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Extreme Heat Vulnerability And Spatial Accessibility To Cooling Centers In Connecticut

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1 ABSTRACT

Extreme heat is becoming an increasingly prevalent and prominent environmental health issue under climate change. The goal of this study is to evaluate heat vulnerability at the census tract level in the state of Connecticut and assess the spatial accessibility to cooling centers – an extreme heat intervention. A variety of environmental and sociodemographic variables related to heat and health were identified based on previous literature and used in a varimax-rotated principal component analysis to reduce dimensionality and identify key components that constitute a heat vulnerability score. In addition, cooling center locations were identified based on news media and a statewide survey of cooling centers and emergency shelters. Kernel density was calculated for cooling centers, and then population density was used to calculate the cooling center-to-population ratio. Finally, the relationship between the heat vulnerability score and cooling center-to-population ratio for each census tract was quantified in a linear regression to identify high heat vulnerable census tracts with relatively low cooling center access. A heat vulnerability score was calculated for 821 of 833 census tracts in the state of Connecticut with a range of scores from 8 to 20. High vulnerability census tracts clustered in urban and metropolitan areas. A total of 248 unique cooling center locations were geocoded, with high cooling center-to-population ratio clusters found to be located around Hartford, New Haven, and Bridgeport. Small clusters of census tracts with a high heat vulnerability score and a low cooling center-to-population ratio were identified around Manchester, Meriden, Milford, New London, Plainville, and Stratford. Urban census tracts are key units for public health interventions pertaining to heat adaptation strategies, including cooling centers. Some urban areas have a comparatively high number of cooling centers that can provide heat relief if utilized properly in conjunction with other heat response strategies. Other urban areas can improve by increasing their number of cooling centers and by using other heat adaptation strategies to help prevent heat exposure. This heat vulnerability index can be used to inform planning and provision of adequate resources to address the needs of heat vulnerable populations.

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3 INTRODUCTION

3.1 Climate Change, Heat, and Health

Extreme weather events including extreme heat events are projected to increase in frequency, duration, and intensity in the northeastern region of the United States, where annual average temperature has already increased by 1.8°F over pre-industrial times and is also projected to increase further by up to 9°F by the end of the 21st century (Dupigny-Giroux et al. 2018). Extreme heat is currently a significant threat to human health and will continue to be a significant threat in the future. Under Representative Concentration Pathway (RCP) 4.5, a moderate global warming and emission scenario (Thomson et al. 2011), it is projected that there will be more than 650 excess deaths per year due to extreme heat by 2050 in the northeastern region of the United States (Dupigny-Giroux et al. 2018). An average of 5,608 deaths per year were attributable to heat in 297 counties in the United States during 1997-2006, among which more than 40% (2,302) were in the Northeast region of the United States (Weinberger et al. 2020).

Extreme heat causes heat-related illness, which is a spectrum of disorders including heat edema, heat cramps, heat syncope, heat exhaustion, and heat stroke (Lugo-Amador et al. 2004, Gauer and Meyers 2019). Heat stroke, the most severe disorder, can often be fatal, especially to vulnerable populations (Epstein and Yanovich 2019). Other adverse health outcomes of extreme heat exposure include cardiovascular, diabetic, gastrointestinal disease, nervous system, psychological, renal, and respiratory morbidity and mortality (Basagaña et al. 2011, Xu et al. 2012, Ye et al. 2012, Yang et al. 2016, Wellenius et al. 2017, Chen et al. 2019, Yoo et al. 2021). Populations especially vulnerable to heat exposure include the elderly, persons who are poor, people of color, persons with alcohol use disorder, persons experiencing homelessness, people without access to air-conditioning, persons who are socially isolated, persons who are outdoor laborers, persons with comorbidities or pre-existing medical conditions including mental conditions, athletes, and military personnel (Lugo-Amador et al. 2004, Sampson et al. 2013, Nayak et al. 2018, Gauer and Meyers 2019).

In addition to increasing due to climate change, heat-related morbidity and mortality also are made worse by the urban heat island effect (Luber and McGeehin 2008). The urban heat island effect describes the phenomenon wherein urban areas experience a higher air temperature than the surrounding rural environment. This is largely due to urban environments absorbing more solar radiation, and having greater heat retention, a greater amount of anthropogenic heat sources, and less evaporative cooling compared to the surrounding rural environment (Kleerekoper et al. 2012, Heaviside et al. 2017). Climate change and an increasing number and size of urban heat islands due to urbanization will lead to more persons being exposed to extreme heat (Luber and McGeehin 2008).

3.2 Prevention of Heat-related Morbidity and Mortality

Identifying local census tracts that are directly impacted by extreme heat is important to help implement adaptation strategies for the prevention of heat-related illness. Examples of these strategies include cool permeable surfaces, reflective roofs, green roofs, green spaces/vegetation, water (e.g., ponds, streams, fountains) with high surface areas and dispersion features, heat warning systems, cooling centers, and risk communication and education about extreme heat (Luber and McGeehin 2008, O'Neill et al. 2009, Kleerekoper et al. 2012).

A heat vulnerability index is a common strategy for assessing vulnerability to heat. Vulnerability is not the same as risk, but is defined as the summation of all risk and protective factors that ultimately determine whether an individual or subpopulation experiences adverse health outcomes (Balbus and Malina 2009, Johnson et al. 2012). A heat vulnerability index developed by Reid et al. mapped heat vulnerability in different geographic regions in the United States at the census tract level and emphasized the northeast region as having generally higher heat vulnerability, although Connecticut was not explicitly mentioned (Reid et al. 2009). Since then, there have been a number of heat vulnerability indices developed in the United States including Michigan (Seroka et al. 2011, Gronlund et al. 2015), Detroit, MI (Conlon et al. 2020), Georgia (Maier et al. 2014), Pittsburgh, PA (Bradford et al. 2015), Philadelphia, PA (Barron et al. 2018, Hammer et al. 2020), Phoenix, AZ (Chuang and Gober 2015), Vermont (Vermont Department of Health 2016), Wisconsin (Christenson et al. 2017), and New York State (Nayak et al. 2018). A Connecticut-specific heat vulnerability index would be useful for planning climate change adaptation to extreme heat.

Development of heat vulnerability indices has been relatively standard, with the majority of published heat vulnerability indices using a principal component analysis or equal weights normalization methods (Bao et al. 2015). The developmental process includes identifying variables demonstrated in the literature to have a relationship between heat and health (Reid et al. 2009). The principal component analysis (PCA) method is used to reduce the number of variables that independently affect the heat vulnerability outcome variable. The variables are then scaled or normalized to allow for comparability among variables which can then be summed to determine a heat vulnerability score (Reid et al. 2009, Conlon et al. 2020). The purpose of a heat vulnerability index is to spatially identify and visualize locations of populations that are vulnerable to extreme heat (Luber and McGeehin 2008, O'Neill et al. 2009).

At the individual level, heat-related illness is preventable through acclimatization, proper hydration, and minimizing activity and exposure to heat (Gauer and Meyers 2019). Previously mentioned adaptation strategies help reduce exposure to heat at the population level. Cooling centers constitute an adaptation strategy used in many urban areas to prevent heat-related illness. Cooling centers are air-conditioned buildings that are available to the public and are designated safe spaces from extreme heat. Cooling centers are especially important for vulnerable populations (Widerynski et al. 2017), including the ones previously mentioned. Greater and more effective use of cooling centers through increased accessibility will prevent more heat-related illness and mortality.

4 METHODS

4.1 Heat Vulnerability Index

Peer-reviewed studies that developed previous heat vulnerability indices in different regions in the United States were used to compile a list of variables for the Connecticut heat vulnerability index. A total of eighteen sociodemographic and environmental variables were chosen from previous heat vulnerability indices (Reid et al. 2009, Nayak et al. 2018, Conlon et al. 2020). The list of variables is presented in Table 1. Data from the United States Census American Community Survey were obtained at the census tract level for 5-year estimates from 2015 to 2019 (United States Census Bureau 2019). Census tracts are geographic areas specified by the United States Census; Connecticut has 833 census tracts. Prevalence data for diabetes were obtained from the Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance System (2013) and population prevalence estimates were used to estimate the percentage of the population with diabetes in each census tract in Connecticut (Centers for Disease Control and Prevention 2013).

Data from the United States Geological Survey National Land Cover Database (NLCD) were obtained in raster format at a 30 meter spatial resolution (Dewitz 2019). Percentages of four different land cover types were calculated by dividing the area of the specific land cover type by the total land area of the census tract. The percentage of developed, high intensity land cover type was calculated for each census tract, as was the percentage of green space land type (deciduous forest, evergreen forest, mixed forest, shrubs, grassland, pasture/hay, and cultivated crops). The latter percentage was then subtracted from 100 to give the percentage of non-green space. The NLCD tree canopy coverage raster was used to calculate the percentage of tree canopy cover for each census tract, which was subtracted from 100 to give the percentage of non-tree canopy cover. The NLCD urban imperviousness raster was used to calculate the percentage of impervious surfaces for each census tract. Terra Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data were obtained to calculate the mean temperature from May 2019 to August 2019 for each census tract. Terra is the NASA satellite that uses the MODIS instrument to provide land surface temperature and emissivity; an 8-day average for land surface temperature with 1 kilometer spatial resolution was specifically used for this study (Wan et al. 2015).

Principal component analysis (PCA) with varimax rotation was applied for dimensionality reduction and to create new independent principal components to construct the heat vulnerability index. Significant components were determined by using 1) the Kaiser criterion, 2) a Scree plot, and 3) cumulative variance being at least 70% (Nayak et al. 2018). The Kaiser criterion kept all components with eigenvalues greater than 1.0. In a Scree plot, eigenvalues were plotted against cumulative variance and components that appeared before a large break were kept for the PCA. Factor scores were normalized and were then categorized and given a score of 1 through 6 based on the z-score, with 1 being more than two standard deviations below the mean, 2 being one to two standard deviations below the mean, 3 being zero to one standard deviation below the mean, 4 being zero to one standard deviation above the mean, 5 being one to two standard deviations above the mean, and 6 being more than two standard deviations above the mean. A score of 1 indicated low vulnerability and a score of 6 indicated high vulnerability. The heat vulnerability index was then created by summing all of the scores from the created significant components for each individual census tract. Census tracts with missing data for any of the initial variables were omitted from the varimax-rotated PCA.

4.2 Cooling Centers

Cooling center locations were obtained from a collaborative Connecticut Department of Public Health and Connecticut Institute for Resilience & Climate Adaptation survey that was sent to the local health director and emergency management director of all towns and municipalities of Connecticut. The survey queried about the addresses and names of cooling centers that were open in 2019. Cooling center locations also were obtained from online websites of local daily newspapers, local weekly newspapers, and Connecticut television news stations. A total of 81 news sites were searched for any articles published in 2019 related to cooling center locations. Google was used to search specific web URLs for keywords within a specified time frame. Cooling center addresses were geocoded using ArcGIS Pro Version 2.7.

Kernel density for cooling centers was calculated from geocoded cooling center locations to create a raster of cooling center distribution density throughout the state. Kernel density is a smoothing process that calculates a magnitude-per-unit area. It is used to create a surface raster image that shows the distribution of spatial availability (Guagliardo 2004, Schuurman et al. 2010). Cooling centers-to-population ratios were calculated using kernel density (cooling centers per square kilometer) and census block group 2015-2019 population density estimates (population per square kilometer) (United States Census Bureau 2019). Census block groups are the second smallest geographic area used by the United States Census Bureau and each census tracks contain one or more census blocks. Census block group population densities were used because they create finer spatial resolution compared to census tracts, allowing for a more accurate cooling center-to-population ratio estimate. For each census tract, the mean cooling center-to-population ratio was calculated from the center-to-population ratio of the census block groups included in it. Linear regression was then performed between the heat vulnerability score and the mean ratio for each census tract. Gaps in cooling center geographic coverage were identified by determining which census tracts were less than one standard deviation below the linear regression line.

5 RESULTS

5.1 Heat Vulnerability Index

There are 833 census tracts in Connecticut, among which 821 were included in the final heat vulnerability index. Census tracts were omitted if there was missing data for any of the variables used in the varimax-rotated PCA. Table 1 displays the description of the variables included in the varimax-rotated PCA and the distribution of each variable. The statistical distribution includes the median and the interquartile range (25^{th} percentile and 75^{th} percentile). Applying the three PCA criteria revealed four significant components, which accounted for 74.1% of the total variance. Table 2 displays the factor loadings for each variable used in the varimax-rotated PCA, the eigenvalues for each component, and the proportion of variance of each component. The first component encompassed environmental, non-English speaking, and Hispanic ethnicity variables and accounted for 32.5% of variance. It included variables representing both the natural and built environment, temperature, speaking English “less than well,” and Hispanic populations. The second component included socioeconomic variables including, speaking English “less than well,” Hispanic populations, person with disabilities, persons below poverty level, less than a high school education, and the unemployed. The third component strictly included elderly and social isolation variables and the fourth component included houses built before 1980 and persons with diabetes.

The spatial distribution of the cumulative heat vulnerability index is displayed in Figure 1. The cumulative heat vulnerability index score for the 821 census tracts had a mean of 13.96, standard deviation of 2.01, median of 14, and interquartile range of 12 to 15. The heat vulnerability index score ranges from 8 to 20. There were a large number of high vulnerability ($\geq$16) census tracts located in urban and metropolitan areas. Major urban clusters include the cities of Hartford, New Haven, Bridgeport, New London and Waterbury.

5.2 Cooling Centers

There was a total of 43 unique cooling center locations from the survey, as well as a total of 221 unique cooling center locations identified by searching through new sites. Of the latter, 37 were outdoor splash pads or outdoor pools and 16 were also identified via the survey. Thus, a total of 248 unique cooling centers were identified (Figure 2). The cooling centers-to-population ratio (cooling centers per 10,000 population) for each census tract is displayed in Figure 3. The cooling centers-to-population ratio had a mean of 1.2, standard deviation of 2.2, median of 0.16, and interquartile range of 3.5×10^{-7} to 1.3. Dark blue indicates a high ratio of cooling centers to population. There were large clusters around Hartford, New Haven, and Bridgeport, and there were smaller clusters around Waterbury and Bristol.

Figure 4 displays the linear regression between the cooling center kernel density and the heat vulnerability index score. There is an overall positive association between the heat vulnerability index score of the census tracts and the cooling center-to-population ratio. The points in red are census tracts that are more than 1 standard deviation below the linear regression line and are in the fourth and fifth quintiles for heat vulnerability (HVI $\geq$16). Figure 5 displays these census tracts spatially in red, with clusters around the towns of Manchester, Meriden, Milford, New London, Plainville, and Stratford.

6 DISCUSSION

The heat vulnerability index showed that many high vulnerability (HVI ≥16) census tracts are located in urban and metropolitan areas, consistent with other heat vulnerability indices in the United States (Reid et al. 2009, Reid et al. 2012, Maier et al. 2014, Nayak et al. 2018, Conlon et al. 2020). The environmental, non-English, and Hispanic component of this HVI accounted for the most variance and also included the greatest number of variables compared to the other components. The land cover variables had particularly high factor loadings. It is well-established that lack of vegetation, green space, or tree canopy coverage and a large percentage of impervious surfaces can contribute to the urban heat island effect (Heaviside et al. 2017, Conlon et al. 2020). Implementing adaptation strategies such as increasing green space, green roofs, and cool permeable surfaces, as well as tree planting, can help reduce the urban heat island effect which can help reduce heat exposure. Hispanic populations and populations that speak English "less than well" also contribute to this component, suggesting that health communication regarding heat needs to be convey in multiple languages.

The socioeconomic component accounted for the second-most variance at 24.1%, indicating that health communication should be clear, available, and accessible to populations of low socioeconomic status. Social interventions such as frequently checking on elderly, individuals with disabilities, or others who are socially isolated can help prevent heat-related emergencies (Luber and McGeehin 2008). Other interventions include direct communication with heat vulnerable individuals, increasing social capital of a community, increasing heat-health educational materials and health communication, and installing external wall insulation, external solar reflective paint, or shutters (Porritt et al. 2012, Kafeety et al. 2020).

One adaptation strategy to reduce extreme heat exposure is cooling centers. Cooling centers provide a stable cool environment for populations to take refuge from extreme heat. From the survey and news site sources, cooling centers were found to be mostly concentrated in urban areas where most of the population is located. In general, cooling centers in Connecticut were distributed appropriately, with more cooling centers located in or around the higher vulnerable census tracts. However, there were still areas where cooling centers were lacking such as clusters of census tracts in and around Manchester, Meriden, Milford, New London, Plainville, and Stratford.

Cooling centers are relatively inexpensive to implement because they take advantage of existing infrastructure such as schools, libraries, recreational centers, or religious centers (Widerynski et al. 2017). Educating the public and specifically high heat-vulnerable populations about heat safety and heat risk will provide the greatest benefit. Regional and local health departments or emergency management agencies can easily implement cooling centers at existing public air-conditioned buildings. While there is a lack of research on the direct health effects of cooling centers, it is broadly accepted that cooling centers in conjunction with other heat response strategies have significant health benefits (Widerynski et al. 2017).

There are limitations in the accessibility analysis performed for Connecticut. In general, cooling center accessibility is a very limited area of study, with previous studies in New York (Nayak et al. 2019), Portland, Oregon (Voelkel et al. 2018), Los Angeles County, California (Fraser et al. 2016), and Maricopa County, Arizona (Fraser et al. 2016, Berisha et al. 2017). Studies that examine spatial accessibility of health facilities often use a gravity model which is typically a two-step floating catchment method (2SFCA) (Yang et al. 2006, Schuurman et al. 2010). The 2SFCA method uses service availability as a ratio of supply to population within a catchment area for individuals and then sums the ratios for a catchment area. The 2SFCA method can allow for greater accessibility discrepancy between two neighboring areas that might otherwise be distorted (Yang et al. 2006). In Connecticut, the lack of data on cooling center facilities such as carrying capacity information and population demand for cooling centers limits the extent to which spatial accessibility can be assessed. However, cooling center location alone provides sufficient information for determining prime areas where cooling centers and other extreme heat interventions are needed. Since cooling centers are a commonly used and inexpensive intervention, lack of cooling centers might indicate an insufficient heat response plan that might be lacking in other extreme heat interventions.

While the cooling center-to-population ratio is important to determine if cooling centers are initially accessible to a vulnerable population, there is more to accessibility than just spatial access. Accessibility often involves availability, affordability, accommodation, and acceptability. For example, cooling centers should be readily available during hot weather, and individuals should be able to easily physically access a cooling center. Not all populations may have the means of transportation to get to a cooling center. In addition, cooling centers should be socially appealing and inviting in order to maximize cooling center attendance. These are all known challenges for accessibility to cooling centers (White-Newsome et al. 2014). The lack of knowledge about the existence and purpose of cooling centers and how cooling centers can be beneficial for populations also act as a social barrier to accessing cooling centers (Widerynski et al. 2017). Individuals should have the means to learn about extreme heat, its effects, and how to protect themselves against it. Education about cooling centers, heat action plans, and heat risk in general can allow vulnerable populations to better protect themselves from extreme heat (Luber and McGeehin 2008, Widerynski et al. 2017).

There were also limitations in development of the heat vulnerability index, including limited availability of data. Housing and building information is critical to creating a complete heat vulnerability index that accurately represents heat exposure (Samuelson et al. 2020). However, this study lacked information at the census tract level for the state of Connecticut on housing characteristics such as presence of air-conditioning, building type, and construction material, each of which is a determinant of indoor heat exposure (Samuelson et al. 2020). As such, housing age was the only proxy used for housing characteristics in this heat vulnerability index.

This heat vulnerability assessment heavily depended on census data. Census tract boundaries can change every ten years leading to consolidating, splitting, or shifting census tracts. Variations in population demographics over time might be a result of dynamic political boundaries rather than actual shifts in population (Karanja and Kiage 2021). In addition, not all census data are available for every geographic area such as the American Housing Survey which generally provides data for populated metropolitan areas. As such, spatial and temporal variations may pose a challenge for tracking vulnerable populations over time.

7 CONCLUSION

Heat vulnerability in Connecticut varies based on geographic area, but generally clusters around urban areas. This heat vulnerability index is specific to Connecticut, and similar indices for other regions may be different depending on the variables used. For future study, different weights might be given to heat-related indicators depending on the literature, for a more comprehensive index. In addition, validation of the heat vulnerability index would be beneficial for improving its reliability and usability. Development and maintenance of heat vulnerability indices should be a dynamic process that involves ongoing efforts to accurately target changing vulnerable populations and qualitative processes to evaluate heat vulnerability.

The heat vulnerability index along with existing locations of cooling centers helped to identify areas in the state of Connecticut where cooling centers might be needed. Furthermore, high heat vulnerability areas and areas with cooling center gaps might be targets for heat adaptation measures, heat intervention strategies, heat response plans, or other policy responses. As climate change rapidly affects the natural and built environment, there is a need to address and protect populations that are particularly susceptible and vulnerable to heat.

8 TABLES AND FIGURES

Table 1. Summary of variables used in the heat vulnerability index

Data Source	Variable	Median (IQR)
US Census American Community Survey (2015 - 2019)	Percentage of population that are 65 years of age or older	16.8 (12.7 - 20.5)
	Percentage of population who identify as black	4.5 (1.4 - 16.3)
	Percentage of population who identify as Hispanic	9.6 (4.6 - 23.8)
	Percentage of population that live alone	27.1 (21.0 - 34.9)
	Percentage of population that are 65 years of age or older and live alone	11.0 (8.0 - 14.5)
	Percentage of population that have less than a high school education	7.2 (4.1 - 13.4)
	Percentage of population between the ages of 18 and 64 that have a disability	8.0 (5.4 - 11.3)
	Percentage of population that is foreign born	11.8 (7.4 - 18.9)
	Percentage of population that speaks English "less than well"	5.2 (2.5 - 11.3)
	Percentage of population that is below the poverty level	6.7 (3.7 - 14.1)
	Percentage of housing that was built before 1980	73.7 (61.9 - 84.8)
	Percentage of civilian labor force that is unemployed	3.5 (2.3 - 5.2)
CDC United States Diabetes Surveillance System (2013)	Percentage of population that has diabetes	6.4 (5.4 - 7.1)
Terra MODIS Land Surface Temperature	Mean temperature in Celsius	27.7 (25.3 - 30.2)
USGS National Land Cover Database (2016)	Percentage of land with high intensity land use	2.8 (0.6 - 8.9)
	Percentage of land with non-green space land cover	72.7 (36.4 - 95.7)
	Percentage of land with non-tree canopy coverage	61.9 (43.4 - 79.3)
	Percentage of land with impervious surfaces	22.6 (8.3 - 41.5)

Table 2. Variance explained and factor loadings outputs for varimax-rotated PCA for each variable at the census tract level (values above 0.50 are bolded).

Variable	Environmental, non-English, and Hispanic Component	Socioeconomic Component	Elderly and Social Isolation Component	Housing and Diabetes Component
Percentage of land with non-green space land cover	**0.89**	0.20	0.09	0.20
Percentage of land with impervious surfaces	**0.86**	0.42	0.02	0
Percentage of land with non-tree canopy coverage	**0.84**	0.35	0.13	0.08
Mean temperature in Celsius	**0.84**	0.34	0.03	0.10
Percentage of population that is foreign born	**0.78**	0	-0.17	-0.31
Percentage of land with high intensity land use	**0.66**	0.47	0.03	-0.23
Percentage of population that speaks English "less than well"	**0.66**	**0.50**	-0.14	-0.25
Percentage of population who identify as Hispanic	**0.56**	**0.67**	-0.18	-0.09
Percentage of population between the ages of 18 and 64 that have a disability	0	**0.82**	0.26	0.10
Percentage of population that is below the poverty level	0.36	**0.80**	-0.01	-0.03
Percentage of population that have less than a high school education	0.45	**0.77**	-0.06	-0.10
Percentage of civilian labor force that is unemployed	0.30	**0.71**	-0.21	0.02
Percentage of population that are 65 years of age or older and live alone	-0.01	-0.08	**0.91**	0.03
Percentage of population that live alone	0.36	0.31	**0.70**	0.04
Percentage of population that are 65 years of age or older	-0.36	-0.39	**0.66**	0.09
Percentage of population that has diabetes	-0.10	-0.10	0.07	**0.75**
Percentage of housing that was built before 1980	0.48	0.27	0	**0.52**
Percentage of population who identify as black	0.47	0.48	-0.12	0.06
Eigenvalue	8.78	2.08	1.43	1.04
Percent Variance Explained	32.5	24.1	11.1	6.4

Figure 1. Connecticut 2019 Heat Vulnerability Index at the census tract level (n = 821). Dark red indicates a high heat vulnerability index score and light yellow indicates a low heat vulnerability index score.

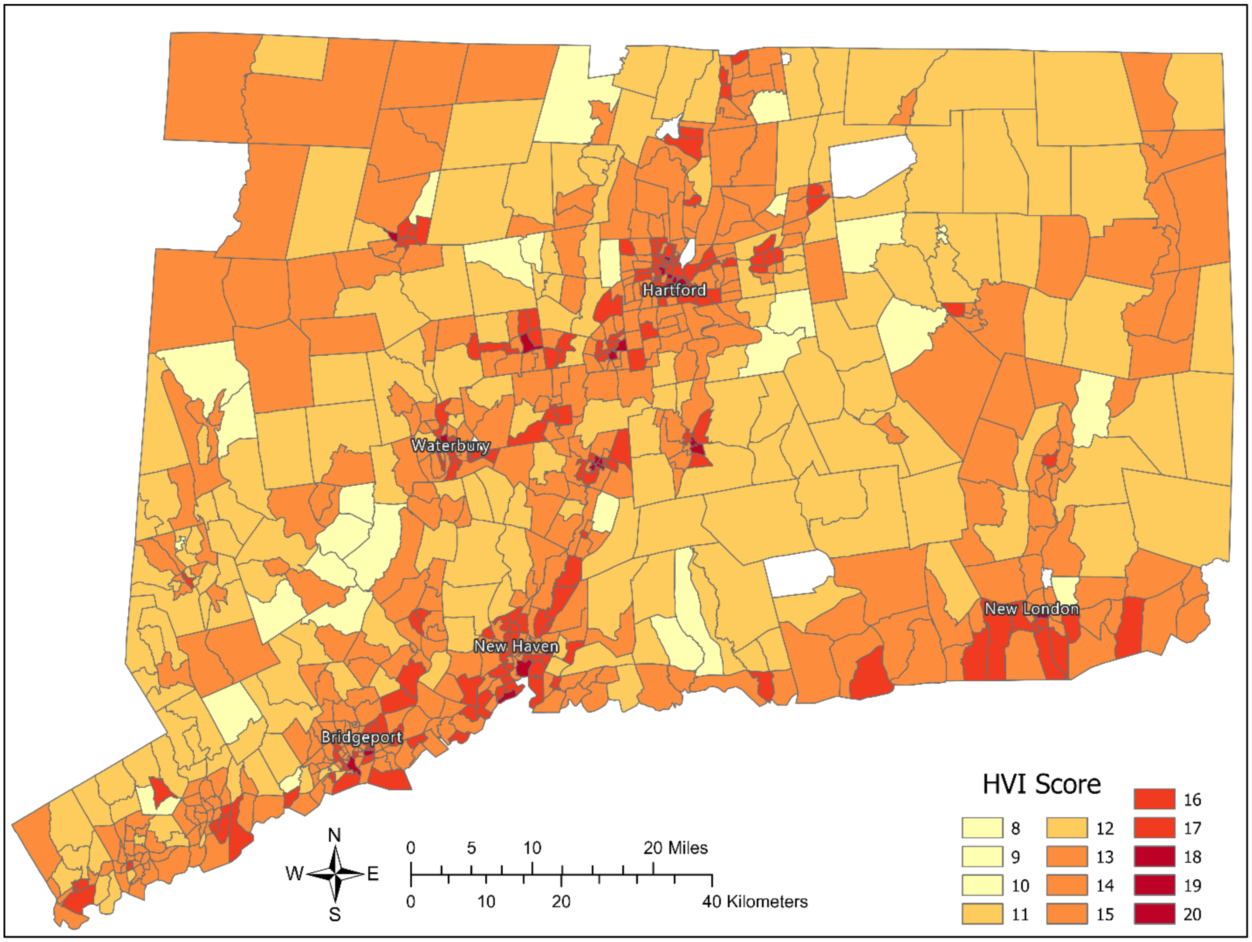


Figure 2. 2019 cooling centers locations in Connecticut (n = 248).

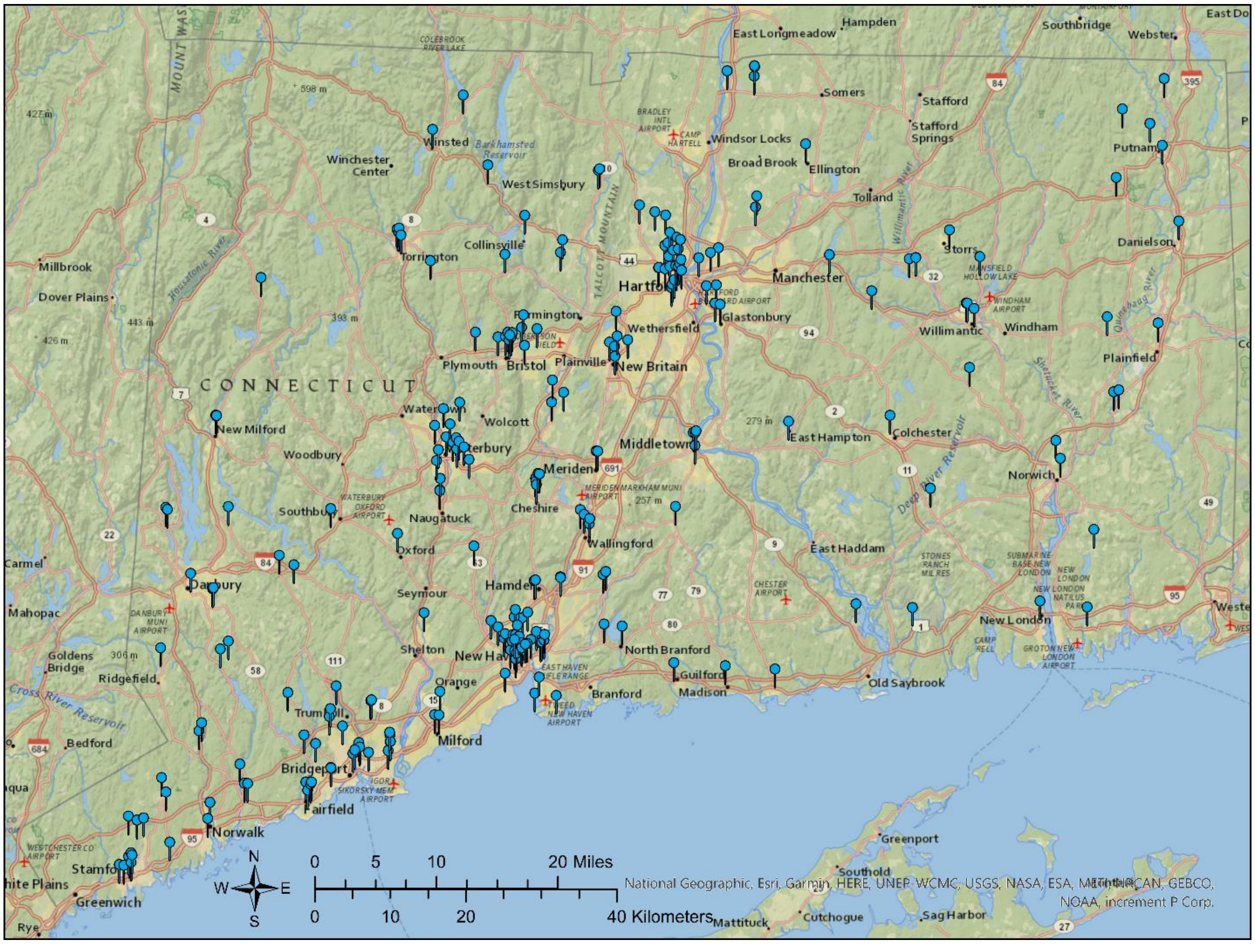


Figure 3. Cooling centers per 10,000 persons in Connecticut for each census tract. Darker blue has a high cooling center-to-population ratio and light blue has a low cooling center-to-population ratio.

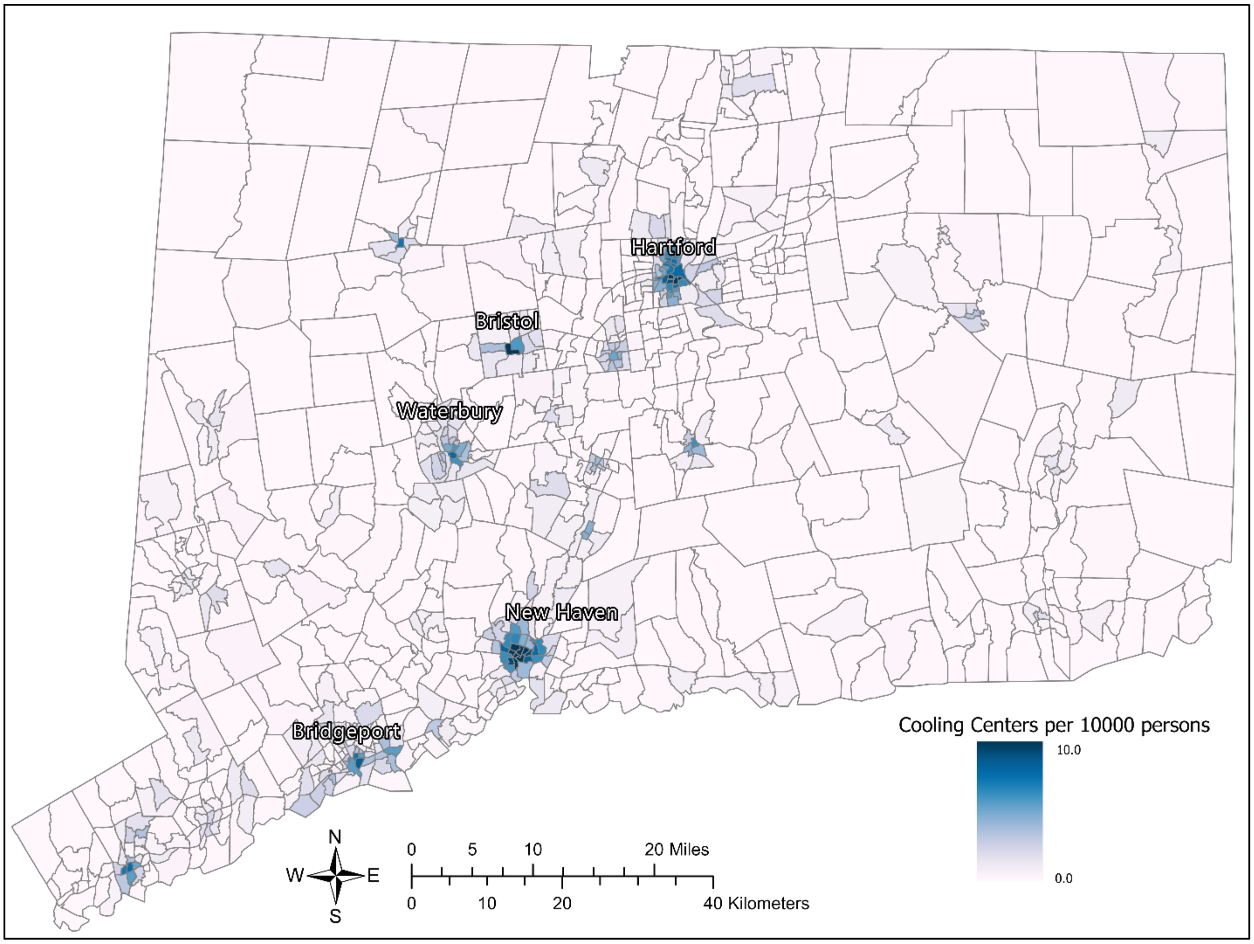


Figure 4. Scatter plot of census tract mean cooling center-to-population ratio by census tract HVI Score. Red points indicate census tracts that are more than one standard deviation below the line of best fit and have a heat vulnerability index score of 16 or greater.

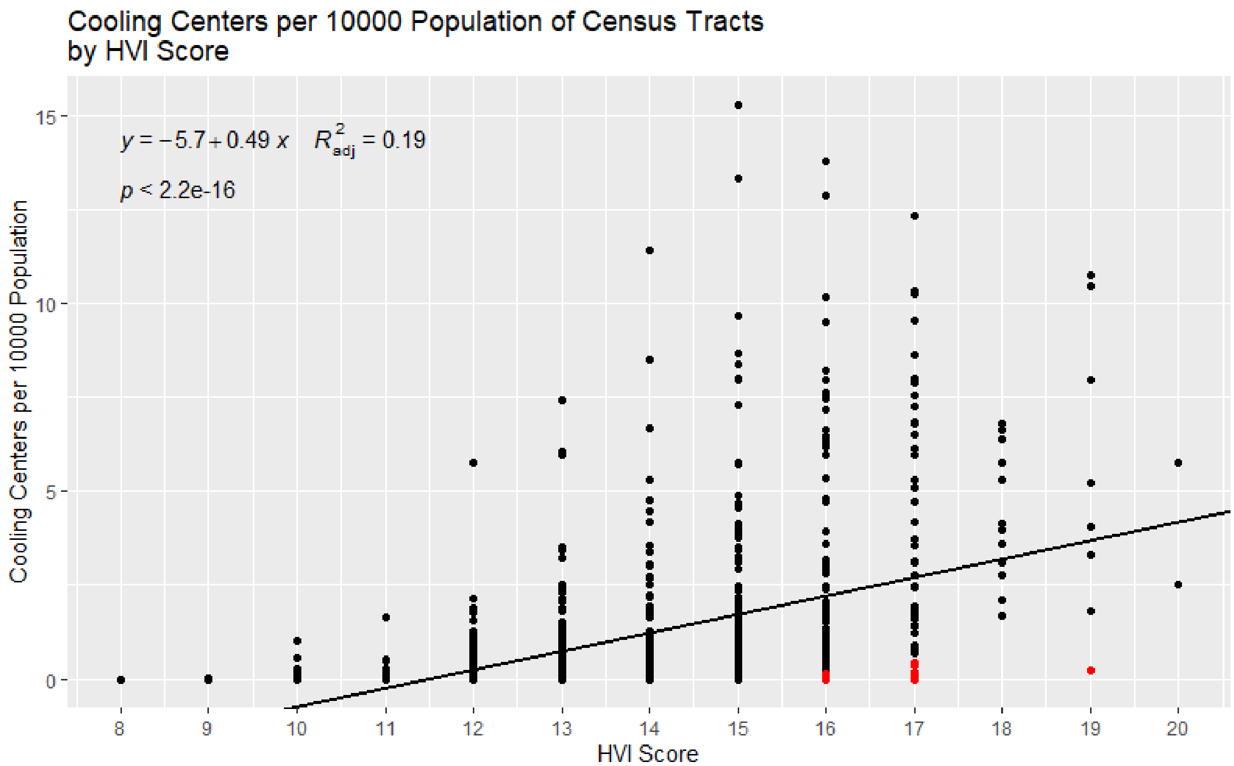
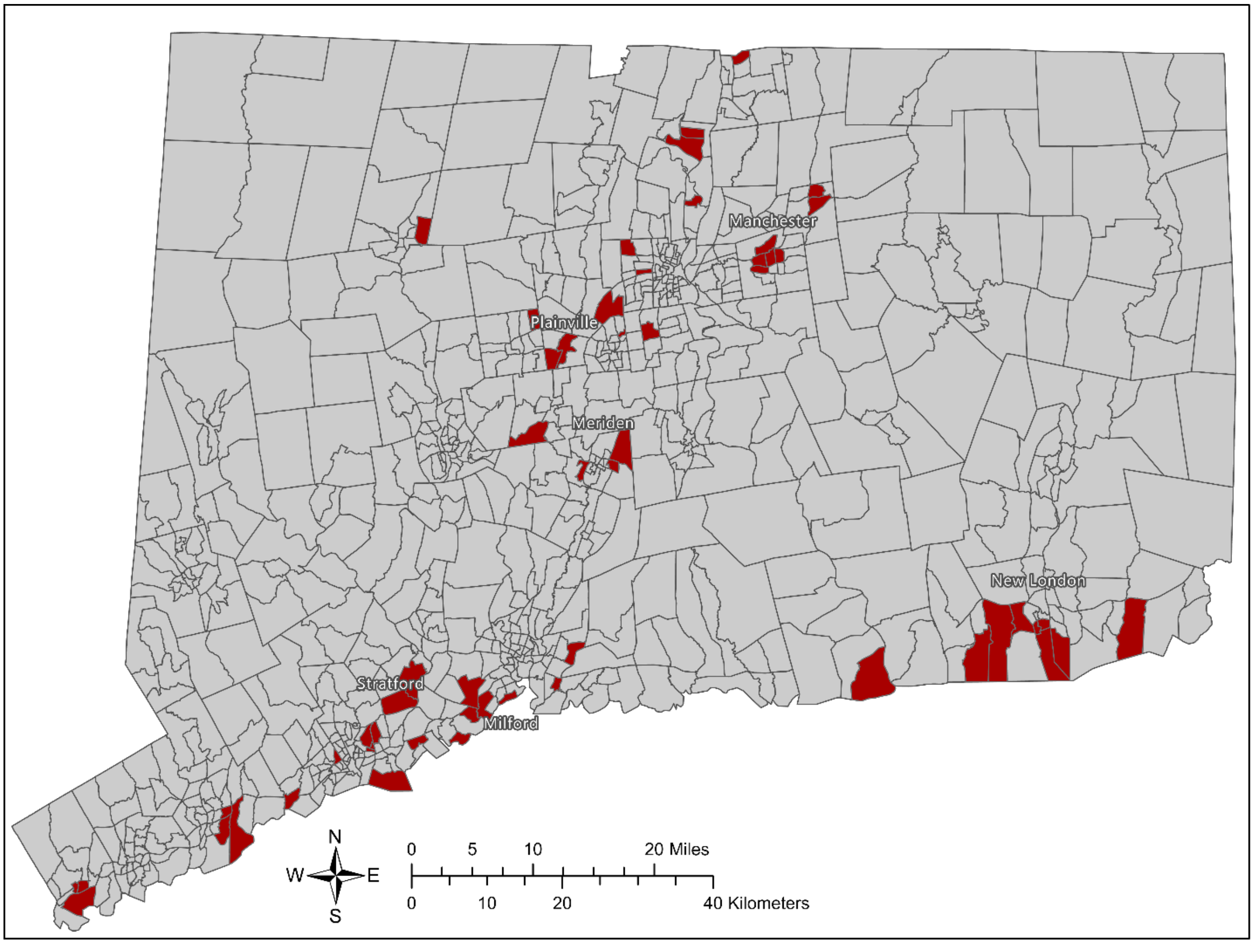


Figure 5. Census tracts (in red) with low cooling center-to-population ratio and a high heat vulnerability score



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