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Bridgeport Urban Development

Leveraging NASA Earth Observations and Sociodemographic Data to Assess Urban Heat Vulnerability and Inform Cool Corridors in Bridgeport, Connecticut

DEVELOP Technical Report
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1. Abstract

Urban environments face hotter temperatures than suburban and rural areas due to higher concentrations of impervious surfaces, heat-retaining buildings, and lack of green space. Bridgeport, Connecticut, which was formerly a national manufacturing hub, is now the densest and most populous city in the state. Bridgeport experiences hotter temperatures, exposing its residents to more extreme temperatures than the surrounding affluent suburbs. Extreme heat affects the health of those exposed to it and intensifies energy demands. Understanding temperature differences is the first step in effectively directing mitigation efforts. Our partner, Groundwork Bridgeport, along with the Yale Urban Design Workshop, are planning a "cool corridors" project, implementing cooling infrastructure to combat urban heat. We used Landsat 8 Thermal Infrared Sensor and Landsat 9 Thermal Infrared Sensor-2 data to conduct a Land Surface Temperature analysis in Google Earth Engine for the county of Fairfield. A Principal Component Analysis was performed to identify indicators of social vulnerability in Bridgeport. We used the SOlar and LongWave Environmental Irradiance Geometry model to identify felt heat on the block level to inform where the partner should locate their cooling interventions to ensure they are most effective and equitable. We focused on the East Side of Bridgeport, which we found was 10 degrees hotter than other areas of Bridgeport and the neighboring town of Fairfield. We integrated our findings using Earth observations and additional sociodemographic and climate data into final communication products for our partners which will facilitate their selection of candidate locations for their Cool Corridors project.

Key Terms

Urban Heat, Land Surface Temperature, Remote Sensing, Social Vulnerability Index, Principal Component Analysis, SOLWEIG Modeling, ArcGIS Pro

2. Introduction

2.1 Study Area

Bridgeport, Connecticut (Figure 1) is situated at the intersection of the Pequannock River and the Long Island Sound (Figure 1), where the Paugussett people originally occupied the area (Rinn, 2020). In the state of Connecticut, Bridgeport is both the most populous city with 148,654 residents and the most densely populated city (U.S. Census Bureau, 2023; Abraham et al., 2023). Bridgeport is in Fairfield County, which has a generally high socioeconomic status: in a study that combined economic, health-related, and educational data to create a "community well-being index", Fairfield County had the 12th highest score among 100 U.S. metropolitan areas. While Fairfield County is home to some of the nation's wealthiest neighborhoods, it is home to some of the poorest as well. For example, 22.9% of people in Bridgeport live under the poverty threshold compared to 9.8% overall for the broader Fairfield County (U.S. Census Bureau, 2023). Bridgeport is also contending with housing and supporting the state's densest population with aging infrastructure systems and housing stocks created in a century-old manufacturing boom (Buchin et al., 2016; U.S. Census Bureau, 2023). Due largely to this extreme density, Bridgeport faces warmer temperatures from its high concentration of impervious surfaces, exposing residents to health hazards related to heat.

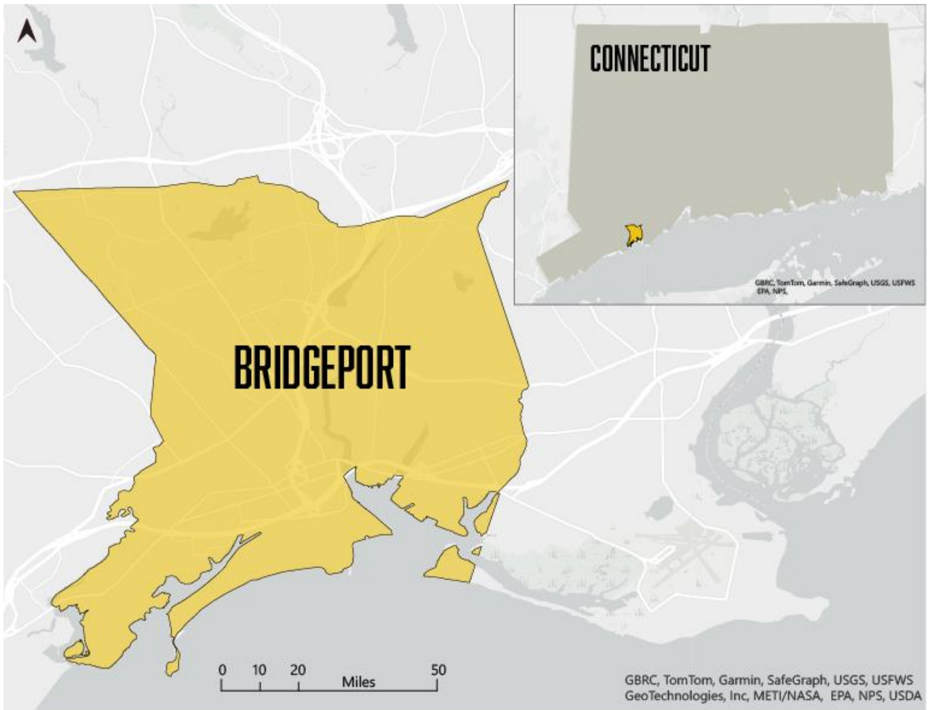

Figure 1. Study area map of Bridgeport inset with a map of its location within Connecticut.

The contemporary problem of urban heat is rooted in the historic industrial development of Bridgeport. By 1915, Bridgeport became the "foremost producer of war materials" in the US, and its booming industry drew job seekers (Bucki, 1980). By 1930, the population of Bridgeport was up to 146,716 people and 70 percent white; in 1950, the total population peaked at 158,709 (Gazillo, 2017). While being over 70 percent white during this time, Bridgeport was a notable stop during the Great Migration as Black Americans moved out of the Southern US in the twentieth century; in the same era, Bridgeport's Black population went from 3,767 people to 6,748 (Gazillo, 2017).

After World War II many people, predominantly white residents, began moving to the suburbs (Rose, 2016). Meanwhile, minority communities were often excluded from these new suburbs through "restrictive covenants," and the Home Owners' Loan Corporation "redlined" the remaining minority, low-income households in cities (Dougherty, 2024). In effect, these central city neighborhoods, which were already the oldest in regions, faced disinvestment and deterioration; by the 1970s, the manufacturing industry in Bridgeport was largely eliminated (Gazillo, 2017).

Because Bridgeport, Connecticut is formed by 1910s worker-housing design, it now features little green space and tree canopy (Eide, 2017). Natural spaces such as trees, vegetation, and soil help regulate temperature by absorbing heat, whereas the built environment typically reflects and retains heat (Corburn, 2009). Rising global temperatures due to anthropogenic climate change have intensified the disproportionate heating of urban areas (Paulina et al., 2015; Buchin et al., 2016). Extreme heat exposure can have dangerous consequences including heat-related illness, human discomfort, and increased energy consumption (Phelan et al., 2015; Filho et al., 2018). Within the existing literature, cooling strategies such as reflective roofing and green infrastructure have been identified to mitigate urban heat; however, access to strategies to cope with urban heat are not always equitable (Chow et al., 2012; Phelan et al., 2015).

Due to decades of disinvestment, Bridgeport has limited municipal resources to address these infrastructure concerns (Eide, 2017). Groundwork Bridgeport, our partner for this project, is a community-based nonprofit organization focused on the sustainable regeneration of neglected urban areas into spaces that empower the community. Groundwork Bridgeport has been supporting Bridgeport community members since 1998 as they seek to make their neighborhoods greener, healthier, and more livable (Groundwork Bridgeport, n.d.). In partnership with the Yale Urban Design Workshop, Groundwork Bridgeport is planning a "Cool Corridors" project, which aims to redress the adverse impacts of urban heat in the East Side neighborhood by locating and adding green space and trees where their cooling effects are most needed.

2.2 Earth Observation Objectives
The Cool Corridors project is an essential intervention in a community facing extreme heat and harmful infrastructure. For Groundwork Bridgeport to best serve the East Side neighborhood, having complete data on temperature within the neighborhood would be essential to ultimately understanding where residents are most vulnerable to heat and which area is best suited for the cooling intervention. Heat is an increasingly impactful danger in Bridgeport and the issue is timely and necessitates a regional analysis. Through this project, we assessed the feasibility of using NASA Earth observations to support Groundwork Bridgeport's Cool Corridors project and identify the specific blocks in Bridgeport's East Side neighborhood that were most vulnerable to urban heat.

We began by conducting an analysis of land surface temperature using data from Landsat 8 Thermal Infrared Sensor (TIRS) and Landsat 9 TIRS-2, a practice that has been adopted by several past researchers (Rajasekar & Weng, 2009; Fu et al., 2019; Yang et al., 2020; Duan et al., 2021). For assessing heat vulnerability, previous studies have created social vulnerability indices; instead of reproducing an existing index, we created our own social vulnerability index to ensure it met our partner's needs and could effectively be integrated with our land surface temperature data products (Schmidtlein et al., 2008; Conlon et al., 2020; Xie & Meng, 2023). We used additional Earth observation products as inputs for a 3D modeling tool called SOlar and LongWave Environmental Irradiance Geometry (SOLWEIG) to assess felt heat in the East Side. While there is precedent for using this model to analyze the felt heat in complex outdoor urban environments (Lindberg et al., 2008), its integration with the previous steps is relatively novel. In this final step, we assessed the feasibility of using SOLWEIG in conjunction with these other methods and whether it would produce practicable results for our partner to locate their cooling interventions.

3. Methodology
3.1 Data Acquisition
We downloaded remote sensing data via the Google Earth Engine (GEE) catalog and the 3D Elevation Program (3DEP) LiDAR Explorer Map from the US Geological Survey (USGS). We used GEE to acquire imagery within our study area and period from Landsat 8 TIRS and Landsat 9 TIRS-2 to analyze land surface temperature (Table 1). Next, we used data related to socio-demographics, economic capacity, commuting habits, and personal health to analyze individuals' vulnerability to urban heat. To create an index of the communities' vulnerability to urban heat using these metrics, we acquired data from the American Community Survey conducted by the US Census Bureau (Table 2). To perform 3D modeling of outdoor thermal comfort, we downloaded digital elevation models (DEM) and LiDAR point clouds from the USGS (Table 3).

Table 1
NASA Earth observations acquired to analyze urban heat distribution.

Platform & Sensor	Data Product	Dates	Acquisition Method	Resolution	Use
Landsat 8 TIRS	Collection 2, Level 2, Tier 1	2013 – 2023, 06/01 – 09/30	Google Earth Engine	30 meters	Analyze and map daytime land surface temperatures.
Landsat 9 TIRS-2	Collection 2, Level 2, Tier 1	2013 – 2023, 06/01 – 09/30	Google Earth Engine	30 meters	Analyze and map daytime land surface temperatures.

Table 2

Datasets and variables used to create a Social Vulnerability Index.

Agency	**Data Product**	**Dates**	**Acquisition Method**	**Relevant Parameters to Use**
US Census Bureau	2021 American Community Survey	2021	Census Dataset Download	Poverty Rate, Rate of Population without High School Diploma, Population over 65 years old, Population over 65 years old and living alone, Population Living Without a Vehicle, Percent of Population considered Minority, Percent of Population with a Disability.

Table 3

Datasets acquired to model outdoor thermal comfort using SOLWEIG.

Source	**Data Product**	**Dates**	**Acquisition Method**	**Resolution**	**Use**
LiDAR	LiDAR DEM	03/11/2016 – 04/16/2016	USGS 3DEP LiDAR Explorer	1 meter	Input for SOLWEIG.
LiDAR	LiDAR Point Cloud	03/11/2016 – 04/05/2016	USGS 3DEP LiDAR Explorer	< 1 meter	Calculate the Digital Surface Model (DSM) & Canopy DSM (CDSM).
National Solar Radiation Database Meteorological Data	Physical Solar Model version 3	07/30/2022	National Solar Radiation Database	2 kilometers	Input weather and climate data for SOLWEIG modeling.
Connecticut ASOS	METAR Data	07/30/2022	ASOS-AWOS-METAR Data Download	N/A	Input precipitation data into SOLWEIG modeling.
Connecticut Metropolitan Council of Governments	Building Footprints	2013	MetroCOG OpenData Portal	N/A	Ancillary data used to create CDSM.

3.2 Data Processing

3.2.1 Urban Heat Data

The Landsat 8 TIRS and 9 TIRS-2 images we acquired were processed and analyzed using a GEE script provided by Dr. Kenton Ross (NASA DEVELOP) that we adapted for our project. We first merged all available images within our study area and period into one collection which we then clipped using a shapefile of Fairfield County. This shapefile includes the coast and inland water features but excludes the Long Island Sound which has a significant cooling effect that would misrepresent average land surface temperatures. We then converted all surface temperature bands in this collection from Kelvin to Fahrenheit. We performed a cloud mask on all images to limit the influence of clouds on our temperature analysis. We then mosaiced any adjacent images in the collection that were taken on the same day.

3.2.2 Social Vulnerability Data

In collaboration with our partners, we selected socioeconomic factors they identified as most significant when defining heat vulnerability. Using the Tidycensus package in the UHEAT 1.0 R program created by the NASA DEVELOP Fall 2020 Arizona Urban Development project (Boogaard et al., 2020), we obtained sociodemographic data from the 2021 5-year American Community Survey at the Block Group level for Fairfield County (Table 2). The Census data we used was percent of population that is elderly (over 65 years old), percent of population with a disability, percent of population without a high school diploma, percent of population over 65 and living alone, percent of population considered a minority, percent of population living in pre-1980 built structures, percent of population without access to a vehicle, and percent of population below the poverty line. Since the Block Group level is such a hyper-local scale, there was limited data available at this level for social factors that contribute to heat vulnerability. Relevant health and transport data were only available at the coarser Census Tract level, so we created our social vulnerability index solely with the Census data available at the Block Group level.

3.2.3 SOLWEIG Inputs

To prepare LiDAR point cloud data for the SOLWEIG model, we converted them to a DSM, a necessary input for the model, using QGIS's Point Cloud Conversion Export to Raster with Triangulation function. We also converted the vertical height measurement of the DSM from feet to meters. We created a Canopy Digital Surface Model (CDSM) by subtracting the DEM from the DSM and setting all pixels within building footprint polygons to zero. The DEM, DSM, and CDSM were then used with the Urban Multi-scale Environmental Predictor pre-processor plugin for QGIS to create the following required inputs for the model: wall aspect, wall height, and sky view factors. Three Census Block Groups of interest in the East Side were determined for the modeling based on their heat and social vulnerability, and all raster inputs were clipped to these areas of interest using the QGIS Clip Raster by Extent function.

3.3 Data Analysis

3.3.1 Urban Heat Assessment

With the processed Landsat 8 TIRS and 9 TIRS-2 imagery, we calculated the median temperature value at every pixel across the entire collection of images. This produced a raster of median daytime land surface temperature over the 10-year period in Fairfield County. We then performed Zonal Statistics on this raster in ArcGIS Pro to determine the average land surface temperature at two spatial scales – by Census Tract and by Block Group. The Census Tract analysis, provided at the county level, allows comparisons to be made between Bridgeport and other areas in the county. The Census Block Group analysis, provided for Block Groups within Bridgeport, reveals finer variations in the distribution of heat.

Spatial comparisons of heat can also be made by creating a factor of difference between the study area and a reference area. Previous DEVELOP projects, such as New York City Transportation & Infrastructure (Schindelman et al., 2023), accomplished this by using a rural reference area. However, in collaboration with our partner, we decided to use the adjacent town of Fairfield as our reference area because it is more suburban and affluent and has more green space and tree canopy than Bridgeport. This comparison is also representative of the extreme disparity in wealth in Connecticut. Highlighting these comparisons between wealth, heat distribution, and access to cooling infrastructure also supports the partner's funding efforts for their Cool Corridors project. To obtain the median land surface temperature for our reference area, we first clipped the median daytime land surface temperature raster using a shapefile of the town of Fairfield. Then, we used a spatial reducer in GEE to calculate the median land surface temperature within the reference area, resulting in a single floating-point value that was subtracted from every pixel in the median daytime land surface temperature raster. This produced a raster image for the entire county in which every pixel represents the result of that difference calculation.

3.3.2 Principal Component Analysis and Social Vulnerability Analysis

The Social Vulnerability Index is a tool that considers factors that may affect an individual's susceptibility to extreme heat, creating a multi-dimensional, more complete understanding of heat vulnerability when paired with the distribution of land surface temperature. For example, people living below the poverty level may not be able to afford air conditioning units. To create our Social Vulnerability Index, we used a Principal Component Analysis (PCA), a statistical processing method that simplifies large datasets but retains their ability to represent variation in the data. This process uses multi-dimensional regression to pick "principal components" that account for a certain proportion of cumulative variation. When conducting the PCA, we had to choose how many principal components to include. To do this, we controlled for variance in a scree plot and compared a parallel analysis of Social Vulnerability Index factors (Figures 2 & 3). We chose to use two principal components because they represent that cumulative variation, as evident by the representation of principle component 3 as a lower eigenvalue in the scree plot, as well as below the simulated mean and simulated 95th percentile (Figure 2).

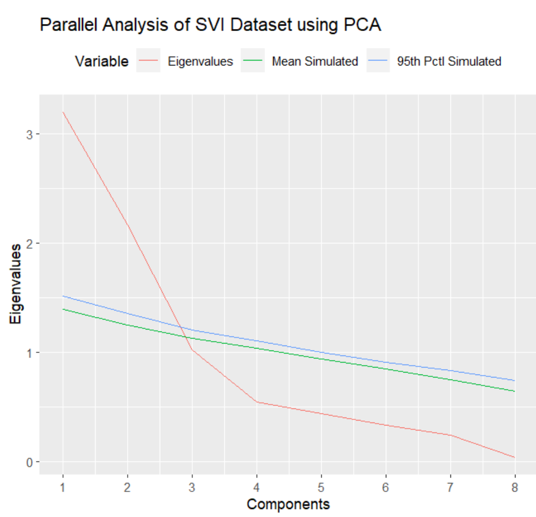

Figure 2. Parallel Analysis of Social Vulnerability Index (SVI) Principal Components

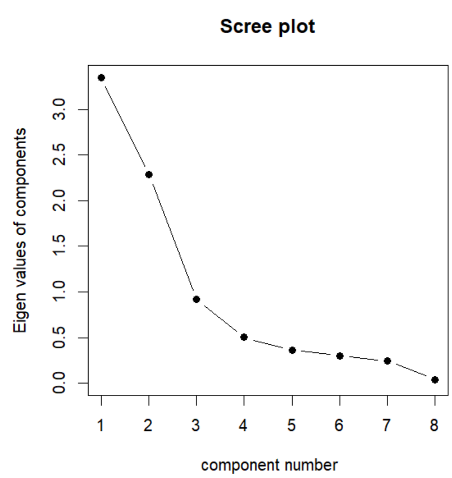

Figure 3. Scree Plot for Principal Components

Once we selected for two principal components, we ran the PCA to create heat vulnerability scores which gave us unique values for each Block Group that represented the composite of each vulnerability category as one. These values were extracted and visualized in ArcGIS Pro 3.0.0, showing the heat vulnerability of every Block Group in Fairfield County. We generated a bivariate map that showed the vulnerability of each Block Group polygon along with the average land surface temperature for the polygon. We used a simple classification from low to high vulnerability to showcase the spectrum based on the extent of vulnerability to heat exposure. Our cumulative variance was 0.67, meaning that principal component 1 (PC1) and principal component 2 (PC2) accounted for 67% of the variance within the Social Vulnerability Index. PC1 best describes the variation within the factors of “Elderly Households”, “No Vehicle Households”, “Pre-1980 Built Structures” and "Population with Disability”, while PC2 best describes the variation between “Adults without a High School Diploma”, “Below Poverty Level” and “Minority” (Figure 4). As it relates to vulnerability to extreme heat, PC2 represents more variables that have a higher correlation with poor health outcomes when it comes to heat-related illness. PC1 shows a higher correlation of factors that may impact mobility, which can also be an issue in prolonged exposure to heat. Ultimately, the bivariate map showed the areas that were facing the most extreme heat exposure and stood to be affected negatively the most on account of their Social Vulnerability Index factors. Identifying areas of extreme vulnerability was the necessary precursor of our next analysis.

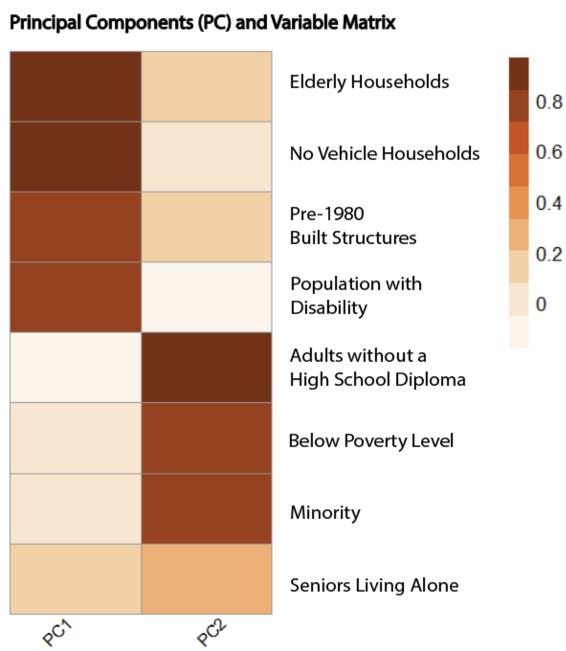

Figure 4. Principal Components Gradient

3.3.3 3D Outdoor Thermal Comfort Analysis

The SOLWEIG model runs via the Urban Multi-scale Environmental Predictor plugin in QGIS. The model measures mean radiant temperature in six different directions (upward, downward, and the four cardinal directions). The mean radiant temperature is a physical construct that considers radiant heat exchange between a human body and its environment (Guo et al., 2020). We input the data and variables processed in section 3.2.4 and ran the model for each area of interest, resulting in raster files of the mean radiant temperature for each of the three Block Groups of interest. In addition, we ran the model for the entirety of the East Side (Appendix A3). These outputs depict the felt temperature for the specified areas at a fine spatial resolution and visualize how distinct features like shadows, vegetation, and buildings influence the distribution of thermal comfort. This model can be used to understand how heat is experienced at a level of fine precision.

4. Results and Discussion

4.1 Analysis of Results

To visualize surface temperature, we took a zonal mean of the spatial median land surface temperature to create a choropleth map where darker reds indicate hotter temperatures (Figure 5). Following patterns of urbanization, Tracts along the coast of Connecticut are shown to be warmer than the suburban interior, with the hottest average temperature being 90.69°F.

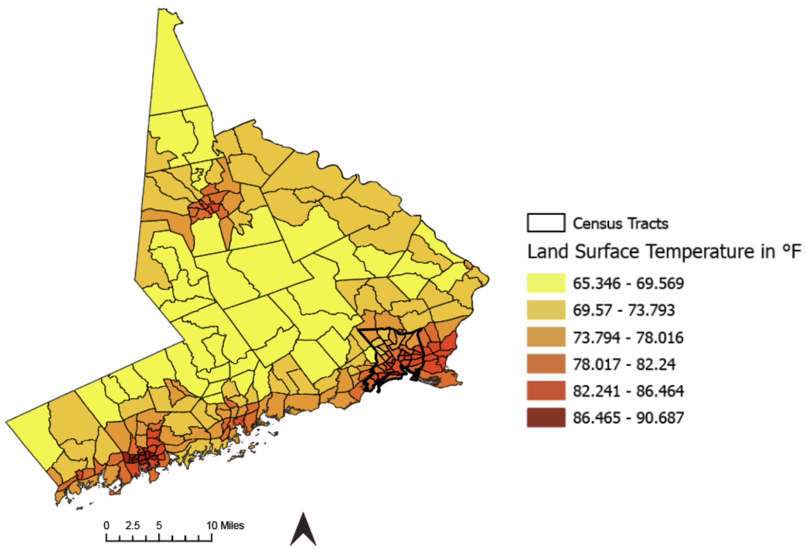

Figure 5. Temperature Distribution for Fairfield County Connecticut Census Tracts

At its hottest, Bridgeport is 10.41°F warmer than its neighbor, the town of Fairfield (Figure 6). The East Side neighborhood, our project's focus, has some of the hottest Block Groups. This is consistent with the hypothesis of our partner who expected the East Side to be hotter due to the East Side's historic industrial development.

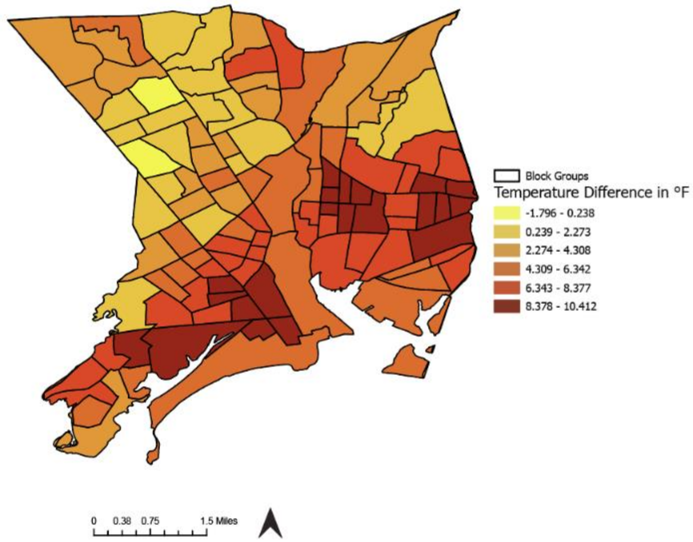

Figure 6. Temperature Difference between Fairfield City and Bridgeport Block Groups

We combined land surface temperature for Bridgeport Block Groups (Appendix A1) with Heat Vulnerability Scores (Appendix A2) to produce a bivariate map of heat vulnerability (Figure 7). Areas of high vulnerability and high heat are demonstrated in dark blue. There are three Block Groups of high heat vulnerability within the East Side. This informed us where to perform the SOLWEIG modeling.

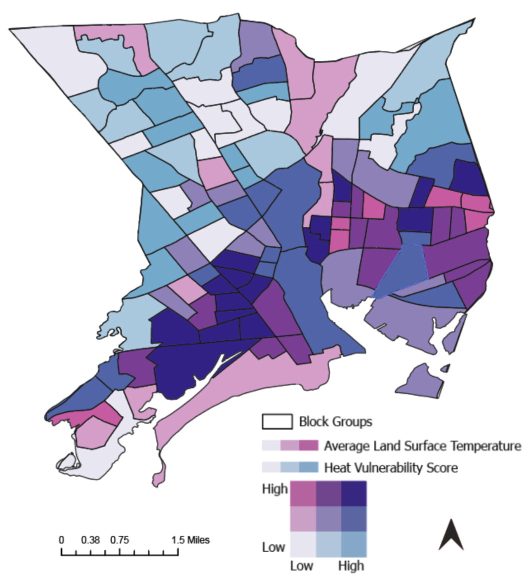

Figure 7. Heat Vulnerability for Bridgeport Block Groups

Figures 8 and 9 demonstrate the felt heat for our previously identified heat-vulnerable Block Groups of the East Side. In some areas of these vulnerable Block Groups, the mean radiant temperature is as hot as 166°F. The hottest surfaces are usually rooftops, shown by some of the buildings on Kossuth Street in Figure 8, or pavements and undeveloped bare land, shown by the large area of high heat in the west of Block Group 4 in Figure 9. Roof temperatures are around 164.52°F while the temperature of other surfaces ranges from 101.38°F to 161.53°F. For our analysis, the input data available to us was collected at varying years, which may cause discrepancies in the accuracy of the model in areas that have seen changes in land use. Furthermore, there was no available CDSM and land cover classification for the East Side that was suitable for SOLWEIG's input requirements. Without a proper CDSM and land cover classification, we could only create a CDSM that excluded pixels in the same locations as building footprints. Other impervious surfaces were therefore included in this CDSM, such as bridges or power lines, causing inaccuracies in how the model calculates shadows and temperatures around vegetation. In addition, the lack of a land cover classification also meant that water could not be differentiated, making the rivers and harbor surrounding the East Side appear much hotter than expected. Including an accurate CDSM and land cover classification would make the output more precise.

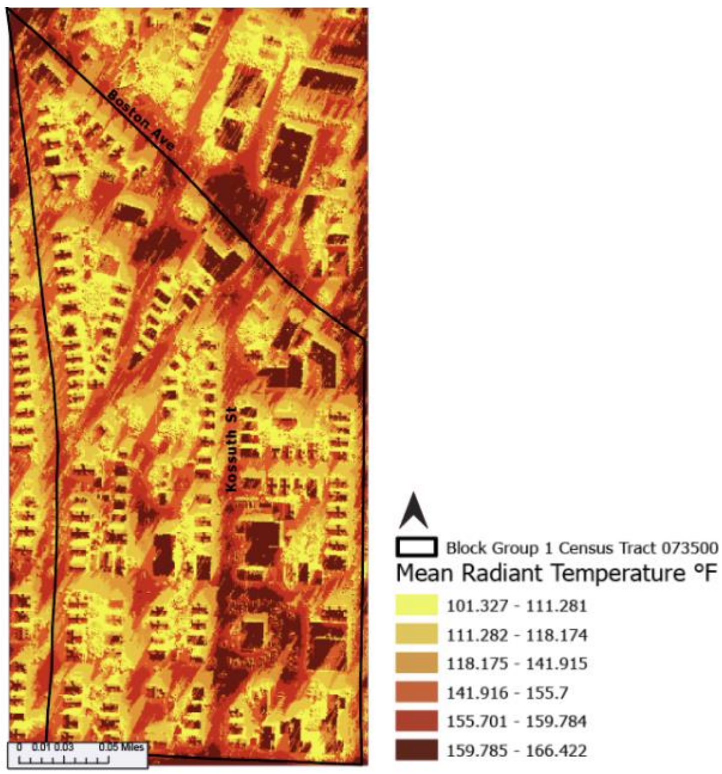

Figure 8. Tract 073500 Block Group 1 Mean Radiant Temperature at 14:30 on 30 July 2022

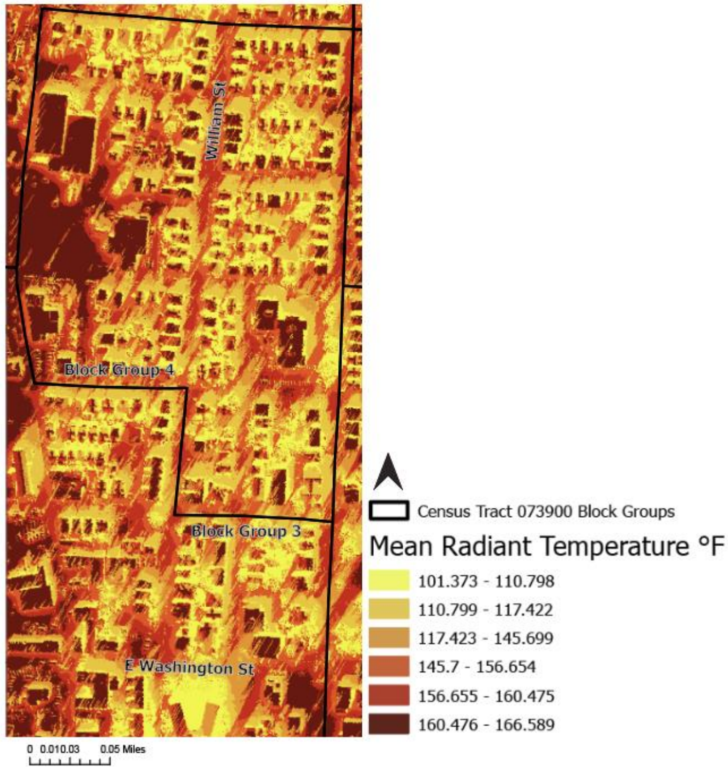

Figure 9. Tract 073900 Block Groups 3 & 4 Mean Radiant Temperature at 14:30 on 30 July 2022

4.2 Feasibility for Partner Use

We found that NASA Earth observations are feasible for informing cooling interventions in Bridgeport. Using Landsat-derived land surface temperature as a proxy for urban heat and its distribution is a useful first step for determining areas of the East Side neighborhood that are hottest and need the most attention. However, the spatial resolution of Landsat 8 and 9 thermal imagery is not detailed enough to locate or plan specific sites for cooling interventions. Thermal imagery with a higher spatial resolution would be desired to distinguish heat at the locations of smaller features such as sidewalks or bus stops.

LST maps are limited as they do not account for felt heat and are just one way to approximate how heat is experienced. Additionally, due to the availability of data, the social vulnerability index did not include health-related factors such as asthma rates, heat-related hospitalizations, or access to air conditioning. This limits the understanding of social vulnerability since it does not provide a comprehensive idea of heat vulnerability. SOLWEIG modeling, although informative, is a newer model with minor bugs and very high processing demands. As mentioned in the previous section, data variability and gaps in data availability may lead to discrepancies in the accuracy of the SOLWEIG model. Including more accurate data inputs for the model would make the output more precise for partner use.

4.3 Future Recommendations

With further resources, we would recommend improving the modeling output of this study by developing or sourcing an accurate CDSM and land cover classification that works with SOLWEIG. We also recommend using the TreePlanter tool which is also provided by the Urban Multi-scale Environmental Predictor plugin. This tool uses the outputs of the SOLWEIG model with given points for the locations of new trees to be planted and determines their effect on heat. This can provide more information in choosing the best places to implement new green spaces. Finally, our partner has expressed interest in collecting more data from households in the East Side about their experiences with extreme heat. This would result in the best possible dataset to use for determining social vulnerability to heat.

5. Conclusions

From this study, we confirm that heat is unevenly distributed in Fairfield County, Connecticut and conclude that Bridgeport is hotter than the town of Fairfield. Our heat assessment using Landsat Earth observations estimated that Bridgeport is about 10°F hotter than the town of Fairfield, which is likely due to the high concentration of impervious surfaces in the built environment of Bridgeport. In the East Side, Block Group 1 in Tract 735 and Block Groups 3 and 4 in Tract 739 both face extremely high temperatures and their residents are highly vulnerable to the harms of heat as indicated by our Social Vulnerability Index. While Landsat's spatial resolution for thermal data isn't fine enough to locate specific sites for intervention, it is still feasible to use for understanding and analyzing the distribution of urban heat. We established a stable median temperature because of the breadth of the dataset and the timescale of available data. The methodologies and end products would help our partner make informed decisions in placing their cooling interventions.

Our joint analysis of LST and social vulnerability confirms the community's concerns that Bridgeport residents are disproportionately vulnerable to the harms of extreme heat, particularly in the East Side. Our end products will be used by our partners as they begin to locate their heat mitigation interventions as the products suggest areas with the greatest need for cooling interventions. Beyond this, the LST analysis at the Block Group level for the city and at the Tract level for the county can be distributed publicly to educate the public and inform additional heat interventions in the region, addressing where there are deficits to enhance equity. These maps would be used by our end users in continued advocacy efforts for infrastructure equity.

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7. Glossary

ArcGIS Pro – Software for creating, analyzing, and sharing maps and spatial data, widely used in geography and urban planning.

Cool Corridors – Pathways or designated areas within cities that have been planned or preserved to maintain cooler temperatures compared to their surroundings.

Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time.

East Side – The eastern part of the city of Bridgeport, Connecticut.

Google Earth Engine (GEE) – A cloud-based platform provided by Google that allows users to analyze and visualize geospatial datasets using satellite imagery and other Earth observation data.

Green Space – Areas within urban environments that are covered with vegetation, such as parks, gardens, and forests.

Heat Vulnerability – The susceptibility of certain populations or areas to the adverse effects of extreme heat, such as heat-related illnesses and mortality.

Impervious Surfaces – Hard surfaces like roads, sidewalks, and buildings that do not allow water to penetrate into the ground.

Land Surface Temperature – The temperature of the Earth's surface as measured from a satellite or aerial sensor. It provides information about the thermal characteristics of the land surface and is often used in studies related to climate, hydrology, and urban heat island effects.

Landsat – A system of NASA and USGS Earth-observing satellites providing continuous and archival open-access imagery at medium spatial, spectral, and temporal resolution.

LiDAR (Light Detection and Ranging) – A form of active remote sensing that reflects lasers off a surface to gain information about it, including texture and distance.

Principal Component Analysis (PCA) – A statistical method for simplifying data while keeping important patterns intact.

Redlined – Describes the areas that the Home Owners' Loan Corporation indicated as unsafe for investment in their Residential Security map. In these maps, they had four classifications, A, B, C, and D, with A being considered the safest for investment and D indicating areas they identified as unsafe for investment, often based on a minority community's presence in the area. The D-rated areas were highlighted in red on the maps.

Remote sensing – Methods and technologies that enable the acquisition of information about a subject from a distance.

Social Vulnerability Index – A measure of how susceptible communities are to disasters or climate change, considering factors like wealth and resources.

SOLWEIG Modelling – A tool for simulating sunlight and heat distribution in cities, helping to understand outdoor comfort levels.

Urban Heat – The phenomenon of elevated temperatures in urban areas compared to their rural surroundings due to human activities, such as heat absorption by buildings, roads, and infrastructure, and reduced vegetation cover.

3DEP – 3-Dimensional Elevation Project

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9. Appendix

Appendix A: Supplemental Figures

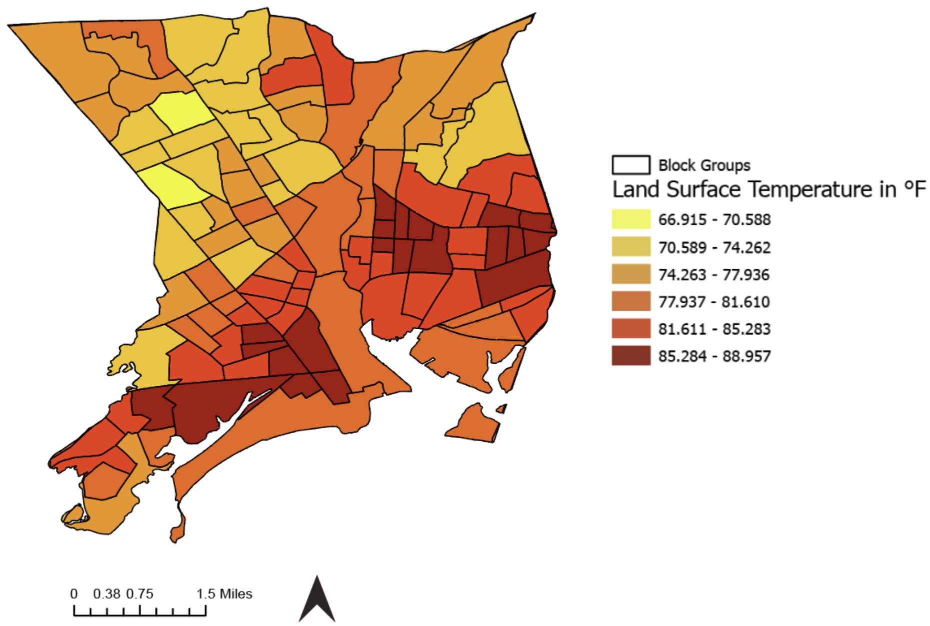

Figure A1. Land Surface Temperature for Bridgeport, Connecticut

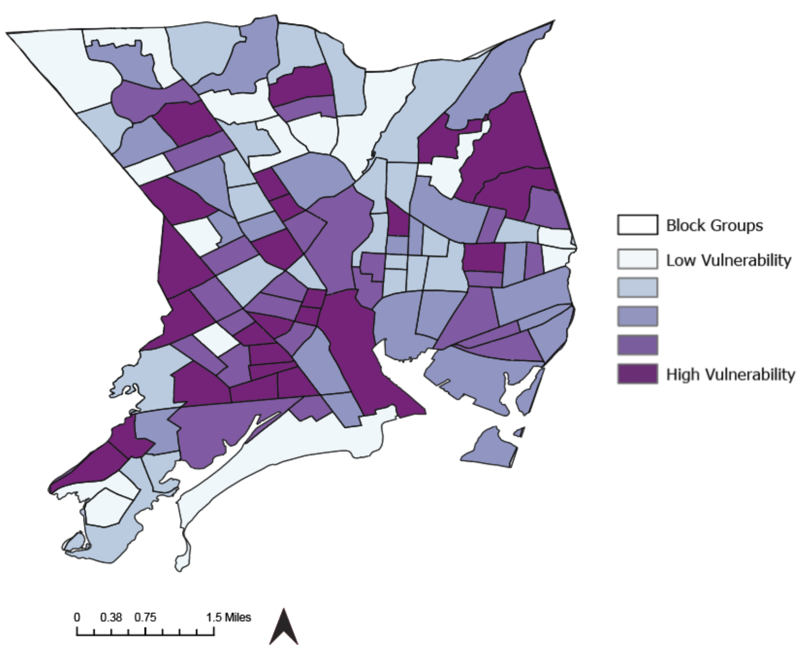

Figure A2. Social Vulnerability for Bridgeport, Connecticut

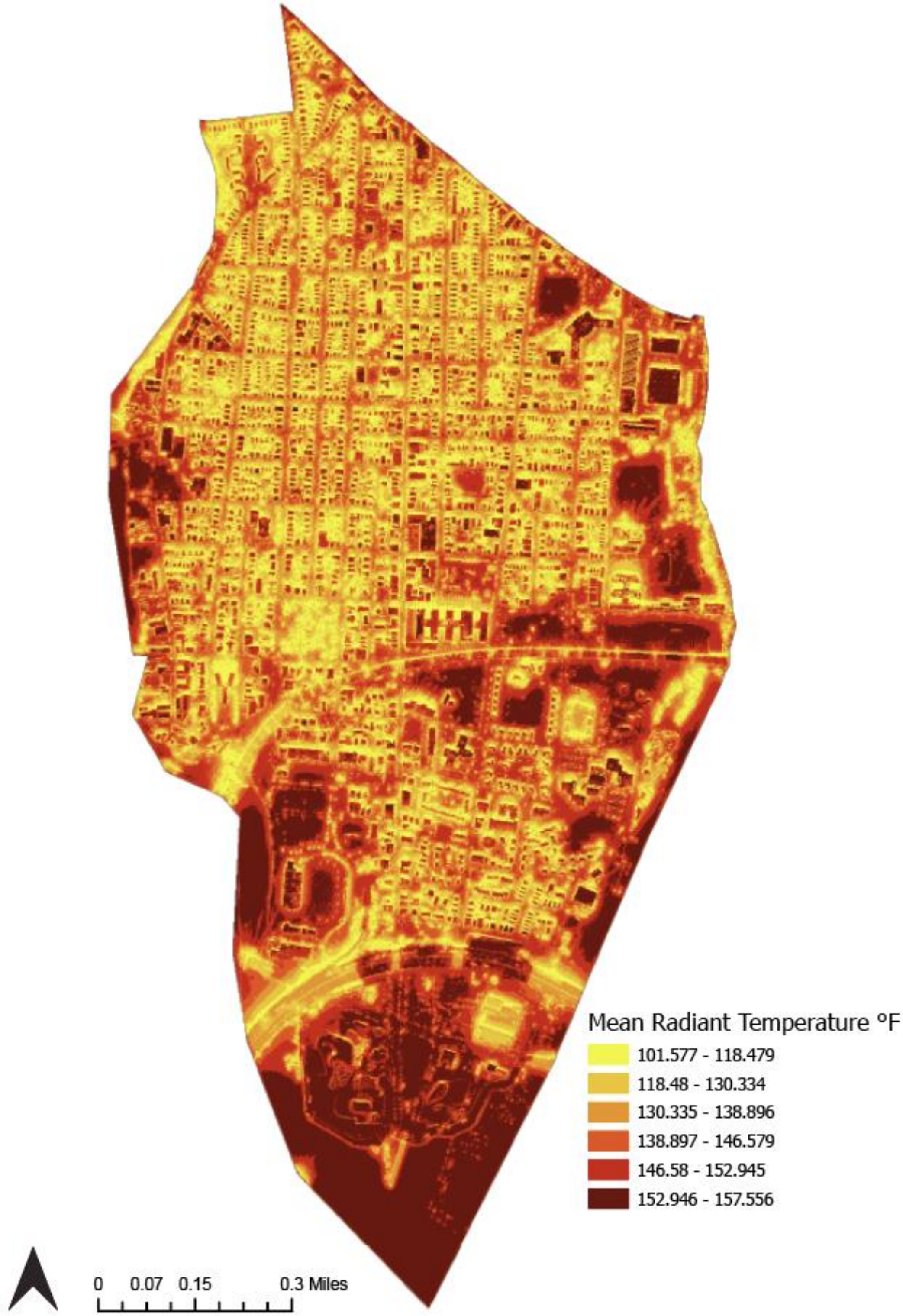

Figure A3. Entire East Side Mean Radiant Temperature, Daytime Average on 30 July 2022