New Jersey Heat Vulnerability Index Technical Documentation

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Introduction

Heat stress is the leading cause of weather-related fatalities within the United States. [1] Since 1900, annual New Jersey temperatures have increased by about 4 °F (as of December 2021), driven by increased global temperatures from greenhouse gas emissions, [2,3] and temperatures are projected to continue increasing throughout the remainder of the 21st century. [3,4] With high greenhouse gas emissions, it is likely that about 70% of New Jersey summers will be warmer than any before 2006 by the middle of the 21st century. And by the end of the 21st century, about 90% of summers are projected to be warmer than any before 2006. [5] Increased summer temperatures will likely increase incidences of heat related illness, hospital admissions, and mortality among vulnerable populations. [6] Similarly, it is expected that heatwaves will become more frequent and longer throughout New Jersey by the middle and end of the 21st century. [7]

Given these trends, it is important to identify the locations of communities and populations that experience increased health vulnerability to extreme and prolonged heat within New Jersey for potential interventions, such as increasing urban tree canopy cover. [8] Vulnerability to heat is broadly defined as degree to which a community or individual is prone to experience the negative outcomes of a high heat event, such as increased injury or mortality rates. One limitation in identifying these communities within New Jersey is a lack of heat-related health outcome data. This lack is driven by few documented historical incidences of heat-related emergency department (ED) visits and mortality in New Jersey. Additionally, high heat events tend to exacerbate other health issues, and heat is not necessarily attributed as a primary cause of a resultant ED visit or mortality. [9]

Therefore, this report identifies communities experiencing vulnerability to extreme heat by utilizing social and environmental indicators that exacerbate heat-related mortality and morbidity (worse health outcomes) as identified in scientific and public health literature. Multiple studies and reports have used heat vulnerability indicators to generate heat vulnerability indices (HVIs) to identify regions of greatest risk to extreme heat at the national [10], state [11–15], and metropolitan

[16–23] scales. These indicators include physical characteristics, such as the percent of the land area with impervious surfaces, and community aspects, such as the proportion of the population above the age of 65, that contribute to disproportionate community morbidity and mortality from an extreme heat event.

A composite HVI was generated using existing census data, natural and built environment data, summer temperature records, and community health data informed by the methodology utilized for New York City [18], the Greater Boston Area [16], and the States of Wisconsin [12,13] and Vermont. [15] The purpose of this effort is to help identify the regions within New Jersey that may be most at risk from extreme heat today and bear special consideration in planning for future climate change.

Methods

Data Sources

Indicator variables contributing to the New Jersey HVI and their sources are listed in Table 1. These indicators were selected by reviewing existing literature and the technical documentation provided for the development of HVIs in other locations within the U.S. [10–23]. Many potential indicators were identified in this investigation, but not all are listed in Table 1. Multiple indicators represented a shared aspect of vulnerability, such as median household income and the percent of a community living below the poverty line representing financial resilience to extreme heat. To reduce redundancy, indicators sharing the same conceptual effects on vulnerability and health outcomes relating to extreme heat were reduced to the one that was found most consistently across other HVIs. Additionally, indicators were compared using the Spearman rank correlation coefficient (ρ). Indicators with a very high correlation ($\rho > 0.8$) with others were reduced to one indicator, again selecting the one most consistent in other HVIs, or were synthesized into a single variable to generate the list in Table 1.

In reviewing the literature, there were indicators that appear in some HVIs and not others, such as the percentage of households with single parent families. [16] Indicators were selected based on either appearance in the documentation for multiple HVIs or a well-established relationship to heat health outcomes in the literature. For example, the proportion of single parent households only appeared in one of the reviewed HVIs and was therefore removed from this analysis. Another example is high blood pressure. While some HVIs included high blood pressure, presumably as a proxy for cardiovascular disease, the literature does not physiologically relate prevalence of hypertension itself to increased morbidity and mortality during an extreme heat event. [24,25] However, other cardiovascular diseases are exacerbated with heat stress. [24] As cardiovascular diseases are exacerbated by high heat, but hypertension does not appear to be one of them, it was removed from the analysis and replaced with coronary heart disease prevalence, [26] the only other cardiovascular disease for which there are easily accessible public data at the census tract resolution.

Finally, the geography of the selected indicators was summarized to the 2010 decennial census tracts, despite the 2020 census having been completed. Some of the selected datasets, such as the census tract-level chronic health data, have not yet been updated to the new 2020 decennial census geography and new census tract divisions at the time of writing. The HVI geography will be updated in future iterations as these data become available.

The selected indicators were classified into three groups (Table 1): Exposure (4 indicators), Sensitivity (8 indicators), and Adaptive Capacity (6 indicators). Exposure represents the physical environmental stressors or characteristics that lead to worse health outcomes at the individual and community level. Sensitivity is the degree to which individual or communities may be affected by extreme heat. Adaptive capacity is the ability of the individual or community to respond to and take action to mitigate the hazards associated with extreme heat and recover from an extreme heat event. Indicators considered and not incorporated into the HVI are listed in Appendix A.

Table 1. List of indicators included in the New Jersey heat vulnerability index with data sources, geographic scales, and notes regarding the individual measurements.

Indicator	Data Source	Geography	Notes and Rationale
		Exposure	
Impervious Cover to Canopy Cover Index	National Land Cover Database 2019 Percent Developed Imperviousness (CONUS) [27] and 2016 USFS Tree Canopy Cover (CONUS) [28]	Census Tract	Impervious surfaces absorb solar radiation and reradiate the energy as heat, which can cause elevated temperatures in urban areas compared to the surrounding rural areas. [29] Higher prevalence of canopy cover, conversely, is linked to cooler temperatures relative to areas lacking tree canopy cover. These two metrics are highly correlated and were combined into a single index by the formula: $-1*([\text{Mean Canopy Coverage} * \text{Tract Area}_1] - [\text{Mean Impervious Coverage} * \text{Tract Area}_2]) / ([\text{Mean Canopy Coverage} * \text{Tract Area}_1] + [\text{Mean Impervious Coverage} * \text{Tract Area}_2])$ The mean canopy and impervious surface coverage were calculated for each census tract before computation. “Tract Area” appears multiple times as the total area pixels within each coverage layer differs minutely due to raster pixels not being aligned and this producing slightly different areas when calculated in ArcGIS. The subscript 1 denotes the tract area calculated for canopy cover and 2 for impervious cover.

			The index was multiplied by -1 so that higher values correspond to more impervious coverage area and, therefore, a greater risk of an urban heat island.
Historical Annual Fine Particulate Matter ($PM_{2.5}$) Concentration	Centers for Disease Control and Prevention (CDC) National Environmental Public Health (EPH) Tracking Network[30] U.S. Environmental Protection Agency (EPA)	County	Particulate matter compounds with extreme heat to increase rates of cardiovascular- and respiratory-related ED visits and mortality. [31,32] The indicator value is computed as the five-year average from 2014 to 2018 for each county. County values were applied to census tracts within each county limit.
Historical Mean Annual Number of Ozone (O_3) Exceedance Days	CDC EPH Tracking Network [30] U.S. Environmental Protection Agency (EPA)	County	Ozone production increases at higher temperatures, which can be hazardous for individuals with respiratory issues and can increase mortality. [31,32] The indicator value is computed as the five-year average of standard exceedance days from 2014 to 2018 for each county. County values were applied to census tracts within each county limit. The number of exceedance days was selected as the indicator as O_3 concentrations were not readily available at the county level through the EPH Tracking Network.
Summer Average Temperature Normals (1991 to 2020)	Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) [33]	Census Tract	This indicator is the average summer (June–August) temperature at each census tract centroid for the years 1991 to 2020. Average summer temperatures are included to account for local temperatures and climates that may modify the urban heat island effect, such as potentially cooling/moderating sea breezes along coastal regions. [34]
Sensitivity			

Percent of Population Over the age of 65	U.S. Census American Community Survey (ACS) 5-Year Estimates (2015–2019)	Tract	Individuals over the age of 65 are at an increased risk for heat related ED visits, mortality, and other heat-related issues during extreme heat events. [29,35–37]
Percent of the Population Under the age of 5	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Young children are at risk for heat illnesses due to a reduced ability to thermoregulate and are dependent on caregivers for reduction to extreme temperatures. [36,38]
Percent of Population with a Disability	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Persons with mobility or cognitive difficulties may have greater difficulty responding and adapting to extreme heat conditions and climate change. [39]
Percent of Housing Structures Built Before 1960	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Older homes are less likely to have central air conditioning [22] and were used as a proxy for potential air conditioning prevalence. Older buildings can also have reduced thermal insulation. [11]
Percent of Workers in Occupations likely requiring Outdoor Labor	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Outdoor workers are likely to experience increased heat exposure and are more vulnerable to heat illness and mortality. [31,39] Here, occupations with a likely outdoor labor component are defined as Census ACS occupation categories of: Building and grounds cleaning and maintenance occupations; Construction and extraction occupations; Farming, fishing, and forestry occupations; Installation, maintenance, and repair occupations; Material moving occupations; Protective service occupations; and Transportation occupations.
Percent of People Living Alone	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Communities and individuals with limited social connection are more vulnerable to heat, especially the elderly. Reduced contact with family or friends may reduce protective behaviors or heat hazard/illness identification. [10,40]
Crude Prevalence of Asthma Among Adults (≥ 18 years) (2018)	CDC EPH Tracking Network [30] CDC Behavioral	Tract (modeled)	Extreme heat and heightened air pollution (such as ground level ozone) during high heat events can exacerbate chronic respiratory issues and increase hospitalization rates. [24,41]

	Risk Factor Survey System (BRFSS) and Population Level Analysis and Community Estimates (PLACES)		
Crude Prevalence of Diabetes Among Adults (≥ 18 years) (2018)	CDC EPH Tracking Network [30] CDC BRFSS and PLACES	Tract (modeled)	Extreme heat increases the risk/rate of hospital visits for diabetes related issues. [10,39,42]
Crude Prevalence of Coronary Heart Disease Among Adults (≥ 18 years) (2018)	CDC EPH Tracking Network [30] CDC BRFSS and PLACES	Tract (modeled)	Heightened temperatures can increase the risk of morbidity mortality associated with coronary heart disease, [26] though some studies [43] have indicated that higher moderate temperatures rather than extreme temperatures have a stronger effect on hospitalizations from coronary heart disease.
Adaptive Capacity			
Percent of the Population Living below the Poverty Line	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	People with lower incomes and living below the poverty line are associated with greater vulnerability to heat stress and a limited capacity to adapt to and recover from extreme heat events. [29,35]
Percent of the Working Age population that is Unemployed	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Unemployment, not including retirement or voluntary unemployment, is associated with greater vulnerability to climate hazards. [11]
Percent of the population Speaking English less than "Very Well" (Linguistic Isolation)	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Limited English proficiency can limit the communication of heat hazard warnings when only communicated in English and limit the employment of protective measures in linguistically isolated during heat related emergencies. [11,21]

Percent of the Population over Age 25 without a High School Degree or Equivalent	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Individuals without a high school education are associated with greater vulnerability to heat and heat-related mortality. [10,35]
Percent of Population that is Non-White (including Hispanic and/or Latino Ethnicity)	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Predominately non-white communities are subject to greater vulnerability to natural hazards, including extreme heat due to social inequities. [39,44]
Percent of Population without Health Insurance	U.S. Census ACS 5-Year Estimates (2015–2019)	Tract	Lower rates of health insurance can reduce hospital and emergency service usage, leading to greater morbidity and mortality from natural hazards, including extreme heat. [45]

Composite HVI calculation

Prior to HVI computation, each indicator was transformed to approximate a normal distribution throughout the state. This process worked to limit the effect of the data outliers and a skewed distribution. [15] While extreme outliers were rare, many of the indicator distributions were heavily skewed, where the bulk of the data is clustered on one end of the distribution and there is a long tail of either higher or lower values causing the data distribution to asymmetric. For example, the indicator of proportion of people living below the poverty line per census tract for the entire state was positively skewed (Figure 1 [*left panel*]).

Each indicator was transformed to fit a more normal distribution utilizing a Box-Cox transformation. [46] The transformation tests a number of exponents (λ) from -5 to 5 to determine an optimal value to best approximate a normal curve by finding which λ value maximizes the log-likelihood function. The transformation is defined as:

$$y(\lambda) = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, & if\ \lambda \neq 0 \\ \log(y), & if\ \lambda = 0 \end{cases}$$

Where $y(\lambda)$ is the transformed indicator and y is the original indicator. Additionally, this formulation of the Box-Cox transformation is only for positive values. In instances were negative or zero values were present, a constant was added to all values of the indicator such that the minimum value became 0.0001. Figure 1 displays histograms comparing the distributions of the percent living below the poverty line by census tract before and after transformation. Note that prior to transformation the distribution is heavily skewed and after the Box-Cox transformation, the histogram more closely resembles a normal distribution. It is important to note that this transformation does not affect the relative rank of each census tract within the indicator but modifies the relative magnitudes of the values to approximate the normal distribution.

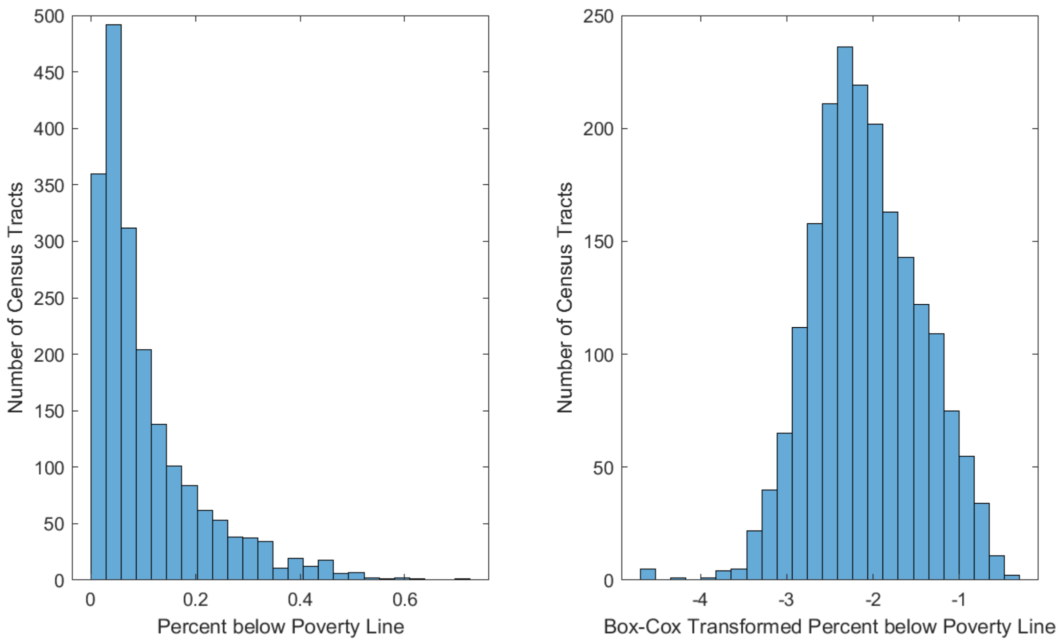

Figure 1. Histograms comparing the distribution of the percent of people living below the poverty line by census tract (left) to the same data after a Box-Cox transformation for normality (right). Note the untransformed data is heavily skewed to the right, a long tail to the right of the distribution peak, while the transformed data better approximates a normal distribution.

Once transformed for normality, each indicator was standardized and mean centered. To standardize the indicator, each was converted into a z score to ensure all indicators were on the same scale and eliminate any effects from comparing different units. [11–13,15,16,47] The z score formulation is given as:

$$z\ score_i = \frac{x_i - \mu}{\sigma}$$

Where the subscript *i* represents the *i*th census tract, x_i is the value of the indicator at census tract i, μ is the mean of the indicator, and σ is the standard deviation of the indicator. The z score values were mean centered, subtracting the mean z score from all values of the indicator, such that the mean was zero and the values represented the number of standard deviations above or below the mean of the transformed indicator.

Within each vulnerability group (exposure, sensitivity, and adaptive capacity), the transformed indicators were averaged to generate a composite group score. These scores were again z score transformed and mean centered to ensure that each group score was in the same units (standard deviations above and below the mean) and averaged into the final composite HVI. The full methodology is described visually in Figure 2.

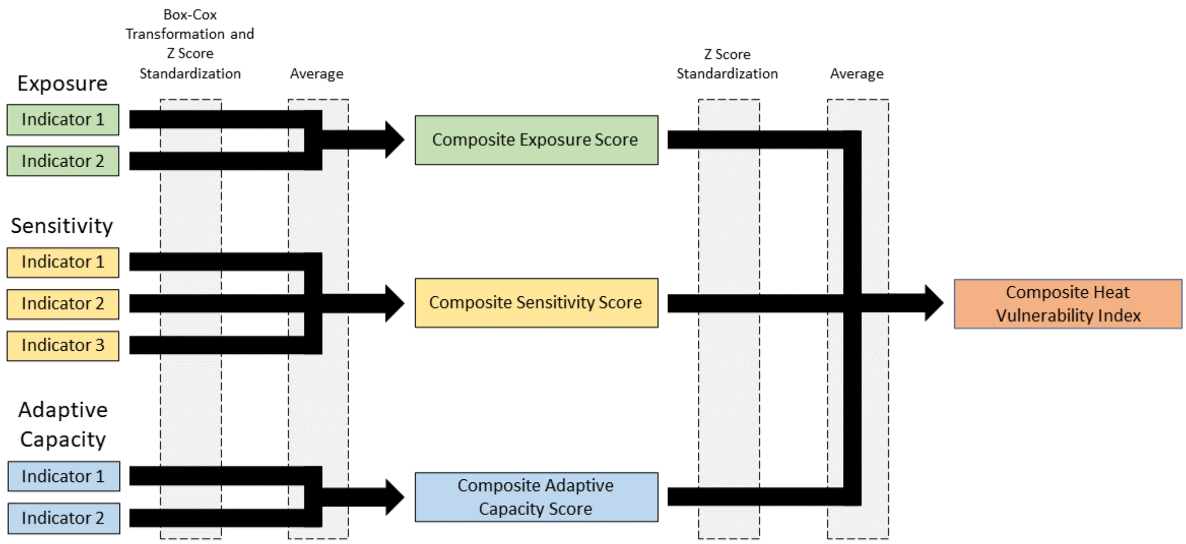

Figure 2. Schematic flowchart detailing composite heat vulnerability index development from indicator variables for each indicator group: Exposure, Sensitivity, and Adaptive Capacity. Grey shaded regions with a dashed boarder indicate data transformations and averaging procedures.

Each indicator, group score, and the composite HVI were aggregated into a single data table. To aid in interpretation, each indicator, score, and the HVI values were divided into 20th percentile bins and ranked 1 to 5 to indicate their magnitude/vulnerability relative to other census tracts throughout the state. 1 indicates the lowest percentile bin for the value, coinciding for the lowest vulnerability category for the variable, and 5 indicates the highest percentile bin, or the highest vulnerability category for the variable. For example, a census tract would indicate a "1" for a relatively low percentage of its population that is aged 65 and over and "5" if the percentage of its 65 and over population is within the highest 20th percentile for the state. Finally, correlation matrices between indicator and between indicator group scores for further analysis can be found in Appendix B.

Usage

While the HVI and indicator data set may be used in numerous ways, practitioners may find it the most useful to "work backwards" from a census tract's HVI score to assess vulnerability. The HVI highlights the regions within the state most vulnerable to extreme heat based on the selected indicators. To determine which community characteristics (indicators) contribute the most to the vulnerability score, a user can view the relative ranks of the group scores (Exposure, Sensitivity, and Adaptive Capacity), see which values are highest (4s and 5s) and then look at the indicators within those categories to see which display the highest relative ranks.

For example, for Census Tract 5003, in Gloucester County, the HVI score is 4, indicating a "Moderate High" vulnerability to extreme heat compared to other census tracts throughout the state. In looking at the group scores, this tract has high values of 4 in the Exposure and Sensitivity Categories. The user can then explore which indicators contribute the most to the high composite scores, such as high normal summer temperatures, a relatively high percentage of its population that is disabled, or a relatively high asthma prevalence. Retaining the indicator and group scores allows policy makers to tailor interventions to the specific needs of vulnerable communities. This information can also help public health professionals create educational information/campaigns specific and most relevant to at-risk communities.

It is important to note that there may be drivers of heat vulnerability that are not adequately captured within this HVI. This tool works as a first-order approximation of relative heat vulnerability throughout the state. When assessing vulnerability of a community, a user should consider unique community characteristics not captured by the selected indicators. Finally, while the ranking system indicates low to high vulnerability, low vulnerability HVI categories (1s and 2s) do not indicate "no vulnerability." These communities can still be subject to increased morbidity and mortality during an extreme heat event.

Alternate HVI Development Methods

HVIs can be developed in different ways and utilize different datasets. Presented within this documentation is the methodology to create a composite HVI by grouping and averaging select indicators. This methodology was selected for clearer stakeholder interpretation and for rapid updates as new data become available. Another common technique to generate HVIs is to utilize principal component analysis (PCA).[10,11,14,17,20,23,47] PCA is technique that uses the covariance between the selected indicators to reduce a large dataset to a smaller number of components that represent the majority of variability of the dataset. PCA can generate derived indicator components from the data that aggregate indicators that vary similarly, but whose grouping may not be obvious. The two primary benefits of this technique are that it reduces the size of the dataset, facilitating scientific interpretation, and it reduces the effect of "double counting" indicators that may be measuring a similar phenomenon (such as median income and poverty rate). [23]

However, there are limitations to the PCA method that made a composite HVI (described above) more appropriate for this work. First, while employed in computer science and machine learning algorithms, PCA usage in this context requires a significant amount of researcher input for each iteration and each step. There are guidelines for the number of principal components to retain for analysis, but it is ultimately up to the researcher and can be arbitrary. PCA can be used on very large datasets, but to ensure that each indicator is well represented by the selected components, a smaller dataset of 11 to 17 indicators was found to be necessary in the development of the New

Jersey HVI, limiting the inclusion of certain indicators (similar to Stafford and Abramowitz [2017] [47]). Additionally, as the data are updated, the nature of each component can change, necessitating a reanalysis of the PCA methodology, the number of retained components, and reinterpretation of the components, and resultant HVI. This would limit the ability of the HVI to be easily and quickly updated an annual or biennial basis as new census and health data become available.

Finally, each component of the PCA-generated HVI is a derived value, relating to multiple indicators. For planners and practitioners, it can be difficult to determine which indicators make their communities vulnerable when they are aggregated into principal components through a complex statistical technique. [48] The purpose of this HVI is to inform areas of greater vulnerability to extreme heat and also to allow the user to easily interpret which characteristics of each census tract contribute to that vulnerability. Therefore, the composite HVI index approach was selected for this effort.

Another consideration in HVI development is weighting of the indicators. [48,49] Certain indicators, or indicator groups, may have a stronger impact on human health during an extreme heat event compared to others. In this case, weighting certain indicators in the HVI average could make a more accurate and representative final index. However, there is a lack of appropriate data to objectively weight each indicator by comparing the selected indicators to morbidity and mortality estimates during extreme heat events. Scientific and public health literature detailing an objectively weighted HVI approach are limited and often location specific. Another common weighting method is to utilize an external panel of experts to determine a general, and somewhat subjective, weighting scheme for the HVI, [49] but that effort is outside of the scope of this report and would still introduce a level of subjectivity into the weighting scheme. Instead, each indicator was weighted equally, which is common among many HVI methodologies.[10,11,13,15,16,18,20–22] Averaging within each indicator group and equally weighting the groups in the final HVI calculation ensures that a group with more indicators in total (i.e., Sensitivity) did not dominate the HVI pattern.

Spatial Distribution

This section presents the geographic distribution of exposure, sensitivity, and adaptive capacity group scores and the final HVI score. Individual indicator scores are presented in the associated Microsoft Excel workbook and attribute data of the HVI Map layer.

Exposure

The regions with the highest exposure group scores (4s and 5s) are dominated by large urban centers to the northeast (Newark, Elizabeth, Jersey City) and southwest (Camden) (Figure 3). These areas have the highest percentage of impervious surface coverage compared to tree canopy cover and represent counties with poorer air quality in general. One caution when interpreting this map: many coastal areas along barrier islands are ranked as having moderate relative vulnerability to heat, designated by the number 3. The heat exposure experienced in coastal areas may be buffered by the effects of the ocean and ocean breezes [34], so it is important to consider these local conditions in analysis. The observed trend is primarily driven by a high impervious to canopy cover index along barrier island communities in New Jersey.

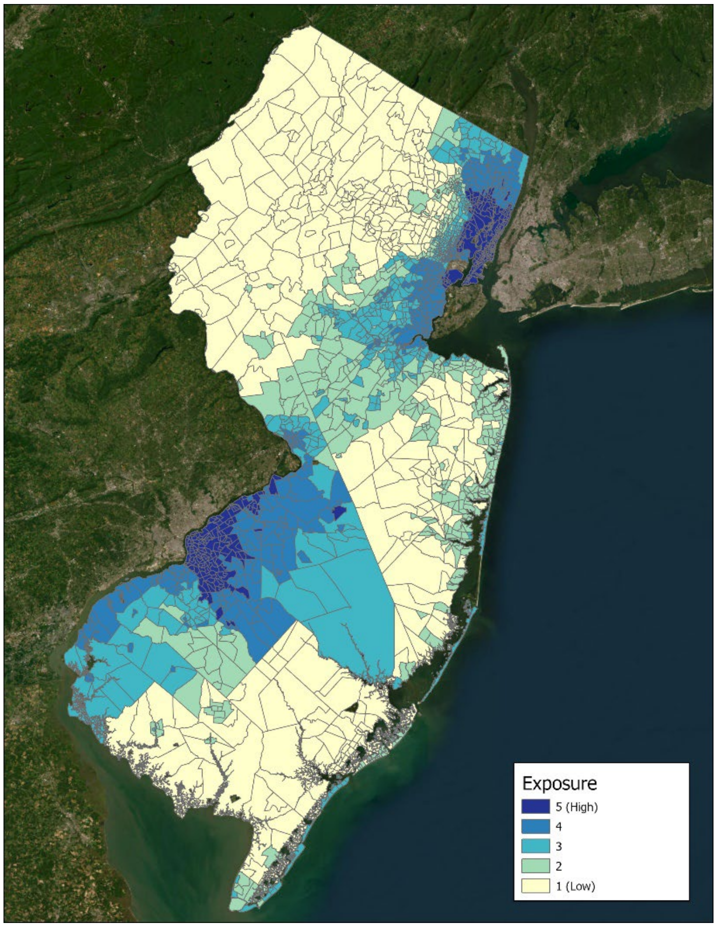

Figure 3. Spatial distribution of the aggregate exposure score where 1 indicates a relatively low exposure score for a census tract and 5 indicates a high exposure score.

Sensitivity

The pattern of regions with greater sensitivity to high heat is somewhat harder to discern. Urban areas have some of the highest sensitivity to extreme heat (Figure 4), driven by older homes, a high prevalence of chronic diseases such as asthma, and a higher percentage of people living alone. There is also a discernable north-south trend, whereby northern areas outside of cities tend to be scored as less sensitive to extreme heat compared to southern regions. These higher sensitivity southern areas tend to coincide with a greater percentage of the population being over the age of 65, a higher disability rate, and higher rates of chronic illnesses.

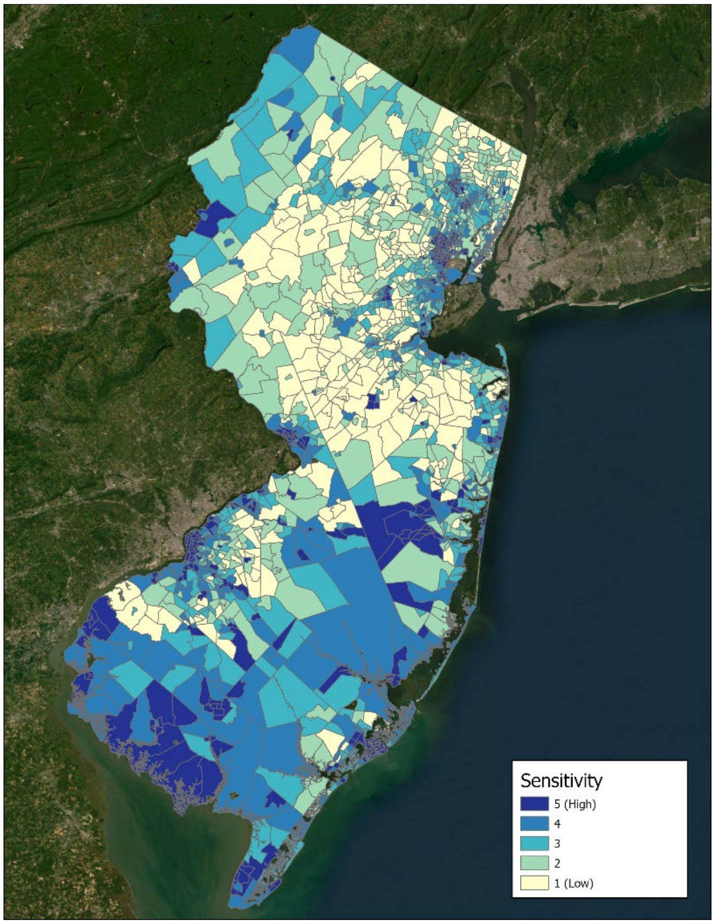

Figure 4. Spatial distribution of the aggregate sensitivity score where 1 indicates a relatively low sensitivity to extreme heat score for a census tract and 5 indicates a high sensitivity score.

Adaptive Capacity

Adaptive capacity is presented on a scale of 1 to 5 where 1 indicates a high adaptive capacity to extreme heat and climate perturbations (lower vulnerability) and 5 indicates a lower adaptive capacity (higher vulnerability). This directionality in scoring was selected to maintain consistency with other indicator groups whereby a higher number indicates greater vulnerability. Outside of highly urban areas such as Newark, Trenton, or Camden, the distribution of lower adaptive capacity does not follow a distinct regional trend (Figure 5). Urban areas have a much lower adaptive capacity (higher vulnerability score) across all adaptive capacity indicators, such as poverty rate or high nonwhite population, without much variation or few indicators dominating the trend.

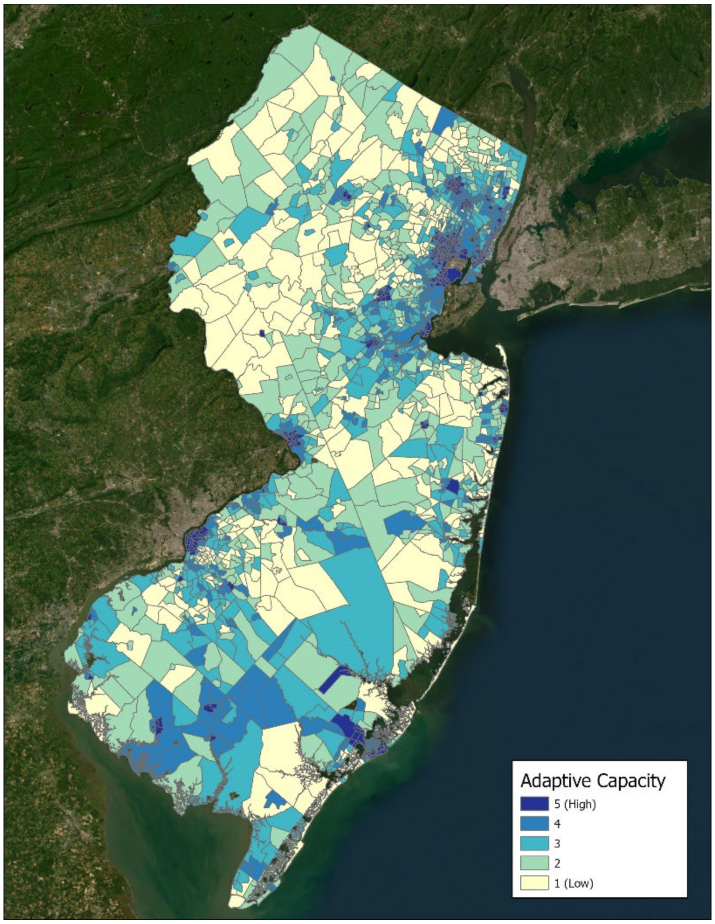

Figure 5. Spatial distribution of the aggregate adaptive capacity score where 1 indicates a relatively high adaptive capacity (low vulnerability) to extreme heat score for a census tract and 5 indicates a low adaptive capacity (high vulnerability) score.

Heat Vulnerability Index

The HVI geography mirrors the trends observed in the indicator groups. The regions with the higher heat vulnerability scores were primarily urban areas, both those associated with larger metropolitan areas such as Newark, and smaller urban areas like Flemington, NJ (Figure 6). Outside of larger urban centers, the southern portion of the state appears to have a higher rate of 3s and 4s (moderate to moderate-high vulnerability) compared to the northwest, likely following the north-south trend observed within the sensitivity component.

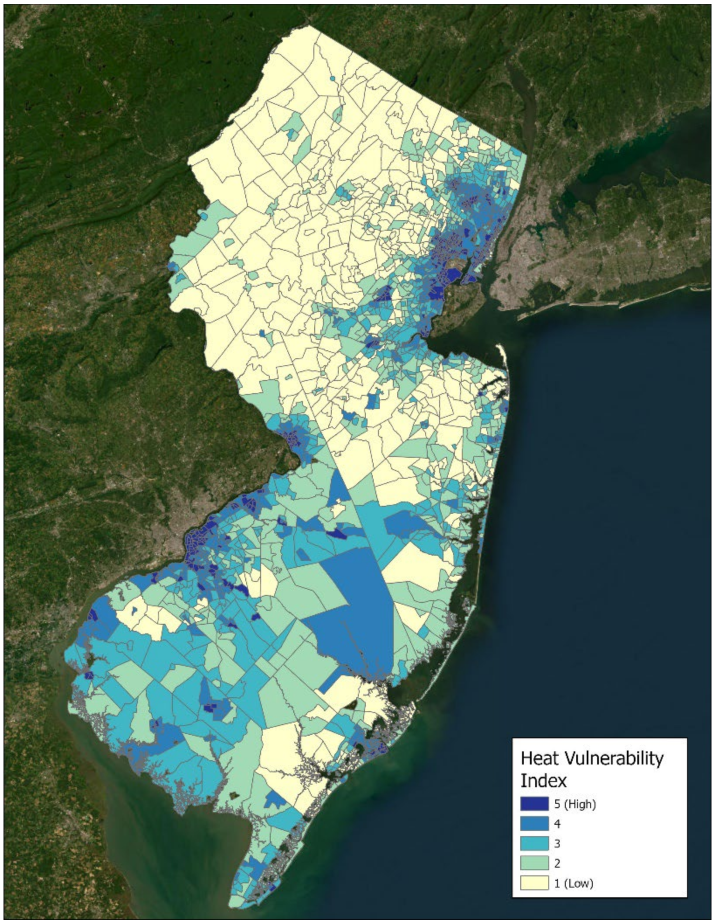

Figure 6. Spatial distribution of the Heat Vulnerability Index where 1 indicates a relatively low calculated vulnerability to extreme heat for a census tract and 5 indicates high vulnerability.

Limitations and Future Steps

The development of the New Jersey HVI is primarily limited by availability of high-resolution health data and other social indicators to predict heat vulnerability. For example, access to air conditioning is extremely important during an extreme heat event, but such a dataset for the whole of the state is not available and had to be approximated by relative age of housing. The health data utilized in this HVI is not age adjusted at the census tract scale, so may introduce bias towards certain age groups with a typically higher incidence of certain illnesses, such as increased diabetes rates among older populations. In terms of exposure, county-level air quality data are included, but local-scale variations in air quality would be preferable when assessing localized vulnerability.

The formulation of the HVI is also not appropriate for describing the vulnerability of census tracts with a high percentage of people living within group quarters, such as prison facilities, university dorms, or nursing homes. These locations require special consideration and often the selected indicators do not adequately represent these populations. For example, a prison population may be vulnerable to extreme heat due to crowding, a lack of air conditioning, and limited access to healthcare. [16,50] However, these parameters are not captured in the HVI and therefore census tracts with more than 90% of the population living within group quarters were not considered and are not included in data output. It is important to note that these locations may still be vulnerable to extreme heat, but the HVI as formulated is not an appropriate measure of vulnerability for locations with a high number of people living within group quarters. Additionally, census tracts with a population of zero (such as an airport) were not considered. Such locations may still present hazardous conditions for workers and people temporarily within these geographies, but the census information reflects residential characteristics. Therefore, these locations are not appropriate to include within the HVI.

Finally, the indicators were selected by literature review of other published HVIs, not by comparing the prevalence of each indicator to health outcomes such as ED visits or mortality rates during high heat events. Ideally, each indicator would have been selected via a heat health outcome analysis to capture those indicators most important specifically to New Jersey. However, these data are unavailable at the resolution needed to establish reliable indicator and health outcome relationships. Lacking those data, it is important to understand that the selected indicators, while good representations of heat vulnerability in general, may not capture relevant all aspects of community heat vulnerability in New Jersey. Finally, the New Jersey HVI is a relative comparison of census tract vulnerability throughout the state and does quantify exact risk to a community from extreme heat. Despite these limitations, the New Jersey HVI represents a basis for local governments, health officials, and stakeholders to understand vulnerability to extreme heat within their communities and plan for future extreme heat with climate change.

Subsequent iterations of the New Jersey HVI may be improved through incorporating an indicator weighting scheme. Equal weighting of the indicators and indicator groups was determined to be the best approach for this effort given an incomplete understanding of the heat vulnerability indicator and health outcome relationship. As extreme heat events become more prevalent with climate change and possibly a greater focus of public health initiatives, these relationships may become more well established in New Jersey, allowing for an objective weighting scheme. Additionally, as research improves, the selected indicators may be modified to better approximate the vulnerability to extreme heat of each community. Another potential improvement would be to adjust indicators to account where most of the population within a census tract resides, especially in larger/more rural tracts. Understanding the population distribution within the tract could better isolate the local air quality and heat island effects experienced by an average resident. This approach can offer a counterbalance to larger census tracts where there is high canopy cover, but the population is concentrated in a few locations with reduced cover.

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Appendix A. List of indicators considered not incorporated into the heat vulnerability index

Table A1. Indicators explored but not included in the heat vulnerability index

Indicator	Contribution to Vulnerability	Rationale for exclusion
Percent of population that is: - Hispanic and/or Latino - Black - American Indian and Native Alaskan - Native Hawaiian and Pacific Islander - Asian - Other Race/Ethnicity - Two or more races/ethnicities	Predominately non-white communities are subject to greater vulnerability to natural hazards, including extreme heat due to social inequities. [39,44]	Individual races and ethnicities were not included within the HVI as there is not specific indications for how each group is uniquely vulnerable to extreme heat within New Jersey. Additionally, diverse communities may necessitate an appropriate weighting scheme to accurately capture heat vulnerability, which is outside the scope of this effort. Instead, following the literature, a larger category of "non-white" was considered.
Percent of the population that is foreign born	Foreign born people within communities may have language barriers and differing cultural context that may make emergency communication regarding extreme heat less effective. [11]	This category produced overlap and high correlation with other indicators such as percent "non-white" and percent speaking English less than "very well," and was therefore excluded.
Percent aged >65 and living alone	Individuals over the age of 65 are at an increased risk for heat related illnesses and especially if they have limited social connection (approximated by living alone). [10–13,15]	Conceptually, this indicator is a combination of the percent of the population aged >65 and percent of population living alone indicators. Correlations between these indicators were not significant but the combined indicator was removed it was assumed to be redundant with the two separate indicators included in the HVI.
Housing density	Housing density can be an indicator of urbanization and crowded conditions that may	This metric had high correlation with the Impervious Cover to Canopy Cover Index and conceptually

	increase exposure to extreme heat. [11,15]	captured the same exposure processes and was therefore not included.
Percent of population with - Ambulatory difficulties - Cognitive difficulties	Persons with mobility or cognitive difficulties may have greater difficulty responding and adapting to extreme heat. [14]	These metrics were assumed to be adequately captured in the percent of the population with a disability indicator, though correlations were insignificant.
Percent of household with overcrowding (more individuals living in a housing unity than there are individual rooms)	More people in enclosed spaces can increase indoor temperatures and worsen indoor air pollution. [16]	It was assumed that this indicator follows income level was not included as it was assumed to be conceptually captured by the percent of people living below the poverty line indicator and only one explored HVI utilized this metric.
Percentage of population living in group quarters	People living in group quarters such as prisons or nursing homes are inherently vulnerable to many hazards, including extreme heat due to lack of agency in building conditions and response. [16,50]	As mentioned in the limitations section, populations living in group quarters require special consideration, must be considered at different geographies (often the size of just the building), and the other metrics of vulnerability do not necessarily capture information regarding these populations. It was therefore removed form the analysis with the understanding that the formulation of the HVI is not suited to adequately measure the vulnerability of these populations.
Percentage of single parent households	Single parent households may have reduced financial capacity to respond to extreme heat. [16]	The proportion of single parent households only appeared in one of the reviewed HVIs and was therefore not included. Additionally, it was assumed that limited financial capacity would be adequately captured in the percent of the

		population living below the poverty line.
Percent of housing units that are renter occupied	Renters may be less well established within the community and are likely to have lower incomes than homeowners. [16]	The proportion of renter occupied housing only appeared in one of the reviewed HVIs and was therefore not included. Additionally, it was assumed that limited financial capacity would be adequately captured in the percent of the population living below the poverty line.
Percent of households without internet access	No internet access may limit the efficacy of extreme heat warnings and reduce awareness of resources for extreme heat. [16]	The proportion of households with internet access only appeared in one of the reviewed HVIs and was therefore not included. Additionally, it was assumed that limited financial capacity could impact internet access and would be adequately captured in the percent of the population living below the poverty line.
Percent of tract area classified as high development	Highly developed areas are likely to have more impervious surface area, heightening the urban heat island. [11–13]	This metric had high correlation with the Impervious Cover to Canopy Cover Index and conceptually captured the same exposure processes and was therefore not included.
Crude prevalence of chronic obstructive pulmonary disease (COPD)	COPD can be exacerbated during an extreme heat event. [19]	COPD was found to correlate highly with prevalence of coronary heart disease and was not included to reduce the potential of "double counting" the indicators' contribution the vulnerable communities.
Crude prevalence of overweight and obesity	Obesity is a known risk factor for heat related morbidity and mortality, and has been included in other, typically more health focused, HVIs. [12,13,15,19]	The prevalence of overweight and obesity was found to correlate highly with prevalence of asthma and was not included to reduce the potential of "double

		counting" the indicators' contribution the vulnerable communities.
Median household income	People with lower (greater) incomes and are associated with greater (lesser) vulnerability to heat stress and a limited capacity to adapt to and recover from extreme heat events. [16,20]	This indicator correlated highly with other indicators related to income, such as the percent of people living below the poverty line, which focuses more directly on financially vulnerable populations. As such, this indicator was not included.
Population density	High population density has been associated with higher ambient temperatures and more urbanicity, increasing exposure to extreme heat. [11–13]	This metric had high correlation with the Impervious Cover to Canopy Cover Index and conceptually captured the same conceptual exposure processes and was therefore not included.

Appendix B. Correlation Tables between Indicators and between Indicator Groups

Table B1. Spearman Correlation Coefficients between Exposure Indicator Variables

	Impervious / canopy cover index	Historical $PM_{2.5}$	Historical O_3	Summer temperatures
Impervious / canopy cover index	1			
Historical $PM_{2.5}$	0.19	1		
Historical O_3	0.11	0.43	1	
Summer temperatures	0.54	0.55	0.38	1

Table B2. Spearman Correlation Coefficients between Sensitivity Indicator Variables

	Percent aged >65	Percent with a disability	Housing built before 1960	Percent in outdoor occupations	Percent aged <5	Percent living alone	Asthma prevalence	Diabetes prevalence	Coronary heart disease prevalence
Percent aged >65	1								
Percent with a disability	**0.00**	1							
Housing built before 1960	-0.21	**0.03**	1						
Percent in outdoor occupations	-0.27	0.49	0.27	1					
Percent aged <5	-0.43	0.05	0.21	0.28	1				
Percent living alone	0.27	0.30	**-0.03**	0.08	-0.08	1			
Asthma prevalence	-0.23	0.59	0.18	0.71	0.23	0.19	1		
Diabetes prevalence	**0.01**	0.50	0.21	0.66	0.14	0.28	0.65	1	
Coronary heart disease prevalence	0.42	0.45	0.11	0.43	-0.05	0.36	0.51	0.74	1

* Bold text indicates non-significant correlations (p value > 0.05)

Table B3. Spearman Correlation Coefficients between Adaptive Capacity Indicator Variables

	Percent below poverty line	Percent unemployed	Percent speaking English less than "Very Well"	Percent without a high school degree	Percent non-white	Percent without health insurance
Percent below poverty line	1					
Percent unemployed	0.37	1				
Percent speaking English less than "Very Well"	0.49	0.14	1			
Percent without a high school degree	0.71	0.33	0.62	1		
Percent non-white	0.59	0.34	0.77	0.66	1	
Percent without health insurance	0.69	0.34	0.66	0.72	0.65	1

Table B4. Spearman Correlation Coefficients between Indicator Group Scores

	Exposure	Sensitivity	Adaptive Capacity
Exposure	1		
Sensitivity	0.23	1	
Adaptive Capacity	0.41	0.59	1