County Health Rankings & Roadmaps
Building a Culture of Health, County by County

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Final Report

Exploring new measures and data sources for integration into the physical environment factor of the CHR&R model to advance community-based planning and decision-making

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Executive Summary

The County Health Rankings & Roadmaps (CHR&R) provides an important, research-based platform for understanding overall community health at the county level in each of the fifty U.S. states to inform community-based efforts to address “upstream” determinants of health. The model demonstrates how factors associated with health behaviors, clinical care, socioeconomics and the physical environment are related to health outcomes (length of life and quality of life). The CHR&R model currently includes physical environment factors reflecting two major areas: air and water quality, and housing and transit. This research examines whether and how the model can integrate additional data or enhance existing data regarding physical environmental factors, looking specifically at two national databases, the National Environmental Public Health Tracking Network maintained by the Centers for Disease Control and Prevention (CDC) and EJScreen maintained by the US Environmental Protection Agency (EPA) as authoritative data sources. We examined a set of measures in the air and water quality focus area, and a set of measures in two new proposed focus areas, toxics and contaminated sites, and climate change, for their potential to add value to the existing CHR&R model. The proposed indicators were evaluated in a systematic step-wise approach based on 1) technical criteria associated with the data to measure the indicator, 2) connection of the indicator to health, and 3) adherence to CHR&R program goals. The smaller set of indicators that moved forward from this screening were then collected and analyzed in detail for the state of New Jersey as an initial analytical surrogate. Based on this analysis, we then present reasoning and arguments to recommend the measures that are most suitable and relevant for inclusion into the CHR&R model, and also explore national scale-up of the selected measures.

I. Introduction

Our research approach will consist of four major tasks:

- **Screening of Indicators -** Conduct an analysis of the proposed set of indicators that results in a step-wise screening for 1) technical criteria related to data accessibility and validity, 2) connection of indicator to health outcomes and 3) adherence to CHR&R program goals/objectives
- **Data Collection and Analysis** – For the measures that moved forward from the literature review screening step, gather and analyze data for these proposed new measures for New Jersey (as an initial analytical surrogate), aggregating data to the county level, where necessary, using up to three methodologies, as relevant.
- **Recommendations for Model Integration -** Examine how the selected measures could be integrated into the County Health Rankings, with oversight and guidance from the CHR&R team.
- **National Scale-up -** Based on the outcome of the second and third tasks above and review by agencies and CHR&R, recommend considerations for national scale-up, as time and resources allow.

For context, the current CHR&R model includes two focus areas for the physical environment health factor. Those are “air and water quality” and “housing and transit.” The physical environment factor accounts for a total of 10% of the overall influence of health factors, and is divided by half (5%) into each of the two focus areas. There are two measures of “air and water quality” (air pollution/particulate matter and drinking water violations) and three measures of “housing and transit” (severe housing problems, driving alone to work, and long commute – driving to work alone.) See Table 1 below for a description of these measures and the overall US value for each.

Table 1. Current Physical Environment Ranked Measures, Model Contribution and Sources

Health Factor Focus Area	Measure		Weight	Source	Year(s)	US Overall
Air and water quality (5%)	Air pollution - particulate matter	Average daily density of fine particulate matter in micrograms per cubic meter (PM2.5)	2.5%	Environmental Public Health Tracking Network	2012	8.7
	Drinking water violations	Indicator of the presence of health-related drinking water violations. Yes indicates the presence of a violation, No indicates no violation.	2.5%	Safe Drinking Water Information System	2016	NA
Housing and transit (5%)	Severe housing problems	Percentage of households with at least 1 of 4 housing problems: overcrowding, high housing costs, or lack of kitchen or plumbing facilities	2%	Comprehensive Housing Affordability Strategy (CHAS) data	2010-2014	19%
	Driving alone to work	Percentage of the workforce that drives alone to work	2%	American Community Survey, 5-year estimates	2012-2016	76%
	Long commute - driving alone	Among workers who commute in their car alone, the percentage that commute more than 30 minutes	1%	American Community Survey, 5-year estimates	2012-2016	35%

In the project's scope of work, we indicated that we would examine five additional or modified measures for the air and water quality focus area, five for a new focus area reflecting *toxics and contaminated sites*, and three for a new focus area reflecting *changing climate conditions*. All are indicators collected by the EJ Screen (EPA) and/or EPHT (CDC) programs.

Our initial set of potentially targeted indicators for these health factor focus areas included the following:

Table 2. Initial Proposed Data for Additional Physical Environment Measures

Health Factor Focus Area	Specific Proposed Measures	Source(s)
Air and Water Quality	Ground Level Ozone	EPHT EJScreen
	Air Toxics	EJScreen
	Particulate Matter (enhancements to the CHR&R current data on particulate matter)	EJScreen
	Proximity of populations and schools to highways	EJScreen
	Specific contaminants of concern for Drinking Water	EJScreen
Toxics and Contaminated Sites	Acute releases (to air and water)	
	Proximity to NPL Sites	EPHT
	Proximity to waste treatment, storage and disposal sites	EPHT
	Proximity to facilities required by USEPA to maintain risk management plans to minimize risk from extremely hazardous materials sites	EPHT
	Proximity to waste water dischargers	EPHT
Changing Climate Conditions	Extreme heat	EPHT
	Extreme Precipitation	EPHT
	Flood Hazard	EPHT

The paper is organized in four sections. The Screening section discusses the results of the first, second and third level screens of our initial set of proposed measures, and resulted in the elimination of some of the initial set of proposed measures. The Data Collection and Analysis section presents the process and results of collecting the data for the set of selected measures that moved forward from the screening process for the state of New Jersey. The Model Integration section summarizes and discusses the results of the analysis, and recommends which measures are most appropriate for integration into the model. Finally, the section on National Scale-up describes considerations for obtaining the data for the entire United States.

II. Screening of Indicators[1]

This project first works through a systematic screening process to evaluate the 13 potential indicators for technical criteria related to data quality (first screen), literature review on importance to health (second screen), and adherence to the criteria that reflect additional CHR&R program goals and objectives beyond data quality and health connections (third screen).

Our reference for analyzing the measures according to these three levels of screens is found within the "Measure Criteria" available on the CHR&R website.[2] We indicated which criteria were evaluated in each step with the following colors:

1. Technical Criteria – Data Quality
2. Connections to Health
3. Additional CHR&R Program Goals

Table 3 below lists all of the measure criteria considered important for a measure to be selected or revised.

[1] *Primary Document References* for this section include:
CDC. National Environmental Public Health Tracking Network. https://ephtracking.cdc.gov/showHome.action
US EPA. EJSCREEN Environmental Justice Mapping and Screening Tool EJSCREEN Technical Documentation, August 2017, available at: https://www.epa.gov/sites/production/files/2017-09/documents/2017_ejscreen_technical_document.pdf

[2] http://www.countyhealthrankings.org/criteria-selecting-or-revising-measures

Table 3. County Health Rankings and Roadmaps – Measure Criteria

CHR&R Program Goals/Objectives & Innovating to Meet Community Needs	Technical/Analytical Feasibility
• The measure reflects important aspects of population health that can be improved (modifiable factors) • The measure and its association to health can be effectively communicated to the media, communities, and other key audiences • With the mindset that fewer measures are better than more, any new measure must bring *added value* without diluting the model • Measures for health outcomes will generally not be changed to ensure consistency, but measures for factors can be expanded, pared, or revised. • New measures must fall within one of the factor areas in the model. • The measure speaks to a current or emerging health issue that *CHR&R* could/should engage in and has the potential to make CHR&R more relevant to a strategic new set of partners • The metric is a more precise measure of the intended construct and/or refines the construct dimensions based on improved understanding of its relation to health (e.g., *CHR* measures community safety with injury deaths because a more proximal measure is unavailable) • The measure keeps *CHR&R* aligned with other metric initiatives (e.g., America's Health Rankings) • The measure will advance efforts to address health equity	• The measure and its association to health are scientifically supported in the literature and/or by analysis of *CHR* data • The measure draws from data that are available at the county level • The measure draws from data sources that are valid, reliable, recognized and used by others • The measure has been tested and used by others in the field • The measure draws from data available for *nearly all counties* nationwide and puts the interests of counties and states ahead of national coverage (i.e. – the ideal is not to have missing data clustered within a particular state) • Data to populate the measure have a short time lag (recently available within the past 3-5 years) • Data to populate the measure will be collected regularly (ideally annually but at least every 3-5 years) and made public by the data stewards • Data to populate the measure are available for free or at low cost • The measure can be ranked (e.g., it has ordinal value) • The measure can be broken down by geographic or population subgroups

Below we present a summary of the results of the step-wise screening process. Details of the analysis for the Technical Criteria and Literature Review are found in Appendices A and B.

A. Technical Criteria: Data Sources, Scale, and Limitations

This part of the screening focused on the quality of the existing EPA and CDC data sources, including appropriateness of the particular measures in terms of scale and access, and other limitations related to the collection and interpretation of the data. Our analysis reflects insights from our review of various sources of information, input received from the CHR&R team, as well as extremely helpful insights that we received from EJScreen and EPHT technical staff at USEPA and CDC, respectively.

Grounded in the CHR&R Technical Criteria shown in Table 3 above, the primary questions addressed in this first level of screening were:

- Is the data readily accessible at free or no cost?
- Is the data scalable to the county level?
- Is the data available for nearly all counties?
- Is the data reliable, valid and updated regularly?
- Is the data used by others?

Appendix A includes the full written analysis of all 13 initial proposed measures.

This review resulted in the elimination of some of the measures due to inadequacy or challenges associated with the data, and thus informs the subsequent steps of the analysis. After the first level of screening, three measures were eliminated, as indicated in pink highlight below:

- *Particulate Matter* – Data not available nationally, and lack of measures that improve on measure already in CHR&R model
- *Specific Contaminants of Concern for Drinking Water* – Data not available nationally
- *Acute Releases* –Data out-of-date and no longer updated

Table 4. Technical Criteria - Screening Summary

Indicator	Source	Moved Forward	Additional Information
Ground Level Ozone	EJScreen/EPHT	Yes	Data not available nationally, but enough interest to continue. Will select the specific measure that best meets other criteria as process continues
Air Toxics	EJScreen/EPHT	Yes	Will select the specific measure(s) that best meets other criteria.
Proximity of Populations to Highways	EJScreen	Yes	Will need to aggregate to county level.
Particulate Matter	EJScreen/EPHT	No	Removed based on data not being available nationally, and no availability of data that improves on what is already in the CHR&R model.
Drinking Water Contaminants	EPHT	No	Removed based on data not being available nationally.
Acute Releases (Air & Water)	EPHT (Historical)	No	Removed based on data being out-of-date or no longer being updated.
Proximity to NPL Sites	EJScreen	Yes	Will need to aggregate to county level.
Proximity to Waste Treatment, Storage,	EJScreen	Yes	Will need to aggregate to county level.

and Disposal Facilities			
Proximity to RMP Sites	EJScreen	Yes	Will need to aggregate to county level.
Proximity to Major Direct Water Dischargers	EJScreen	Yes	Will need to aggregate to county level.
Extreme Heat	EPHT	Yes	Number of days and events moved forward.
Extreme Precipitation	EPHT	Yes	
Flood Hazards	EPHT	Yes	Flood Hazard area and Populations impacted by flood hazards moved forward

B. Literature Review: Connections to Health

This portion of the screening focused on identifying health impacts associated with the ten indicators that moved forward after the screening for data technical criteria. The primary question that this review addresses is how much is the measure and its association to health is scientifically supported in the literature and/or by analysis of *CHR* data.

Much of the information below is drawn directly from the EJScreen and EPHT websites that describe the support for the indicators in the platform. In addition, scientific literature was scanned to uncover any new or recent studies (last three years) on the health impacts of the environmental factors, and this information is integrated within the discussion for each measure.

The detailed review of the ten remaining indicators is found in Appendix B.

After examining literature for connections between the ten remaining physical environment measures and human health impacts, we eliminated five additional indicators, as indicated in pink highlight in the table below. For the proximity to polluting sites indicators, there was little strong evidence of specific health impacts with causal relationships to site proximity, and for extreme precipitation, likewise there is not sufficient evidence that it impacts health as an occurrence, as distinct from the flooding that can occur from precipitation events, which is captured in another indicator.

- *Proximity to NPL Sites*
- *Proximity to Waste Treatment, Storage and Disposal Sites*
- *Proximity to RMP Sites*
- *Proximity to Major Direct Water Dischargers*
- *Extreme Precipitation* – not a direct connection to health outcomes, likely very loose correlations with health because of great variability in impacts depending on climate and geology of area.

Table 5. Literature Review - Screening Summary

Indicator	Source	Moved Forward	Additional Information
Ground Level Ozone	EJScreen/EPHT	No	Although connections to health impacts are strong, considerations of co-variance and similar health impacts to PM2.5, and lack of a complete national data set resulted in omitting this variable from the data collection and analysis step.
Air Toxics	EJScreen/EPHT	Yes	
Proximity of Populations to Highways	EJScreen	Yes	
Proximity to NPL Sites	EJScreen	No	Limited strong ties to health impacts
Proximity to Waste Treatment, Storage, and Disposal Facilities	EJScreen	No	Limited strong ties to health impacts
Proximity to RMP Sites	EJScreen	No	Limited strong ties to health impacts
Proximity to Major Direct Water Dischargers	EJScreen	No	Limited strong ties to health impacts
Extreme Heat	EPHT	Yes	
Extreme Precipitation	EPHT	No	Limited strong ties to health impacts, and also variable in occurrence year to year
Flood Hazards	EPHT	Yes	

C. Adherence to CHR&R Program Goals/Objectives

For the five indicators that remained after the two literature reviews, we then looked at adherence to other program goals and criteria of CHR&R model integration.

Indicators were assessed for:

- *Modifiability* – Are there some identifiable actions communities can take to alter the impact, if not the incidence of the condition?
- *Ability to be effectively communicated* – Can the measure and its association to health can be effectively communicated to the media and communities?
- *Value-Added* – Does the new measure add value to set of current measures without diluting the model?
- *Relation to Current Health Outcomes in Model* – Does the new indicator measure something that affects one of the outcomes currently in the model (premature death, poor or fair health, poor or fair mental health days, poor or fair physical health days, low birthweight)?
- *Emerging Issue* – Does the measure speak to a current or emerging health issue that has the potential to make CHR&R more relevant?
- *Advances equity* – Does the measure advance efforts to address health equity?

The table below displays the ratings that each of the remaining five indicators received on these six criteria from our Rutgers team, and experts at EPA and CDC. The indicators with the greatest number of "Yes" ratings were Proximity to Highways and Extreme Heat.

Table 6. Summary of Screening for CHR&R Goals/Objectives
(Y = Yes, N = No, U = Uncertain)
Order of Rating: Rutgers, EPA, CDC

Indicator	Modifiable	Effectively Communicated	Adds Value	Relates to Current Health Outcomes	Emerging Issue	Advances Equity
Ground Level Ozone	Y,Y,Y	U,Y,Y	U,Y,Y	U,Y,Y	N,Y,U	N,Y,U
Air Toxics	U,Y,Y	U,Y,U	U,Y,Y	U,Y,Y	N,Y,U	Y,Y,Y
Proximity to Highways	Y,U,Y	Y,Y,Y	Y,Y,Y	Y,Y,Y	Y,Y,Y	Y Y,Y
Extreme Heat	(impacts) Y,U,Y	Y,Y,Y	Y,Y,Y	Y,Y,Y	Y,Y,Y	Y,U,Y
Flood Hazard	(impacts) Y,U,Y	Y,Y,Y	Y,Y,Y	Y,U,Y	Y,Y,Y	U,U,Y

The team consulted with Senior Project Advisor, Dr. Michael Greenberg, who strongly recommended maintaining the ground level ozone indicator given the evidence of its impacts on health and long-standing efforts to address ozone due to its health effects. After this screening and consultation with Dr. Greenberg, the team decided to advance all five remaining indicators to the next step of data collection and analysis for New Jersey. While it appears that Proximity to Highways is the strongest match to these criteria, with the two climate indicators also scoring strongly, the other measures also scored well enough to move forward to the next step to examine the data for ease of access and processing, ability to aggregate to the county level, and variability by county.

Some of the considerations regarding each indicator that emerged from this step of the screening to keep in mind for incorporation into final recommendations are:

- *Ground Level Ozone* - Ground level ozone results when oxides of nitrogen (NOx) react with volatile organic compounds (VOCs) in the presence of sunlight. Emissions sources of NOx and VOCs include industrial operations, electric utilities, motor vehicles. Extensive documentation points to the respiratory health impacts of ground level ozone. While communication about the health effects of ground level ozone may be challenging given its impact as a regional pollutant, there is a long history in the United States of communicating about ozone health impacts with strong familiarity with "bad air quality days" that can be heard by the general public via mass media weather reports. As a regional pollutant, ground level ozone is only somewhat modifiable with local regulations. It is strongly connected to health outcomes, however, its association is with respiratory health outcomes which is currently not in the CHR&R model. Further analysis is needed to examine if this variable co-varies closely at the county level with the PM2.5 measure currently in the model.
- *Air Toxics* – Hazardous air pollutants, also known as air toxics, are pollutants for which evidence points to health outcomes including cancer, reproductive effects, and other conditions. Control of hazardous air pollutants is generally at the federal and state levels with the United States Environmental Protection Agency regulates a list of 187 hazardous air pollutants from sources including mobile sources (e.g. cars and trucks), stationary sources (e.g. factories, refineries, power plants) and some indoor sources (e.g. building materials, cleaning solvents.) Given that

mobile and stationary sources are a major contributor to hazardous air pollutants, there are clear equity issues associated with these pollutants given the prevalence of those sources in communities with significant populations of low income residents and people of color.

- *Proximity to Highways* – This indicator comes out strongly on CHR&R program criteria because it is easy for the public to understand and communicate it and it affects health outcomes already reflected in the CHR&R model, namely poor mental health days associated with noise, stress and smells. Highway proximity is clearly connected with equity in terms of minority and lower income populations that are typically located closer to major highways. Evidence of connections between emissions from mobile sources and health are strong. Local regulations may have the ability to affect new development near highways and also modify the impact of highways through structural barriers.
- *Extreme Heat* – This indicator is also very easy to communicate and has strong equity considerations as those most impacted by extreme heat are those with other health conditions or disabilities and those living without air conditioning as well as residents living in urban areas where there is exposure to urban heat island effect. As there are no climate indicators currently in the model, integrating this indicator would add value and would not be measuring anything similar to current indicators. It is also modifiable in terms of impacts of heat on populations through local actions like warning systems, cooling centers or air conditioning assistance programs. It can be tied to the health outcomes of poor mental and physical health days as well.
- *Flood Hazard* – Like heat, this indicator is also very easy to communicate due to its visibility and experiential nature, and has some equity considerations as those most impacted by extreme flooding in their homes are often those living in floodplains where housing is cheaper and also those without means to remediate flood damages. As there are no climate indicators currently in the model, integrating this indicator would add value and would not be measuring anything similar to current indicators. It is also modifiable in terms of impacts of flooding on populations through local actions like evacuation programs, mitigation and repair assistance programs and in terms of incidence through local development ordinances. It can be tied to the health outcomes of poor mental and physical health days as well.

III. Data Collection and Analysis

Building from our analysis of data limitations from the screening steps, combined with the weight of evidence regarding connection of the potential indicators to health and adherence to other CHR&R program criteria, we made a determination of the subset of data to focus our attention on for development of indicators for the CHR&R. Again, this determination was developed along with input from the CHR&R staff and input from EPA and CDC.

After the screening, the following indicators were examined through three scenarios to understand the data in more detail and examine the results produced for New Jersey.

Table 7. Data Variables Collected for Analysis

Variable Name	Full Descriptive Name	Description (including units)[3,4]	Scale	Source
DSLPM	NATA Diesel Particulate Matter	Diesel particulate matter level in air, µg/m^3	Block Group	EPA EJScreen
RESP	NATA Respiratory Hazard Index	Air toxics respiratory hazard index (ratio of exposure concentration to health-based reference concentration)	Block Group	EPA EJScreen
PTRAF	Traffic Proximity	Count of vehicles (AADT, avg. annual daily traffic) at major roads within 500 meters of block centroid, divided by distance in meters (not km)	Block Group	EPA EJScreen
Number of Sq Mi within FEMA flood zones	Flood Vulnerability - Number of Square Miles within FEMA flood zones	Estimates of the Special Flood Hazard Area (SFHA) with a 1% annual chance of coastal or riverine flooding, per county (Square Miles)	County	CDC EPHT
% Area within FEMA flood zones	Flood Vulnerability – Percent Area (sq mi) within FEMA flood zones	Percent - Percent Area (square miles) Within FEMA Designated Special Flood Hazard Area	County	CDC EPHT
Number of People within FEMA flood zones	Flood Vulnerability – People within FEMA flood zones	Provide population estimates of the number of people within the Special Flood Hazard Area	County	CDC EPHT
Number of Housing Units within FEMA flood zones	Flood Vulnerability – Housing Units within FEMA flood zones	Provide estimates of the number of housing units within the Special Flood Hazard Area, per county	County	CDC EPHT
Extreme Heat Days -abs	Number of Extreme Heat Days – Absolute Threshold	Total number of days that are a combination of the following parameters (1) temperature or heat index and (2) absolute (e.g., 90°F, 95°F, 100°F, 105°F) values threshold	County	CDC EPHT
Extreme Heat Days - rel	Number of Extreme Heat Days – Relative Threshold	Total number of days that are a combination of the following parameters (1) temperature or heat index and (2) relative (e.g., 90^{th}, 95^{th}, 98^{th}, and 99^{th} percentile values) threshold	County	CDC EPHT
Extreme Heat	Number of	Days with extreme heat events for each	County	CDC

[3] Taken from EPA's EJScreen Technical Documentation. (2017) Retrieved from https://www.epa.gov/ejscreen/technical-documentation-ejscreen
[4] Taken from CDC's EPHT Indicator Website. Retrieved from https://ephtracking.cdc.gov/showIndicatorPages

Events -abs	Extreme Heat Events – Absolute Threshold	combination of the following parameters (1) temperature or heat index, (2) absolute (e.g., 90°F, 95°F, 100°F, 105°F), and (3) durations of consecutive days (e.g., 2 or more, 3 or more)		EPHT
Extreme Heat Events -rel	Number of Extreme Heat Events – Relative Threshold	Days with extreme heat events for each combination of the following parameters (1) temperature or heat index, (2) relative (e.g., 90^{th}, 95^{th}, 98^{th}, and 99^{th} percentile values) threshold, and (3) durations of consecutive days (e.g., 2 or more, 3 or more)	County	CDC EPHT

Note: Even though the Extreme Precipitation indicator did not move forward through the screening process, because of relevance of considering emerging climate hazards that may become important to health in the coming years, and because of the presence of a dataset, this variable was included in the data collection.

Aggregation Methods:

For the data that is only available at the block group scale, we have downloaded the .csv files and connected them to United States Census TIGERLINE files for United States Counties. County centroids have been created so that ratio scenarios can be run to aggregate these data into a single county data value (i.e. individual determinant/population ratio; individual determinant/density ratio; and nearest neighbor analysis, as appropriate.)

SCENARIO I

In Scenario I, individual determinant ratios were computed for each EPHT indicator at the county level based on the following 7 population-based factors:

- Total population
- Minority population
- Low income population
- EJ Index - Average of percent minority and percent low income
- EJ Index - Average of minority and low income (count)
- Linguistically isolated population
- Elderly and physically disabled populations

For EJScreen data, individual determinant ratios were computed for data variables NATA Diesel Particulate Matter (DSLPM), NATA Respiratory Hazard Index (RESP), and Traffic Proximity (PTRAF) indicators at the block group level based on the same factors.

The formula used for calculating individual determinant ratio by population-based factors is as follows:

$$= \frac{I_c/I_s}{P_c/P_s}$$

Here, I_c is Indicator Value for the County/Block Group,
I_s is sum of Indicator Values for all the Counties/Block Groups in the State,
P_c is Population of the County/Block Group,
P_s is Population of the State

SCENARIO II

In Scenario II, individual determinant ratios were calculated for each EPHT indicator based on county area in square miles. For EJScreen data, the same was calculated for the 3 EJScreen indicators - DSLPM, RESP, and PTRAF - based on block group area in square miles.

The formula used for calculating Individual determinant ratio by area in square miles is as follows:

$$= \frac{I_c/I_s}{A_c/A_s}$$

Here, I_c is Indicator Value for the County/Block Group,
I_s is sum of Indicator Values for all the Counties/Block Groups in the State,
A_c is Area of the County/Block Group in square miles,
A_s is Area of the State in square miles

SCENARIO III

In Scenario III, spatial statistics were run for each EPHT indicator as well as the 3 EJScreen indicators - DSLPM, RESP, and PTRAF.

The following three tools – **High/Low Clustering tool, Hot Spot Analysis, and Cluster and Outlier Analysis** – were used for this analysis.

- **High/Low Clustering tool** was run for each mentioned indicator and the analysis reports were saved.
  - A default setting that used INVERSE_DISTANCE as the spatial relationship and NONE as standardization was maintained for consistency throughout the analysis.
- **Hot spot, and Cluster and Outlier Analysis** tools were run for each mentioned indicator and new feature classes were developed.
  - The hot spot analysis' default setting included INVERSE_DISTANCE as the spatial relationship and NONE as standardization. The cluster and analysis tool's default setting included INVERSE_DISTANCE as the spatial relationship, NONE as standardization, and 0 as Number of Permutations. All other optional parameters remained as defaults.

Outcomes –EJScreen Data

General Findings –

- Ratio values greater than 1 were found to concentrate around urban areas, cities, and along major roadways.
- Determinant land area ratios ranged in value from 0 – 900.
- Determinant population ratios ranged from 0 – 215.

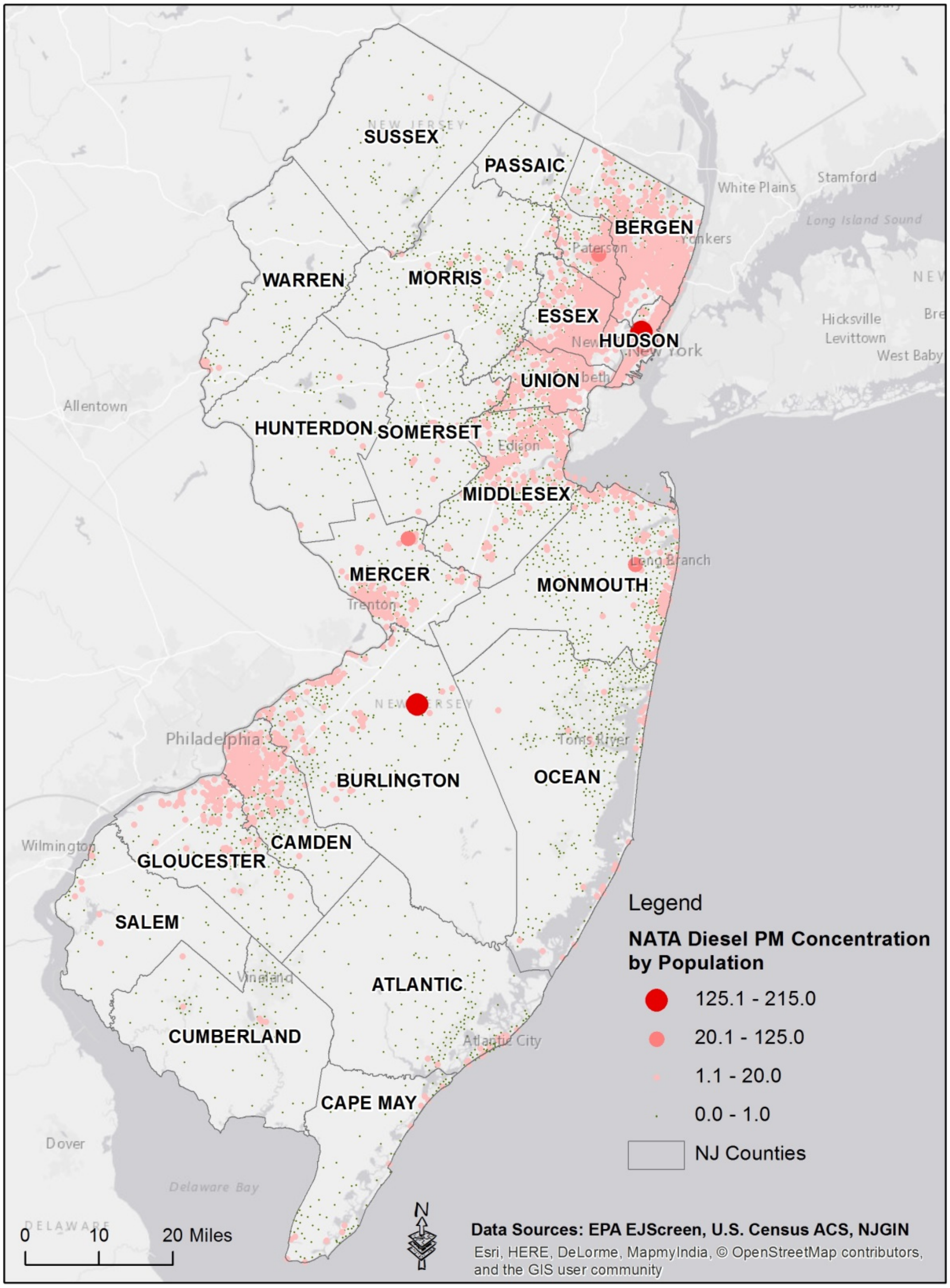
NATA Diesel Particulate Matter (DSLPM)

Findings (by population and land area) -

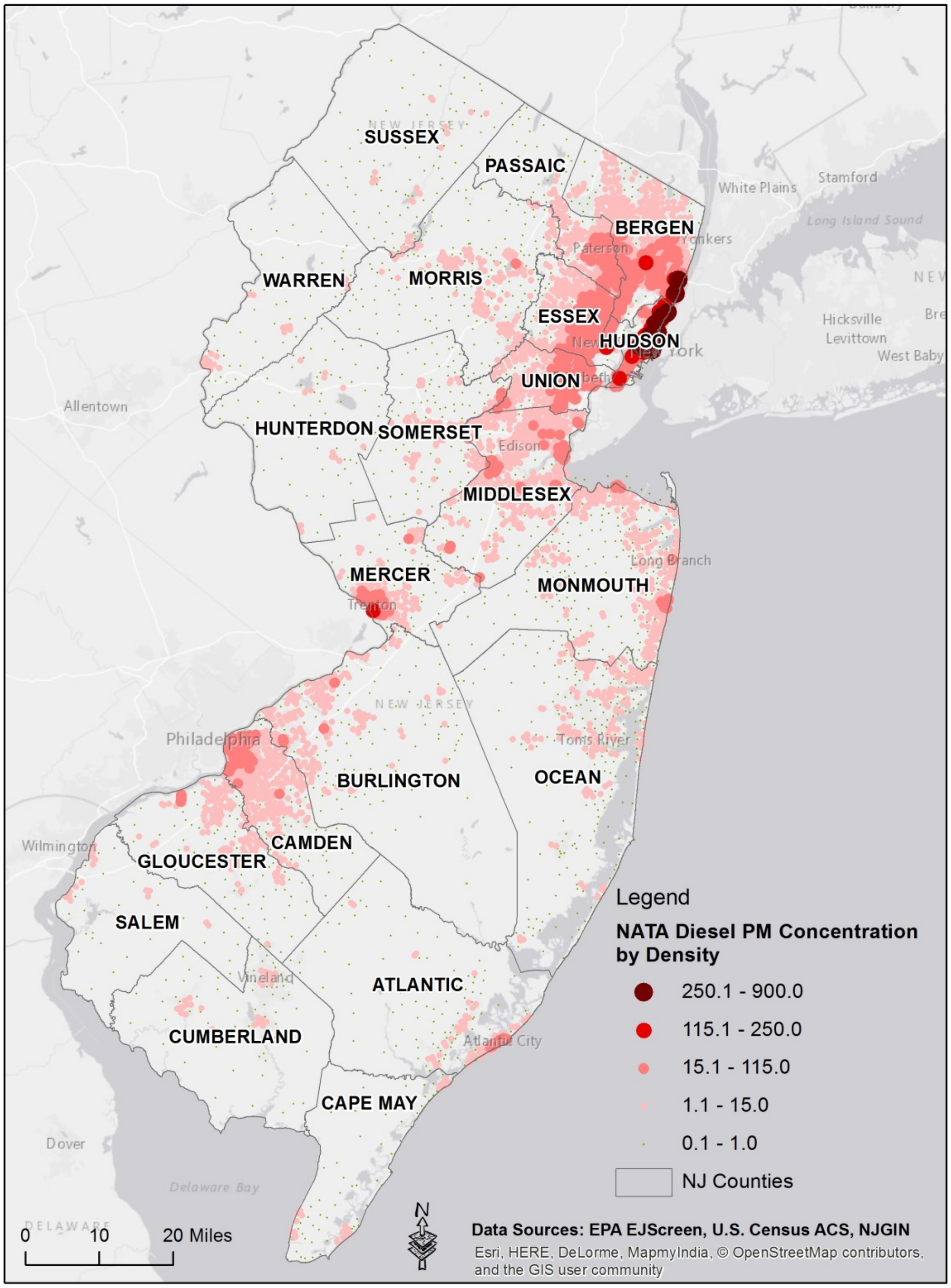
- Overall density of particulate matter is highest in block groups near the New York City region, and more specifically in Hudson and Bergen Counties.
- Concentrations of higher values were found in urban areas such as Camden, Trenton, Elizabeth, Newark, and Paterson.
- When examined against population values, Diesel Particulate Matter showed the highest values in Hudson, Passaic, and Monmouth Counties.
- Diesel Particulate Matter values were highest in areas with high population densities.

The maps below show Particulate Matter ($\mu g/m^3$) by population (or by the number of people distributed over a U.S. Census Block Group) as well as by land area (in square miles). The areas of the maps with the darkest points are where concentrations of particulate matter are highest in relation to both population and land area.

NATA Diesel Particulate Matter (PM) Concentration by Population



NATA Diesel Particulate Matter (PM) Concentration by Density



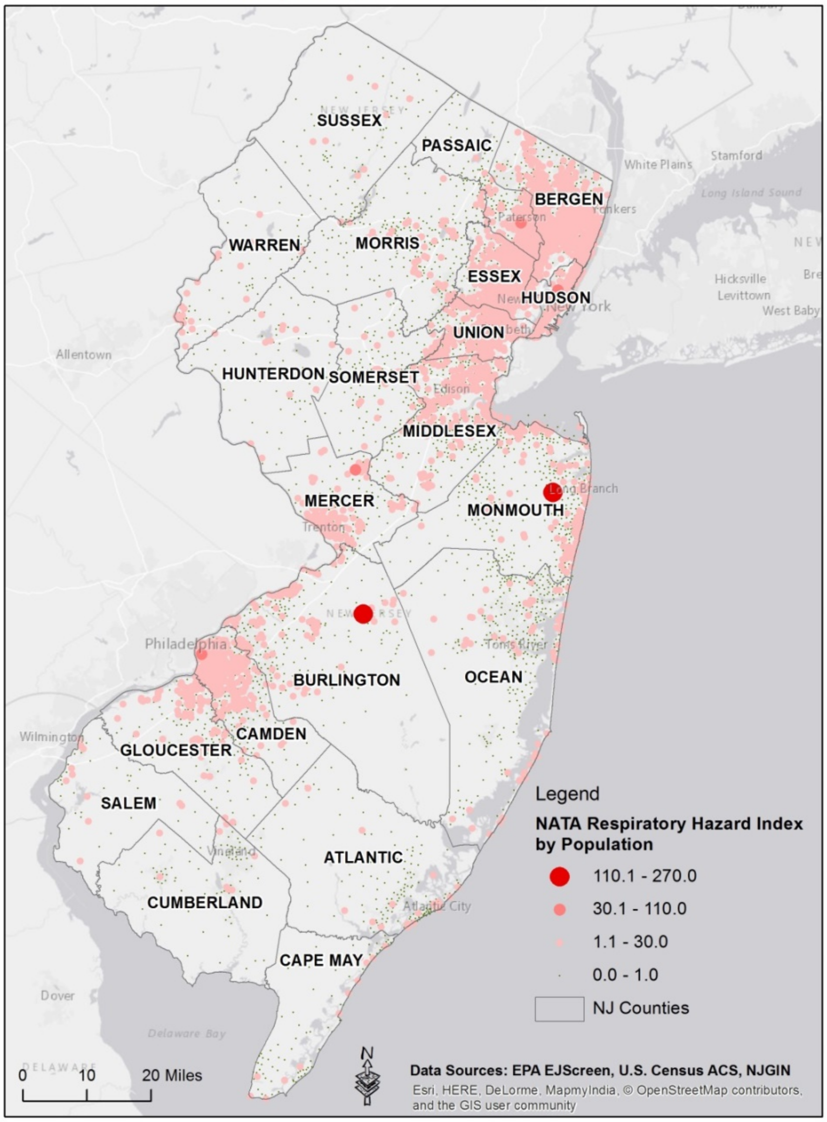
NATA Respiratory Hazard Index (RESP)

Findings (by population and land area) -

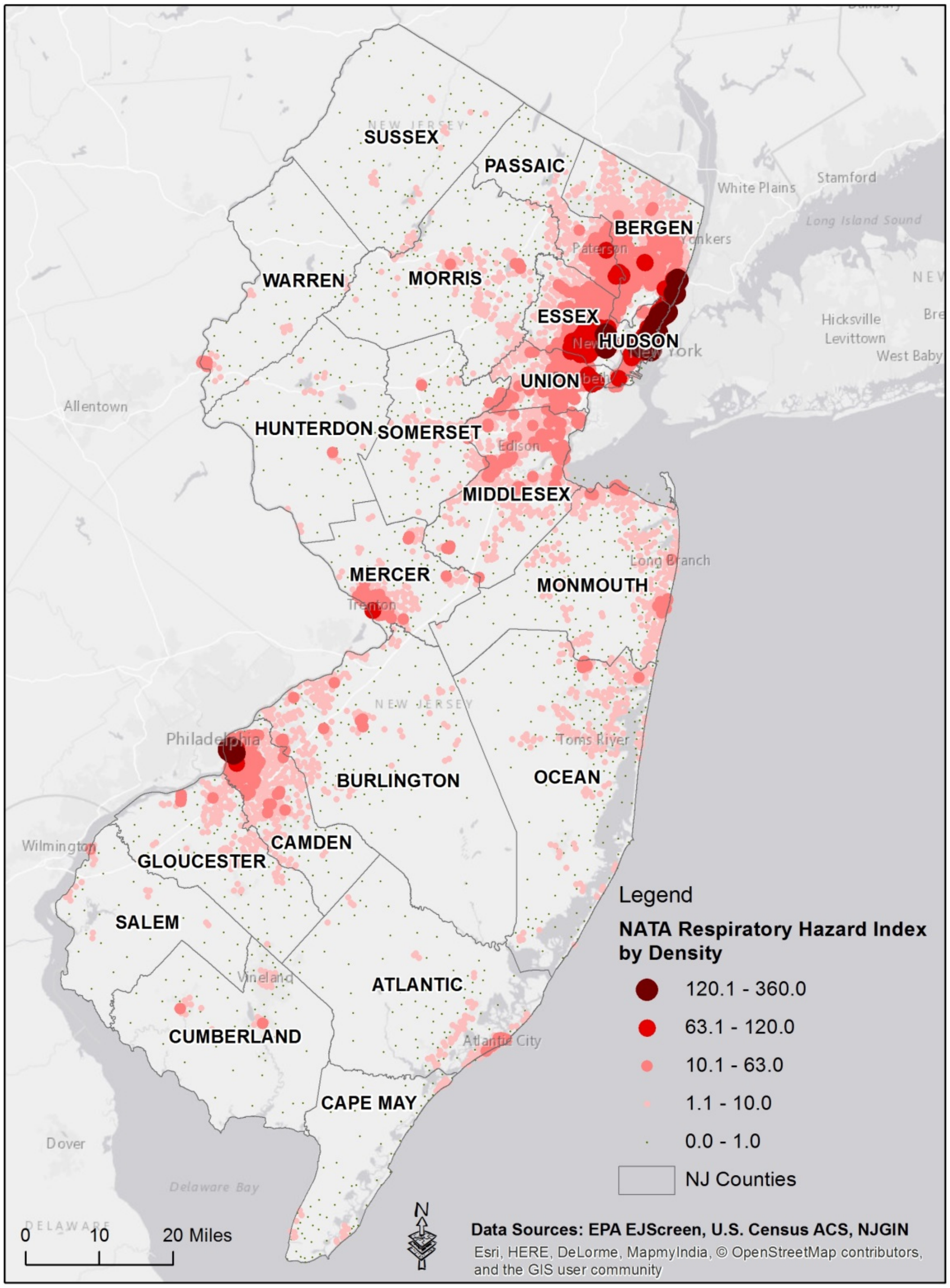
- Respiratory Hazard Index values were highest in urban areas, specifically in Camden, Trenton, Princeton, Phillipsburg, and municipalities closest to the New York City region.
- High values in Hudson, Passaic, and Monmouth Counties.
- As per its primary 2-factor demographic index (D_RESP_2), most block groups in New Jersey have a negative value for this index, and only a few block groups in urban areas (Camden, Trenton, Newark, Elizabeth, and Jersey City) have very high positive values.

The maps below show Respiratory Index values by population (or by the number of people distributed over a U.S. Census Block Group) as well as by land area (in square miles). The areas of the maps with the darkest points are where concentrations of Index values are highest in relation to both population and land area.

NATA Respiratory Hazard Index by Population



NATA Respiratory Hazard Index by Density

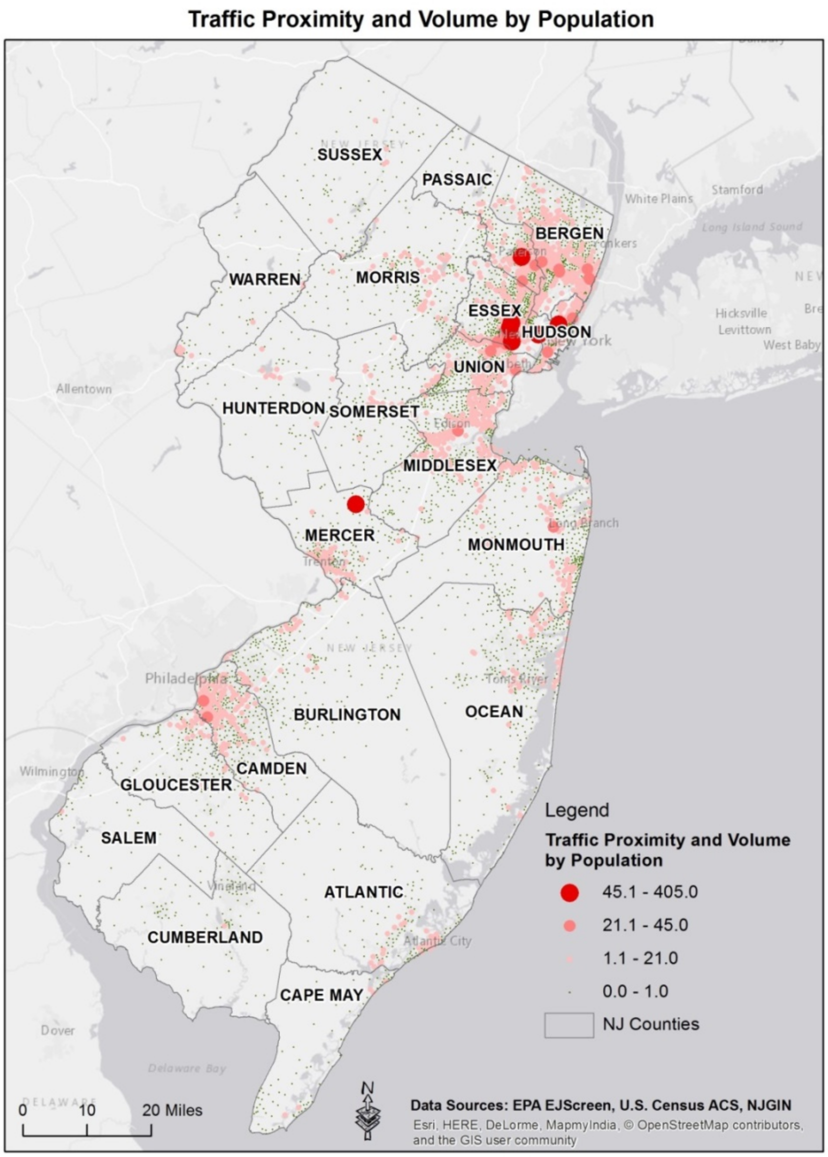


Traffic Proximity (PTRAF)

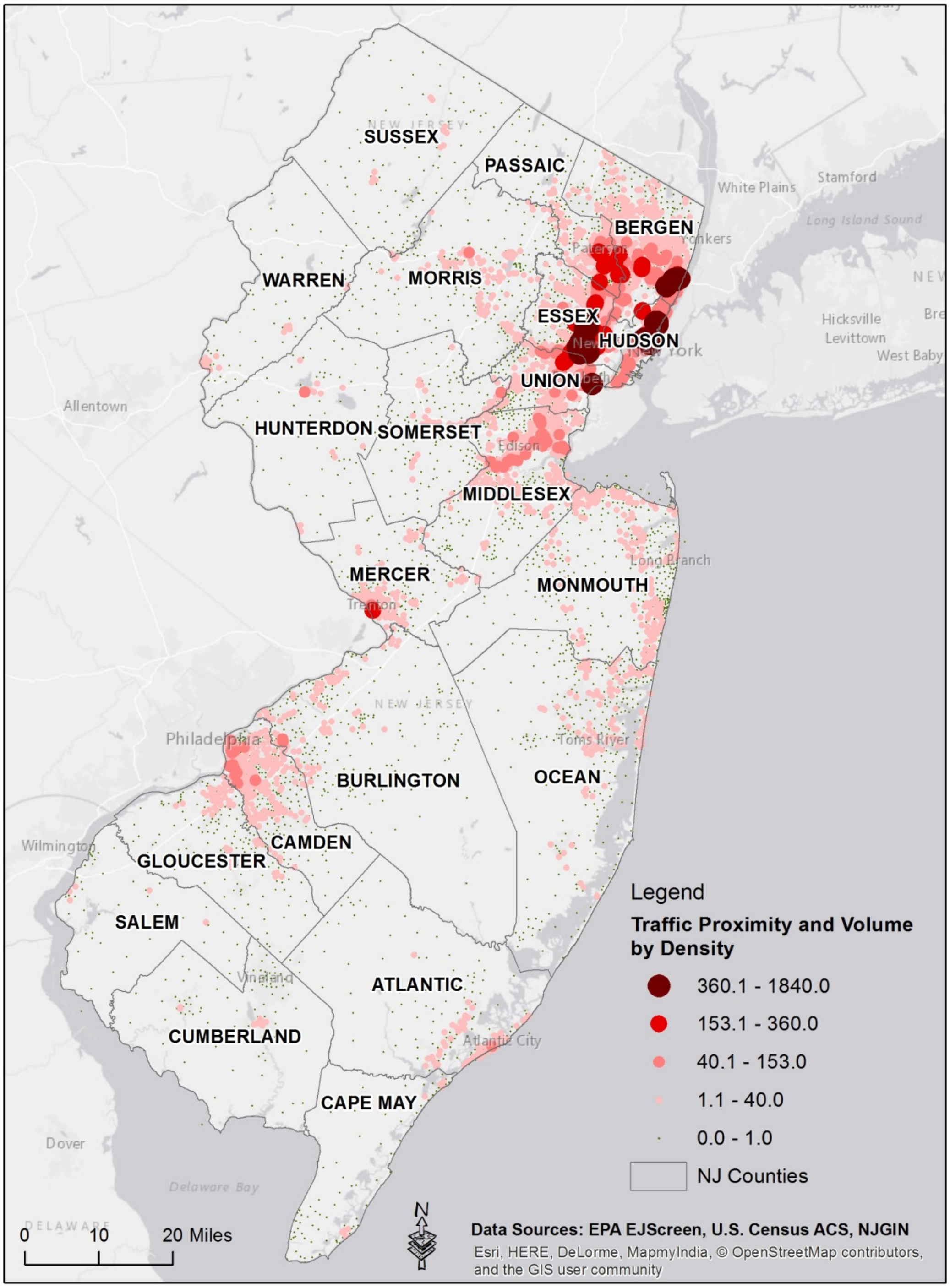
Findings (by population and land area) -

- Traffic proximity and volume have high values in areas such as Princeton, Paterson, Newark, and Jersey City.
- Traffic proximity and volume are concentrated in areas with the highest population densities (i.e. urban centers).
- Density of traffic is highest in areas in Hudson (Jersey City), Bergen (North Bergen), Essex (Newark), and Union (Elizabeth) Counties.

The maps below show Traffic Proximity (count of vehicles within 500 meters of a block centroid) by population (or by the number of people distributed over a U.S. Census Block Group) as well as by land area (in square miles). The areas of the maps with the darkest points are where concentrations of Traffic Proximity values are highest in relation to both population and land area.



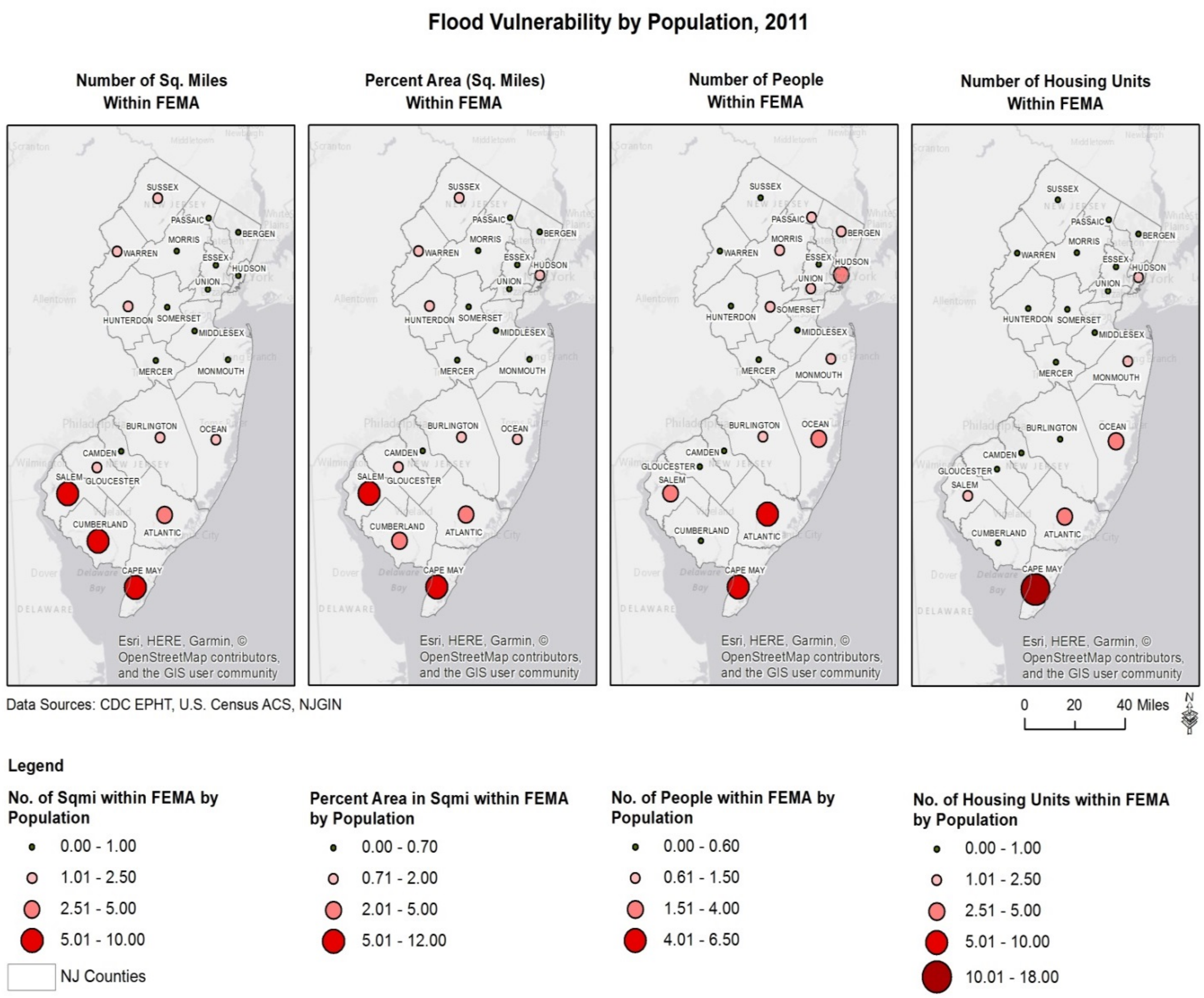
Traffic Proximity and Volume by Density



Outcomes –EPHT Data

General Findings –

- Determinant ratio values by area for these indicators concentrate around highly urbanized areas such as the northeast and southwest regions.
- With respect to population, upper end values are found alternatively in less-populated areas.



Flood Vulnerability - Number of Square Miles within FEMA flood zones and Percent Area (sq. mi) within FEMA flood zones

Findings (by population and land area) -

- Highest values shown in less-populated counties such as Salem, Cape May, and Cumberland.

Flood Vulnerability – People within FEMA flood zones

Findings (by population and land area) -

- The number of people within FEMA flood zones are concentrated in counties along the coast in southern jersey (e.g. Cape May, Atlantic, and Ocean).

- Cape May County has the highest concentration of housing units within FEMA by population.

Flood Vulnerability – Housing Units within FEMA flood zones

Findings (by population and land area) -

- Housing units within FEMA flood zones are concentrated along the coast.

Number of Extreme Heat Days – Absolute Threshold

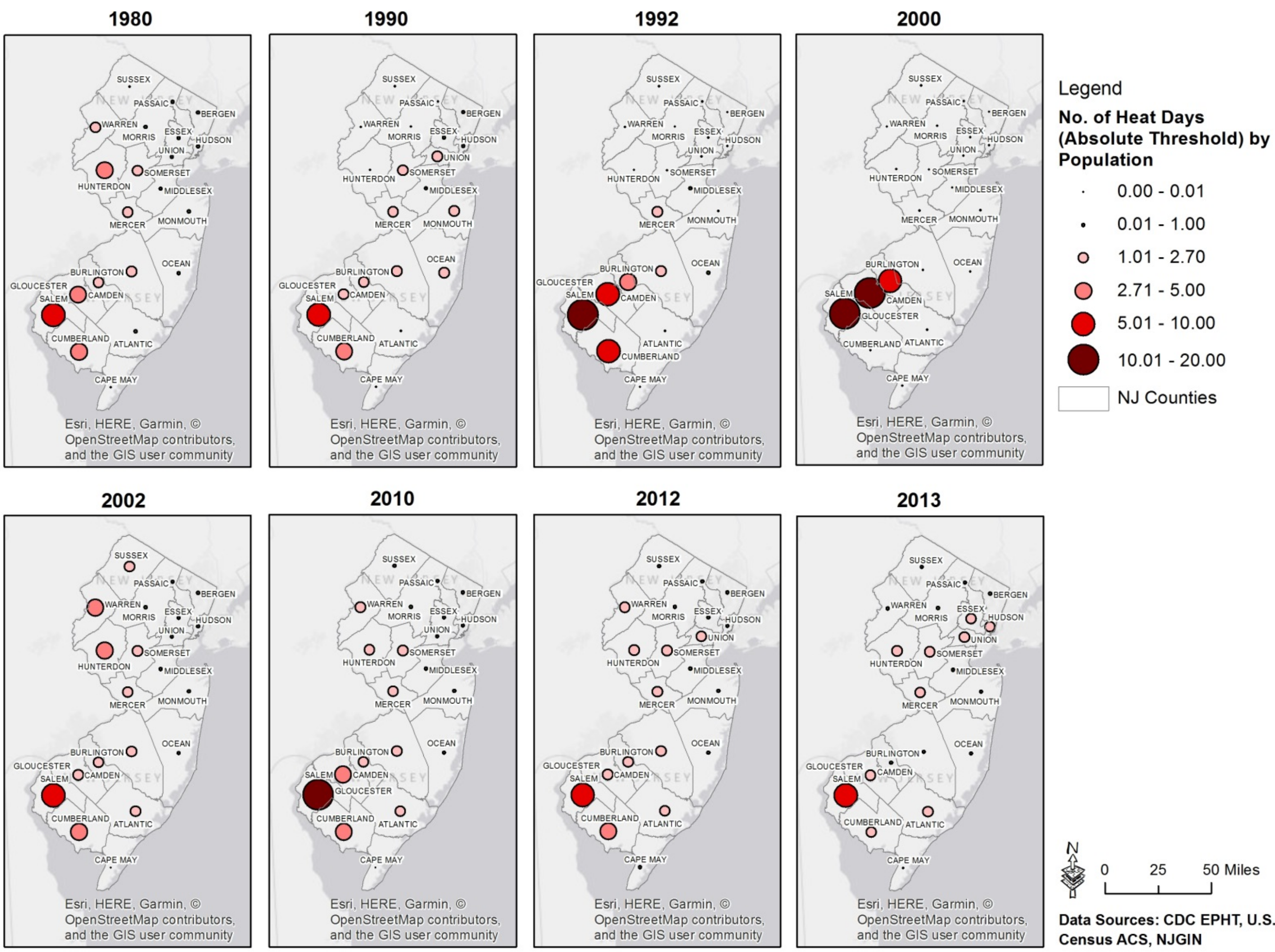
Findings (by population and land area) -

- Number of extreme heat days show higher values for less-populated counties such as Salem, Cumberland, Gloucester, Warren, and Hunterdon.

Disclaimer –

- Important Note: These indicators do not follow these trends for the years - 1990, 1992, and 2000 (the data for these 3 years contain zero values)

Number of Heat days (Absolute Threshold) by Population



Number of Extreme Heat Days – Relative Threshold

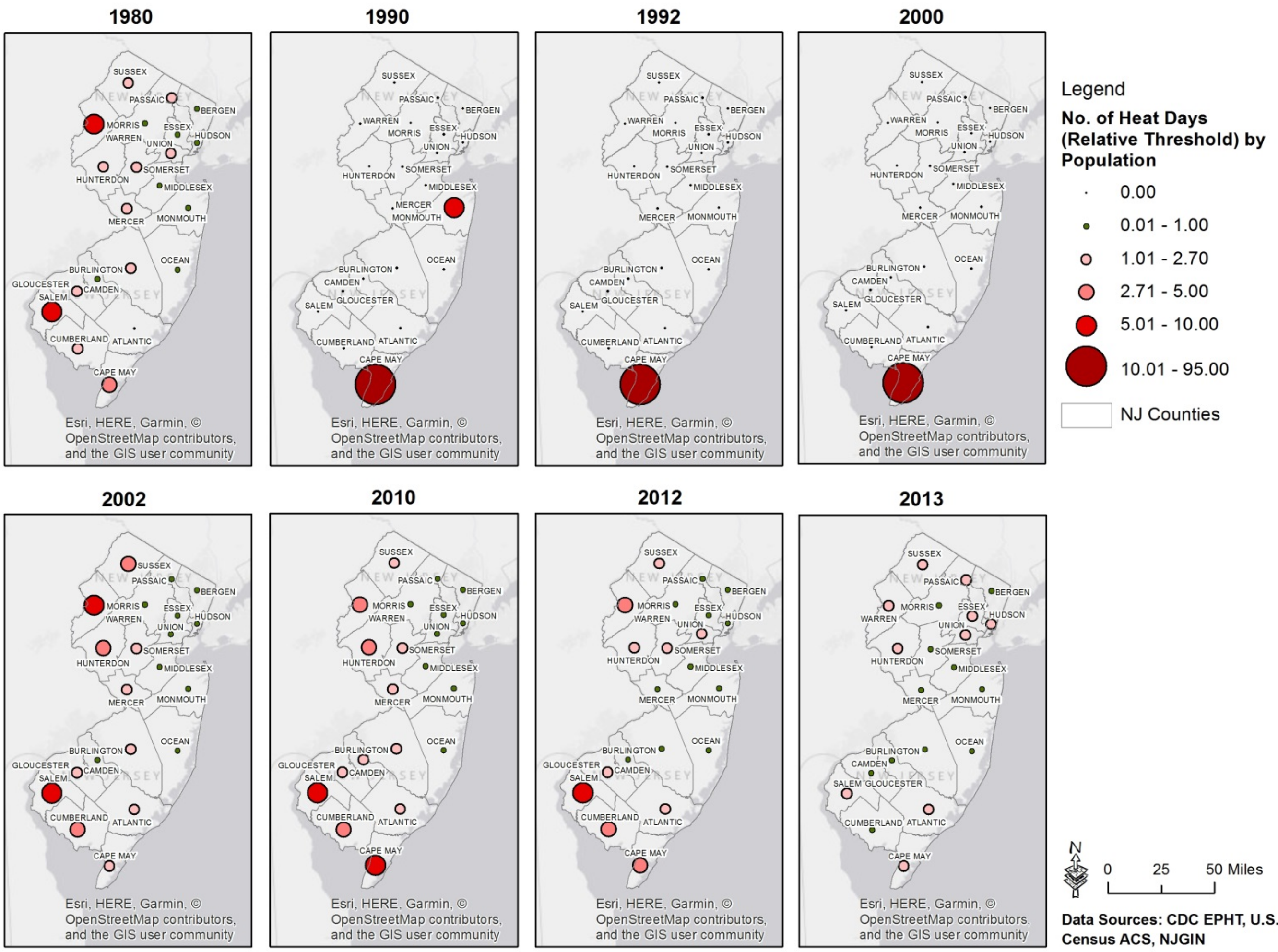
Findings (by population and land area) -

- Number of extreme heat days show higher values for less-populated counties such as Salem, Cumberland, Gloucester, Warren, and Hunterdon.

Disclaimer –

- Important Note: These indicators do not follow these trends for the years - 1990, 1992, and 2000 (the data for these 3 years contain zero values)

Number of Heat days (Relative Threshold) by Population



Number of Extreme Heat Events – Absolute Threshold

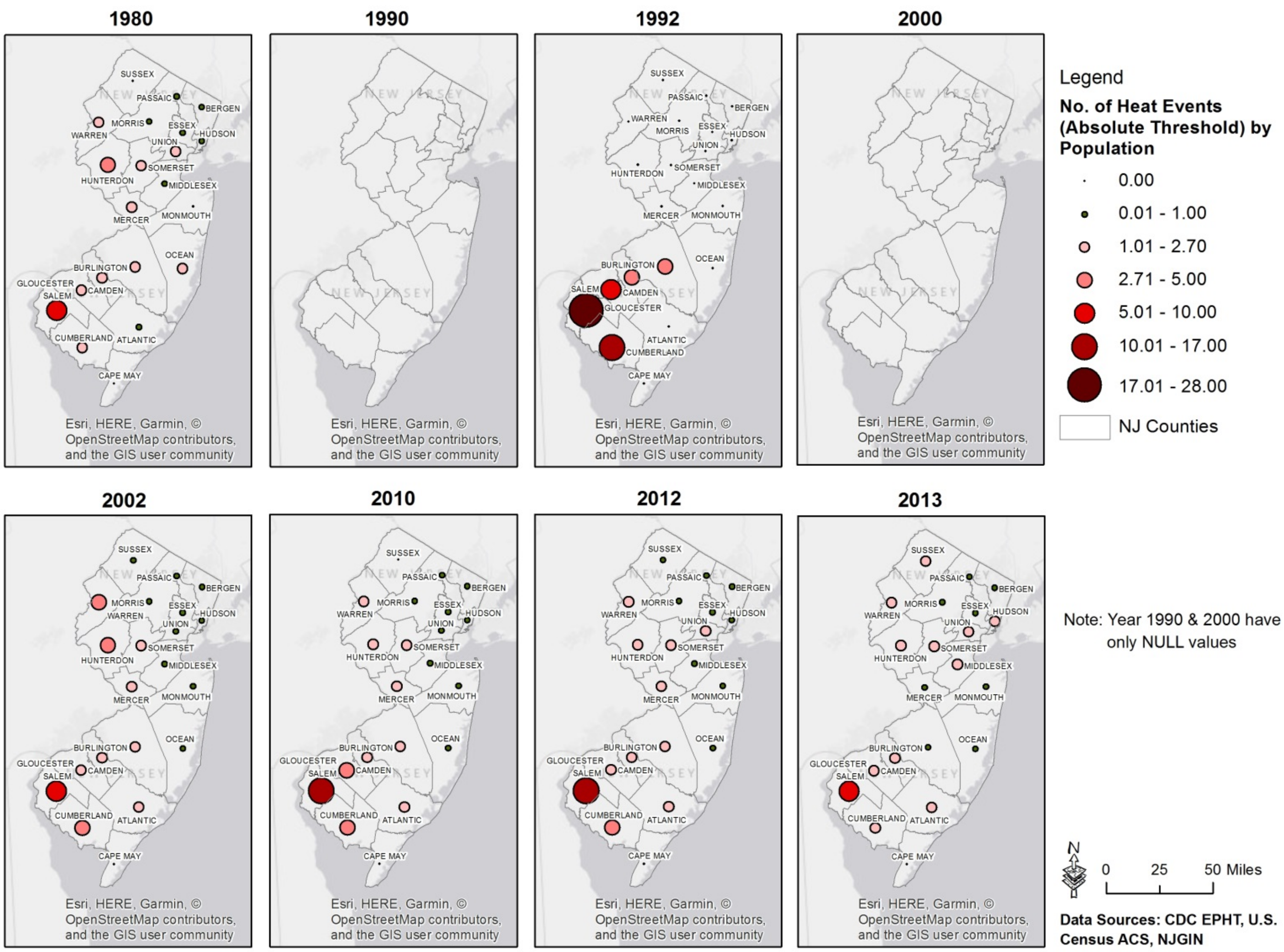
Findings (by population and land area) -

- The number of extreme heat events show higher values in predominantly non-urban areas similar to the number of extreme heat days by population data.

Disclaimer –

- Important Note: These indicators do not follow these trends for the years - 1990, 1992, and 2000 (the data for these 3 years contain zero values)

Number of Heat Events (Absolute Threshold) by Population



Number of Extreme Heat Events – Relative Threshold

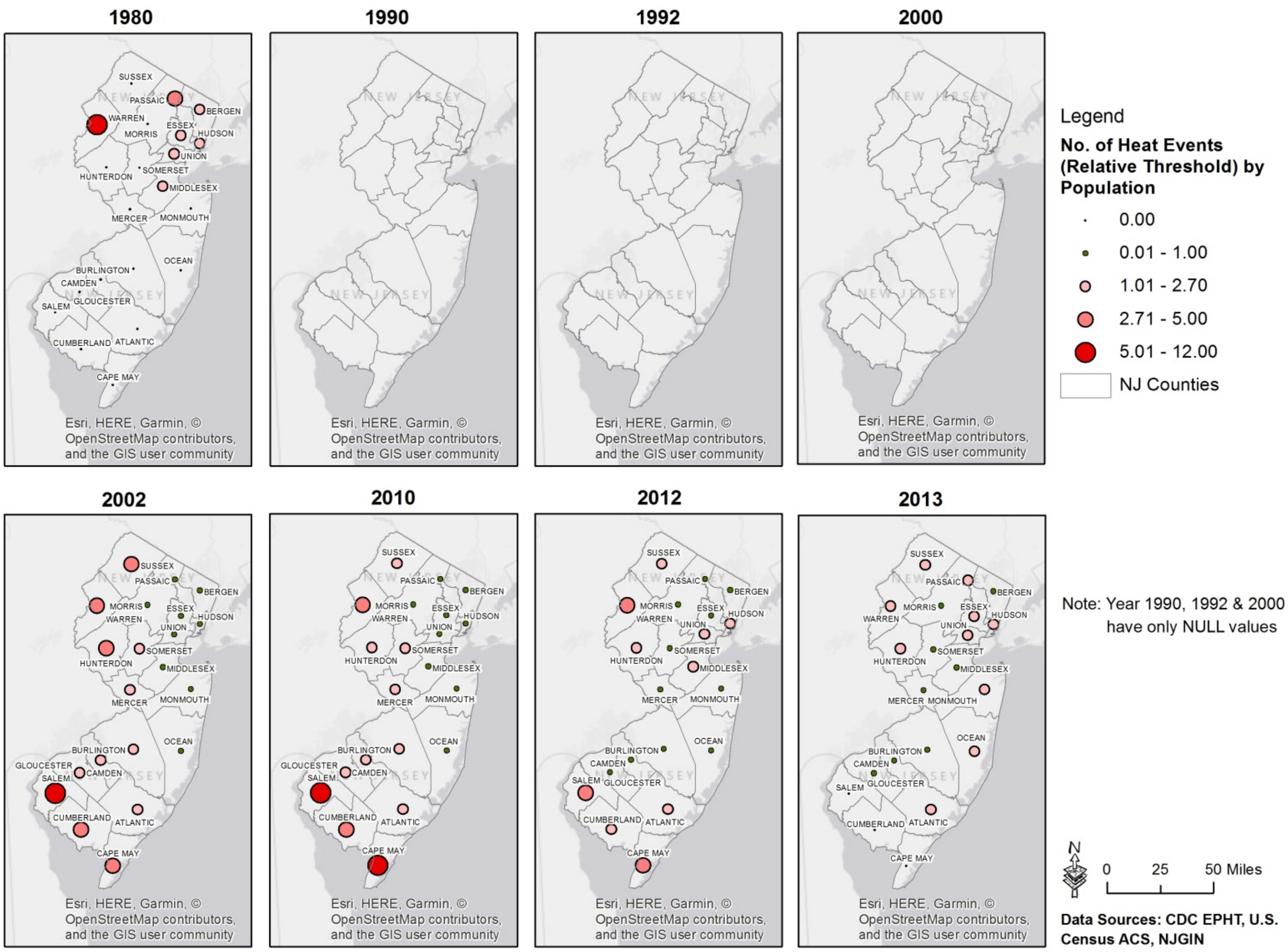
Findings (by population and land area) -

- Similarly to the absolute threshold findings, the number of extreme heat events show higher values in predominantly non-urban areas.

Disclaimer –

- Important Note: These indicators do not follow these trends for the years - 1990, 1992, and 2000 (the data for these 3 years contain zero values)

Number of Heat Events (Relative Threshold) by Population



IV. Summary and Recommendations on Measures for Model Integration

The Rutgers team worked with the CHR&R team to determine whether and which of the analyzed indicators is/are most suitable for integration into existing County Health Rankings metrics. These recommendations result from integrating the findings from the screening steps, data collection, as well as the national scale-up considerations, and include advice from consultation with our partners at CDC and EPA.

In Appendix C, we summarize the documentation and methodology regarding the steps that were taken to work with the data measures throughout the project. Based on our analysis reflected in Appendix C, we offer the following insights to inform the decision about modifying the model and conclude with some overarching thoughts.

It is important to note that we did not develop recommendations regarding the relative weights of any new measures selected in terms of how much they should contribute within the 10% impact that is currently allocated to physical environment indicators and how that new allocation would be allowable due to shuffling of the other existing indicators. We also recognize that the addition of new sources of health impacts (e.g. sources of pollution) may prompt revisiting the 10% impact threshold. Such an undertaking would necessitate integrating input from a panel of experts, along with perhaps an analysis of other similar indicators and how they are integrated into other health models would be necessary, and these analyses are outside the scope of the current project.

Recommendations for Model Integration:

We make the following recommendations to the CHR&R program staff regarding enhancements to the physical environment factor in the CHR&R model:

1. Add "**Climate Conditions**" as a new Health Factor Focus Area**.**

We recommend the addition of "Climate Conditions" as another focus area into the physical environmental factor. The measure(s) that could be selected as indicators in this area are ***Extreme Heat*** (number of days of extreme heat or number of extreme heat events – relative) and/or ***Flood Vulnerability*** (percent of area in flood hazard zones, or percent of people/housing units in flood hazard zones). We feel that both of these indicators have merit and would add value to the model, and the decision about which one(s) to include should rest on further deliberation with experts in climate, health and modeling. The National Climate Assessment[5] discusses how climate change may very well trump many of the CHR&R indicators with regard to impact on health and, at minimum, climate will affect many of the existing CHR&R indicators. For this reason, the addition of a climate conditions new health factor focus area may also elevate a discussion as to the relative contribution of physical environment factors to the overall contributions of health in the CHR&R model.

2. Add or modify **Air and Water Quality Focus Area**

We recommend consideration of ozone, air toxics and/or proximity to highways to the Air and Water Quality focus area, and refer to points raised on earlier page 11 for consideration of strengths and weaknesses of each measure.

We note in particular that traffic proximity captures impacts that aren't associated with the other two air

[5] US Global Climate Change Research Program, https://nca2014.globalchange.gov/

quality measures. That is, it also affects stress levels associated with noise, and perhaps increased prevalence of pedestrian and auto crashes, etc. which are connected to health outcome indicators collected in the model (poor mental health days, premature death).

Overall Summary and Concluding Thoughts

To summarize, the indicators for ozone, air toxics, traffic proximity, extreme heat and flood vulnerability are recommended for consideration for integration into the Physical and Environmental Factors portion of the CHR&R model for their ability to add value to the five existing measures in the model. That is, they are measures that have the clear impact on health outcomes and contribute of the new measures in comparison with the existing Physical Environment measures.

One issue to point out is the synergy of these indicators. Over the past 25 years, greater attention is paid in the United States to the disproportionate burden of environmental pollutants in communities with large populations of low income residents and residents of color. Currently, the CHR&R model incorporates a particulate matter indicator as the only ambient physical environment measure, yet, more and more, the public is interested in better understanding the synergy of various polluting sources in a community as well as understanding the synergistic effect that cumulative exposures may have on health. Thus, representing a single air quality indicator may not adequately represent the cumulative burden that multiple sources of different air pollutants may have on health and well-being. For example, geographic areas with high particulate matter measures also likely to have high ground level ozone and other air contaminants. However, a very preliminary scan comparing ozone non-attainment days with PM2.5 levels in NJ counties indicates that they do not co-vary strongly together, and may both explain different types of hazard sources that are not geographically identical.

Some impacted communities disproportionately affected by extreme heat and are likely to have greater exposure to mobile sources of pollutants. Far outside the scope of this project, there may be value in considering how to best reflect the synergy of community-based environmental pollutants on health as part of the CHR&R model. One idea could be to develop an overall air quality index that integrates various air pollutants (e.g. ozone, particular matter, air toxics). Another option is to consider a measure that integrates multiple variables to capture the cumulative effect of many of the physical environment factors on health. For example, urban counties may have high ozone levels and also contain many industrial facilities that release air toxics, populations near highways, and are subject to the heat events. So, those indicators could intersect and a cumulative indicator could serve to best reflect these intersecting impacts.

Finally, we reiterate that for this project we only proposed to look at a very small subset of “physical environment” indicators, based on an initial list of indicators available from EJScreen and EPHT. We recognize that there could also be a need to look more comprehensively at the physical environment contribution to health and to examine if other indicators that measure emerging or persistent environmental threats and hazards that are connected to human health impacts should be considered.

V. National Scale-up Considerations

Data at the county level accessible through EPHT is generally available for the entire U.S., with some exceptions for Alaska and Hawaii. Because CHR&R has included some data sets that omit these states, this should not automatically exclude these data. That is a decision for CHR&R staff to make based on the strength of the measure to add value to the model despite any gaps in national coverage.

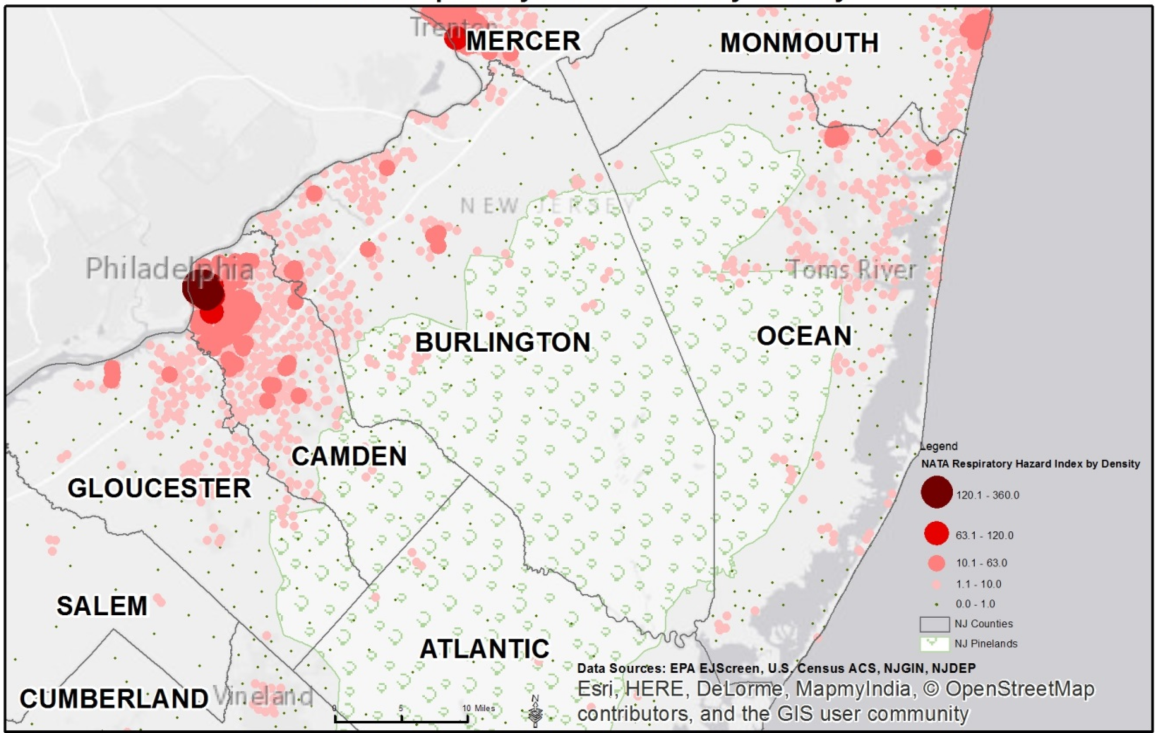
For the data from EJScreen that is enumerated at the sub-county level, data need to be first aggregated to the county level. To do this, EPA staff recommend using the known geography method. For the Census geography, a county contains Census tracts and a tract contains block groups. The county FIPS code shows what block groups are within a given county. Using Census-defined centroids for each of the respective block group level variables, the process then involves intersecting or spatially joining the attributes from the block group level to the county level. Using parameters such as the centroids should be completely contained within the county boundary or some other similar defining parameter. Limitations of this approach could be that you miscount data that crosses county boundaries (i.e. over-representing a variable in one county and under-representing the value in another).

An alternative approach to consider for national scale up would be through the use of the Make Feature Layer script. This script can be used to find the proportional value for each block group within counties and then aggregated to the county level. The Make Feature Layer tool (located within Esri's ArcMap Data Management toolkit), creates a temporary layer file that is held within the current working session of ArcMap. This temporary file can be used to complete additional analyses such as intersecting with other data layers. More specifically, you can set up the tool parameters so that a polygon split policy (i.e. Use Ratio Policy) is implemented prior to any aggregation. The split policy allows the user to specify attributes of interest to be included in the proportioning step and an intermediary data layer is created. This new data layer is only held in the current working session and needs to be processed through additional geoprocessing tools for the outcome to become permanent.

Another concern that may arise in joining block group data to a larger geographic unit is that the true picture of the dispersion or distribution of the indicator throughout the county will be masked or lost by aggregation into one county figure. As an example, we show the NATA Respiratory Hazard Index map for southern New Jersey, highlighting Burlington County in particular. Using a county figure, we know that Burlington County comes out as one of the worst in New Jersey for certain air pollutants. However, as the map shows, the areas with high readings on this air toxic measure are clustered heavily along the urbanized western edge of the county that is near to industrial facilities along the Delaware River and the many mobile and stationery pollution sources near Philadelphia.

Much of the rest of the area of the county has relatively low air pollutant levels. Sometimes these differences will match where populations are clustered (i.e. higher pollution levels where more people live), so that the high "average" reading of the county at least may help to indicate the fact that more people are exposed to these higher levels. But it is important to recognize that the aggregated figure will not be a true measure of the "health" of the air in the county as a whole. We realize that this is an inherent reality of the CHR&R model, given that all data is aggregated to the county level, particularly in less homogeneous counties with highly variable physical and environmental conditions in one disproportionately small part of the county versus the rest of the county. We recommend that looking at the distribution of the block group level data may be important, therefore, in describing how to interpret the county-level value to users of the model findings.

NATA Respiratory Hazard Index by Density



Appendices

A. Detailed Screening Analysis – Technical Criteria
B. Detailed Screening Analysis – Literature Review: Health Connections
C. Data Documentation and Methodology
D. Detailed Analysis – Climate Variables
E. Data Justification Table (Attached spreadsheet file)

Appendix A: Detailed Screening Analysis – Technical Criteria

AIR AND WATER QUALITY

1. Ground Level Ozone

Accessibility and Source of Measure:

Ground level ozone is a variable in both EJScreen and EPHT.

EJScreen:

Ozone Summer seasonal (May – September) average of daily maximum 8-hour concentration in air (ppb)

Source: EPA OAR fusion of model and monitor data[6]

EPHT[7]:

Days Above Regulatory Standard (monitor only, or monitor and modeled)

1. Number of days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard (NAAQS)
2. Number of person-days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard (NAAQS)

Source: The monitoring data comes from the U.S. Environmental Protection Agency (EPA) Air quality System (AQS). When AQS data are available from multiple monitors for a given county and day, the highest 8-hour maximum (daily) ozone concentration among all the monitors is selected for purposes of creating daily county level data. EPA provides modeled estimates of ozone using Downscaler (DS) model, which uses a statistical approach to fuse monitoring data in areas where monitors exist, and relies on Community Multiscale Air Quality (CMAQ) modeled output in areas without monitors. DS modeled estimates are available by census tract centroid-the geographic center of the census tract.

Scalability:

For EJScreen, tract estimates are assigned to block groups. EPA measures non-attainment at the county level. See below.

For EPHT, the scale is county (explained above). County level ozone measures are created using monitor data when available and using modeled estimates for days and locations without such data. Daily county level modeled estimates are obtained by selecting the maximum value observed among all the census tracts within each county. A limited number of U.S. monitors have suitable data, so modeling is an important complement to monitoring data.

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[6] For methods, see EPA Report EPA-454/S-15-001: https://www.epa.gov/greenbook/green-book-8-hour-ozone-2008-area-information

[7] see https://ephtracking.cdc.gov/showIndicatorPages.action?selectedContentAreaAbbreviation=15&selectedIndicatorId=79&selectedMeasureId=

National Coverage:

When using only monitors for the ambient ozone levels, some counties are left out. Ozone estimates were not available for Alaska or Hawaii for use in the 2017 version of EJScreen, due to a lack of CMAQ modeling. The air quality models are limited to the contiguous US so there are no fused data for these states.

Validity and Reliability:

The 2017 version of EJScreen uses ozone data that are based on 2013 monitoring and modeling estimates (U.S. EPA, 2015a). Data from several years ago may no longer be as representative of current conditions as they were at the time the data was collected. Emissions related to ozone generally have decreased in the intervening years.

The number of high ozone days per year varies, which makes tracking trends over time difficult to analyze or interpret. The variability is largely due to the fact that: a) the number of high ozone days is related to temperature (as a result, there will be more high ozone days in hotter summers), and b) there are a small number of events (high ozone days) per year, so for statistical reasons, this type of measure may vary. The model predictions are used to fill in air quality estimates in areas and at times without monitoring data. For counties without monitoring data, temporal (seasonal) and spatial (regional) biases in the modeled estimates, can influence the accuracy of the measures.

Variation within counties may exist but will not be captured in this measure. Larger areas will have a broader range of pollution values and perhaps more monitors that may measure a high value on a given day. Thus, estimates for larger areas may be biased higher than estimates for smaller areas. The number of days that exceed the EPA NAAQS or other health benchmarks does not provide information regarding the severity (max concentrations) of potential exposures.

Use:

EPA uses the *N*ational Ambient Air Quality Standards (NAAQS) for ground-level ozone, and has strengthened the standards for ground-level ozone to a standard of 70 parts per billion (ppb) averaged over 8-hours. Based on 2012-2014 data, 241 counties with monitors did not meet the updated standards.

The indicator for the number of days with maximum 8-hour average ozone concentration from over the standard from EPHT can be used to inform policy makers and the public of the potential hazards within a state (by county) during a year. For example, the number of days per year that ozone is higher than the NAAQS can be used to communicate the number of days that sensitive persons (such as people with asthma) may be exposed to unhealthy levels of ozone. [8]

Other Limitations and Concerns:

CHR&R used to use this measure in the county health rankings model and found no limitations to the data. CHR&R decided to select fine particulate matter as the preferred air quality measure in the model because they could only have one air quality measure and evaluated PM2.5 as a better measure, and also found that there was a strong association between the two.

8

Seewww.epa.gov/air/airtrends/2007/report/groundlevelozone.pdf andwww.epa.gov/air/airtrends/aqtrnd00/pdffiles/aqioz.pdf

The relationship between ambient concentrations and personal exposure is largely unknown and variable depending upon pollutant, activity patterns, and microenvironments.

The effort required to obtain all the data may indicate that a central system is needed to gather the data and calculate the measures. The comprehensive geographic coverage provided by the modeled ozone estimates must be balanced against its tendency for under prediction or over prediction at higher concentrations.

2. **Air Toxics**

Accessibility and Source of Measure:

Air Toxics is a variable in both EJScreen and EPHT. Each system contains multiple measures of air toxics taken from NATA.

EJScreen:

1. Diesel particulate matter level in air
2. Cancer risk: Lifetime cancer risk from inhalation of air toxics
3. Air toxics respiratory hazard index (ratio of exposure concentration to health-based reference concentration)

Source: EPA NATA[9]

EPHT:

1. Annual average cancer risk estimates per million (Benzene, formaldehyde, acetaldehyde, carbon tetrachloride, 1,3-butadiene)
2. Annual average air concentration estimates in microgram per cubic meter
3. Percent of cancer risk estimates by source (point, nonpoint, onroad, nonroad, secondary, other)
4. Percent of cancer risk estimates from all sources

Source: EPA NATA

The National-Scale Air Toxics Assessment (NATA) is EPA's ongoing comprehensive evaluation of air toxics in the U.S (U.S. EPA, 2012). The assessment includes four steps that focus on each emissions year:

1. Compiling a national emissions inventory of air toxics emissions from outdoor sources
2. Estimating ambient and exposure concentrations of air toxics across the United States
3. Estimating population exposures across the United States
4. Characterizing potential public health risk due to inhalation of air toxics including both cancer and non-cancer effects

NATA estimates cancer risk or noncancer implications of many of the 187 air pollutants classified as HAPs, as well as diesel particulate matter (DPM). NATA uses emissions estimates from the National Emissions Inventory (NEI), which is updated every three years. The NEI includes all of the Toxics Release Inventory (TRI) reporting facilities that release hazardous air pollutants

Scalability:

[9] https://www.epa.gov/national-air-toxics-assessment

For EJScreen, publicly-available NATA, PM2.5, and ozone estimates are at tract resolution, and tract level is the resolution used for EJScreen. Each block group was assigned the NATA or PM or ozone score of the tract containing it. If air toxics is selected for further analysis, the team will evaluate valid aggregation methods to the county level.

For EPHT, the measures are provided at the county level.

National Coverage:

There are variations in detail and completeness of inventories from different geographical regions.

The results used default, or simplifying, assumptions where data were missing or of poor quality.

Validity and Reliability:

Data from recent years may no longer be as representative of current conditions as they were at the time the data was collected. The NATA-based indicators used in EJScreen (2011) in particular should be viewed with this in mind, because emissions of air toxics generally have decreased in the intervening years.

2005 and 2011 measures are not comparable due to refinements in the modeling approach.

Use:

The measures can be used to:

- Prioritize emission sources as potential targets for risk reduction activities and for further study
- Identify locations of interest for further investigation
- Provide a starting point for local-scale assessments
- Demonstrate the spatial distribution of air toxics

Other Limitations and Concerns:

CHR&R staff reported that the program considered air toxics as a measure, but similar to the decision regarding ozone, determined that it captured similar conditions and likely co-varied strongly with the measure for air particulate matter.

There is a concern as to whether there is a justifiable causal link between air toxins and cancer. Also, CHR&R prefers not to include disease specific outcomes in health factors.

These measures are based on modeling data alone. The data should not be used as a sole means for identifying localized hotspots or to compare risks at local levels.

EPA suggests that the results of this assessment be used cautiously, as the overall quality and uncertainties of the assessment vary from location to location as well as from pollutant to pollutant (Eastern Research Group Inc., 2010). There are limitations in data, computer models used, default assumptions used routinely in any risk assessment, and the overall design of the assessment.

EPA's NATA website has extensive documentation of all of the data and methods used in developing the

NATA indicators, as well as discussions of uncertainty, caveats, and limitations in the NATA estimates. That information is not repeated here, but it is important that anyone using NATA data understand these issues, so anyone using EJScreen should consult the NATA documentation (www.epa.gov/nata)

The following are important specific limitations noted by U.S. EPA (2010c):

— The results do not include impacts from sources in neighboring countries (i.e., Canada or Mexico).
— The results do not reflect exposures and risk from all compounds.
— The results do not reflect all pathways of exposure.
— The results reflect only compounds released into the outdoor air.
— The results do not fully reflect variation in background ambient air concentrations.
— The results might systematically underestimate ambient air concentration for some compounds (U.S. EPA, 2010a).
— The results may not accurately capture sources that have episodic emissions (e.g., prescribed burning or facilities with short-term deviations such as startups, shutdowns, malfunctions, and upsets).
— Estimates of risk are uncertain.

3. Proximity of Populations and Schools to Highways

Accessibility and Source of Measure:

EJScreen:

Traffic proximity and volume: Count of vehicles (AADT, avg. annual daily traffic) at major roads within 500 meters, divided by distance in meters (not km), calculated from 2014 U.S. DOT traffic data.[10]

Measures of traffic proximity in EJScreen are based on average annual daily traffic (AADT) estimates in the Highway Performance Monitoring System (HPMS) dataset in the Department of Transportation (DOT) National Transportation Atlas Database (NTAD). The HPMS highway data is maintained by states and compiled by DOT.

For the 2017 version of EJScreen, a total of 11,078,297 Census 2010 blocks were analyzed to find all road segments within 500 meters of each block's internal point, or the nearest single segment if none were found within 500 meters.

Scalability:

The data is at the block group level. The count of vehicles per day within 500 meters of a block centroid, divided by distance in meters, presented as the population-weighted average of blocks in each block group. Adjustments are made so that the minimum distance used is reasonable when very small.

The HPMS data are collected at the state level, and the traffic counting program is designed to cover all interstate, principal arterial, other National Highway System and HPMS sample sections on a 3-year maximum cycle where at least one-third of roads are counted each year.[11]

If selected for further analysis, the team will investigate methods to aggregate the measure to the county

[10] https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm
[11] More details on the HPMS are available at http://www.fhwa.dot.gov/policyinformation/hpms.cfm

level.

National Coverage:

Available for the entire nation.

Validity and Reliability:

There is a concern with all of the proximity factors in: how the point sources are picked, consistency in reporting them (reliability issue), and validity of any causal impacts to surrounding populations.

CHR&R staff had looked into this factor at one time, and found that GIS highway layers were not always good. However, if EJScreen uses them and finds them reliable, this is no longer a concern.

Use:

It is unclear how the EJScreen measure is used and who might be using it.

We found this information below about a measure developed by CDC that could be relevant to consider as an alternative to the EJScreen measure:

To characterize the U.S. population living close to major highways, CDC examined data from several sources using Geographical Information Systems (GIS). Three data sources were used for this assessment: 1) the 2010 U.S. census (available at http://www.census.gov/2010census), 2) 2006–2010 American Community Survey (ACS) 5-year estimates (available at http://www.census.gov/acs), and 3) 2010 (Quarter 3) road network data from NAVTEQ, a commercial data source that provides comprehensive road information for the United States (available at http://www.navteq.com). Seven sociodemographic variables were examined. Data on age, sex, and race/ethnicity were obtained from the 2010 census; data on nativity, language spoken at home, educational attainment, and poverty status were obtained from the ACS.

The census tract is the smallest geographic unit of analysis available for the variables of interest in the ACS data. ESRI ArcGIS v10 GIS software was used to create circular buffers of 150 meters around all major highways, and the proportion of each census tract included within the buffer area was calculated. This area proportion was then applied to the census tract-level data from the 2010 census and ACS to estimate the number of persons living within 150 meters of a major highway for the total population and by sociodemographic characteristics. Census tract count estimates were summed to obtain state and national estimates. The proportion of the population living within 150 meters of a major highway was calculated for each category of the seven sociodemographic variables, using category-specific denominators derived from the 2010 census and ACS.

Limitations and Concerns:

Any indicator of residential proximity addresses exposures relevant to the residences within a block group, and would not capture most exposures that occur away from the home, such as at work, at school or during a commute.

4. Particulate Matter *Already in CHR&R

Particulate matter is measured in both EJScreen and EPHT. It is also the air quality measure that is currently in the CHR&R model. It is measured in ***average daily density of fine particulate matter in***

micrograms per cubic meter (PM2.5).[12]

Accessibility and Source of Measure:

EJScreen:

Measure: PM2.5 levels in air, µg/m3 annual avg. (2012)

Source: EPA, OAR (fusion of model and monitor data).[13].

EJScreen's PM2.5 data are estimated from a combination of monitoring data and air quality modeling. Ambient PM2.5 concentration is estimated by EPA's Office of Research and Development using a Bayesian space–time downscaling fusion model approach.[14]

EPHT:

1. Annual average PM2.5 levels (monitor only, monitor and model)
2. PM2.5 - Days above regulatory standard (monitor only, monitor and model)

Air monitors are limited by their locations, measuring only up to a certain distance in any direction, and their sampling structure, from one sample every day to once per week. **The *County Health Rankings* use this combination of monitor and modeled information provided by the Environmental Public Health Tracking Network.**

Scalability:

County level estimates are modeled from the information provided by the monitors. Further, these estimates are based on seasonal averages.

National Coverage:

PM2.5 estimates were not available for Alaska or Hawaii for use in the 2017 version of EJScreen, due to a lack of CMAQ modeling. The air quality models are limited to the contiguous US so there are no fused data for these states.

Validity and Reliability:

Data from several years ago may no longer be as representative of current conditions as they were at the time the data was collected (2013 from EJScreen). Emissions related to PM2.5 generally have decreased in the intervening years.

High-resolution estimates of PM2.5 are very difficult to develop for the entire United States. Block groups vary widely in geographic area—some are larger than 100 square kilometers, but a substantial

[12]https://ephtracking.cdc.gov/showIndicatorPages.action?selectedContentAreaAbbreviation=15&selectedIndicatorId=79&selectedMeasureId=
http://www.countyhealthrankings.org/measure/air-pollution-particulate-matter

[13]For methods, see EPA Report EPA-454/S-15-001 https://www.epa.gov/greenbook/green-book-pm-25-2012-area-information

[14]This approach is described in a series of three published journal articles (Berrocal, Gelfand, & Holland, 2010a, 2010b, 2011).

fraction are smaller than 1 sq. km in area. This makes it challenging to develop relevant spatial data.[15]

Monitors provide reliable estimates where they are located, but suitable PM2.5 data are available at fewer than 900 monitors in the United States. While urban areas tend to have PM2.5 monitors, more than two-thirds of U.S. counties lack any monitoring data, so modeling is an important complement to monitoring. Methods based on CMAQ alone, monitors alone, CMAQ-MATS and the downscaling approach all provide somewhat different estimates. (See EJScreen manual, pp.40-41)

The percentage of days during which the EPA NAAQS or other health benchmarks are exceeded does not provide information regarding the severity (maximum concentrations) of potential exposures. Even with these limitations, trends in $PM_{2.5}$ levels are a useful measure to describe public health concerns within these areas.

Populations in counties without monitors may be exposed to concentrations that exceed a standard. The indicator uses the highest value of all monitors in the area so that larger counties with more monitors may have a broader range of pollution values and greater potential to measure a high day than smaller counties with fewer monitors. The model predictions are used to fill in air quality estimates in areas and at times without monitoring data. For counties without monitoring data, temporal (seasonal) and spatial (regional) biases in the modeled estimates, can influence the accuracy of the measures

Because the number of high $PM_{2.5}$ days per year can vary considerably, tracking trends over time needs to be done carefully. The variability is largely due to the fact that: a) the number of high $PM_{2.5}$ days is related to meteorological factors (e.g., temperature and mixing heights), and b) few events (high $PM_{2.5}$ days) occur per year, so for statistical reasons, this type of measure may vary.

While this measure estimates the average annual concentration of fine particulate pollution in the county, it can miss important short-term fluctuations in air quality (such as stagnation events), local patterns (high concentrations near roads and other major sources), and other pollutants (such as ozone, etc.). Even within counties with low average fine particulate matter concentrations, locations can experience days of dangerously elevated levels, which can place individuals at risk for serious cardiovascular problems. It should be noted that these data are derived from only one air quality model among several. Like all models, this air quality model has errors. For data that utilize a different underlying model, please see the CDC Wonder Environmental data. Both of these models produce smoothed estimates of air quality that may obscure local conditions. You might also consider contacting air quality experts in your state who will have more detailed knowledge of within-county differences in air quality.

Use:

The indicator can be used to inform the public and policy makers of the degree of potential exposures within a state (for counties with monitors) during a year. For example, the percentage of days per year that $PM_{2.5}$ is higher than the NAAQS can be used to communicate to sensitive populations, such as those with asthma, the percentage of days that they may be exposed to unhealthy levels of $PM_{2.5}$; this is similar

[15] Vaidyanathan A., Dimmick WD, Kegler SR, and Qualters JR:Statistical Air Quality Predictions for Public Health Surveillance: Evaluation and Generation of County level Metrics of $PM_{2.5}$ for the Environmental Public Health Tracking Network. IJHG, 2013. Published: 14 March 2013 (doi:10.1186/1476-072X-12-12)

to the level used in the Air Quality Alerts that inform these sensitive populations when and how to reduce exposure.

Other Limitations and Concerns:

CHRR used to use the measure of percent PM2.5 days above standard. They switched to average daily concentration because it was being updated more often. Also, there was a national standard or goal with which to align.

Another limitation is that there is a lot of dichotomous data in the PM2.5 days above standard with a small distribution.

Finally, in terms of health connections, a prior review conducted by CHR&R showed that high PM days were not necessarily correlated with health risks.

5. Specific Contaminants of Concern for Drinking Water

Accessibility and Source of Measure:

EPHT:
Indicators for nine contaminants in Community Water Systems: Arsenic, Atrizine, DEHP, Disinfection Byproducts, Nitrates, PCE, TCE and Uranium.

For arsenic, for example, measures include:

Level of Contaminant in Finished Water

- Yearly distribution of number of Community Water Systems (CWS)by maximum arsenic concentration (cut-points: 0-5, >5-10,>10-20, >20-30, >30 µg/L arsenic).
- Yearly distribution of number of CWS by mean arsenic concentration (cut-points: 0-5, >5-10, >10-20,>20-30, >30 µg/L arsenic).
- Mean concentration of arsenic at CWS-level, by year.

Potential Population Exposure to Contaminants in Finished Water

- Yearly distribution of number of people served by CWS by maximum arsenic concentration (cut-points: 0-5, >5-10,>10-20, >20-30, >30 µg/L arsenic).
- Yearly distribution of number of people served by CWS by mean arsenic concentration (cut-points: 0-5, >5-10, >10-20,>20-30, >30 µg/L arsenic).

Source: SDW Information System (SDWIS)

Scalability:

Community Water System by County

(The finest detail will be the approximate point location of the community water distribution system represented by water withdrawal point, water distribution extents, principal county served, or principal city served.)

National Coverage:

Measurement is only taken at sufficiently small scale in EPA grantee states (32 states).

Validity and Reliability:

Measures do not account for the variability in sampling, numbers of sampling repeats, and variability within systems. Concentrations in drinking water cannot be directly converted to exposure, because water consumption varies by climate, level of physical activity, and between people (EPA 2004). Due to errors in estimating populations, the measures may overestimate or underestimate the number of affected people.

Samples are taken once a year (surface sources), once every three years (groundwater sources), or once every nine years (for sources with a waiver). Frequency of sampling is based on compliance with the MCL, the lower the measured concentration the fewer samples will be taken and some years there may be no sampling for arsenic.

Ground water systems may have multiple wells with different arsenic concentrations that serve different parts of the population. Compliance samples are taken at each entry point to the distribution system. In systems with separate wells serving some branches or sections of the distribution system, the system mean would tend to underestimate the arsenic concentration of people served by wells with higher arsenic concentrations.

Exposure may be higher or lower than estimated if data from multiple entry points for water with different arsenic levels are averaged to estimate levels for the PWS.

Use:

These measures can assist by addressing the following surveillance functions:

- Distribution measures provide information on the number of CWS and the number of people potentially exposed to arsenic at different concentrations.
- Maximum concentrations provide information on the peak potential exposure to arsenic at the state level.
- Mean concentrations at the CWS level provide information on potential exposure at a smaller geographic scale.

Other Limitations and Concerns:

When considering individual contaminants, CHR&R was unsure which contaminant to choose. There are limitations how and when particular measures are updated, and no consistency when certain contaminants are tested for from place to place. CHR&R also was not sure which contaminant would have the clearest connections to health, and they could change over time.

<u>TOXICS AND CONTAMINATED SITES</u>

6. Acute Releases (to air and water)

Accessibility and Source of Measure:

The dataset is no longer being maintained and is not publicly available.

In case the data become actively available in the future, we provide the information below:

EPHT: Acute Toxic Substances Releases

1. Number of Reported Acute Toxic Substance Release Incidents
2. Percent of Reported Acute Toxic Substance Release Incidents with at Least One Injury or Fatality
3. Percent of Reported Acute Toxic Substance Release Incidents with Evacuation Ordered
4. Rate of Injuries or Fatalities Due To Reported Acute Toxic Substance Release Incidents per 100,000 population
5. Rate of Reported Acute Toxic Substance Release Incidents per 100,000 population

Source:

National Toxic Substance Incident Program (NTSIP) was created by CDC/ATSDR in 2010 to replace the Hazardous Substance Emergency Events Surveillance (HSEES) (Duncan & Orr, 2010). NTSIP began funding seven state health departments to actively gather information on acute toxic substance release incidents. States develop agreements with local stakeholders (e.g., police, fire departments, poison control centers, media) to routinely report incidents. State health departments enter reported toxic substance release information in an ATSDR created web-based system. The information includes: location, time (e.g., day, night, weekday, and weekend), type (e.g., transportation, fixed-facility), type of industry, contributing factor (e.g., equipment failure, operator error, weather related), victims (e.g., employees, general public, emergency responders), injuries (e.g., respiratory system irritation, trauma injuries, and dizziness), public health actions (e.g., evacuation, decontamination). Specific information on injured persons is collected including age, type, extent of injuries, distance from incident, population group and type of protective equipment used.

Scalability:

Data are available at the county level.

Number measures are derived by aggregating releases (i.e. all releases, with injuries, etc.) Percent measures are derived by dividing the corresponding number measure by total number of releases.

Rate of injuries or fatalities measure is derived by dividing the number of injuries or fatalities due to reported incidents by the county population and multiplying by 100,000.

Rate measure is derived by dividing the number of reported incidents by the county population and multiplying by 100,000.

National Coverage:

Geographic coverage is limited.

Validity and Reliability:

These data include only those incidents reported to the state health department per their agreements with local stakeholders. The number of incidents is subject to underreporting as local stakeholders may be unaware of an incident or did not report an incident to the state health department.

Artificial variation may exist between states and within states.

Each funded state collaborates with local stakeholders to routinely report incidents. Some states may have more access to sources for reporting information about incidents and injuries than others (ATSDR, 2014). For example, not all states have access to poison control centers, occupational injury reporting sources and hospital discharge data.

The number of incidents per state and per county may vary because of factors related to population size, the types of industry, number of facilities, or frequency of transport and not because of factors related to preventative measures.

This indicator represents reported incidents only and may underrepresent the true number of incidents. Caution should be used when comparing counties, even counties within the same state, as differences may be due to differences in the reporting process or simply the volume of toxic substances used, stored, or transported within the county and not necessarily a reflection on safety practices within the county.

Use:

It is unclear if this dataset had any regular use or users when it was maintained. If maintained with reliability at some point in the future, it could be used to examine patterns and trends in location of reported acute toxic substance incidents, types of industries and substances involved, contributing factors and the resulting injuries and public health actions (e.g., evacuations, decontamination), and to inform interventions and policies designed to prevent or mitigate the effects of future incidents.

Other Limitations and Concerns:

CHR&R's concern is about the impact of this factor on health of surrounding areas. CHR&R assessed that if something gets released in a place, that doesn't necessarily affect that place, so if probably not appropriate as a county-level indicator.

7. Proximity to National Priority List Sites

Accessibility and Source of Measure:

EJScreen:

Count of proposed and listed NPL sites within 5 km (or nearest one beyond 5 km), each divided by distance in kilometers

The count of sites proposed and listed on the National Priorities List (NPL), each represented by a point on the map (latitude/ longitude coordinate), within 5 km of the average resident in a block group, divided by distance, calculated as the population-weighted average of blocks in each block group. Adjustments are made if there are no NPL sites within 5 km, and so that the minimum distance used is reasonable when very small.

Source: Calculated from EPA CERCLIS database

Scalability:

Measured at the block group level. If this measure is selected for further analysis, the team will explore appropriate methods to aggregate the data to the county scale.

Each Census block group in the United States was assigned a proximity score that was the population-weighted sum of block-level proximity scores.

National Coverage:

Calculated for all US locations.

Validity and Reliability:

A single point location (latitude/ longitude coordinates) for each proposed and listed NPL site was obtained from EPA's CERCLIS database. The database does not provide details on the boundaries of each site, so this point data had to serve as a way to represent site locations. For residents close to very large sites, the available data may not provide an accurate representation of proximity to relevant portions of the site. These points are approximations of the locations of sites, and are not necessarily at the "center" of a given site. In a few cases a site's coordinates were located in a major body of water according to the database, so EPA manually specified new, plausible, nearby coordinates for use in EJScreen.

Use:

It is unclear if these data are being used or have any regular users.

Other Limitations and Concerns:

Concern with all of the proximity factors are in: how the point sources are picked, consistency in reporting them (reliability issue), and validity of any causal impacts to surrounding populations.

As with all proximity-based indicators, proximity alone may not represent any actual risk or even exposure.

8. Proximity to Waste Treatment, Storage, and Disposal Facilities

Accessibility and Source of Measure:

EJScreen:
Count of TSDFs (treatment, storage and disposal facilities) within 5 km (or nearest beyond 5 km), each divided by distance in kilometers.

The count of all commercial TSDF facilities within 5 km, divided by distance, presented as population-weighted averages of blocks in each block group. Adjustments are made if there are none within 5 km, and so that the minimum distance used is reasonable when very small.

Source: Calculated from EPA RCRA Info database.

Scalability:

Measured at the block group level. If this measure is selected for further analysis, the team will explore appropriate methods to aggregate the data to the county scale.

Each block group in the United States was assigned a proximity score that was the population-weighted sum of block-level proximity scores. This score can be thought of as the number of facilities per kilometer of distance from the average person.

National Coverage:

Calculated for all U.S. locations.

Validity and Reliability:

A single point location (latitude/ longitude coordinates) for each listed site was obtained from EPA's database. The database does not provide details on the boundaries of each site, so this point data had to serve as a way to represent site locations. For residents close to very large sites, the available data may not provide an accurate representation of proximity to relevant portions of the site. These points are approximations of the locations of sites, and are not necessarily at the "center" of a given site. In a few cases a site's coordinates were located in a major body of water according to the database, so EPA manually specified new, plausible, nearby coordinates for use in EJScreen.

Use:

It is unclear if these data are being used or have any regular users.

Other Limitations and Concerns:

Concern with all of the proximity factors are in: how the point sources are picked, consistency in reporting them (reliability issue), and validity of any causal impacts to surrounding populations.

As with all proximity-based indicators, proximity alone may not represent any actual risk or even exposure.

9. **Proximity to RMP Sites**

Accessibility and Source of Measure:

EJScreen:
Count of RMP (potential chemical accident facilities required to have a risk management plan) facilities within 5 km (or nearest one beyond 5 km), each divided by distance in kilometers

The 2017 version of EJScreen uses locational information retrieved from the RMP database in March 2017. A total of 19,925 RMP facilities were included in the proximity indicators and related EJ indexes in this version of EJScreen.

Source: Calculated from EPA RMP database, retrieved 03/2017
https://www.epa.gov/rmp/riskmanagement-plan-rmp-ruleoverview

Scalability:

Measured at the block group level. If this measure is selected for further analysis, the team will explore appropriate methods to aggregate the data to the county scale.

Each block group in the United States was assigned a proximity score that was the population-weighted sum of block-level proximity scores. This score can be thought of as the number of RMP facilities per kilometer of distance from the average person.

National Coverage:

Calculated for all U.S. locations.

Validity and Reliability:

A single point location (latitude/ longitude coordinates) for each listed site was obtained from EPA's database. The database does not provide details on the boundaries of each site, so this point data had to serve as a way to represent site locations. For residents close to very large sites, the available data may not provide an accurate representation of proximity to relevant portions of the site. These points are approximations of the locations of sites, and are not necessarily at the "center" of a given site. In a few cases a site's coordinates were located in a major body of water according to the database, so EPA manually specified new, plausible, nearby coordinates for use in EJScreen.

Use:

It is unclear if these data are being used or have any regular users.

Other Limitations and Concerns:

Concern with all of the proximity factors are in: how the point sources are picked, consistency in reporting them (reliability issue), and validity of any causal impacts to surrounding populations.

As with all proximity-based indicators, proximity alone may not represent any actual risk or even exposure.

It should be noted that some concerns related to proximity to facilities are already accounted for in NATA indicators for ambient air pollutants (e.g., cancer risk and hazard indexes), but NATA is based on one year of reported annual releases, which would not account for accidental releases unless they occurred that year.

10. Proximity to Waste Water Dischargers

Accessibility and Source of Measure:

EJScreen: Wastewater discharge indicator

Toxicity-weighted stream concentrations at stream segments within 500 meters, divided by distance in kilometers (km).

The toxicity-weighted concentration in stream reach segments within 500 meters of a block centroid, divided by distance in meters, presented as the population-weighted average of blocks in each block group. Adjustments are made so that the minimum distance used is reasonable when very small.

The wastewater discharge indicator takes into account pollutant loadings from the Discharge Monitoring Report (DMR) Loading Tool (which include NPDES DMR discharges and TRI releases) for toxic chemicals reported to the Toxics Release Inventory. The data were input into the RSEI model to incorporate chemical toxicity and fate and transport in order to estimate concentrations of pollutants in downstream water bodies (i.e., stream reaches) and derive a toxicity-weighted concentration. The indicator was developed using data including loadings from NPDES major and minor dischargers from the DMR Loading Tool, TRI releases, location of the discharges, decay rates for each chemical, and reach location information into which the chemical is discharged. All the necessary hydrography is available in the RSEI modeling environment.

Source: RSEI, NPDES, DMR, and TRI loadings by chemical; RSEI model results mapped to NHD Version 2.0 stream reach segments.

Scalability:

The EJScreen indicator takes into account proximity from the stream reaches to census blocks. It is unclear if this measure could be aggregated to the county scale in a reliable and valid manner.

National Coverage:

The NHD used by RSEI does not include stream reach segments for Alaska.

Validity and Reliability:

It is necessary to find updated documentation on this new variable regarding validity, reliability and update factors.

Use:

It is unclear if there are any uses or users of this data, as it is relatively new.

Other Limitations and Concerns:

As with all proximity-based indicators, proximity alone may not represent any actual risk or even exposure.

CHANGING CLIMATE CONDITIONS

11. Extreme Heat

Accessibility and Source of Measure:

EPHT: Historical Extreme Heat Days and Events
Measures:

1. Number of Extreme Heat Days
2. Dates of Extreme Heat Days
3. Number of Extreme Heat Events
4. Dates of Extreme Heat Events

Source: North American Land Data Assimilation System (NLDAS) data, available at the $1/8^{th}$-degree grid (approximately, 14X14 km), consist of 103,936 grid cells.

CDC receives raw, grid-level, modeled North American Land Data Assimilation System (NLDAS) data from National Aeronautics and Space Administration (NASA) which is then evaluated and processed to create county-level measures of extreme heat on the National Tracking Network. (See below).

Note: EPHT also has other heat-related indictors including Future Projections, Heat Stress, Heat Vulnerability and Heat-related Mortality, but these will likely not meet CHR&R program goals concerning not including health considerations within environmental factors, and including highly reliable data (with regard to the future projections).

Scalability: Measures are at the county level in EPHT.

Data processing and scaling process (From EPHT website):

> We convert grid-level data to U.S. Census tract and county level estimates to determine population exposure to extreme heat and enable linkage with health datasets. We use a multi-stage geo-imputation approach to convert grid-level meteorological data. We first assign each U.S. Census block centroid to a NLDAS grid cell based on a containment relationship, and estimate block-level estimates of daily heat metrics from hourly grid-level data. Using block-level population as weights, we then calculate a population-weighted average of daily heat metrics by U.S. Census tracts. From this Census tract level data product, we create average county-level estimates of daily heat metrics using tract population as weights.
>
> We then calculate the 90th, 95th, 98th, and 99th percentile values for daily heat metrics. The percentiles are specific to each geography (e.g., Census tract or county) and summer months across for all available years of data. We then identify extreme heat days for each combination of the following parameters (1) temperature or heat index and (2) absolute (e.g., 90°F, 95°F, 100°F, 105°F) or relative (e.g., 90th, 95th, 98th, and 99th percentile values) threshold. We also identify extreme heat events for each combination of the following parameters (1) temperature or heat index, (2) absolute (e.g., 90°F, 95°F, 100°F, 105°F) or relative (e.g., 90th, 95th, 98th, and 99th percentile values) threshold, and (3) durations of consecutive days (e.g., 2 or more, 3 or more).

National Coverage:

Grid cells cover the entire United States, excluding Alaska and Hawaii.

Validity and Reliability:

Modeled data perform relatively well in estimating temperature; however, the estimates may differ when compared to weather station-based observations. The differences vary by region and some are expected from a meteorological perspective. As a result, an area may be described as having higher or lower temperatures than actually occurred.

County-level estimates of temperature and heat index are obtained by processing modeled data, which are available by1/8th-degree grid. The process of converting grid-level data to county-level estimates using a population-weighted centroid approach may lead to potential misclassification of temperature and heat index for some areas.

NLDAS modeled meteorologic data may not accurately reflect the true temperature and heat index values in each county.

Use:

Other Limitations and Concerns:

People in different regions have varying degrees of acclimatization to heat. The flexibility of the tool could help in calibrating definitions to reflect that. However, the tool does not prescribe the most appropriate definition of extreme heat for specific geographic regions because of the lack of consensus in the weather-related scientific literature.

12. Extreme Precipitation

Accessibility and Source of Measure:

EPHT:

1. Number of extreme precipitation days
2. Monthly estimates of precipitation

Source: North American Land Data Assimilation System (NLDAS) data, available at the 1/8th-degree grid (approximately, 14x14 km), consist of 103,936 grid cells.

Scalability:

Available at the county level.

From the EPHT website:

> We convert grid-level data to U.S. Census tract and county level estimates to determine population exposure to extreme precipitation and enable linkage with health datasets. We use a multi-stage geo-imputation approach to convert grid-level precipitation data. We first assign each U.S. Census block centroid to a NLDAS grid cell based on a containment relationship, and estimate block-level estimates of daily total precipitation from hourly grid-level data. Using block-level population as weights, we then calculate a population-weighted average of daily total precipitation by U.S. Census tracts. From this Census tract level data product, we create average county-level estimates of daily total precipitation using tract population as weights.
>
> We then calculate the 90th, 95th, 98th, and 99th percentile values of daily total precipitation. The percentiles are specific to each geography (e.g., Census tract or county) and across for all available years of data. We then identify extreme precipitation days for each combination of the following parameters (1) absolute (e.g., 0.01 inches, 1 inch, 2 inches, and 3 inches) or relative (e.g., 90th, 95th, 98th, and 99th percentile values) threshold.
>
> We also provide monthly average daily total precipitation (in inches) by county.

National Coverage:

Grid cells cover the entire United States, excluding Alaska and Hawaii.

Validity and Reliability:

Modeled data perform relatively well in estimating precipitation;[6] however, the estimates may differ when compared to weather station-based observations. The differences vary by region; some differences can be expected from a meteorological perspective. As a result, an area may be described as having higher or lower precipitation levels than what actually occurred.

Census tract and county level estimates of precipitation are obtained by processing modeled data, which are available by 1/8th - degree grid. The process of converting grid-level data to Census tract and county-level estimates using a population-weighted centroid approach may lead to potential misclassification of precipitation for some areas.

People in different regions have varying degrees of acclimatization to precipitation. The flexibility of the tool could help in calibrating definitions to reflect that. However, the tool does not prescribe the most appropriate definition of extreme precipitation for specific geographic regions because of the lack of consensus in the weather-related scientific literature.

Use:

It is unclear how this data is used.

Other Limitations and Concerns:

NLDAS modeled meteorological data may not accurately reflect the true precipitation levels in each Census tract or county.

13. **Flood Hazards**

Accessibility and Source of Measure:

EPHT: Flood Vulnerability
Measures:

1. Number of Square Miles Within FEMA Designated Special Flood Hazard Area
2. Percent Area (square miles) Within FEMA Designated Special Flood Hazard Area
3. Number of People Within FEMA Designated Special Flood Hazard Area
4. Number of Housing Units Within FEMA Designated Special Flood Hazard Area

Sources: Federal Emergency Management Agency (FEMA) - National Flood Hazard Layer, 2011, LandScan USA Nighttime population estimates, 2010

Scalability: Available at the county scale

National Coverage:

Check: Does it cover the entire US? Jen – Is the sentence below correct?

The National Flood Hazard Layer does not have complete spatial coverage for the contiguous US.

Validity and Reliability:
There is uncertainty in the calculation and depiction of coastal flood hazards

Estimates in riverine areas may have a larger error than estimates in coastal areas, due to uncertainties in the LandScan data.

Use:

- These data can be used to estimate the number of residents and housing units per county in a 100-year flood zone
- Informing a vulnerability analysis or a risk assessment study allows comparison across states and counties; such comparison can be used to target interventions.

Other Limitations and Concerns:

CHR&R is interested in this measure, but has no experience with this data.

If using the "people within zones" measure, the data provided by FEMA do not consider seasonality when estimating coastal populations.

Appendix B: Detailed Screening Analysis – Literature Review: Health Connections

Air and Water Quality

Ground Level Ozone

The relationship between ambient concentrations of ground level ozone and personal exposure is largely unknown and variable depending upon pollutant, activity patterns, and microenvironments.

According to research presented at EJScreen, toxicological and epidemiological studies have established an association between exposure to ambient ozone and a variety of health outcomes, including reduction in lung function, increased inflammation and increased hospital admissions and mortality. In the 2006 Air Quality Criteria Document for Ozone, a comprehensive review of the clinical and epidemiological evidence was inconclusive about a possible threshold for ozone-induced health effects. EPA concluded that if a population threshold level exists, it is near the lower limit of ambient ozone concentrations in the United States. Several subpopulations may experience susceptibility to ozone-induced health effects, including older adults, children, individuals with preexisting pulmonary disease and those with higher exposure levels such as outdoor workers (U.S. EPA, 2006). A recent review of studies identifying subgroups susceptible to ozone found the strongest evidence for greater sensitivity among the elderly and also the unemployed (Bell et al, 2014).

The main health concern of exposure to ambient ground-level ozone is its effect on the respiratory system, especially on lung function. Several factors influence these health impacts, including the concentrations of ground-level ozone in the atmosphere, the duration of exposure, average volume of air breathed per minute (ventilation rate), and the length of intervals between short-term exposures. Most of the evidence on the health impacts of ground-level ozone comes from animal studies and controlled clinical studies of humans focusing on short-term acute exposure. Clinical studies have documented an association between short-term exposure to ground-level ozone at concentrations of 200–500 µg/m3 and mild temporary eye and respiratory irritation as indicated by symptoms such as cough, throat dryness, eye and chest discomfort, thoracic pain, and headache (WHO 1979, 1987). Temporary decrements in pulmonary function have been found in children at hourly average ground-level ozone concentrations of 160–300 µg/m3. Similar impacts were observed after 2.5-hour exposure of heavily exercising adults and children to concentrations of 240 µg/m3 (WHO 1987). Lung function losses, however, have been reversible and relatively mild even at concentrations of 360 µg/m3, with a great variety of personal responses (Chilton and Sholtz 1989). Full recovery of respiratory functions normally occurs within 24 to 48 hours after exposure (WHO 1987).

Exposure to elevated concentrations of ground-level ozone has been shown to reduce physical performance, since the increased ventilation rate during physical exercise increases the effects of exposure to ground-level ozone. There is no evidence that smokers, children, older people, asthmatics, or individuals with chronic obstructive lung disease are more responsive to ground-level ozone exposure than others. Ground-level ozone may, however, make the respiratory airways more responsive to other inhaled toxic substances and bacteria. In addition, a synergistic effect of ground-level ozone and sulfur dioxide has been found, indicating that sulfur dioxide potentiates the effects of ground level ozone (WHO 1979).

Besides short-term impacts, the potential for irreversible damage to the lungs from repeated exposure over a longer period of time has been a health concern. Some studies have found an association between accelerated loss of lung function over a longer period of time (five years) and high oxidant levels in the atmosphere (Detels et al. 1987).

Evidence suggests that exposure to short-term peak concentrations of ground-level ozone damages human health but that these impacts are relatively mild and reversible at ground-level ozone levels exceeding current U.S. and WHO standards and guidelines. Although repeated exposure to peak concentrations may result in cumulative impacts on lung function, inhibiting recovery, no clear evidence for such chronic effects of ground-level ozone exists.

In general, as concentrations of ground-level ozone increase, both the number of people affected and the seriousness of the health effects increase. Also, more people with lung disease visit doctors or emergency rooms and are admitted to the hospital. When ozone levels are very high, everyone should be concerned about ozone exposure.

Many of these effects can lead to increased school or work absences, visits to doctors and emergency rooms, and hospital admissions. Research also indicates that ozone exposure can increase the risk of premature death from heart or lung disease, although more research is needed to understand how ozone may affect the heart and cardiovascular system (Airnow).

Based on a panel study of children in Leipzig, a non-linear (quadratic) concentration–response relationship was identified between ozone and respiratory symptoms. Results indicate that using ozone as a linear covariate might be a misspecification of the model, which might explain non-uniform results of several field studies in health effects of ozone. The study concludes that there is urgent demand for forecasting episodes of high ozone that may help susceptible persons to avoid high exposure (Schlink et al, 2006).

A computer model called the Ozone Risk Assessment Model (ORAM) was developed to evaluate the health effects caused by ground-level ozone (O_3) exposure. ORAM was coupled with the U.S. Environmental Protection Agency's (EPA) Third-Generation Community Multiscale Air Quality model (Models-3/CMAQ), the state-of-the-art air quality model that predicts O_3 concentration and allows the examination of various scenarios in which emission rates of O_3 precursors (basically, oxides of nitrogen [NO_x] and volatile organic compounds) are varied. The principal analyses in ORAM are exposure model performance evaluation, health-effects calculations (expected number of respiratory hospital admissions), economic valuation, and sensitivity and uncertainty analysis through a Monte Carlo simulation. As a demonstration of the system, ORAM was applied to the eastern Tennessee region, and the entire O_3 season was simulated for a base case (typical emissions) and three different emission scenarios. The results indicated that a synergism occurs when reductions in NO_x emissions from mobile and point sources were applied simultaneously. A 12.9% reduction in asthma hospital admissions is expected when both mobile and point source NO_x emissions are reduced (50 and 70%, respectively) versus a 5.8% reduction caused by mobile source and a 3.5% reduction caused by point sources when these emission sources are reduced individually (Sanhueza et al, 2003).

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Air Toxics

Air toxics, often referred to as hazardous air pollutants (HAPs), are pollutants that are known or suspected to cause cancer or other serious health effects, such as reproductive effects or birth defects, or adverse environmental effects. Most air toxics originate from transportation and industry, including motor vehicles, industrial facilities and power plants.

According to EJScreen, a chemical's listing as an HAP is based on evidence of cancer or other adverse health effects or environmental effects associated with exposure to the chemical, as determined by EPA and the initial list in the Clean Air Act Amendments of 1990. EPA's Integrated Risk Information System (IRIS) program documents the health risks associated with these chemicals and serves as a basis for the analysis of health implications (U.S. EPA, 2012c). Air toxics cancer risk and non-cancer impacts have been included in other EPA EJ screening tools. HAPs are emitted from a wide variety of sources and disperse around the sources, especially downwind. In some cases, these substances react with other constituents in the atmosphere or break down to other chemicals, and most are eventually removed through precipitation or other atmospheric processes. People are exposed in their daily activities in and around their homes, at school or work, and while moving about the area. They inhale the substances, exhale or excrete some portion of them, and have the potential for incurring adverse effects from the portion that stays in the body.

According to Environmental Public Health Tracking (EPHT), air toxics are known or suspected to cause cancer or other serious health effects, which can include damage to the immune system, as well as neurological, reproductive, developmental, respiratory and other health problems.

Among the air toxics included in the 2011 National-Scale Air Toxics Assessment (NATA) by EPA, formaldehyde, benzene, acetaldehyde, carbon tetrachloride, and 1,3-butadiene were the top five contributors to the overall cancer risks nationwide. In addition, there are good agreements between the ambient concentrations and the NATA modeling results for these pollutants (Eastern Research Group Inc., 2010).

Benzene in the air comes from burning coal and oil, gasoline service stations, and motor vehicle exhaust (ATSDR, 2007; U.S. EPA, 2010b). Acute (short-term) inhalation exposure of humans to benzene may cause drowsiness, dizziness, headaches, as well as eye, skin, and respiratory tract irritation, and, at high levels, unconsciousness. Chronic (long-term) inhalation exposure has caused various disorders in the blood, including reduced numbers of red blood cells and aplastic anemia, in occupational settings. Reproductive effects have been reported for women exposed by inhalation to high levels, and adverse effects on the developing fetus have been observed in animal tests. Increased incidences of leukemia (cancer of the tissues that form white blood cells) have been observed in humans occupationally exposed to benzene. EPA has classified benzene as known human carcinogen for all routes of exposure.

Formaldehyde is used mainly to produce resins used in particleboard products and as an intermediate in the synthesis of other chemicals (ATSDR, 1999; U.S. EPA, 2010b). Exposure to formaldehyde may occur by breathing contaminated indoor air, tobacco smoke, or ambient urban air. Acute and chronic inhalation exposure to formaldehyde in humans can result in respiratory symptoms, and eye, nose, and throat irritation. Limited human studies have reported an association between formaldehyde exposure and lung and nasopharyngeal cancer. Animal inhalation studies have reported an increased incidence of nasal squamous cell cancer. EPA considers formaldehyde a probable human carcinogen (Group B1).

Acetaldehyde is mainly used as an intermediate in the synthesis of other chemicals (National Center for Biotechnology Information; U.S. EPA, 2010b). Residential fireplaces and woodstoves are the two highest sources of emissions, followed by various industrial emissions. As a result, many individuals are exposed to acetaldehyde by breathing ambient air. Acute exposure results primarily in irritation of the eyes, skin, and respiratory tract. Erythema, coughing, pulmonary edema, and necrosis may occur at higher acute exposure levels. Symptoms of chronic exposure to acetaldehyde in humans resemble those of alcoholism. EPA considers acetaldehyde a probable human carcinogen (Group B2) based on inadequate human cancer studies and animal studies that have shown nasal tumors in rats and laryngeal tumors in hamsters. While animal studies have demonstrated that acetaldehyde may be a potential developmental toxin, no information is available on the reproductive or developmental effects in humans.

Carbon tetrachloride is a solvent for oils, fats, lacquers, varnishes, rubber waxes, and resins, and a starting material in the manufacturing of organic compounds (National Center for Biotechnology Information; U.S. EPA, 2010b). Humans can be exposed to carbon tetrachloride in ambient air through accidental release from production and uses, as well as from its disposal in landfills where it may evaporate into the air or leach into groundwater. Indoor exposure results from building materials or products such as cleaning agents. Human symptoms of acute exposure include headache, weakness, lethargy, nausea, and vomiting. Acute exposure to higher levels or chronic exposure produces liver and kidney damage in humans. Human data on the carcinogenic effects of carbon tetrachloride are limited; animal studies show that ingestion increases the risk of liver cancer, leading EPA to classify carbon tetrachloride as a probable human carcinogen (Group B2).

1,3-butadiene is used in the production of rubber and plastics, as well as in copolymers such as acrylics (National Center for Biotechnology Information; U.S. EPA, 2010b). Moto vehicle exhaust is a common source, and as a result 1,3-butadiene is usually found in ambient air at low levels in both urban and suburban areas. Acute exposure by humans results in irritation of the eyes, nasal passages, throat, and lungs. Epidemiological studies have reported a possible association between 1,3-butadiene exposure and cardiovascular disease as well as increased incidence of leukemia from occupational exposure. Meanwhile, animal studies have reported tumors at various sites from 1,3-butadiene exposure. EPA has classified 1,3-butadiene as carcinogenic to humans by inhalation.

Although ambient concentrations of air toxics are generally low, so-called hot spots might exist where concentrations of one or more air toxics, and consequent exposures of area populations, could be elevated. Such areas may be in proximity to one or more pollution sources or may be affected by transient or sustained localized conditions that lead to elevated concentrations of some pollutants.
A study by the Health Effects Institute provides useful information on measurements of a series of air toxics at truck terminals. It also illustrates the challenges encountered in defining and documenting air pollution hot spots without accounting for the role of meteorologic conditions or establishing adequate background sites for comparison (Health Effects Institute, 2012).

Another study by the Health Effects Institute provided valuable information about ambient and personal concentrations of PM2.5 and a large number of air toxics and demonstrated elevated ambient

concentrations (compared with other areas in New Jersey and across the United States) of some air toxics in both of these lower-socioeconomic-status neighborhoods. At the same time, the findings illustrate the difficulties of defining an area a priori as a potential hot spot — or as a control location. The design of future exposure and health effects studies in hot spots will need to take multiple pollutant sources and meteorologic factors into consideration to achieve sufficient contrasts in pollutant concentrations between appropriately chosen hot spots and background locations (HEI, 2011).
A 2009 study by HEI showed that although environmental exposures to air toxics are generally low, the potential for widespread chronic exposure and the large number of people who are exposed have led to concerns regarding their impact on public health. Estimation of the health risks of exposure to air toxics is complicated by the fact that there are multiple sources of air toxics. These may be outdoor and indoor (e.g., environmental, tobacco smoke, building materials, consumer products, and cooking). Personal exposure monitoring requires extensive time and equipment, but the science is not yet at a point at which exposures to VOCs and PAHs can be reliably predicted from time–activity patterns and microenvironmental concentrations alone.

An NIH study examined links between racial residential segregation and estimated ambient air toxics exposures and their associated cancer risks using modeled concentration estimates from the U.S. Environmental Protection Agency's National Air Toxics Assessment. Multivariate modeling showed that, after controlling for tract-level SES measures, increasing segregation amplified the cancer risks associated with ambient air toxics for all racial groups combined. This segregation effect was strongest for Hispanics. Results suggest that disparities associated with ambient air toxics are affected by segregation and that these exposures may have health significance for populations across racial lines (Morello-Frosh, 2006).

A paper by Delfino discussed evidence for linkages between asthma and exposure to air toxics. Outdoor ambient air pollutant exposures in communities are relevant to the acute exacerbation and possibly the onset of asthma. However, the complexity of pollutant mixtures and etiologic heterogeneity of asthma has made it difficult to identify causal components in those mixtures. Occupational exposures associated with asthma may yield clues to causal components in ambient air pollution because such exposures are often identifiable as single-chemical agents (e.g., metal compounds). However, translating occupational to community exposure-response relationships is limited. Of the air toxics found to cause occupational asthma, only formaldehyde has been frequently investigated in epidemiologic studies of allergic respiratory responses to indoor air, where general consistency can be shown despite lower ambient exposures. The specific volatile organic compounds (VOCs) identified in association with occupational asthma are generally not the same as those in studies showing respiratory effects of VOC mixtures on non-occupational adult and pediatric asthma.

In addition, experimental evidence indicates that airborne polycyclic aromatic hydrocarbon (PAH) exposures linked to diesel exhaust particles (DEPs) have proinflammatory effects on airways, but there is insufficient supporting evidence from the occupational literature of effects of DEPs on asthma or lung function. In contrast, non-occupational epidemiologic studies have frequently shown associations between allergic responses or asthma with exposures to ambient air pollutant mixtures with PAH components, including black smoke, high home or school traffic density (particularly truck traffic), and environmental tobacco smoke. Other particle-phase and gaseous co-pollutants are likely causal in these associations as well. Epidemiologic research on the relationship of both asthma onset and exacerbation to air pollution is needed to disentangle effects of air toxics from monitored criteria air pollutants such as particle mass. Community studies should focus on air toxics expected to have adverse respiratory effects based on biological mechanisms, particularly irritant and immunological pathways to asthma onset and exacerbation.

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Proximity of Populations and Schools to Highways

Proximity to motor vehicle traffic is associated with increased exposures to ambient noise, toxic gases and particulate matter including diesel particulates. Residential proximity to traffic has been associated with various health impacts, particularly asthma exacerbation and possibly onset of asthma, as well as mortality rates (Baumann et al., 2011; Health Effects Institute, 2010). Proximity to traffic has also been associated with subclinical atherosclerosis (a key pathology underlying cardiovascular disease (CVD)), prevalence of CVD and coronary heart disease (CHD), incidence of myocardial infarction, and CVD mortality (Hoffman et al., 2009). Vehicle-related emissions of various pollutants—ultrafine and other components of PM2.5, lead and other metals, and mobile source air toxics such as benzene, nitrogen oxides (NOx), hydrocarbons and carbon monoxide (CO)—are believed to contribute to these health effects. Vehicles also emit precursors that add to ambient ozone and PM2.5.

Additionally, EPA's 2005 NATA estimated that mobile emissions accounted for about 30% of average cancer risk from the pollutants in NATA, mainly from benzene (U.S. EPA, 2009c). However, the spatial accuracy of NATA's mobile source impacts is limited, because local estimates are based on countywide total mobile source emissions roughly allocated to each part of the county based on presence of major roads. The traffic indicator in EJScreen provides a more detailed analysis of the volume and location of traffic than was used in NATA. Also, NATA captures only some of the impacts associated with traffic, so the traffic indicator is a useful complement.

Traffic proximity is also associated with noise, which is a risk factor for various health problems. Workplace and transportation-related noise have been associated with release of stress hormones; sleep disturbance; hypertension; altered heart rate; ischemic heart disease; myocardial infarction; and, among the elderly, risk of stroke (Sørensen et al., 2011). In one study, for example, among those older than 64.5 years of age, the stroke incidence rate ratio was 1.27 per 10 dB more road traffic noise (Sørensen et al., 2011). Whether noise or other factors account for it, local traffic volume is a predictor of stress (which itself is associated with significant health risks). In 2010, Yang & Matthews concluded that, "[a]t the neighborhood level, the presence of hazardous waste sites and traffic volume were determinants of self-rated stress even after controlling for other individual characteristics" (2010, p. 803).

Epidemiologic studies of the impacts of proximity to traffic often utilize distances of 50–1,500 meters to define a cutoff between less and more exposed locations (Health Effects Institute, 2010). For example, a major study of coronary heart disease prevalence used distances greater than 200 meters as the reference group and found adjusted odds ratios of 1.08 for residences within 100–200 meters, 1.71 for 50–100 meters and 1.55 within 50 meters of a major road. Only 15% of participants lived within 200 meters of a major road, and only 3% within 50 meters in this study of heart disease (Hoffman et al., 2009). Additionally, a distance cutoff of 500 meters captures exposures of concern for most definitions of mobile source impact. In a review of numerous prior studies of proximity to roads, in combination with a modeling case study, Zhou & Levy (2007) suggested that a distance of 500 meters should capture exposures of concern, although impacts may be largely limited to just 100 meters from roads for ultrafine particles and PM2.5 mass from mobile sources alone. A critical review of literature on traffic-related air pollution in 2010 "identified an exposure zone within a range of up to 300 to 500 meters from a highway or a major road as the area most highly affected by traffic emissions… and estimated that 30% to 45% of people living in large North American cities live within such zones" (Health Effects Institute, 2010, p. 7-5). A 2009 analysis of PM2.5 levels in Southern California found that traffic within 300 meters of a monitor was the most informative predictor of monitored PM2.5 levels, out of a wide range of factors considered such as various distances from roads, population density and the presence of industry (Krewski et al., 2009).

On the other hand, some studies have shown a dramatic drop in at least ultrafine levels within the first 100 meters downwind from a freeway, and an even sharper (essentially immediate) drop in the upwind direction (Zhu, Hinds, Kim, & Sioutas, 2002). This pattern has been seen in more recent measurements—levels on California highways (measured using monitors on vehicles) were compared to levels near those roads (roughly 50–300 meters away), and black carbon levels in particular were as much as 10 times higher on the road than near the road, for 1- hour averages (Fujita, Campbell, Zielinska, Arnott, & Chow, 2011). The same study found much higher levels (generally 2–5 times higher) on the road than near the road, for PM2.5 mass, CO, NO, NOx, VOCs, benzene, toluene, ethylene, xylene, formaldehyde and acetaldehyde. This reinforces the idea that exposures very close to a busy highway are most important, and that levels drop rapidly within tens of meters, falling to much lower levels within the first 50–300 meters (Spengler et al., 2011).

A study by Byoung explored the association between the proximity from schools to highways and industrial facilities, and children's school performance and health hazards. The study found that schools located closer to highways and industrial facilities had higher risks of respiratory and neurological diseases than those located farther away, and that schools located closer to major highways had a higher percentage of students failing to meet the state standards than the latter after controlling for the location of schools, student expenditure, school size, student–teacher ratio, and free lunch enrollment. In addition, a larger percentage of black, Hispanic, or economically disadvantaged children attended schools nearest to pollution emissions than white students (Kweon, 2016).

Brugge et al. note that there is growing evidence of a distinct set of freshly-emitted air pollutants downwind from major highways, motorways, and freeways that include elevated levels of ultrafine particulates (UFP), black carbon (BC), oxides of nitrogen (NOx), and carbon monoxide (CO). People living or otherwise spending substantial time within about 200 m of highways are exposed to these pollutants more so than persons living at a greater distance, even compared to living on busy urban streets. Evidence of the health hazards of these pollutants arises from studies that assess proximity to highways, actual exposure to the pollutants, or both. Taken as a whole, the health studies show elevated risk for development of asthma and reduced lung function in children who live near major highways. Studies of particulate matter (PM) that show associations with cardiac and pulmonary mortality also appear to indicate increasing risk as smaller geographic areas are studied, suggesting localized sources that likely include major highways. Although less work has tested the association between lung cancer and highways, the existing studies suggest an association as well. While the evidence is substantial for a link between near-highway exposures and adverse health outcomes, considerable work remains to understand the exact nature and magnitude of the risks (Brugge et al, 2007).

A study by Genereux (2008) evaluated whether proximity to highway interacts with individual and neighborhood socioeconomic status (SES) to influence birth outcomes, and found that in wealthy neighborhoods, proximity to highway was associated with an elevated odds of PTB, LBW and SGA birth. Counterintuitively, high SES mothers may be more likely than low SES mothers to experience adverse births associated with residential proximity to highway.

An NIH study investigated personal exposures to fine particulate matter air pollution (PM2.5), and to its traffic-related fraction, in a group of urban children with asthma. Regression models showed a stronger, more robust association of school site with personal measurements for EC than those for PM(2.5). High traffic pollution exposure was found to coincide with the weekday early morning rush hour, with higher personal exposures for participants living closer to a highway (<500 ft). A significant linear relationship of home distance from a highway with personal EC pollution exposure was also found (up to 1000 ft). This supports the assumptions by previous epidemiological studies using distance from a highway as an index of traffic PM exposure. These results are also consistent with the assumption that traffic, and especially smoke emitted from diesel vehicles, is a significant contributor to personal PM exposure levels in children living in urban areas such as the South Bronx, NY (Spira-Cohen et al, 2010)

A San Francisco study observed differences in air pollutant concentrations between schools near to highways versus those more distant (or upwind) from major roads. Using a two-stage multiple-logistic regression model, they found associations between respiratory symptoms and traffic-related pollutants. Among those living at their current residence for at least 1 year, the adjusted odds ratio for asthma in relationship to an interquartile difference in NO_X was 1.07 (95% confidence interval, 1.00–1.14). Findings support the hypothesis that traffic-related pollution is associated with respiratory symptoms in children (Kim, et al, 2004).

Another study of schools and traffic proximity was carried out in Canada (Amram, 2011). Data on public elementary schools in Canada's 10 most populous cities were obtained from online databases. School addresses were geocoded and proximity to the nearest major road, defined using a standardized national road classification scheme, was calculated for each school. Based on measurements of nitrogen oxide concentrations, ultrafine particle counts, and noise levels in three Canadian cities, authors conservatively defined distances < 75 m from major roads as the zone of primary interest. Census data at the city and neighborhood levels were used to evaluate relationships between school proximity to major roads, urban density, and indicators of socioeconomic status.

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Proximity to National Priority List Sites

The contaminants in NPL sites may reach humans in a number of ways. Volatile contaminants may enter the atmosphere and reach individuals via the inhalation route. Particularly in dry climates or seasons, contaminants on the surface of some sites can become airborne and reach people directly through inhalation or indirectly after being deposited on surfaces that people may contact. Contaminants can also enter the food chain if the wind disperses them onto land used for agriculture. Some contaminants may migrate into groundwater. People may be exposed via drinking water derived from the aquifer, through vapor intrusion into their residences or through other routes.

Data from the 1988 National Maternal and Infant Health Survey files were linked with data from the 1990 Environmental Protection Agency National Priorities List of hazardous waste sites to determine whether any relationship existed between living in proximity to hazardous waste sites and low birthweight. The odds ratio for low birthweight versus normal birthweight was 1.03 (95% confidence interval [95% CI] = 0.98–1.16), and remained at 0.99 (95% CI = 0.86–1.16) when adjusted for maternal age, parity, infant sex, prenatal care, and behavioral and socioeconomic factors. Very low birthweight, infant and fetal death, prematurity, and congenital malformation were not found to be associated with living in the vicinity of a hazardous waste site during pregnancy. Merging a large population database with environmental data proved to be an innovative but not very efficient method of assessing the risks of low birthweight related to the environment (Sosniak et al, 1994).

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Proximity to Waste Treatment, Storage, and Disposal Facilities

The substances at TSDF facilities may reach humans in a number of ways. Volatile substances may enter the atmosphere and reach residents via the inhalation route. Particularly in dry climates or seasons, substances on the surface of some sites may be entrained in the atmosphere and reach people directly through inhalation or indirectly after being deposited on surfaces that people may contact or on arable land. Some substances may migrate from the site into groundwater. People may be exposed via drinking water derived from the aquifer, through vapor intrusion into their residences or through other routes.

A study looked at the relationship between birth defects in racial or ethnic minority children born during 1983 – 1988 and the potential exposure of their mothers to contaminants at hazardous waste sites in California. The greatest association was between potential exposure and neural tube defects (OR=1.54, 95% CI=0.93 – 2.55), particularly anencephaly (OR=1.85, 95% CI=0.91 – 3.75). The strongest association between birth defects and potential exposure was among American Indians/Alaska Natives (OR=1.19, 95% CI=0.62 – 2.27). Despite the limitations of this study, the consistency of these findings with previous studies suggests an association between environmental risk factors and birth defects. This is particularly relevant to minority populations (Orr et al, 2002).

A review study looked at the most recent information on waste arisings and waste disposal options in the world, in the European Union (EU), in Organisation for Economic Co-operation and Development (OEDC) countries, and in some developing countries (notably China) and (ii) the potential direct and indirect impact of waste management activities on health. The main conclusion of the overall assessment of the literature is that the evidence of adverse health outcomes for the general population living near landfill sites, incinerators, composting facilities and nuclear installations is usually insufficient and inconclusive. There is convincing evidence of a high risk of gastrointestinal problems associated with pathogens originating at sewage treatment plants.

Lesley Rushton described that there is little evidence for an association with reproductive or developmental effects with proximity to incinerators. Studies of cancer incidence and mortality in populations around landfill sites or incinerators have been equivocal, with varying results for different cancer sites. Many of these studies lack good individual exposure information and data on potential confounders, such as socio-economic status. The inherent latency of diseases and migration of populations are often ignored. Waste management workers have been shown to have increased incidence of accidents and musculoskeletal problems. The health impacts of new waste management technologies and the increasing use of recycling and composting will require assessment and monitoring (Rushton, 2003).

Porta et al. performed a systematic review of the available epidemiological literature on the health effects in the vicinity of landfills and incinerators and among workers at waste processing plants to derive usable excess risk estimates for health impact assessment. The study found that in most cases the overall evidence was inadequate to establish a relationship between a specific waste process and health effects; the evidence from occupational studies was not sufficient to make an overall assessment. For community studies, at least for some processes, there was limited evidence of a causal relationship and a few studies were selected for a quantitative evaluation. In particular, for populations living within two kilometres of landfills there was limited evidence of congenital anomalies and low birth weight with excess risk of 2 percent and 6 percent, respectively. The excess risk tended to be higher when sites dealing with toxic wastes were considered. For populations living within three kilometres of old incinerators, there was limited evidence of an increased risk of cancer, with an estimated excess risk of 3.5 percent. The confidence in the evaluation and in the estimated excess risk tended to be higher for specific cancer forms such as non-Hodgkin's lymphoma and soft tissue sarcoma than for other cancers (Porta et al, 2009).

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Proximity to RMP Sites

The primary health concerns with RMP facilities are the accidental release of substances and fires or explosions. The sudden release of relatively large quantities of acutely toxic substances can cause serious health effects including death after inhalation or dermal exposure. These effects may be prompt or may occur or persist for some time after exposure. Fires may affect neighboring areas and the associated smoke may expose people to toxic combustion products. Explosions may cause material damage and injuries to people in neighboring areas. Local residents, as well as workers and emergency responders, may suffer severe adverse effects.

Although not looking at health effects, a study examined whether the racial makeup of a community near a chemical-processing site is characteristic of the city, county, or community as a whole. In essence, does the racial makeup of a community vary by distance from a chemical-processing facility? The results show that as one moves further from a facility, the characteristics of the community reflect less and less the makeup near the site. The percentage of African Americans living near a chemical-processing site tends to be much higher when compared to population characteristics further from the site (Pine et al, 2002).

Industrial pollution has been suspected as a cause of non-Hodgkin lymphoma (NHL), based on associations with chemical exposures in occupational studies. The study does not provide strong evidence that living near manufacturing industries increases NHL risk (DeRoos, et al, 2010).
Regarding cancer risk, a study sought to review available epidemiologic studies of cancer risk and its association with residence in a neighborhood characterized by industrial sites. During the years from 1980-1997, some authors reported significant associations between lung cancer risk and residential proximity to (a) smelters, (b) complex industrial areas, and (c) other localized emission sources. There was some evidence that leukemia and lymphomas occurred in the neighborhoods that contained industrial sites (Benedetti, 2001).

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Proximity to Major Direct Water Dischargers

Water pollutants can have human health or adverse ecological effects, depending on concentration in the water, exposure to the water, toxicity of the particular chemical and other factors.

However, we could not find evidence in the literature that demonstrates a connection between living close to a contaminated stream segment and/or water discharger and human health. There are too many uncertainties about exposure routes between contaminated water and nearby populations.

Reference:

Thompson, Terrence, et al. "Chemical safety of drinking water: assessing priorities for risk management." (2007).

Changing Climate Conditions

Extreme Heat

Extreme heat is an important weather hazard associated with excess mortality and morbidity. Exposure to extreme heat is already a significant public health problem and the primary cause of weather-related mortality in the U.S. High ambient temperatures can cause health effects such as heat cramps, heat exhaustion, heat syncope, and heat stroke. Monitoring health effects associated with extreme heat requires temperature and relative-humidity data at highly resolved spatio-temporal scales.

The literature on the epidemiology of health effects due to extreme heat does not provide a consistent definition of temperature thresholds that constitute an extremely hot day or an extreme heat event. Further, it is inappropriate to use the same definition or threshold in all geographic areas because the effects of extreme heat are affected by behavioral and physiological adaptability of the residents in a particular area. Therefore, this tool allows the user to examine different definitions of extremely hot days and extreme heat events, and offers the user the ability to choose absolute (e.g., 90°F, 95°F, 100°F, 105°F) or relative (e.g., 90th, 95th, 98th percentile values) thresholds, and durations of 2 or 3 minimum consecutive days for extreme heat events.

The WHO reports that extreme high air temperatures contribute directly to deaths from cardiovascular and respiratory disease, particularly among elderly people. In the heat wave of summer 2003 in Europe for example, more than 70 000 excess deaths were recorded. High temperatures also raise the levels of ozone and other pollutants in the air that exacerbate cardiovascular and respiratory disease. Pollen and other aeroallergen levels are also higher in extreme heat. These can trigger asthma, which affects around 300 million people. Ongoing temperature increases are expected to increase this burden.

A study determined the relative importance of heat exposure and the built environment, socioeconomic vulnerability, and neighborhood stability for heat mortality (Philadelphia, PA, USA) or heat distress (Phoenix, AZ, USA), using an ecologic study design. Phoenix neighborhoods with more heat exposure, Black, Hispanic, linguistically and socially isolated residents, and vacant households made more heat distress calls. Philadelphia heat mortality neighborhoods were more likely to have low housing values and a higher proportion of Black residents (Uejio, et al, 2011).

Another study modeled how climate change could cause an increase in regional summer ozone-related asthma emergency department visits for children aged 0–17 years of 7.3% across the New York City metropolitan region by the 2020s. This effect diminished with inclusion of ozone precursor changes. When population growth is included, the projections of morbidity related to ozone are even larger (Sheffield et al, 2011).

References:

Patz, Jonathan A., et al. "Impact of regional climate change on human health." *Nature* 438.7066 (2005): 310.

Sheffield, Perry E., et al. "Modeling of regional climate change effects on ground-level ozone and childhood asthma." *American journal of preventive medicine* 41.3 (2011): 251-257.

Uejio, Christopher K., et al. "Intra-urban societal vulnerability to extreme heat: the role of heat exposure and the built environment, socioeconomics, and neighborhood stability." *Health & Place* 17.2 (2011): 498-507.

WHO. “Climate change and health” Fact sheet, Updated July 2017, http://www.who.int/mediacentre/factsheets/fs266/en/.

Extreme Precipitation

Extreme weather events can impact human health directly through injuries, drowning, hypothermia, infectious diseases, and persistent effects on mental health,[2] as well as indirectly through infrastructure and economic vulnerability, water resource concerns (e.g., scarcity, pollution), and harvest losses. However, observations of specific effects around historical and current trends in severe thunderstorms and tropical cyclone events are limited. Lower-lying and coastal areas, as well as urban areas with more impermeable surfaces, are particularly vulnerable to the effects of floods and storms. However, the effects during the episode are not well-documented, and would likely vary greatly depending on how accustomed the population is to heavy rain and how well road surfaces handle drainage. Flooding that occurs after heavy rains has more well-documented health effects. (See next section).

Tracking precipitation along with health outcomes intends to provide information to increase preparedness, awareness, and resilience among communities and stakeholders about the effects of extreme precipitation. Public health professionals working on climate and health issues would benefit from surveillance information as their framework recognizes identification of climate impacts and vulnerabilities as their primary step. The goal is to use surveillance as a stepping stone towards policies and decision making to equip local communities with the necessary tools to assess vulnerabilities, burden, and build overall resilience against effects of extreme precipitation.

Flood Hazards

Floods are the second deadliest of all weather-related hazards in the United States, accounting for approximately 98 deaths per year, most due to drowning (Ashley et al., 2008). Flooding associated with tropical storms result in the highest number of deaths.

In addition to the immediate health hazards associated with extreme precipitation events when flooding occurs, other hazards can often appear once a storm has passed. Elevated waterborne disease outbreaks have been reported in the weeks following heavy rainfall, although other variables may affect these associations. Water intrusion into buildings can result in mold contamination that manifests later, leading to indoor air quality problems. Buildings damaged during hurricanes are especially susceptible to water intrusion. Populations living in damp indoor environments experience increased prevalence of asthma and other upper respiratory tract symptoms, such as coughing and wheezing, as well as lower respiratory tract infections such as pneumonia, respiratory syncytial virus (RSV), and RSV pneumonia (Institute of Medicine, 2004).

Floods are also increasing in frequency and intensity, and the frequency and intensity of extreme precipitation is expected to continue to increase throughout the current century. Floods contaminate freshwater supplies, heighten the risk of water-borne diseases, and create breeding grounds for disease-carrying insects such as mosquitoes. They also cause drownings and physical injuries, damage homes and disrupt the supply of medical and health services.

A historical cohort study was conducted by telephone interview for new episodes of illness in all age groups, and for psychological distress in adults, following severe river flooding on 12 October 2000 in the town of Lewes in Southern England. Having been flooded was associated with earache and a significant increase in risk of gastroenteritis with depth of flooding. Adults had a four-times higher risk of psychological distress defined as a score of > or = 4 in response to the 12-item General Health Questionnaire (GHQ-12). Psychological distress may explain some of the excess physical illness reported by flooded adults and possibly by children as well. (Reacher et al, 2004).

References:

Ahern, Mike, et al. "Global health impacts of floods: epidemiologic evidence." *Epidemiologic reviews* 27.1 (2005): 36-46.

Ashley, S. T., and W. S. Ashley, 2008: Flood fatalities in the United States. Journal of Applied Meteorology and Climatology, 47, 805-818.

Reacher, M., et al. "Health impacts of flooding in Lewes: a comparison of reported gastrointestinal and other illness and mental health in flooded and non-flooded households." *Communicable Disease and Public Health* 7.1 (2004): 39-46.

Institute of Medicine. “Damp Indoor Spaces and Health.” Washington, DC: The National Academies Press, 2004. doi:10.17226/11011

WHO “Climate change and health” Fact sheet, Updated July 2017, http://www.who.int/mediacentre/factsheets/fs266/en/

Other References for Literature Review:

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2. ATSDR (2013). NTSIP Annual Report, 2010. U.S. Department of Health and Human Services, Environmental Health Surveillance Branch, Division of Toxicology and Human Health Sciences. Atlanta, Georgia. Available at: http://www.atsdr.cdc.gov/ntsip/reports.html
3. CDC. National Environmental Public Health Tracking Network. Available at: https://ephtracking.cdc.gov/showHome.action
4. Environmental Protection Agency (EPA). (2014). Health and Ecological Hazards caused by Hazardous Substances. Available at: http://www2.epa.gov/emergency-response/health-and-ecological-hazards-caused-hazardous-substances
5. Occupational Safety and Health Administration (OSHA). (2014). Available at: https://www.osha.gov/SLTC/hazardoustoxicsubstances/index.html
6. National Transportation Safety Board NTSB. (2005). Collision of Norfolk Southern freight train 192 with standing Norfolk Southern local train P22 with subsequent hazardous materials release at Graniteville, South Carolina. January 6, 2005. Available at: http://www.ntsb.gov/investigations/AccidentReports/Reports/RAR0504.pdf.
7. The New York Times. Jury awards BP workers $100 million in lawsuit. December 18, 2009. Available at: http://www.nytimes.com/2009/10/30/business/30labor.html.
8. US EPA. EJSCREEN Environmental Justice Mapping and Screening Tool EJSCREEN Technical Documentation, August 2017. Available at: https://www.epa.gov/sites/production/files/2017-09/documents/2017_EJScreen_technical_document.pdf
9. World Health Organization (WHO). (2011). "Known and Unknowns on Burden of Disease Due to Chemicals: A Systematic Review" Environmental Health 10: 9. Available at: http://www.ehjournal.net/content/10/1/9.

Appendix C: Data Documentation and Methodology

Data Documentation and Methodology for CHR&R Project

Task Number	Period of Performance	Products
1 – Literature Review	Months 1-3	Literature Reviews 1 & 2, CHRR_DataJustifications.xlsx
2 – Data Preparation	Months 2-7	CHRR_DataJustifications_v1.30.xlsx

Task 1 (Period of Performance: Months 1-3)

- Data were downloaded from respective primary sources: EPA EJScreen Application – https://EJScreen.epa.gov/mapper/ and the CDC EPHT Application - https://ephtracking.cdc.gov/showHome.action
- **Data Measures_Sources_Notes_jlw** Excel spreadsheet was created to take the information from the Literature Review(s) and synthesize the information for movement forward in the data analysis piece.

Task 2 (Period of Performance: Months 2-7)

- The Data Measures table was moved forward into the data assimilation process and was used to download needed data and further examine each data variable's availability and overall descriptive statistics. The deliverable developed from this process was titled "**CHRR_DataJustifications_v1.30.xlsx**" and contained a sheet for EJScreen data and a separate sheet for EPHT data.
- The **CHRR_DataJustifications_v1.30.xlsx** document provided the basis to make justifications on whether each data variable (measure) would be moved forward for the data analysis piece of the project. This spreadsheet is color coded based on the decision made.
- The downloaded data was attached to the TIGER/Line county boundaries 2016 shapefile (for county level EPHT data) and the TIGER/Line census block groups 2016 shapefile (for census block group level EJScreen data) in GIS.
  - Match rate for each EPHT data join was documented in **CHRR_DataPullsNeeded_EPHT_02-26-2018.xlsx**.
- Centroids were created for each indicator data set that is at the county level (EPHT) and block group level (EJScreen).
  - The Feature to Point tool was used to create centroids at the mathematical center of each polygon.
  - All National datasets were projected into WGS 1984 Web Mercator for consistency. (Intermediary Product: **EJSCREEN_V4_USPR_Public_03-26-2018.gdb; EPHT_WM_04-02-2018.gdb**)
  - **NOTE: Because centroids were created using U.S. Census enumeration units, centroids have been developed for areas over water. These may need to be removed as the analysis moves forward.**
- 2016 5-Year Total Population data by county for the United States was downloaded from the U.S. Census ACS website. Those data were joined to the EPHT data with 100% match rate.
- New Jersey data (from both EPHT and EJScreen) were isolated and exported as new data to be used in the scenario work. The data were projected using the NAD 1983 NJ State Plane Projection System.
  - **File Geodatabase: CHR&R_NJ_04-02-2018.gdb**

- 2016 5-Year Poverty Status in the Past 12 Months by Disability Status by Employment Status for the Population 20 to 64 Years data by block group for NJ counties were downloaded from the U.S. Census ACS Website. The data were joined to the EJScreen data with 100% match rate. A new field for elderly and disabled populations by block group was computed by summing the population over 64 years and disabled population between 20 to 64 years.
- Data for minority, low income, linguistically isolated, elderly and disabled populations by block group were exported from the EJScreen Data. The data were aggregated at county level and joined to the EPHT data with 100% match rate.
- Average minority and low income population by county was computed for the data as the EJ Index by count.
- Average percent minority and percent low income population by county was also computed for the data as the EJ Index by percent.
- The data were then analyzed in 3 ways in 3 separate scenarios – I, II and III.

SCENARIO I

- In Scenario I, individual determinant ratios were computed for each EPHT indicator at the county level based on the following 7 population-based factors:
  - Total population
  - Minority population
  - Low income population
  - EJ Index - Average of percent minority and percent low income
  - EJ Index - Average of minority and low income (count)
  - Linguistically isolated population
  - Elderly and physically disabled populations
- For EJScreen data, individual determinant ratios were computed for DSLPM, RESP, and PTRAF indicators at the block group level based on the same factors.
- The formula used for calculating individual determinant ratio by population-based factors is as follows:

$$= \frac{I_c / I_s}{P_c / P_s}$$

Here, I_c is Indicator Value for the County/Block Group,

I_s is sum of Indicator Values for all the Counties/Block Groups in the State,

P_c is Population of the County/Block Group,

P_s is Population of the State

SCENARIO II

- In Scenario II, individual determinant ratios were calculated for each EPHT indicator based on counties' area in square miles. For EJScreen data, the same was calculated for 3 EJScreen indicators - DSLPM, RESP, and PTRAF - based on block groups' area in square miles. Area in square miles' field for both the datasets was calculated using the Calculate Geometry tool in GIS.
  - **File Geodatabase: CHR&R_NJ_06-15-2018.gdb**
- The formula used for calculating Individual determinant ratio by area in square miles is as follows:

$$= \frac{I_C / I_S}{A_C / A_S}$$

Here, I_c is Indicator Value for the County/Block Group,

I_s is sum of Indicator Values for all the Counties/Block Groups in the State,

A_c is Area of the County/Block Group in square miles,

A_s is Area of the State in square miles

- An excel sheet of indexes of all fields and their descriptions was made for the EJ Screen and EPHT data. **(Product: <u>EJScreen_Index_DescriptionsV4_Pub_06-21-2018.xlsx; CHRR_EPHT_Index_07-06-2018.xlsx</u>)**
- All the Scenario I and II ratios were plotted using graduated symbols for each EJScreen and EPHT indicator. For each EPHT indicator, a combined map with 4 individual determinant ratios (Total population, EJ index by count, linguistically isolated, elderly and disabled population) was made for mutual comparison. The maps were analyzed and the findings/trends were noted down.

DELIVERABLES:

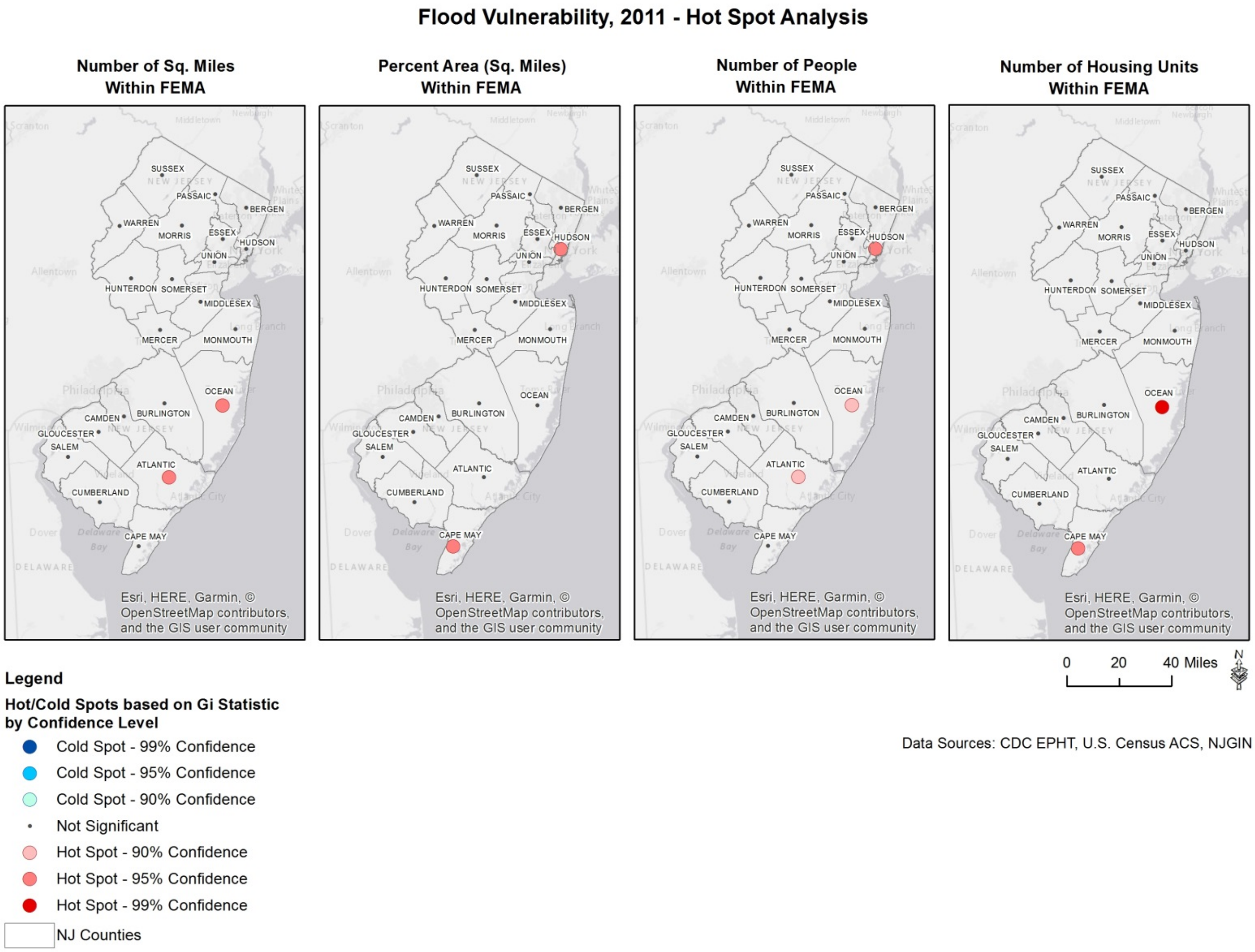
- All the Scenario I and II ratios for Extreme Heat and Extreme Precipitation indicators were exported into excel.
- Line graphs with time (in years) on y-axis were made for each of these indicators for each County in New Jersey.
- The graphs were analyzed and the observations were noted down.

<u>SCENARIO III</u>

- In Scenario III, spatial statistics were run for each EPHT indicator and 3 EJScreen indicators - DSLPM, RESP, and PTRAF.
- The following three tools – **High/Low Clustering tool, Hot Spot Analysis, and Cluster and Outlier Analysis** – were used for this analysis.
- High/Low Clustering tool was run for each mentioned indicator and the analysis reports were saved.
  - A default setting that used INVERSE_DISTANCE as the spatial relationship and NONE as standardization was maintained for consistency throughout the analysis.
- Hot spot, and cluster and outlier analysis tool was run for each mentioned indicator and the resulting feature classes **(<u>CHR&R_NJ_S_III_05-28-2018.gdb</u>)** and ArcMap files were saved.
  - The hot spot analysis' default setting included INVERSE_DISTANCE as the spatial relationship and NONE as standardization. The cluster and analysis tool's default setting included INVERSE_DISTANCE as the spatial relationship, NONE as standardization, and 0 as Number of Permutations. All other optional parameters were not entered.
- Maps were plotted for the scenario III outputs for each specified indicator. These maps with the high/low clustering reports were analyzed and the findings/trends were noted down. **(<u>Scenario_III_Obs_06-04-2018.doc</u>)**

Appendix D: Detailed Analysis – Climate Variables

Flood Vulnerability – Hot Spot Analysis and Cluster Outlier Analysis



Flood Vulnerability, 2011 - Cluster and Outlier Analysis

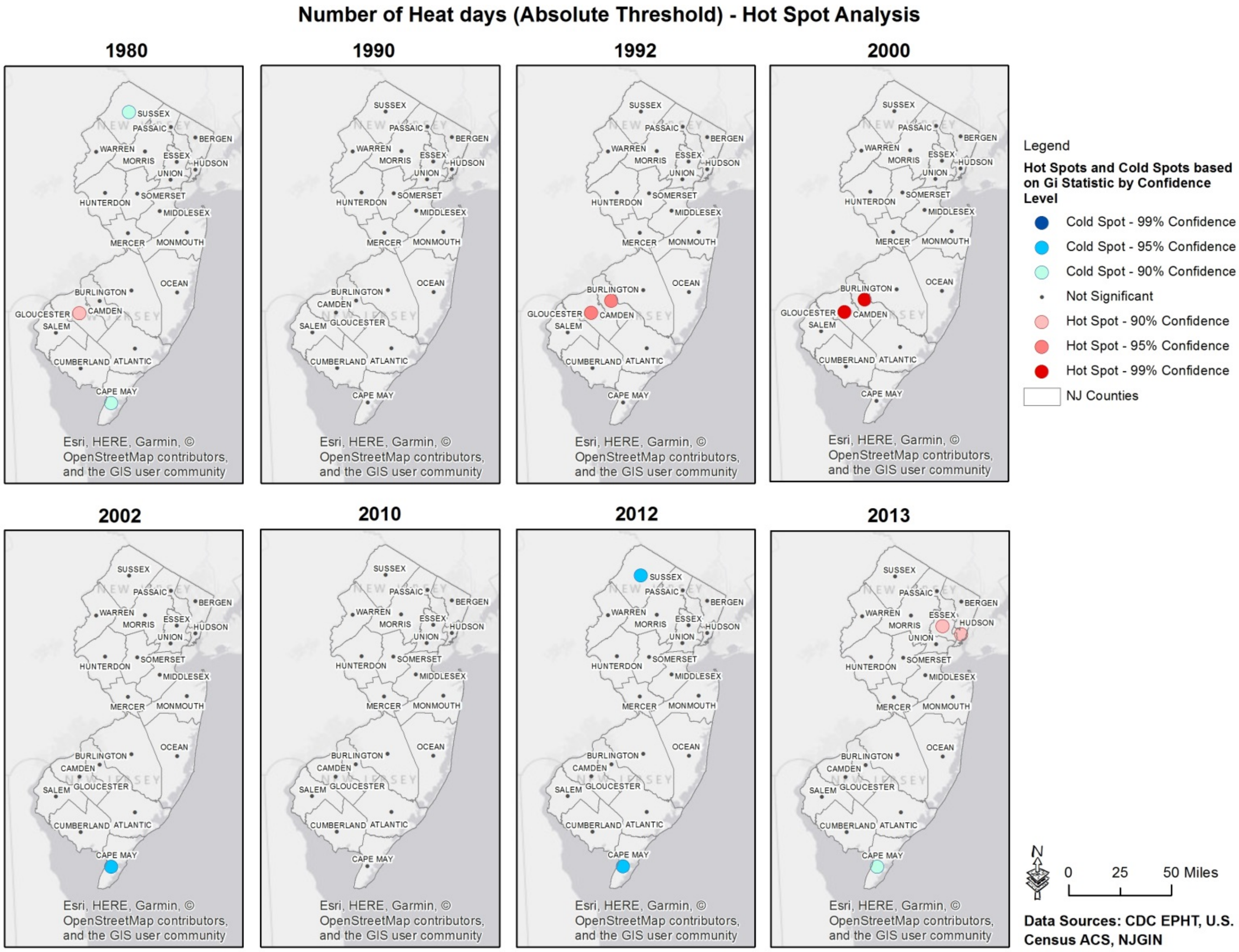
Number of Sq. Miles Within FEMA | **Percent Area (Sq. Miles) Within FEMA** | **Number of People Within FEMA** | **Number of Housing Units Within FEMA**

Legend

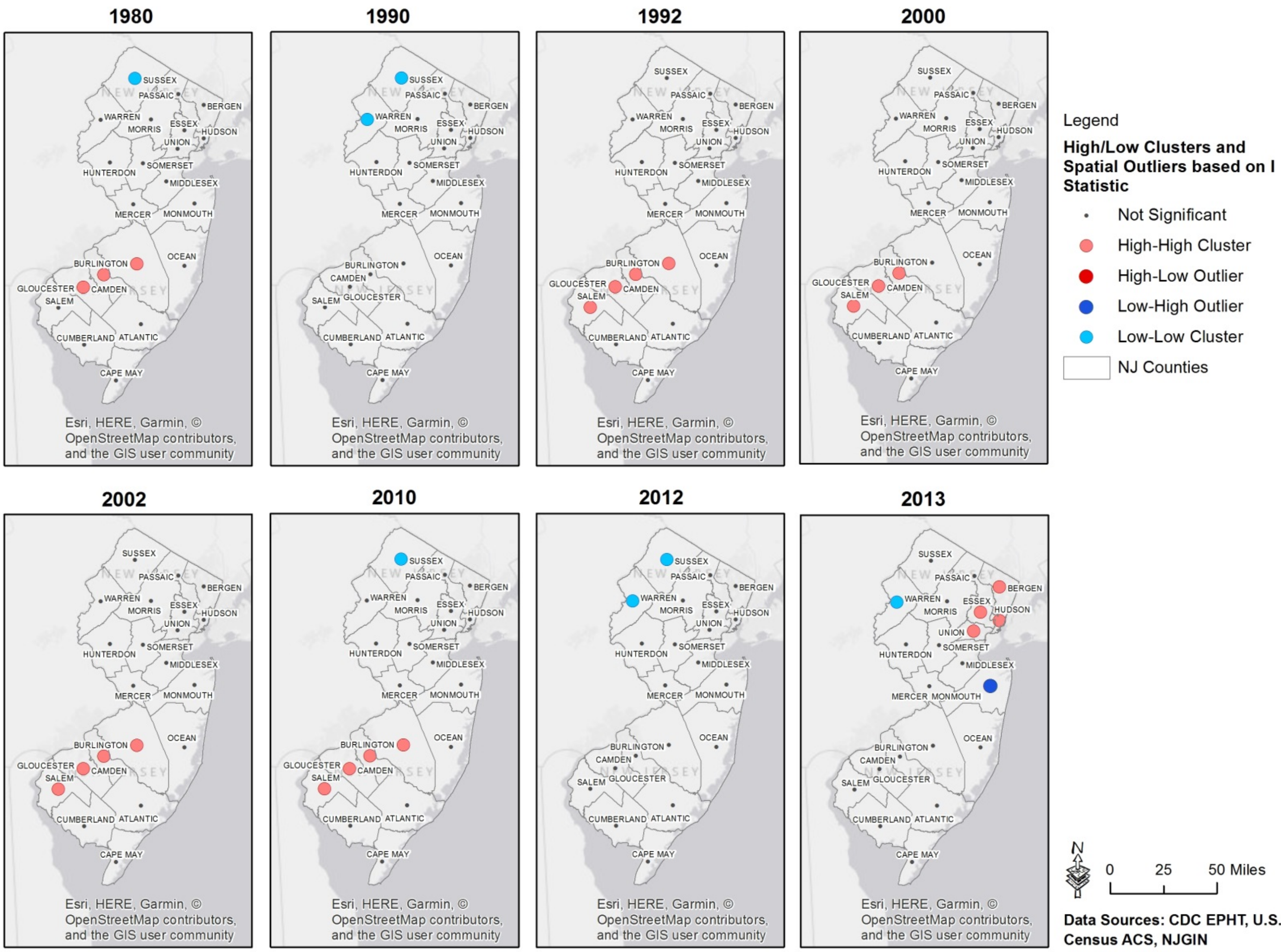
- NJ Counties
- Not Significant
- High-High Cluster
- High-Low Outlier
- Low-High Outlier
- Low-Low Cluster

Data Sources: CDC EPHT, U.S. Census ACS, NJGIN

Number of Heat Days (absolute threshold) – Hot Spot Analysis and Cluster Outlier Analysis

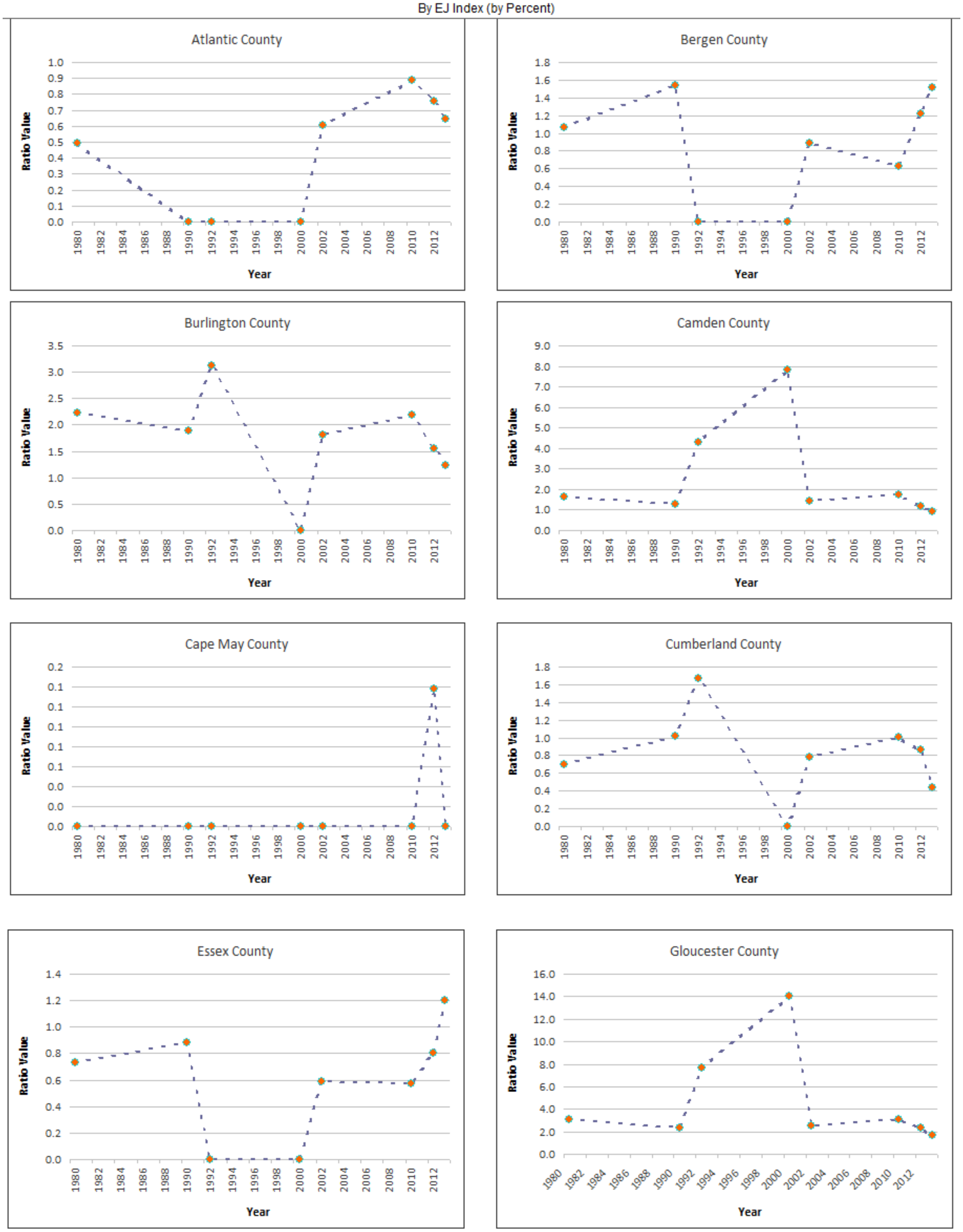


Number of Heat days (Absolute Threshold) - Cluster and Outlier Analysis



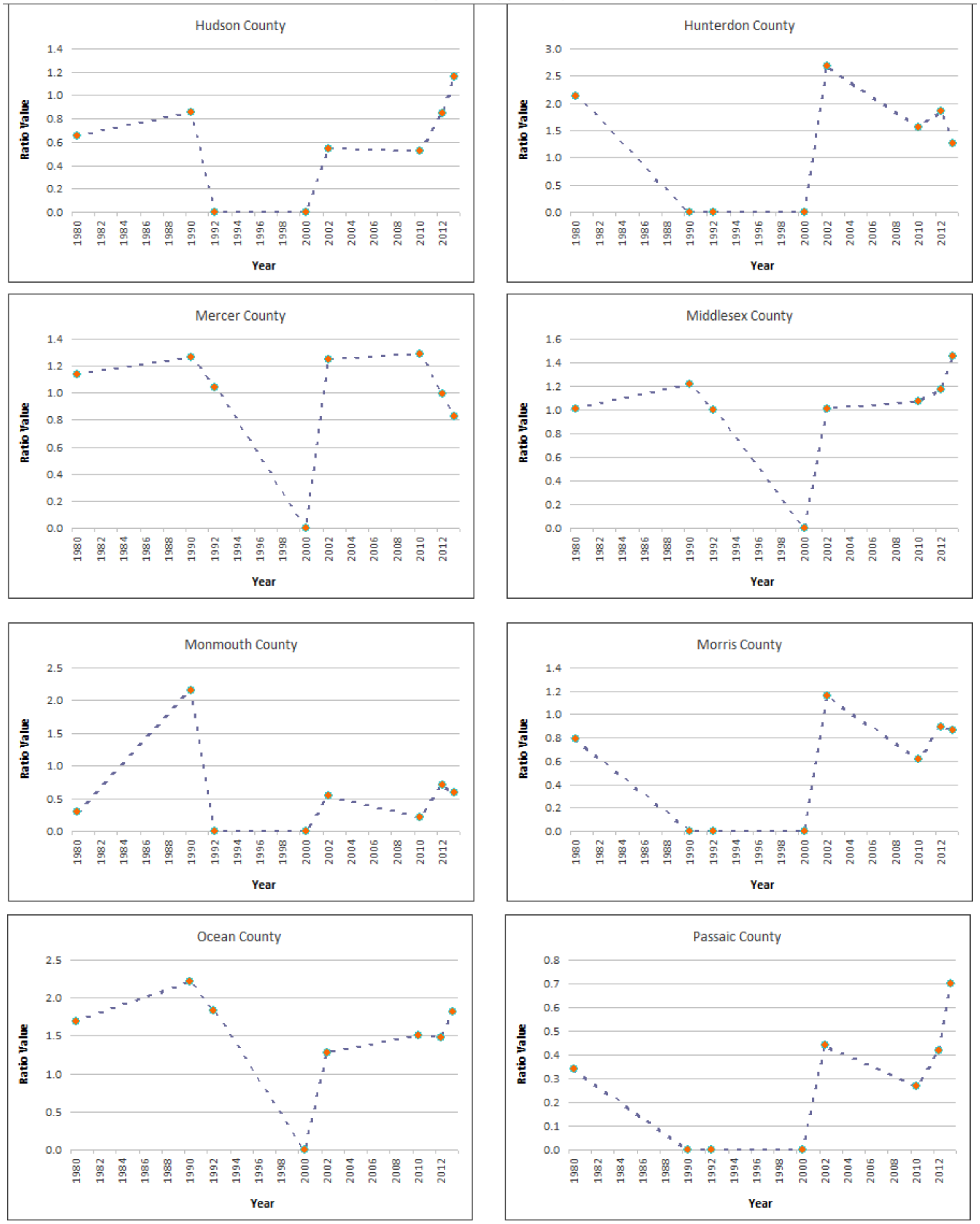
Number of Heat Days (Absolute Threshold)

By EJ Index (by Percent)



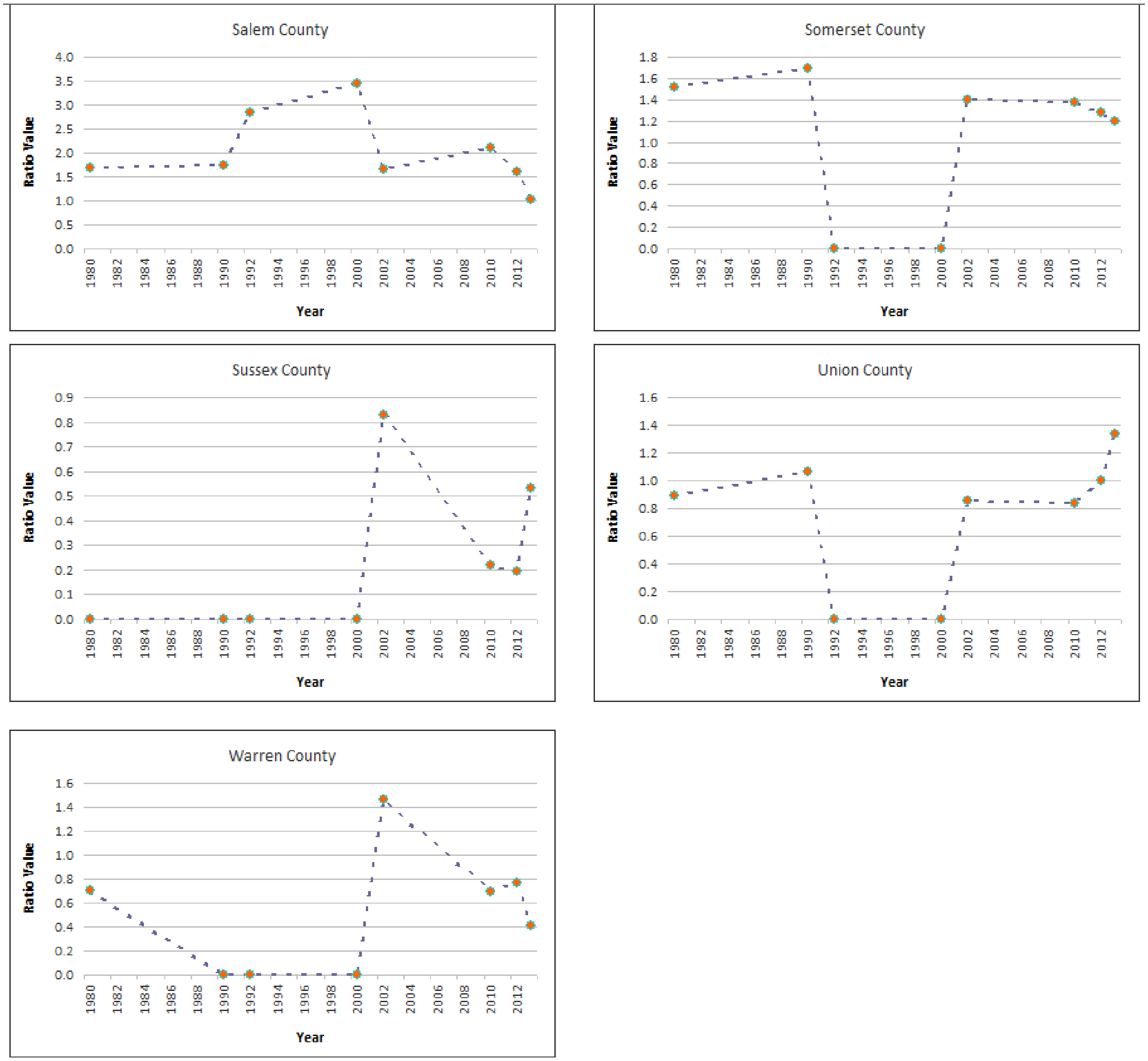
Number of Heat Days (Absolute Threshold)

By EJ Index (by Percent)

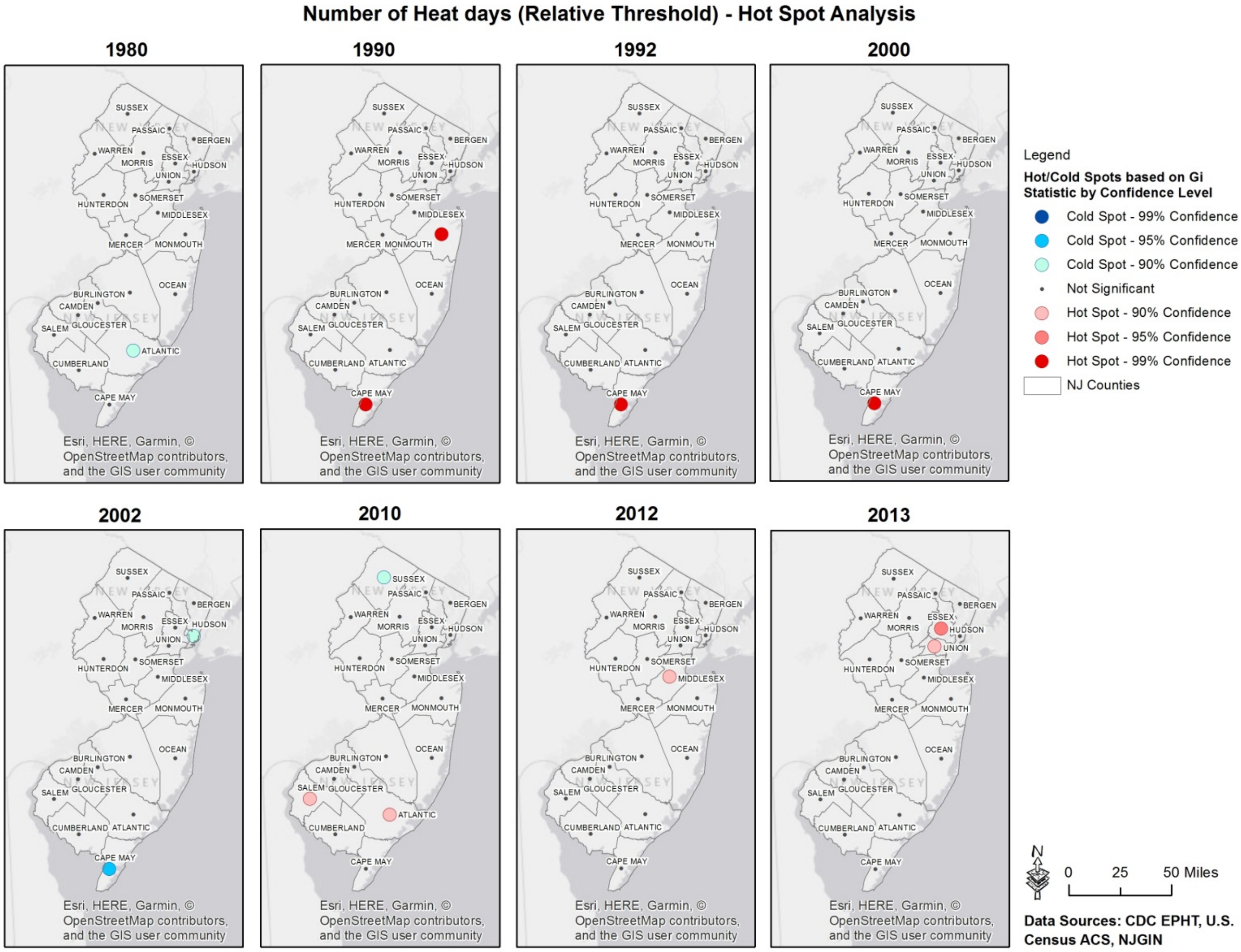


Number of Heat Days (Absolute Threshold)

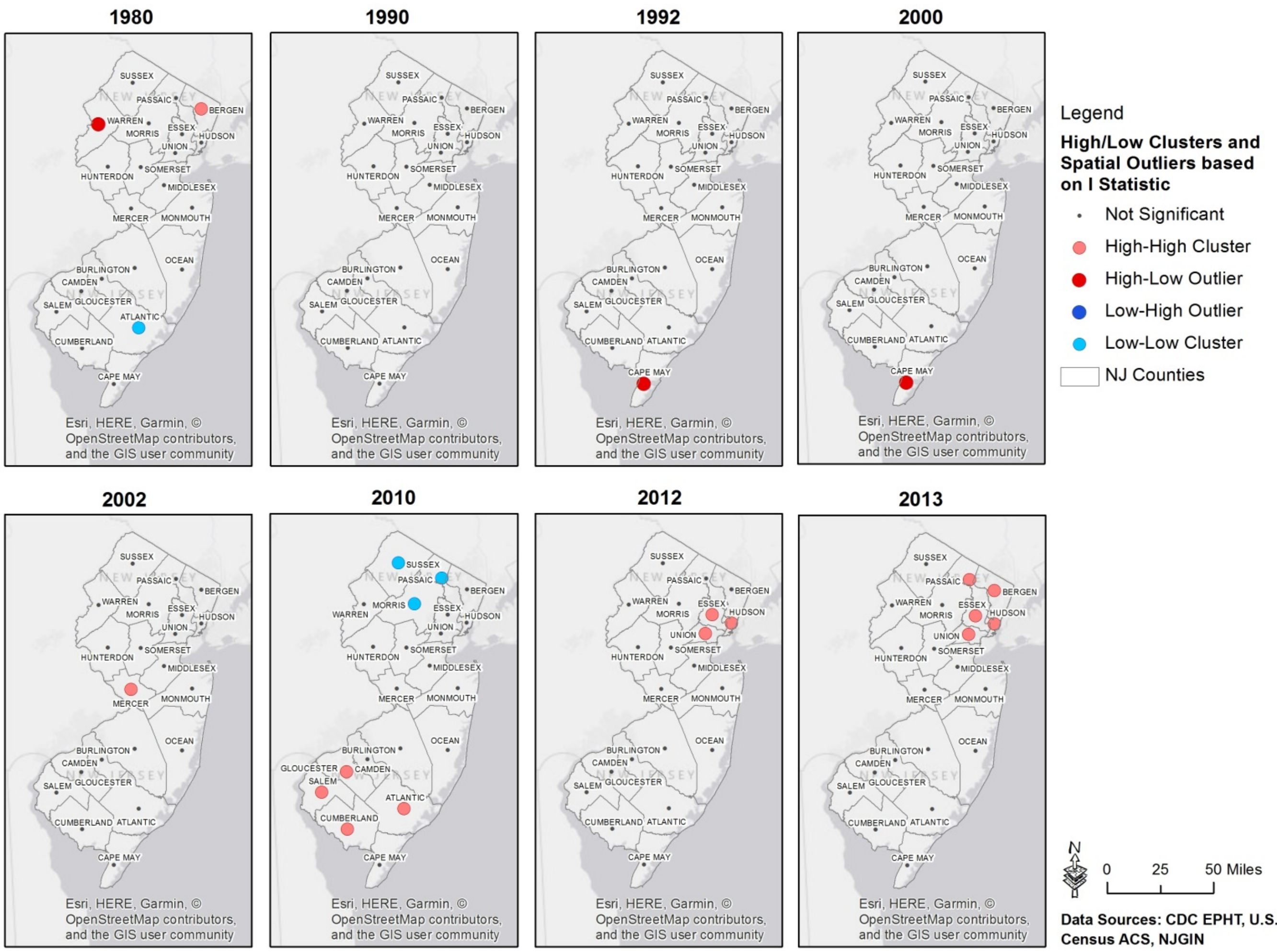
By EJ Index (by Percent)



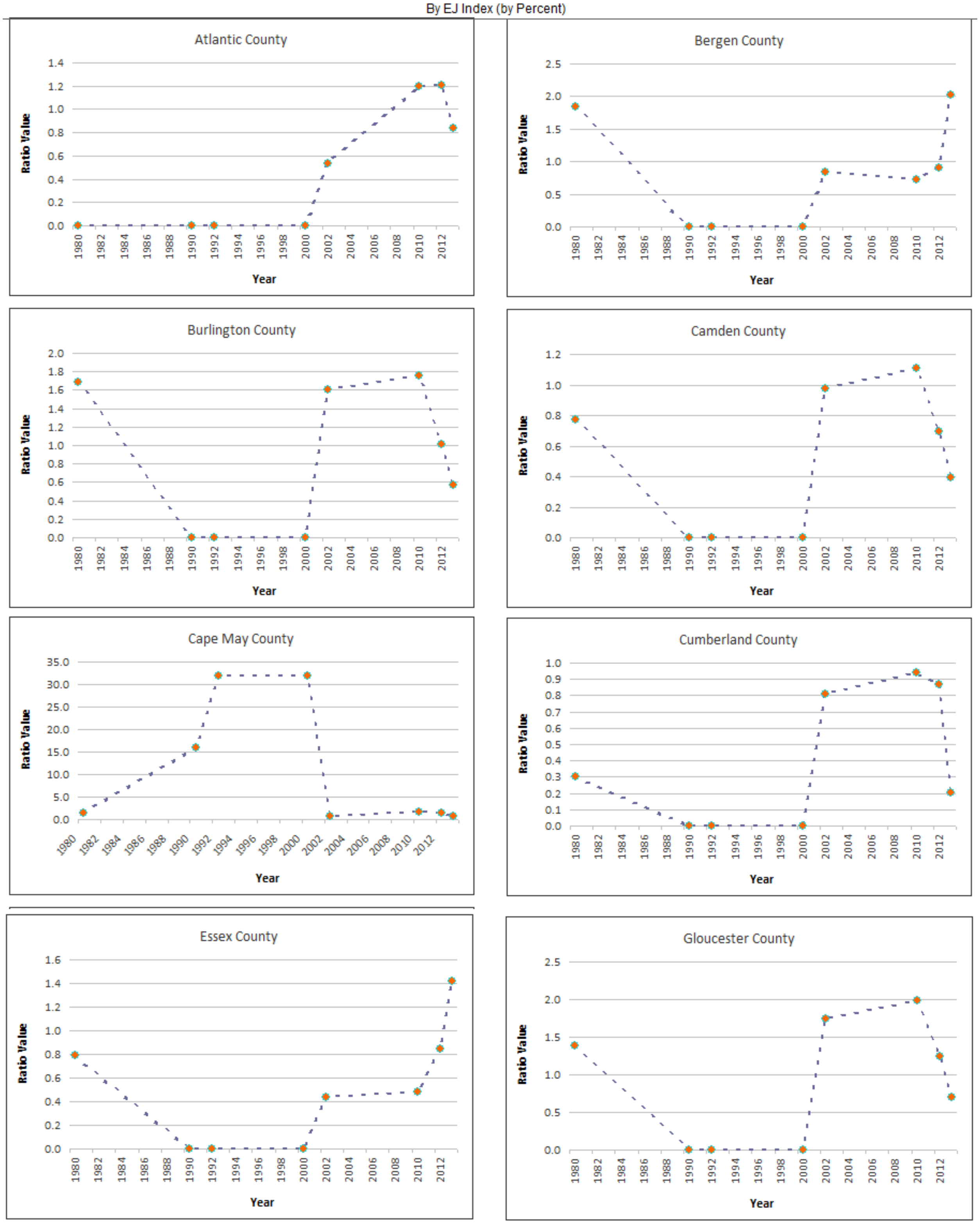
Number of Heat Days (relative threshold) – Hot Spot Analysis and Cluster Outlier Analysis



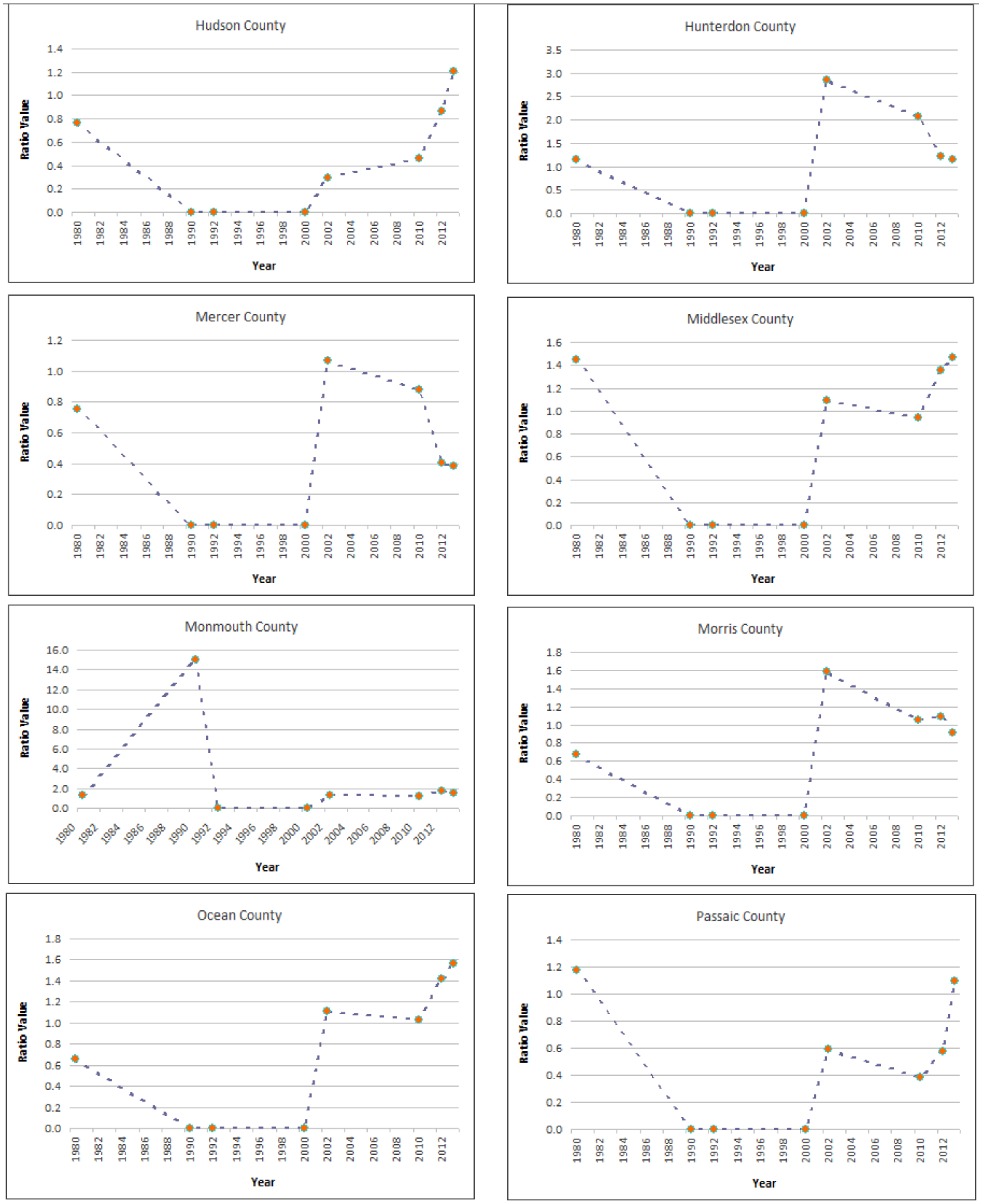
Number of Heat days (Relative Threshold) - Cluster and Outlier Analysis



Number of Heat Days (Relative Threshold)
By EJ Index (by Percent)

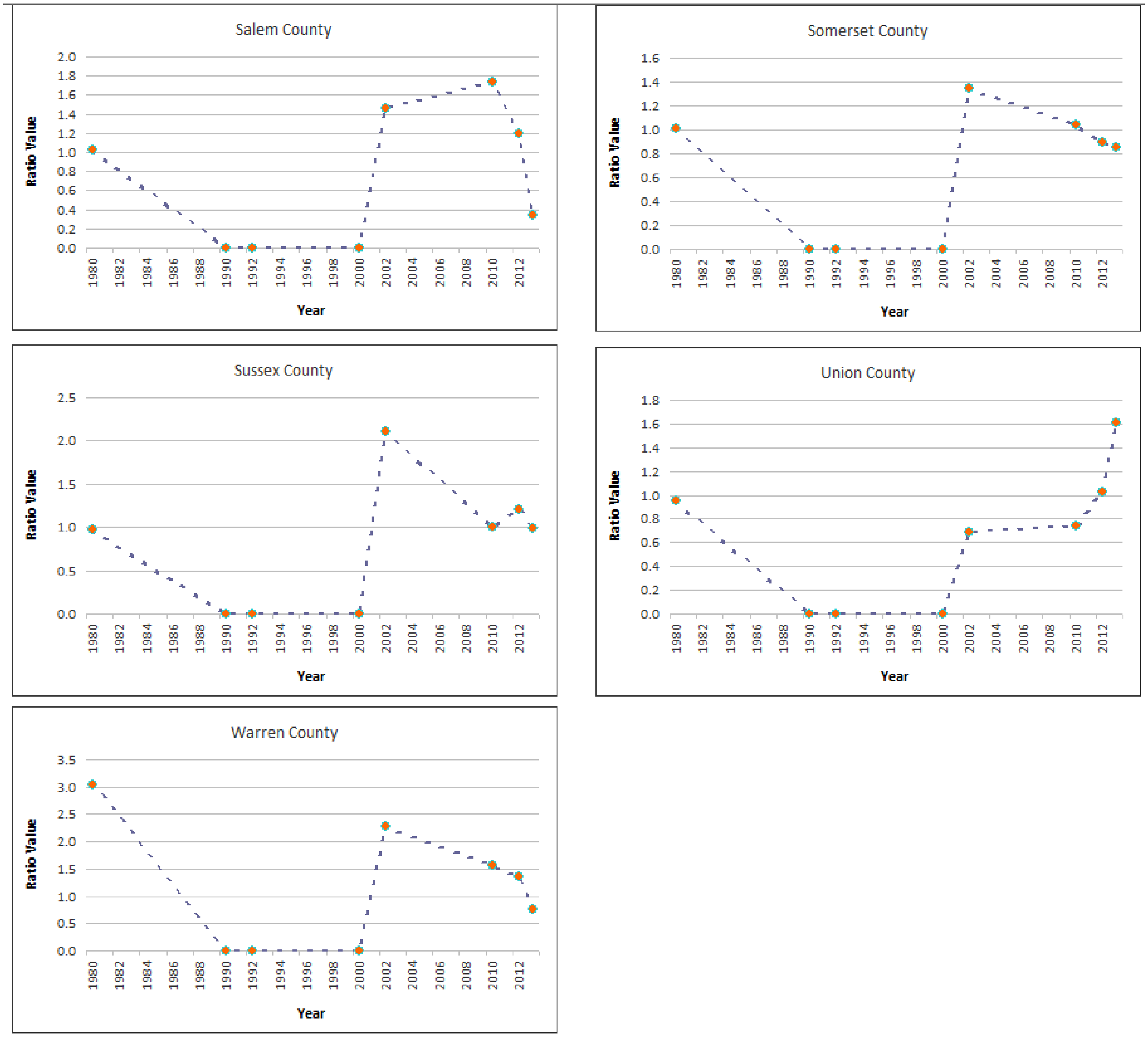


Number of Heat Days (Relative Threshold)
By EJ Index (by Percent)

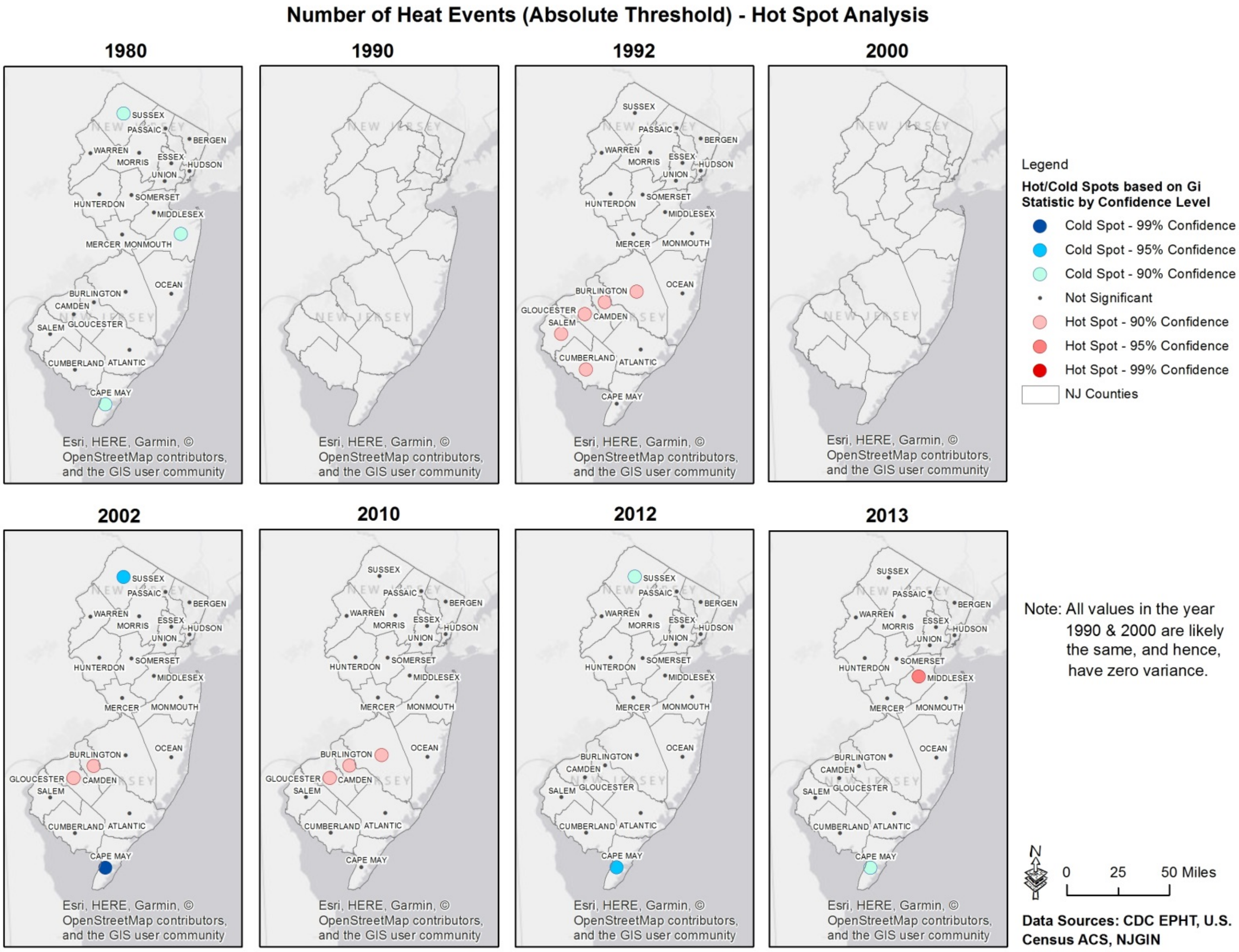


Number of Heat Days (Relative Threshold)

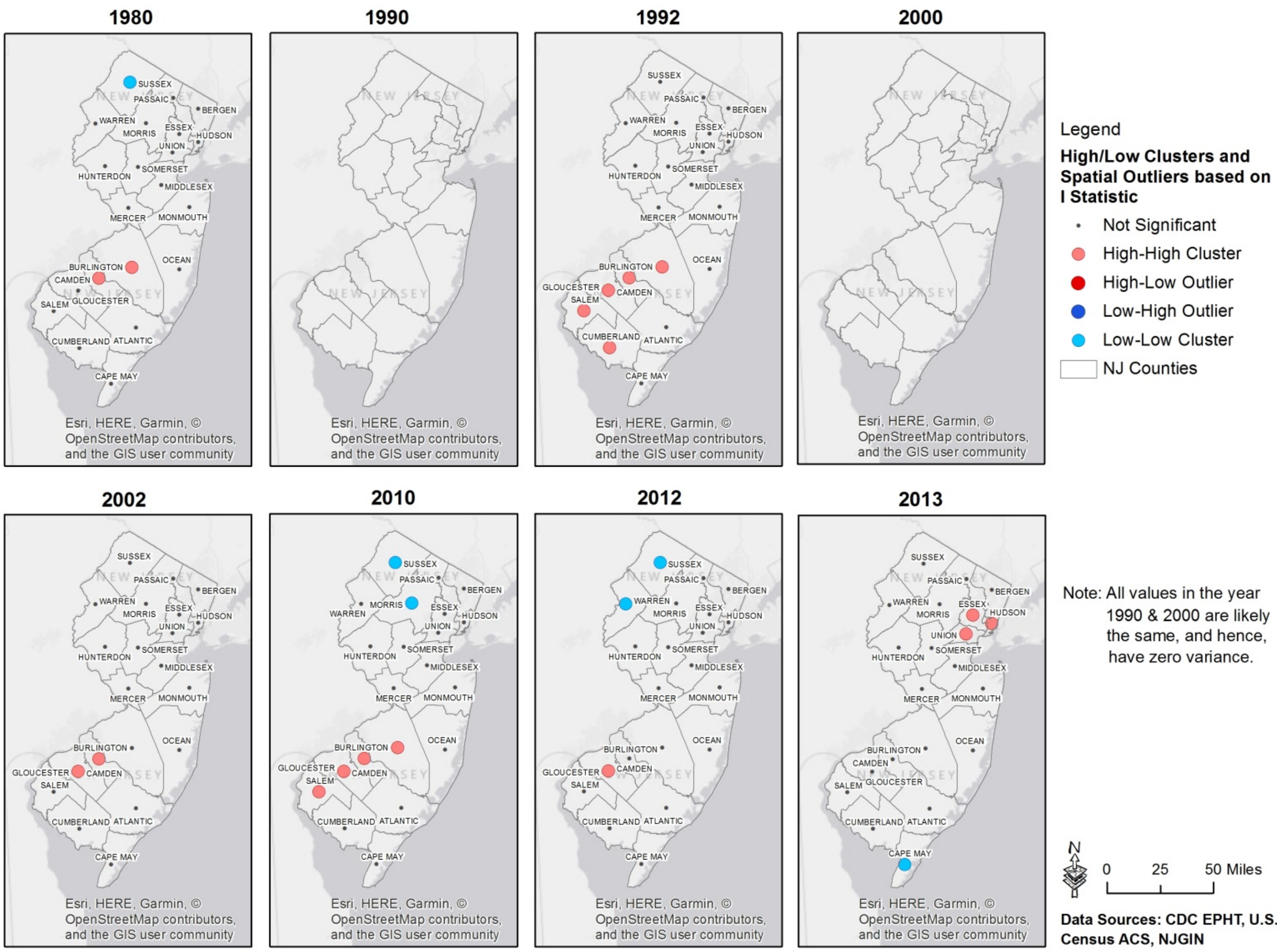
By EJ Index (by Percent)



Number of Heat Events (absolute threshold) – Hot Spot Analysis and Cluster Outlier Analysis

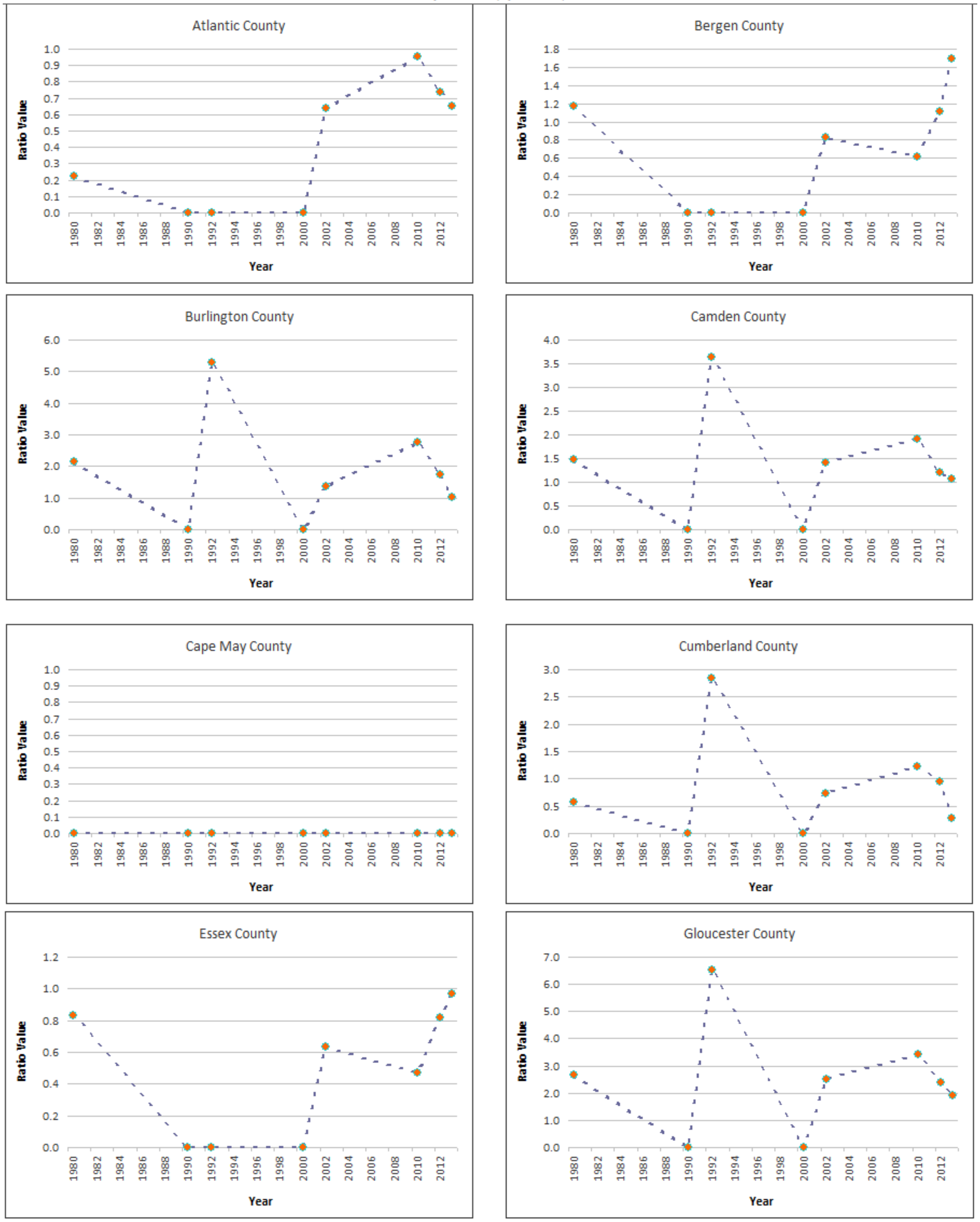


Number of Heat Events (Absolute Threshold) - Cluster and Outlier Analysis



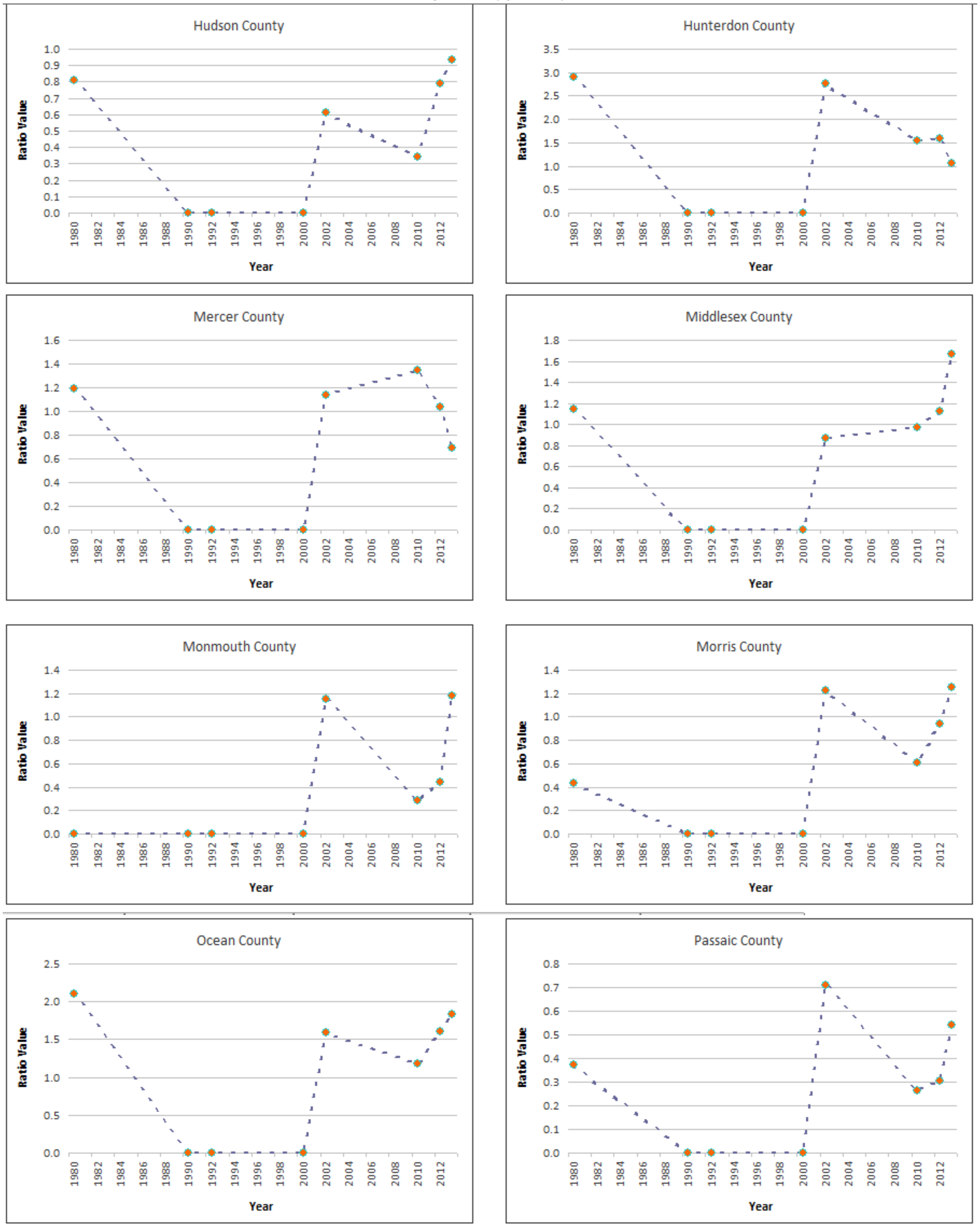
Number of Heat Events (Absolute Threshold)

By EJ Index (by Percent)



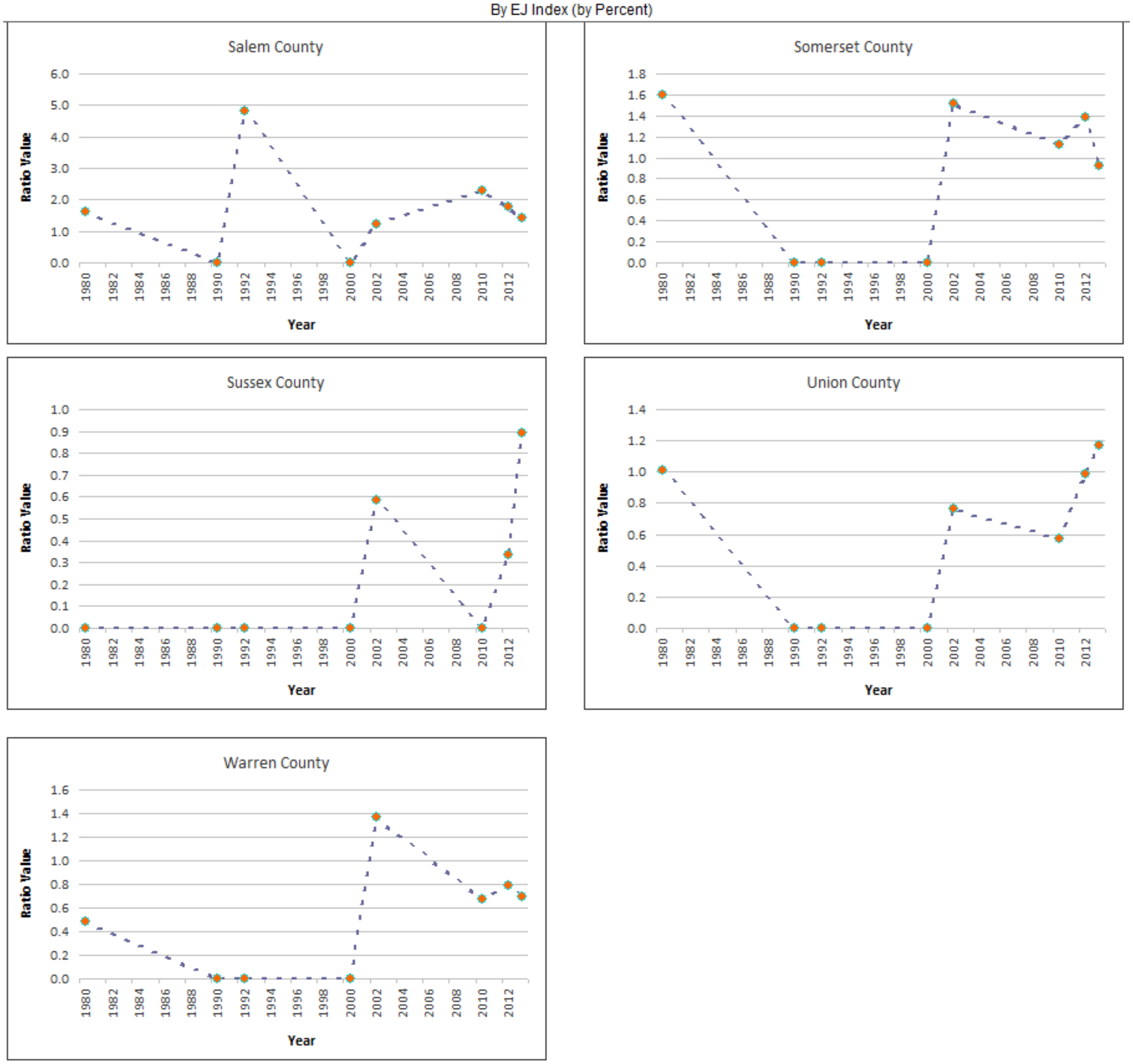
Number of Heat Events (Absolute Threshold)

By EJ Index (by Percent)

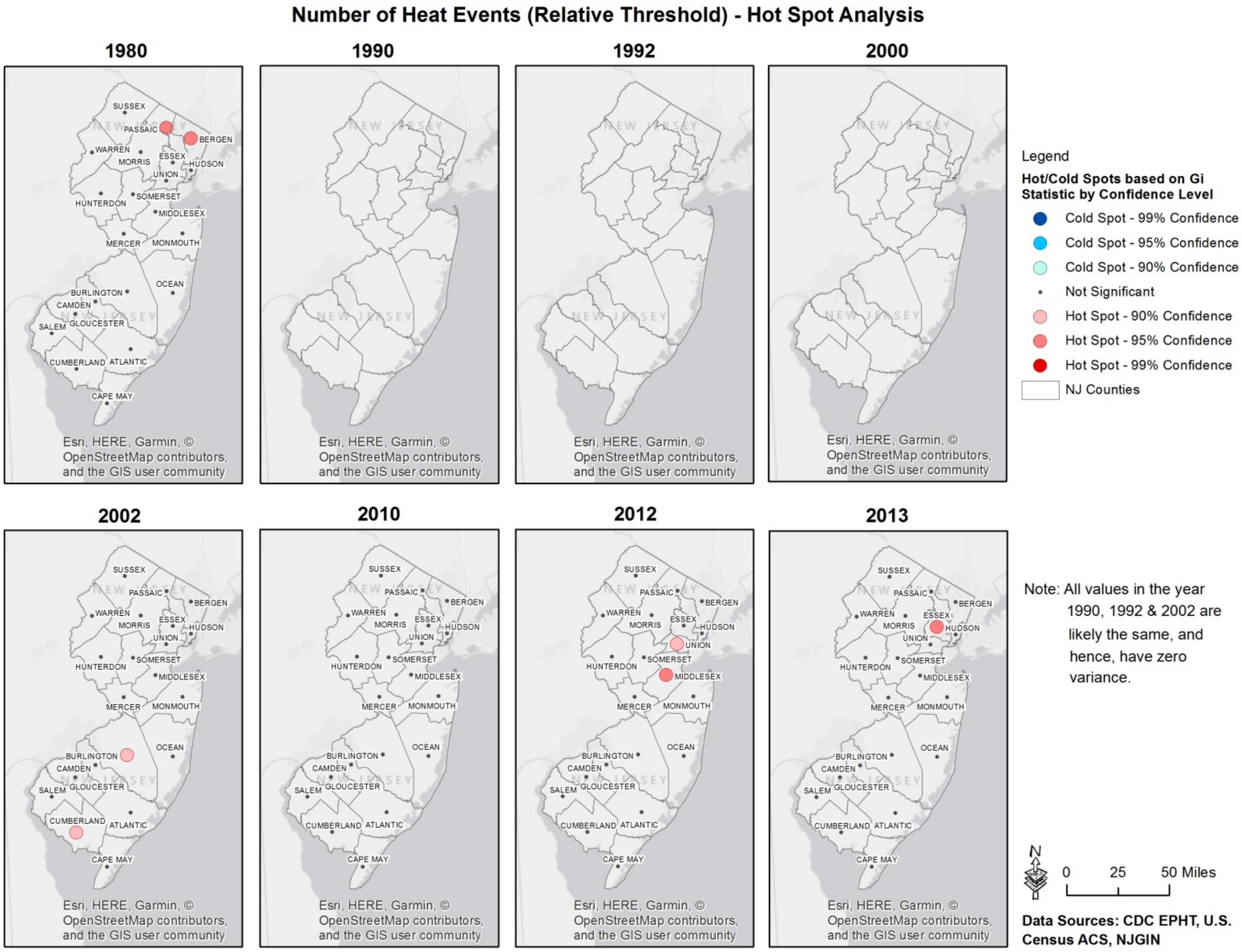


Number of Heat Events (Absolute Threshold)

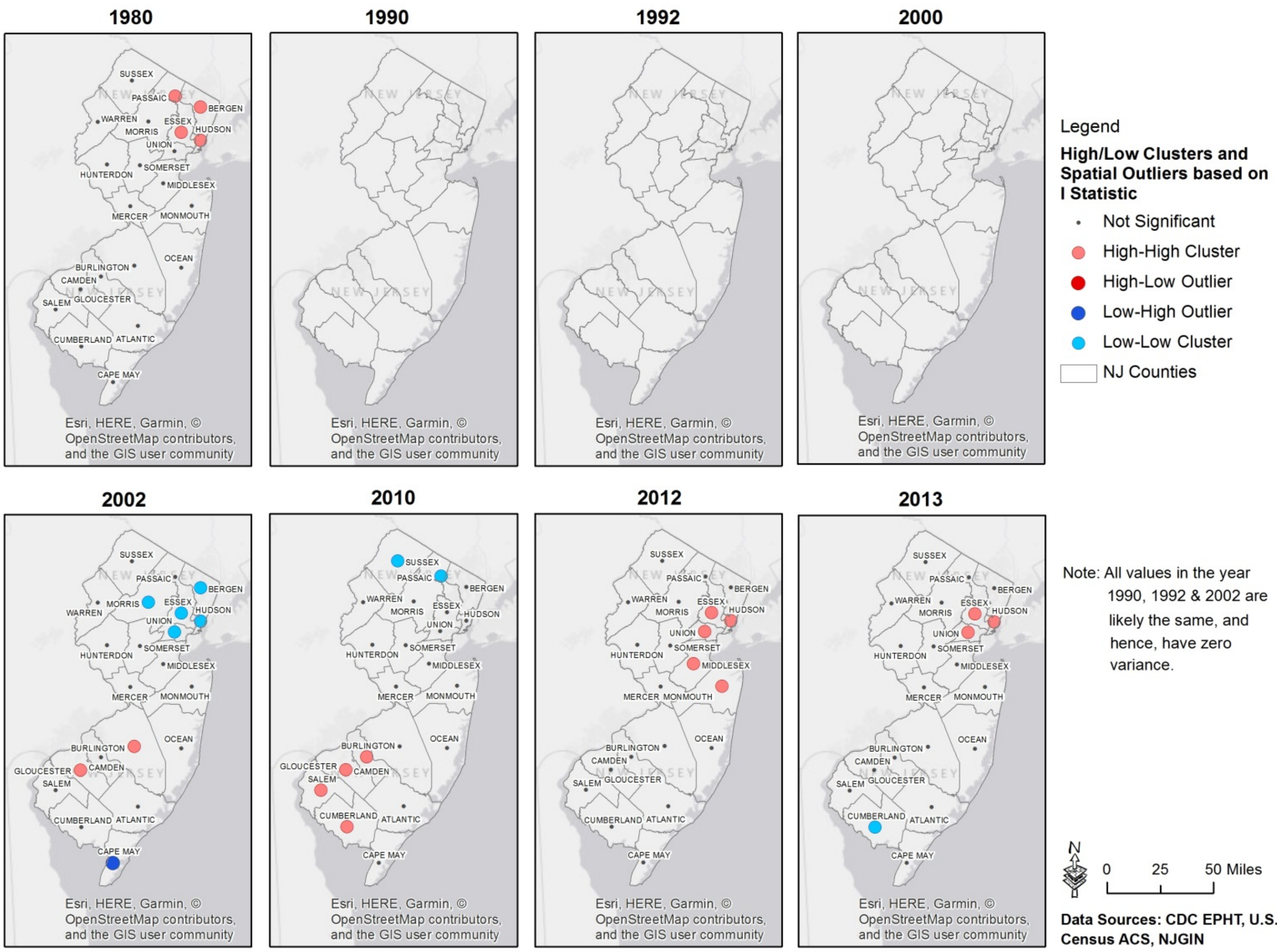
By EJ Index (by Percent)



Number of Heat Events (relative threshold) – Hot Spot Analysis and Cluster Outlier Analysis

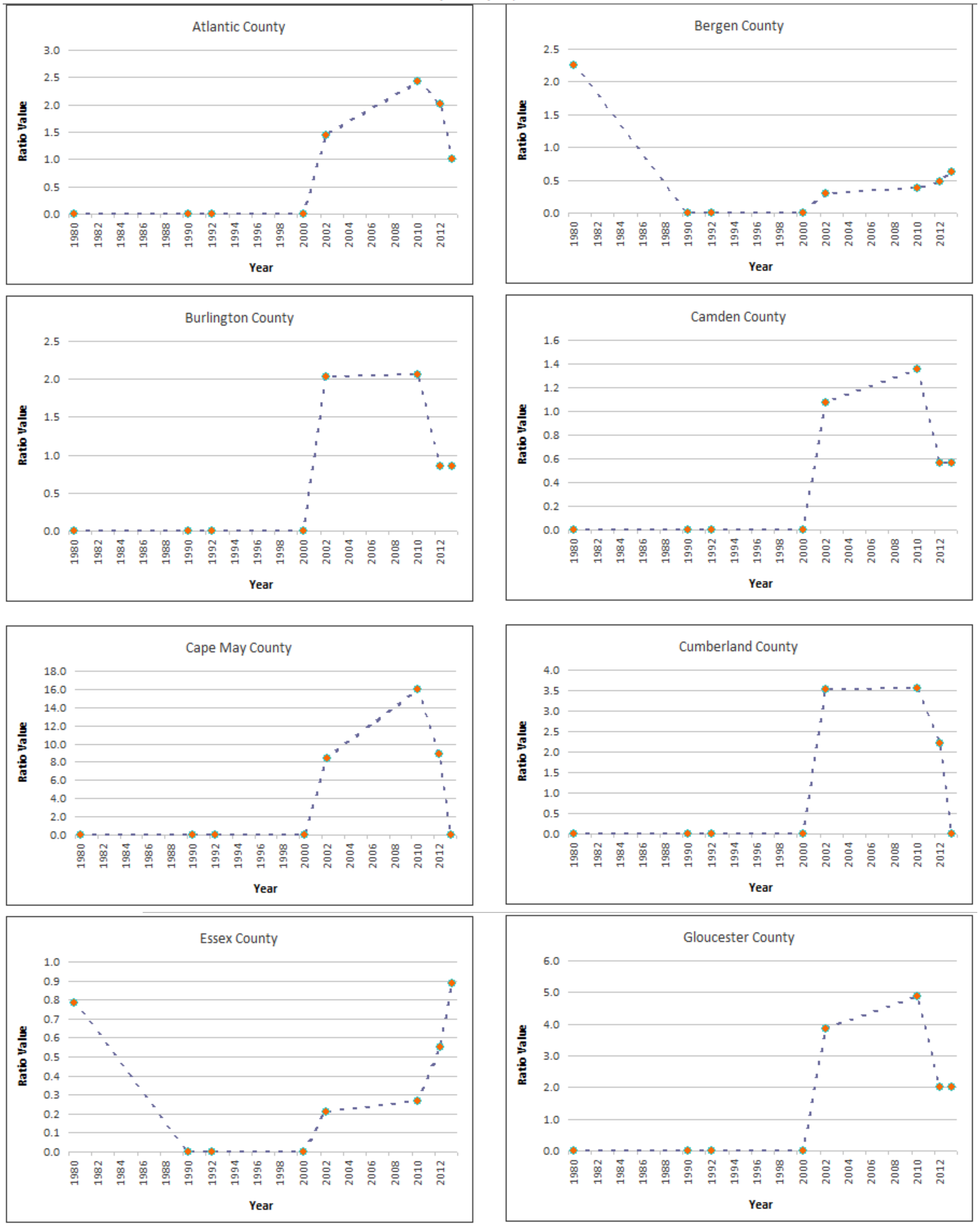


Number of Heat Events (Relative Threshold) - Cluster and Outlier Analysis

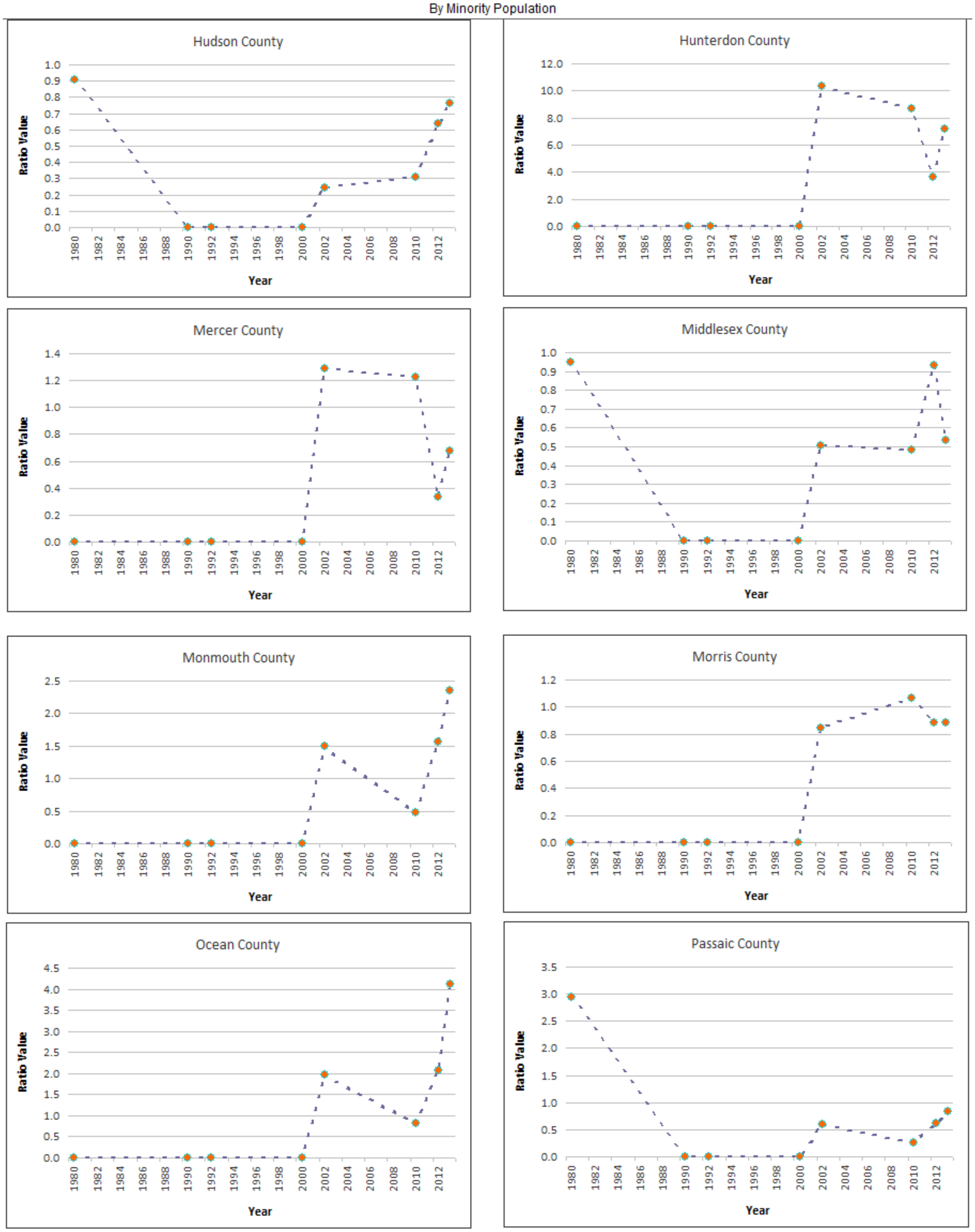


Number of Heat Events (Relative Threshold)

By Minority Population

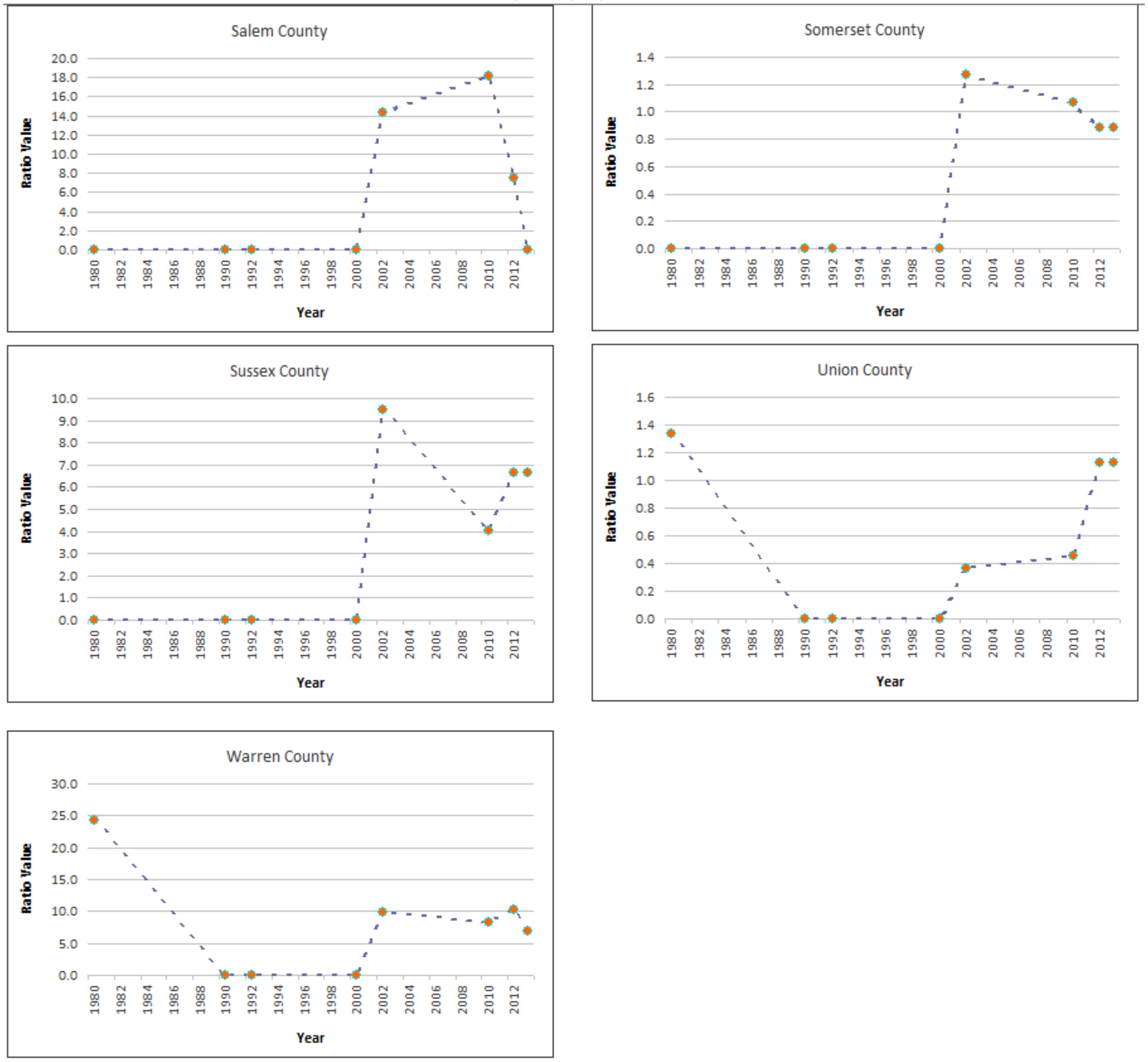


Number of Heat Events (Relative Threshold)
By Minority Population

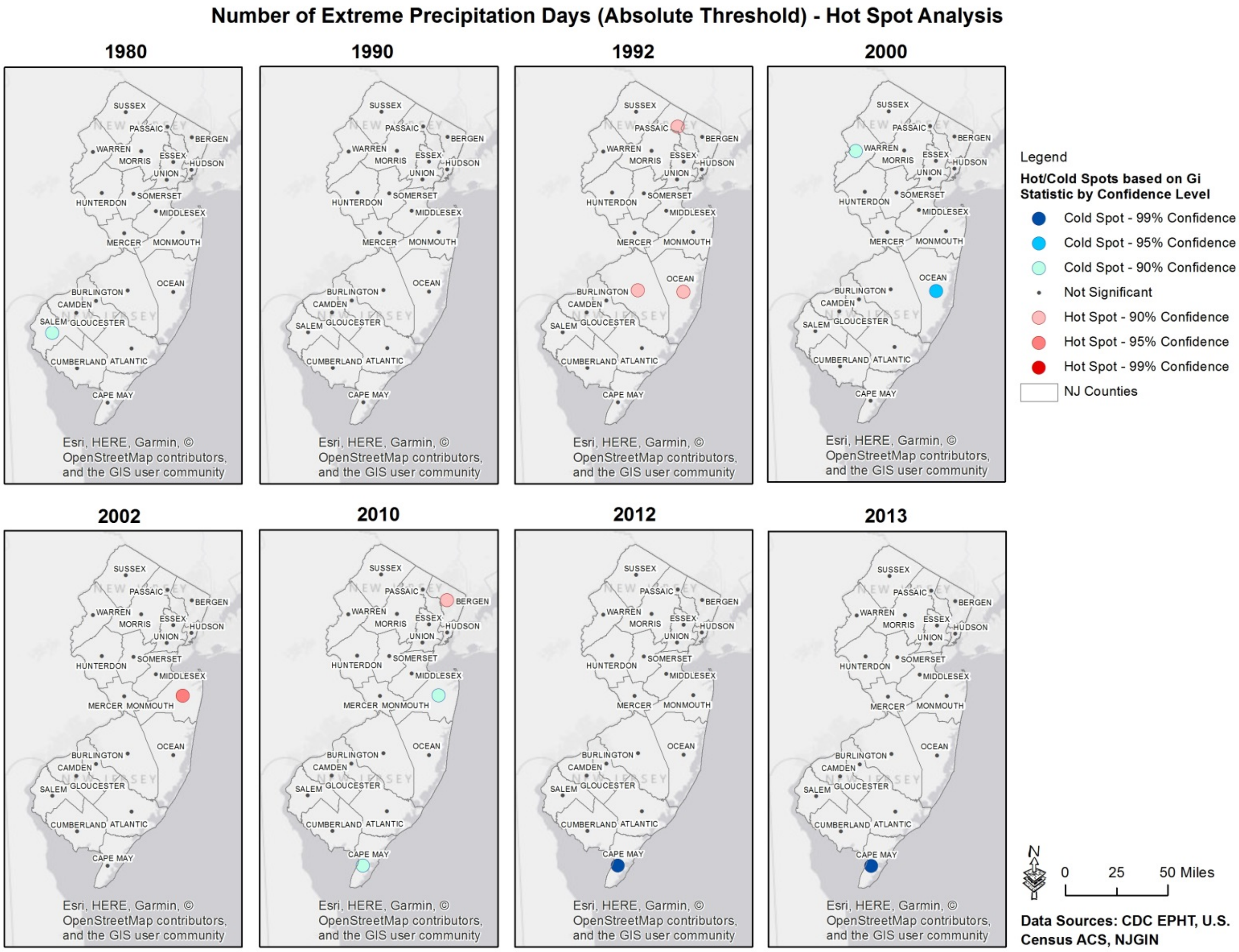


Number of Heat Events (Relative Threshold)

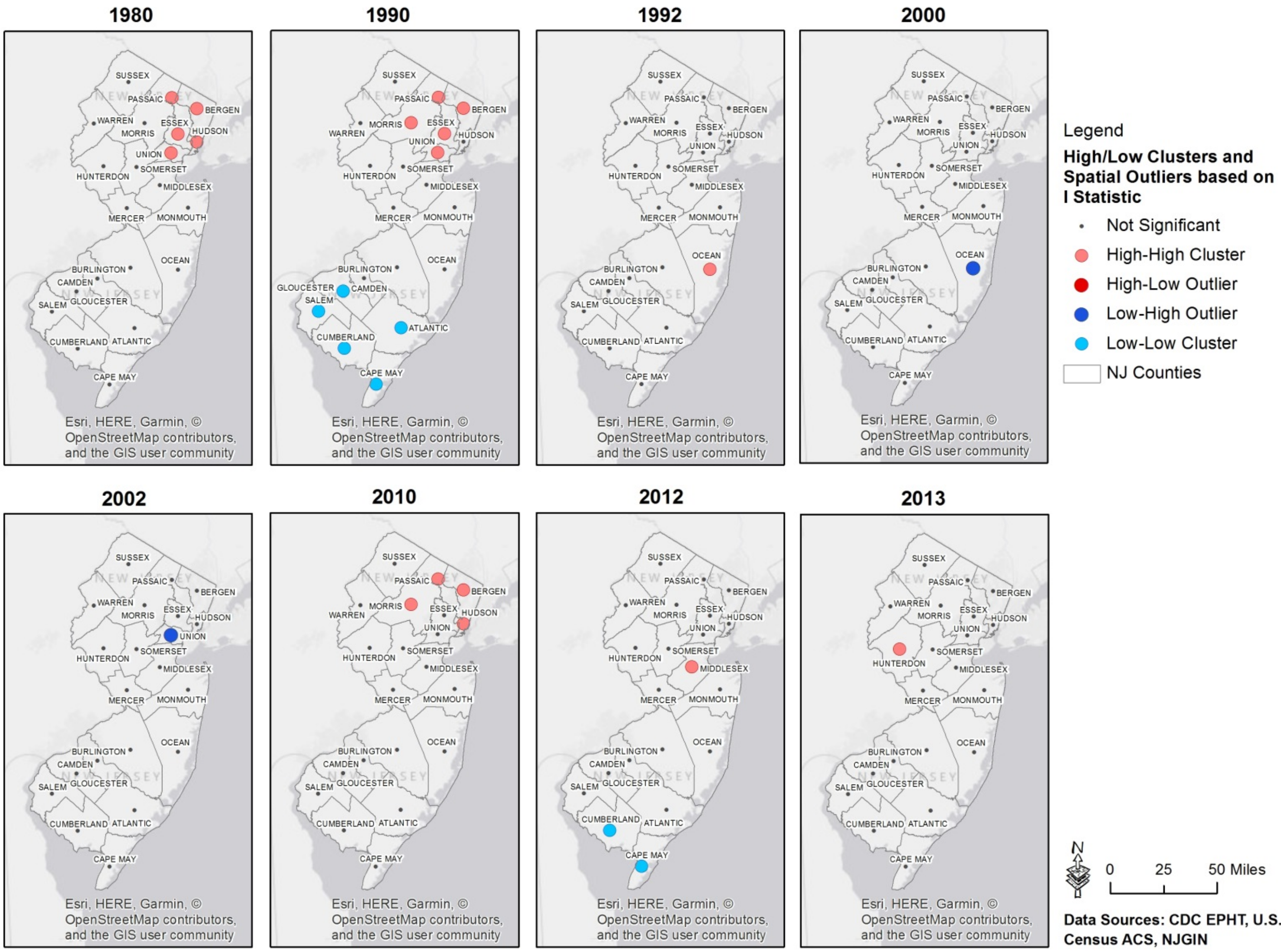
By Minority Population



Number of Extreme Precipitation Days (absolute threshold) – Hot Spot Analysis and Cluster Outlier Analysis



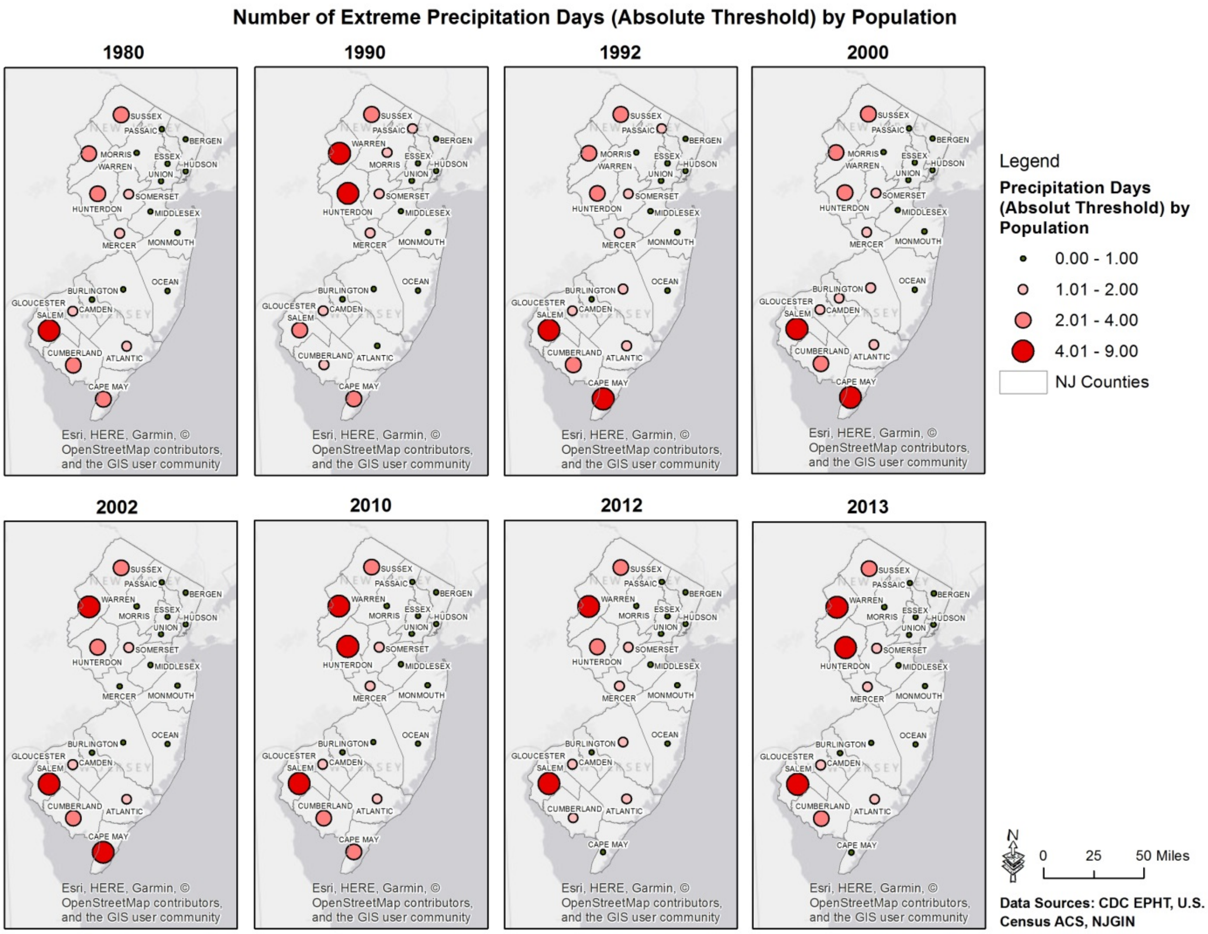
Number of Extreme Precipitation Days (Absolute Threshold) - Cluster and Outlier Analysis



Number of Extreme Precipitation Days – Absolute Threshold

Findings (by population and land area) -

- The number of extreme precipitation days show higher values in less-populated counties such as Salem, Warren, and Hunterdon.
- For densely populated areas such as Hudson, Essex, and Union the values were less than 1.



Appendix E: Data Justification Tables

Color Legend	Label
	Removed based on CHR&R criteria
	Removed based on data not being available Nationally
	Removed based on data being out-of-date or no longer being updated

EJScreen

Data Variable	Indicator/Measure	Limitations	Health Connection	CHRR Criteria
Ozone Summer Seasonal Average of daily maximum 8-hour concentration in air (ppb)	**Ground Level Ozone**	Data not available in Alaska or Hawaii because of lack of CMAQ monitors.	Medium. The relationship between ambient concentrations and personal exposure is largely unknown and variable depending upon pollutant, activity patterns, and microenvironments.	Medium
Ozone	Ozone Concentration Score	Null values present in Alaska and Hawaii		
D_OZONE_2	Ozone Level in Air--Primary EJ Index based on Primary 2-factor Demographics	Null values present in Alaska and Hawaii		
B_OZONE	Bin Ozone Concentration Score	Null values present in Puerto Rico		
Diesel particulate matter level in air	**Air Toxics**	Could be capturing same thing as particulates. Modeled data - quality varies. From 2011 - might not be current	Medium. The relationship is complicated by multiple sources, indoor and outdoor. Ambient concentrations are usually low - hot spots more important, but complicated by weather	Medium. Overlap with PM 2.5?
DSLPM	NATA Diesel Particulate Matter	Null values spread out		
D_DSLPM_2	Diesel Particulate Matter Level in Air--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
P_DSLPM	Percentile NATA Diesel Particulate Matter	Null values spread out		
P_DSLPM_D2	Percentile Diesel Particulate Matter Level in Air--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
B_DSLPM	Bin NATA Diesel Particulate Matter			
B_DSLPM_D2	Bin Diesel Particulate Matter Level in Ai--Primary EJ Index based on Primary 2-factor Demographics			
Cancer Risk:Lifetime cancer risk from inhalation of air toxics	**Air Toxics**			Prefer not to use disease specific indicators.
CANCER	NATA Cancer Risk	Null values spread out		
D_CANCR_2	Air Toxics Cancer Risk--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
P_CANCR	Percentile NATA Cancer Risk	Null values spread out		
P_CANCR_D2	Percentile Air Toxics Cancer Risk--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
B_CANCR	Bin NATA Cancer Risk			
B_CANCR_D2	Bin Air Toxics Cancer Risk--Primary EJ Index based on Primary 2-factor Demographics			
Air Toxics respiratory hazard index	**Air Toxics**		? Could be better than cancer risk or ambient diesel?	Medium - Disease-specific but could be more tied to equity
RESP	NATA Respiratory Hazard Index	Null values spread out		
D_RESP_2	Air Toxics Respiratory HI--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
P_RESP	Percentile NATA Respiratory Hazard Index	Null values spread out		
P_RESP_D2	Percentile Air Toxics Respiratory HI--Primary EJ Index based on Primary 2-factor Demographics	Null values spread out		
B_RESP	Bin NATA Respiratory Hazard Index			
B_RESP_D2	Bin Air Toxics Respiratory HI--Primary EJ Index based on Primary 2-factor Demographics			
Traffic proximity and volume	**Proximity of Populations and Schools to Highways**	Data not available in Alaska or Hawaii because of lack of CMAQ monitors	Medium	High
PTRAF	Traffic Proximity	No null values present in data		
D_PTRAF_2	Traffic Proximity and Volume--Primary EJ Index based on Primary 2-factor Demographics	No null values present in data		
P_PTRAF	Percentile Traffic Proximity	No null values present in data		
P_PTRAF_D2	Percentile Traffic Proximity and Volume--Primary EJ Index based on Primary 2-factor Demographics	No null values present in data		
B_PTRAF	Bin Traffic Proximity	No null values present in data		
B_PTRAF_D2	Bin Traffic Proximity and Volume--Primary EJ Index based on Primary 2-factor Demographics	No null values present in data		
PM2.5 levels in air, ug/m3 annual average (2012)	**Particulate Matter**	Data not available in Alaska or Hawaii because of lack of CMAQ monitors. Data is modeled for up to 2/3 of U.S. counties. Highly pop. Counties may be biased higher. High variability due to weather and few events.	High	Medium
PM25	PM 2.5 Concentration Score	Null values present for Alaska, Hawaii, and Puerto Rico		
D_PM25_2	PM 2.5 Level in Air--Primary EJ Index based on Primary 2-factor Demographics	Null values present for Alaska, Hawaii, and Puerto Rico		
P_PM25	Percentile PM 2.5 Concentration Score	Null values present for Alaska, Hawaii, and Puerto Rico		
P_PM25_D2	Percentile PM 2.5 Level in Air--Primary EJ Index based on Primary 2-factor Demographics	Null values present for Alaska, Hawaii, and Puerto Rico		
B_PM25	Bin PM 2.5 Concentration Score			
B_PM25_D2	Bin PM 2.5 Level in Air--Primary EJ Index based on Primary 2-factor Demographics			
Count of proposed and listed NPL sites within 5 km	**Proximity to National Priority List Sites**		Low	Low
PNPL	Superfund Proximity			
D_PNPL_2	NPL Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
P_PNPL	Percentile Superfund Proximity			
P_PNPL_D2	Percentile NPL Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
B_PNPL	Bin Superfund Proximity			
B_PNPL_D2	Bin NPL Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
Count of TSDFs (hazardous waste management facilities) within 5 km	**Proximity to Waste Treatment, Storage, and Disposal Facilities**		Low	Low
PTSDF	TSDF Proximity			
D_PTSDF_2	TSDF Proximity--Primary EJ Index based on Primary 2-factor Demographics			
P_PTSDF	Percentile TSDF Proximity			
P_PTSDF_D2	Percentile TSDF Proximity--Primary EJ Index based on Primary 2-factor Demographics			
B_PTSDF	Bin TSDF Proximity			
B_PTSDF_D2	Bin TSDF Proximity--Primary EJ Index based on Primary 2-factor Demographics			
Count of RMP (potential chemical accident management plan) facilities within 5 km	**Proximity to RMP Sites**		Low	Low
PRMP	RMP Proximity			
D_PRMP_2	RMP Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
P_PRMP	Percentile RMP Proximity			
P_PRMP_D2	Percentile RMP Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
B_PRMP	Bin RMP Proximity			
B_PRMP_D2	Bin RMP Facility Proximity--Primary EJ Index based on Primary 2-factor Demographics			
Wastewater discharge (toxicity-weighted stream concentrations at stream segments within 5(	**Proximity to Major Direct Water Dischargers**	Does not include Alaska	Low - No Data	Low
PWDIS	Wastewater Discharge Indicator	null values present for Alaska		
D_PWDIS_2	Cumulative Direct Discharge Pollution—Primary EJ Index based on Primary 2-factor Demographics	null values present for Alaska		
P_PWDIS	Percentile Wastewater Discharge Indicator	null values present for Alaska		
P_PWDIS_D2	Percentile Cumulative Direct Discharge Pollution—Primary EJ Index based on Primary 2-factor Demographics	null values present for Alaska		
B_PWDIS	Bin Wastewater Discharge Indicator			
B_PWDIS_D2	Bin Cumulative Direct Discharge Pollution—Primary EJ Index based on Primary 2-factor Demographics			
Presence of health-related drinking water violations	Drinking Water Violations			

EPHT

Data Variable	Indicator/Measure	Justification	Limitations	Health Connection	CHRR Criteria
Days Above Regulatory Standard	Ground Level Ozone	CHRR selected fine particulate matter over this one - felt pm2.5 was better			
Number of days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard	Days Above Regulatory Standard (Monitor only)	Data available for Counties that pass the completeness criteria only	Only counties that have at least 75% of the days monitored during the ozone seasons are considered complete.		
Number of person-days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard	Days Above Regulatory Standard (Monitor only)	Data available for Counties that pass the completeness criteria only	Only counties that have at least 75% of the days monitored during the ozone seasons are considered complete.		
Number of days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard	Days Above Regulatory Standard (Monitor + Modeled)		Null values in Alaska, Hawaii & Puerto Rico		
Number of person-days with maximum 8-hour average ozone concentration over the National Ambient Air Quality Standard	Days Above Regulatory Standard (Monitor + Modeled)		Null values in Alaska, Hawaii & Puerto Rico		
Annual average cancer risk estimates per million	Air Toxics	Data given by 5 Pollutants that are identified as the top five contributors to the overall cancer risks nationwide.	Null Values in Puerto Rico		
Annual average air concentration estimates in microgram per cubic meter	Air Toxics	Data given by 5 Pollutants that are identified as the top five contributors to the overall cancer risks nationwide.	Null Values in Puerto Rico		
Percent of cancer risk estimates by source	Air Toxics	Data given by 6 possible sources for each of the 5 Pollutants that are identified as the top five contributors to the overall cancer risks nationwide.	Null Values in Puerto Rico		
Percent of cancer risk estimates from all sources	Air Toxics	Same as EPHTN_M479_D	Null Values in Puerto Rico		
Annual PM2.5 Level	Particulate Matter				
Annual average ambient concentrations of PM2.5 in micrograms per cubic meter (based on seasonal averages and daily measurement)	Annual PM2.5 Level (Monitor Only)	Data available for Counties that pass the completeness criteria only	Only monitors that have at least 11 observations for each of the four calendar quarters are considered complete.		
Annual average ambient concentrations of PM2.5 in micrograms per cubic meter (based on seasonal averages and daily measurement)	Annual PM2.5 Level (Monitor + Modeled)		Null values in Alaska, Hawaii & Puerto Rico		
PM2.5 Days Above Regulatory Standard	Particulate Matter				**Highly variable - Influenced by weather?**
Percent of days with PM2.5 levels over the National Ambient Air Quality Standard (NAAQS)	PM2.5 Days Above Regulatory Standard (Monitor Only)	Data available for Counties that pass the completeness criteria only	Null values are spread out.		
Number of person-days with PM2.5 over the National Ambient Air Quality Standard (NAAQS)	PM2.5 Days Above Regulatory Standard (Monitor Only)	Data available for Counties that pass the completeness criteria only	Null values are spread out.		
Percent of days with PM2.5 levels over the National Ambient Air Quality Standard (NAAQS)	PM2.5 Days Above Regulatory Standard (Monitor + Modeled)		Null values in Alaska, Hawaii & Puerto Rico		
Number of person-days with PM2.5 over the National Ambient Air Quality Standard (NAAQS)	PM2.5 Days Above Regulatory Standard (Monitor + Modeled)		Null values in Alaska, Hawaii & Puerto Rico		
Yearly distribution of number of Community Water Systems by maximum arsenic concentration	Specific Contaminant of Concern for Drinking Water	Data by cut-point intervals: 0-5, >5-10, >10-20, >20-30, >30 μg/L arsenic	Data held by States and not with CDC or EPA, potential for incomplete data		
Yearly distribution of number of CWS by mean arsenic concentration	Specific Contaminant of Concern for Drinking Water	Data by cut-point intervals: 0-5, >5-10, >10-20, >20-30, >30 μg/L arsenic	Data held by States and not with CDC or EPA, potential for incomplete data		
Mean concentration of arsenic at CWS-level, by year	Specific Contaminant of Concern for Drinking Water	Data structured by each CWS by county.	Data held by States and not with CDC or EPA, potential for incomplete data. Null values are spread out.		
Yearly distribution of number of people served by CWS by maximum arsenic concentration	Specific Contaminant of Concern for Drinking Water	Data by cut-point intervals: 0-5, >5-10, >10-20, >20-30, >30 μg/L arsenic	Data held by States and not with CDC or EPA, potential for incomplete data		
Yearly distribution of number of people served by CWS by mean arsenic concentration	Specific Contaminant of Concern for Drinking Water	Data by cut-point intervals: 0-5, >5-10, >10-20, >20-30, >30 μg/L arsenic	Data held by States and not with CDC or EPA, potential for incomplete data		
Number of Reported Acute Toxic Substance Release Incidents	Acute Releases (air and water)		Null values are spread out.		
Percent of Reported Acute Toxic Substance Release Incidents with at least one injury or fatality	Acute Releases (air and water)		Null values are spread out.		
Percent of reported acute toxic substance release incidents with evacuation ordered	Acute Releases (air and water)		Null values are spread out.		
Rate of injuries or fatalities due to reported acute toxic substance release incidents per 100,000 population	Acute Releases (air and water)		Null values are spread out.		
Rate of reported acute toxic substance release incidents per 100,000 population	Acute Releases (air and water)		Null values are spread out.		
				Medium	**Medium/High**
Number of Extreme Heat Days	Extreme Heat	Measure was calculated only for months May through September. Relative Threshold: 90th Percentile, Heat Metric: Daily Maximum Temperature	Does not include Alaska and Hawaii	**Medium**	**Medium/High**
Dates of Extreme Heat Days	Extreme Heat	Data available for individual days May through September by County.		**Medium**	**Medium/High**
Number of Extreme Heat Events	Extreme Heat	Measure was calculated only for months May through September. Minimum Duration Days: 2 Days, Relative Threshold: 90th Percentile, Heat Metric: Daily Maximum Temperature	Does not include Alaska and Hawaii	**Medium**	**Medium/High**
Dates of Extreme Heat Events	Extreme Heat	Data available for individual days May through September by County.			
Heat Vulnerabilitly					
Heat-related Mortality					
Heat stress ED Visits					
Heat stress Hospitalizations					
	Extreme Precipitation	No Data			
Number of Square Miles within FEMA designated special flood hazard area	Flood Hazards		Null Values in Puerto Rico.	**High**	**High**
Percent area (sq miles) within FEMA designated special flood hazard area	Flood Hazards		Null Values in Puerto Rico.	**High**	**High**
Number of people within FEMA designated special flood hazard area	Flood Hazards	Count of People as per 2010 US Census Block Group Data and 2010 Landscan Nighttime Raster Data	Null Values in Puerto Rico. Should consider recalculating these values ourselves with the latest ACS data	**High**	**High**
Number of housing units within FEMA designated special flood hazard area	Flood Hazards	Count of Housing Units as per 2010 US Census Block Group Data and 2010 Landscan Nighttime Raster Data	Null Values in Puerto Rico. Should consider recalculating these values ourselves with the latest ACS data		