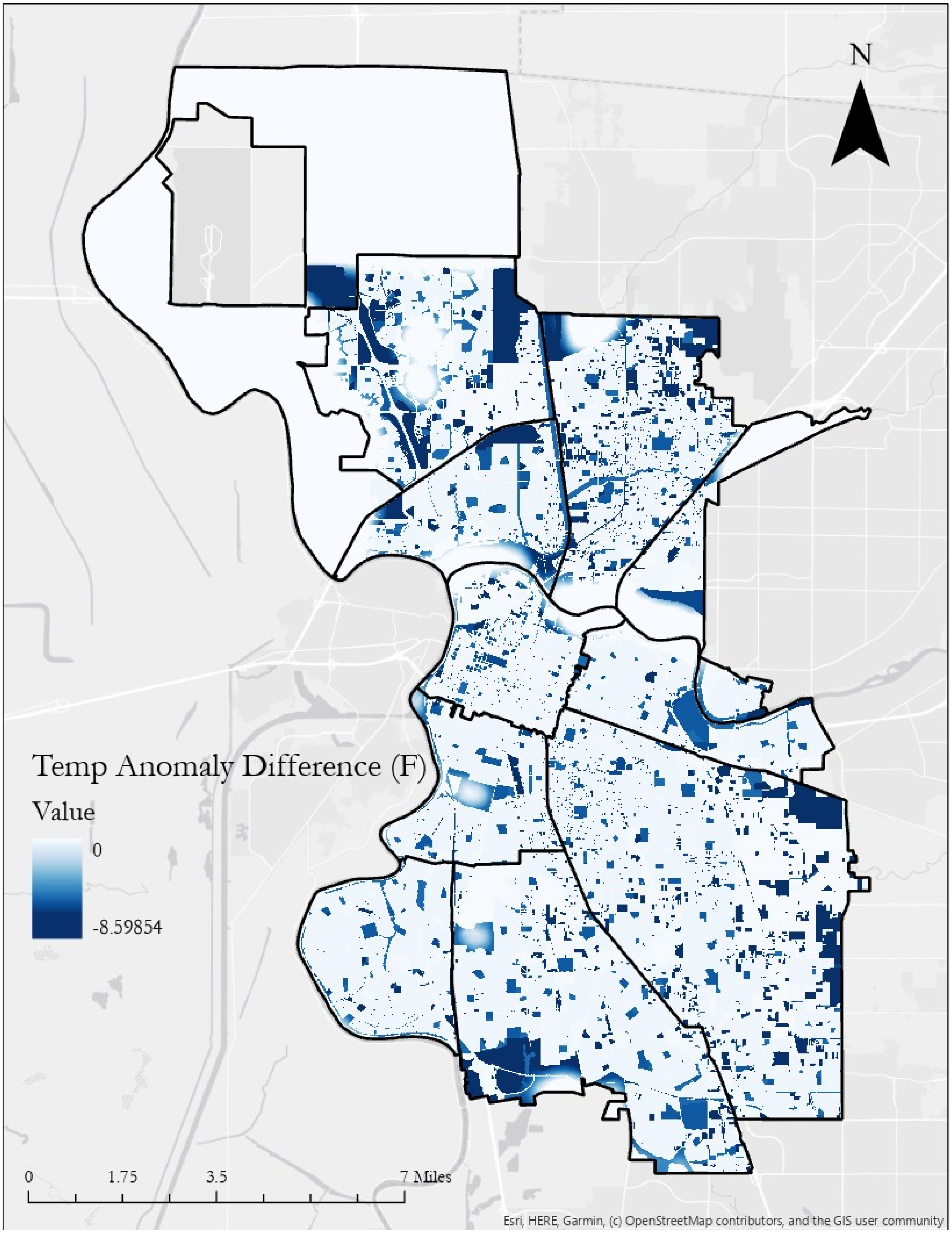

Figure B5. Difference in Temperature Anomaly between 10% Tree Canopy Increase and Current Conditions

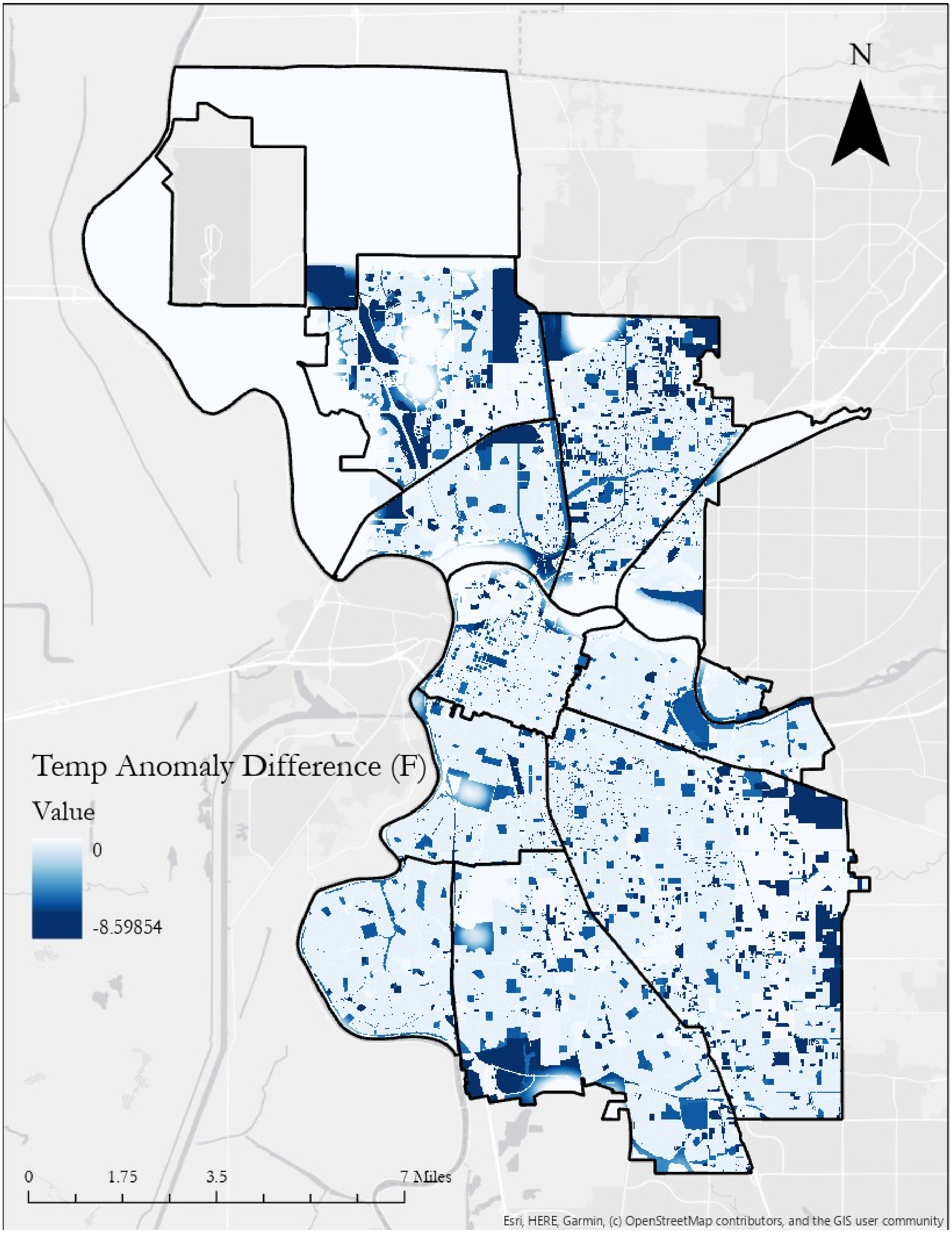

Figure B6. Difference in Temperature Anomaly between 20% Tree Canopy Increase and Current Conditions

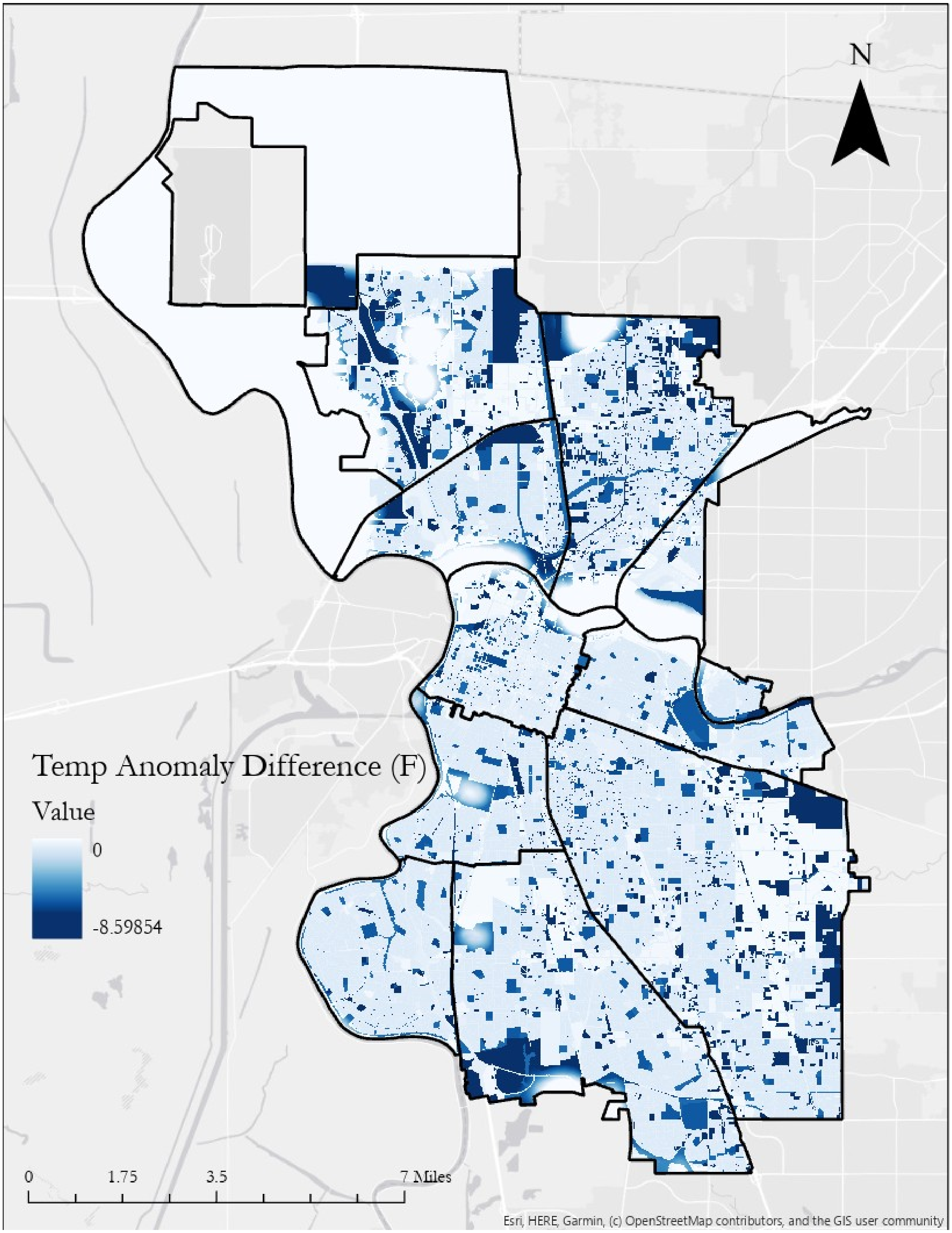

Figure B7. Difference in Temperature Anomaly between 30% Tree Canopy Increase and Current Conditions

Appendix C

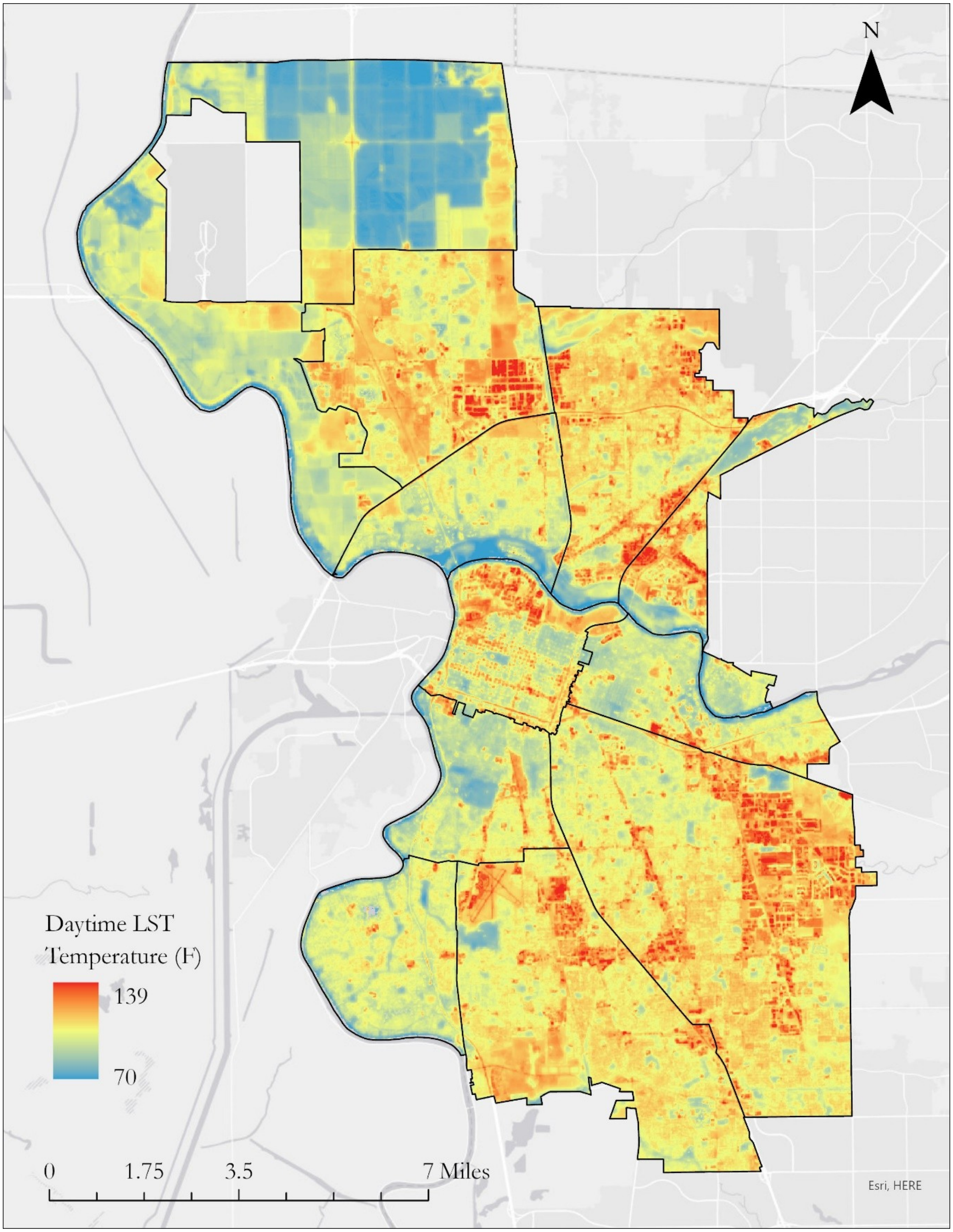

Figure C1. Daytime Averaged Land Surface Temperature

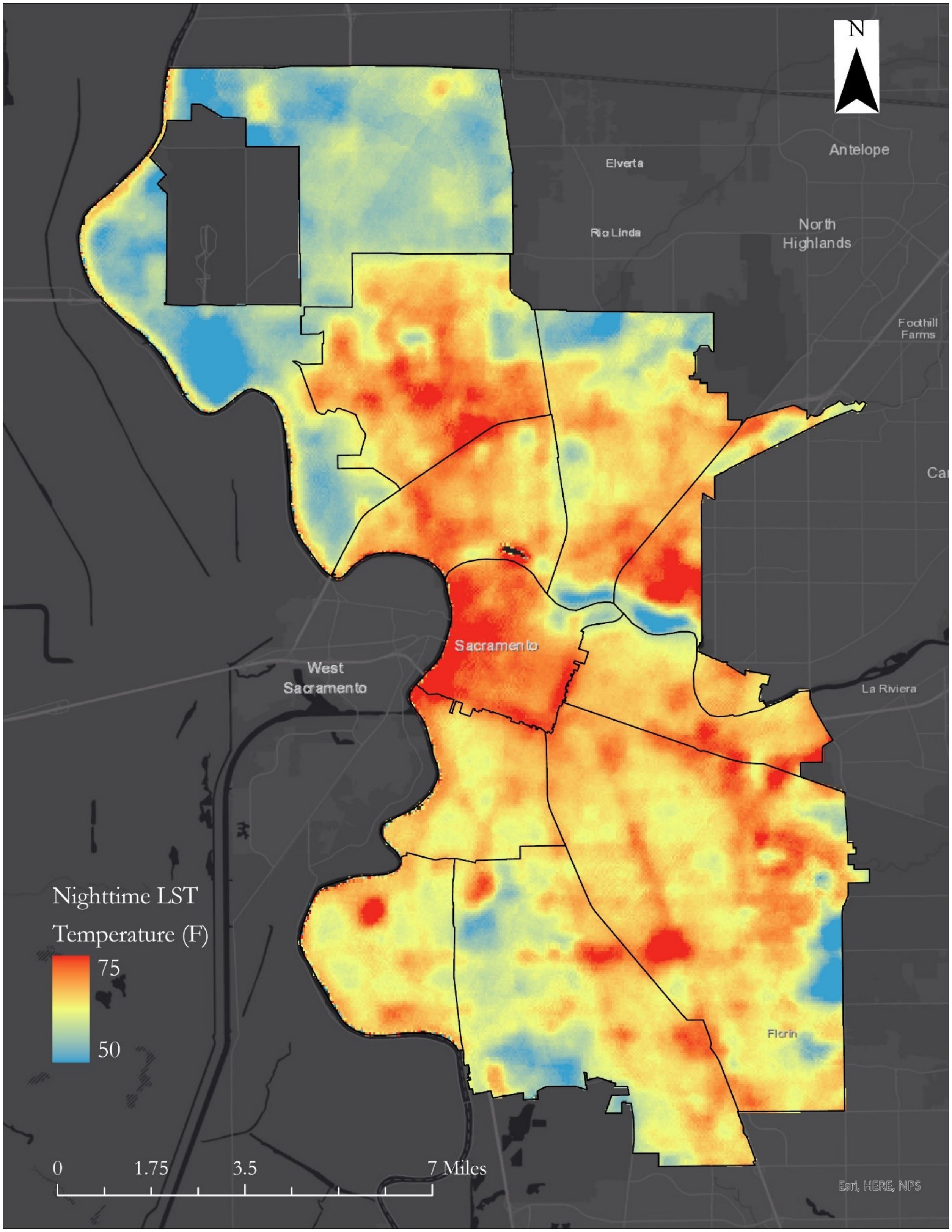

Figure C2. Nighttime Averaged Land Surface Temperature

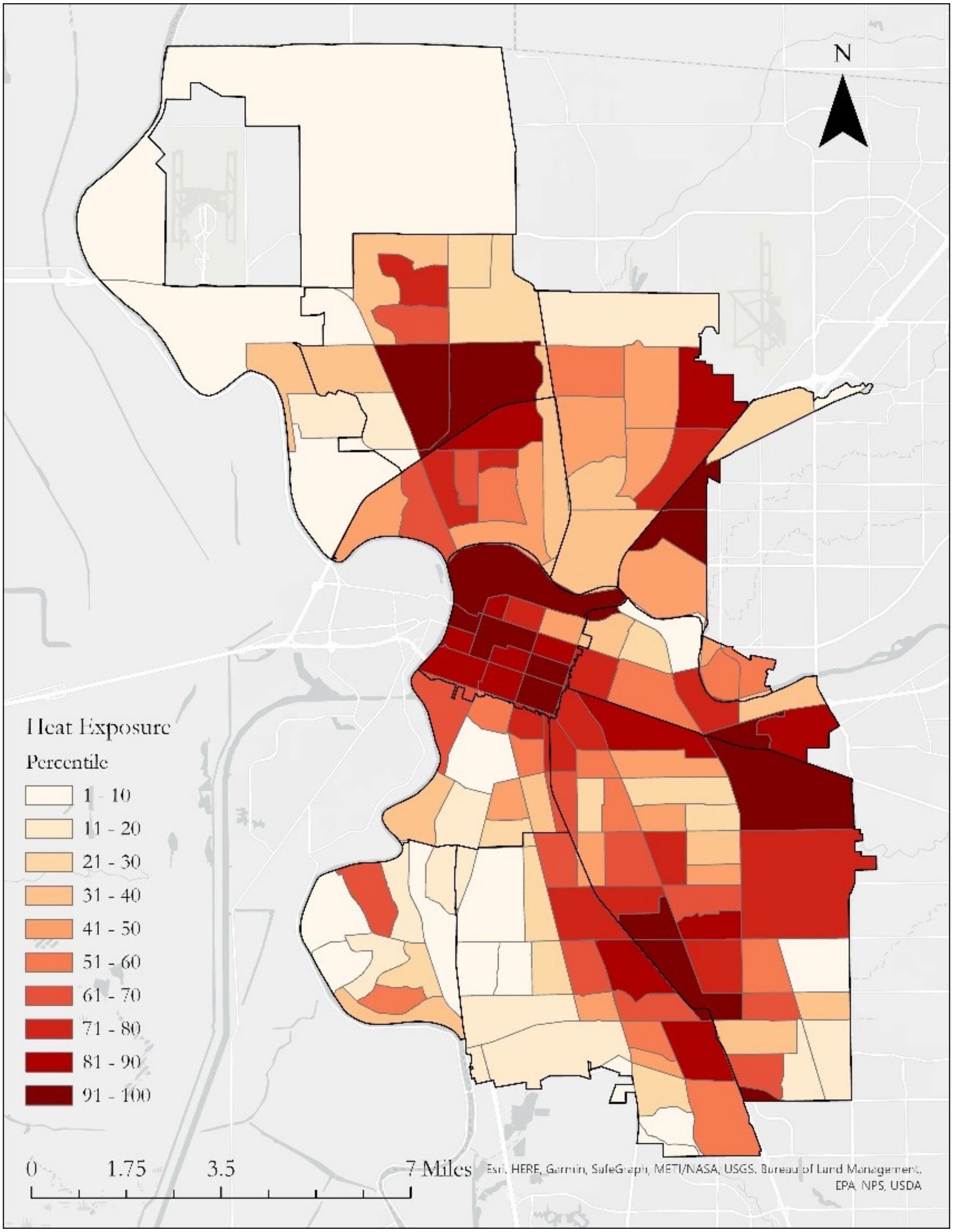

Figure C3. Heat Exposure Percentiles for the City of Sacramento

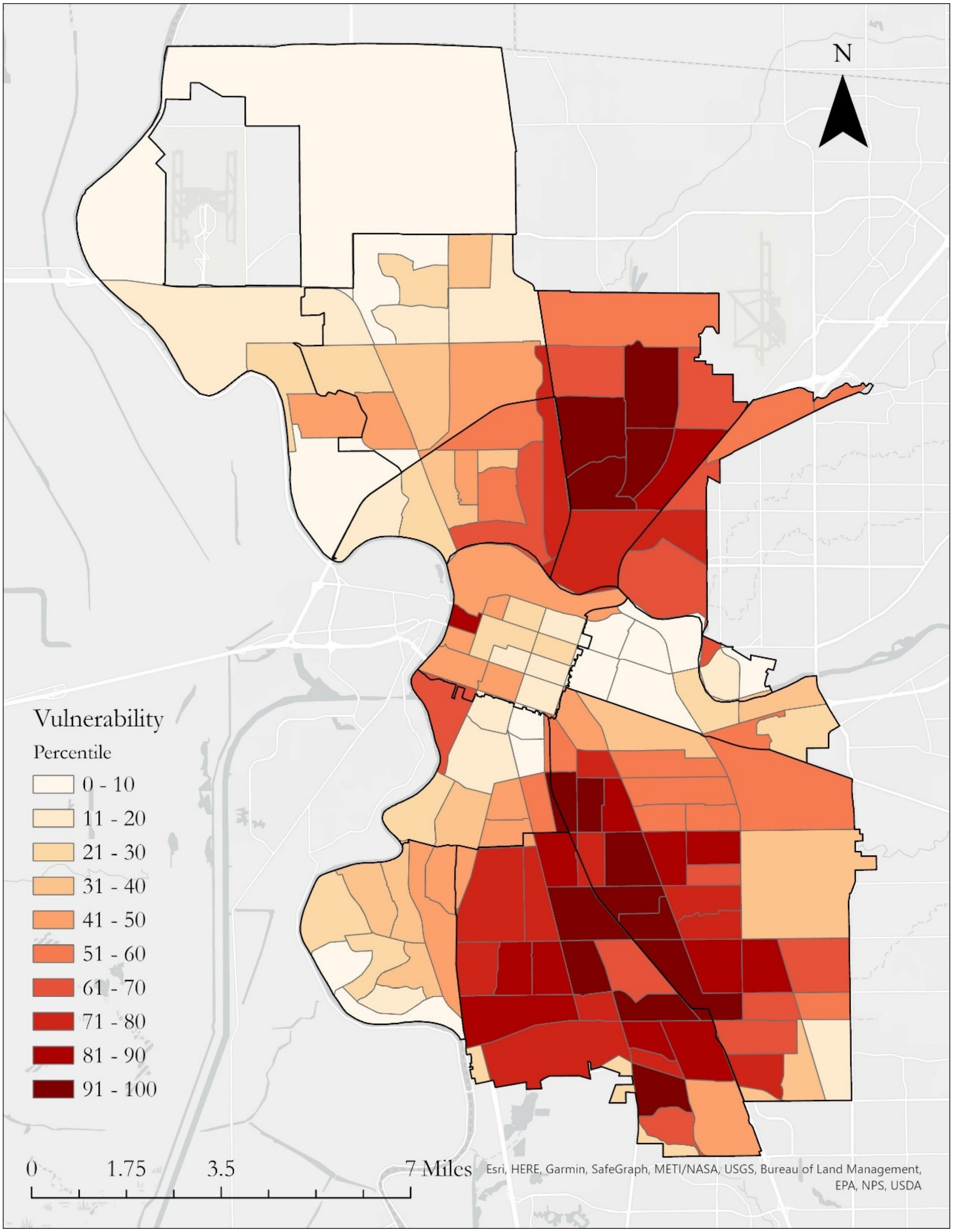

Figure C4. Social Vulnerability Percentiles for the City of Sacramento

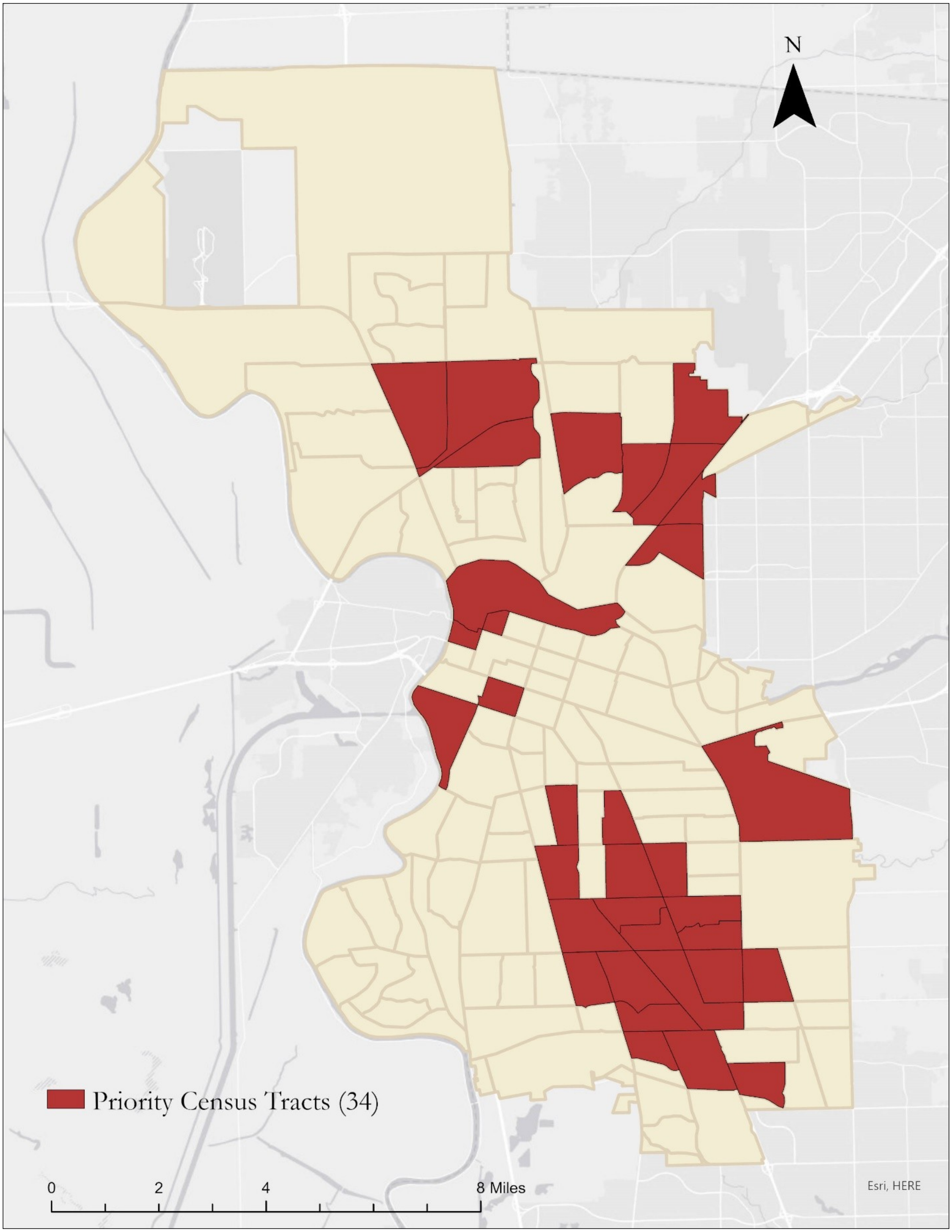

Figure C5. Priority Census Tracts (Low Current Capacity for Extreme Heat Mitigation and Very High-Risk Population).