ABSTRACT

Title of Dissertation:	EXPOSURE TO EXTREME HEAT EVENTS AND CHRONIC RESPIRATORY DISEASES AMONG A NATIONALLY REPRESENTATIVE SAMPLE OF THE UNITED STATES POPULATION
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Previous studies have shown that extreme weather events are on the rise in response to our changing climate. Such events are projected to become more frequent, more intense, and longer lasting. A consistent exposure metric for measuring these extreme events as well as information regarding how these events lead to ill health are needed to inform meaningful adaptation strategies that are specific to the needs of local communities.

Using federal meteorological data corresponding to 17 years (1997-2013) of the National Health Interview Survey, this research: 1) developed a location-specific exposure metric that captures individuals' "exposure" at a spatial scale that is consistent with publicly available county-level health outcome data; 2) characterized the United States' population in counties that have experienced higher numbers of *extreme heat events* and thus identified population groups likely to experience future events; and 3) developed an empirical model describing the association between exposure to *extreme heat events* and hay fever.

This research confirmed that the natural modes of forcing (e.g., El Niño-Southern Oscillation), seasonality, urban-rural classification, and division of country have an impact on the number *extreme heat events* recorded. Also, many of the areas affected by *extreme heat events* are shown to have a variety of vulnerable populations including women of childbearing age, people who are poor, and older adults. Lastly, this research showed that adults in the highest quartile of exposure to *extreme heat events* had a 7% increased odds of hay fever compared to those in the lowest quartile, suggesting that exposure to extreme heat events increases risk of hay fever among US adults.

EXPOSURE TO EXTREME HEAT EVENTS AND CHRONIC RESPIRATORY
DISEASES AMONG A NATIONALLY REPRESENTATIVE SAMPLE OF THE
UNITED STATES POPULATION

by

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Dedication

...because He who is in you is greater than he who is in the world. ~ 1 John 4:4

To Christopher Upperman, my best friend, husband and peacock. Thank you for all of your love, support, help, encouragement, and dedication.

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It always seems impossible until it's done. ~ Nelson Mandela

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Chapter 1: Introduction

Recent studies suggest that extreme heat events will become more frequent, more intense, and of longer duration in the decades ahead due to climate change (Le Treut et al., 2007; Mues et al., 2012). In the United States (US) temperatures have increased at a rate of 0.1º F per decade since the 1990s and the prevalence of extreme weather events has grown (T. R. Karl & Knight, 1997; Meehl, Tebaldi, Teng, & Peterson, 2007; Williams Jr, Menne, Vose, & Easterling, 2007; T. Karl, 2008).The impact of such events on human health and wellbeing is a significant public health concern because a small change in the mean of a meteorological variable can lead to a large change in the number of rare events (e.g., increase in extreme heat days compared to decrease in extreme cold days). Although a large body of literature exist on the impact of climate change on infectious diseases (Colwell, 1996; de Magny et al., 2008; Epstein, 2001; Lipp, Huq, & Colwell, 2002; Patz, Epstein, Burke, & Balbus, 1996; Randolph, 2009; Rosenthal, 2009; Semenza & Menne, 2009), less is known about the effects of increased exposure to extreme weather events and the worsening and genesis of chronic diseases in westernized societies where the life expectancy of the geriatric population is increasing, more older adults are living with existing chronic diseases, and the prevalence of many chronic diseases are steadily increasing.

Among residents in the US, the increased disease burden is likely to be exposed differentially across geographic regions (T. Karl, 2008; Parry, 2007; US EPA, 2008).

Research by O'Neill *et al.* (2005) and Yu *et al.* (2010) have highlighted the association between place of death, race, and socioeconomic status during short-term heat events (O'Neill, Zanobetti, & Schwartz, 2005; Yu, Vaneckova, Mengersen, Pan, & Tong, 2010). With the expected growth in the older adult population across the US and projected increases in the frequency, duration and intensity of extreme heat events, there is an urgent need to quantify the magnitude of chronic disease burden as well as identify the most vulnerable population.

Understanding how the attributes of a changing climate will impact susceptible populations with chronic respiratory diseases and how the disease burden vary by demographics (urban vs. rural, gender, ethnicity, socioeconomic status (SES), and disease status) will help to guide future adaptation strategies across the US. Prior studies have linked heat waves and hot weather with a higher incidence of mortality in both rural and urban environments (Curriero et al., 2002; Davis, Knappenberger, Michaels, & Novicoff, 2003; Gasparrini & Armstrong, 2011; J. E. Jackson et al., 2010). These studies have highlighted the role of place, race, and socioeconomic status in the heat wave-mortality link. Given the future projections of an increase in the old and elderly populace to 21% by 2030, this is both public health and economic concern (He, Sengupta, Velkoff, & DeBarros, 2005; Pillsbury, Miller, Boon, & Pray, 2010). Since the aging population is more sensitive to health complications from hot weather episodes—because aging is known to impair the temperature control mechanism of the body—additional stress by extreme heat events and acute and chronic diseases can disrupt the quality of life for many (Ebi & Meehl, 2007; Federal Interagency Forum on Aging-Related Statistics, 2008; Worfolk, 2000). Moreover, the health of children are also a concern because they eat, drink, and breathe proportionally more than

adults, making them more susceptible to thermal stress, infectious diseases, and other environmental hazards (Cooper, Marshall, Vanderlinden, & Ursitti, 2011). Identifying the impacts on the elderly and other vulnerable populations are current unknowns that this project aims to answer.

Previous studies have proposed simple and tentative hypothesized schemas of the relationship between attributes to a changing climate and the exacerbation of chronic diseases in order to encourage new research ventures that fill the void knowledge (D'amato et al., 2007; Shea, Truckner, Weber, & Peden, 2008; D'amato, Cecchi, D'amato, & Liccardi, 2010). For example, in the case of chronic respiratory diseases, extreme heat events are thought to directly affect plant phenology—such as germination, onset of greening, flowering and growing season length (W. Easterling et al., 2007; Kunkel, 2009; M. D. Schwartz, Ahas, & Aasa, 2006). The earlier onset of the flowering season and longer duration of exposure to pollen can result in wheezing, emergency room visits among asthmatics, and hay fever (US EPA, 2008). The Robert Wood Johnson Foundation projects that 158 million people will be living with chronic conditions by 2040 (University of California, Institute for Health & Aging, & Robert Wood Johnson Foundation, 1996). This is important because small increases in risk among the people with respiratory ailments will have significant impacts on morbidity rates and healthcare costs.

The purpose of this thesis is to develop empirical models to describe the relationship between exposure to extreme heat events and chronic diseases such as allergic rhinitis, commonly referred to as hay fever. This is important because prior studies have suggested that such extreme events will become more frequent, more intense, and longer lasting in

response to our changing climate. This was accomplished using a novel county-level *extreme heat event* exposure metric, which was linked to 17 years of hay fever data. These 17 years of data are used because they incorporate the years in which questions of interest were consistently collected by the National Center for Health Statistics (NCHS) for the National Health Interview Survey (NHIS). The central hypothesis of this dissertation is that exposure to extreme heat events contributes to the exacerbation of chronic respiratory diseases. The following specific aims are addressed in this dissertation:

1) Develop a location-specific exposure metric that captures individual's "exposure" to extreme heat events at a spatial scale that is consistent with publically available county-level health outcome data.

2) Characterize the US population in counties that have experienced *extreme heat events* and thus identify population groups likely to experience future events.

3) Develop an empirical model describing the association between exposure to *extreme heat events* (developed under Aim 1) and hay fever.

These research aims are addressed in three different manuscripts included in this dissertation, and the overall dissertation is organized into six chapters described as follows. Chapter 2 provides background information supporting the creation of a extreme heat exposure metric for use in environmental epidemiology studies. Chapter 3 is a manuscript titled "Frequency of Extreme Heat Event as a Surrogate Exposure Metric for Examining the Human Health Effects of Climate Change" published in PLOSOne in December 2015 (Romeo Upperman et al. 2015). Chapter 4 is a manuscript titled "Geographic and Demographic Variability in County Level Exposure to Extreme Heat Events Using National

Data Sets, 2010-2013" that describes the prevalence of chronic disease in counties that experience the most extreme heat events. Chapter 5 is a manuscript titled "Frequency of Extreme Heat Events and Hay Fever Prevalence in the United States, 1997-2013" that is pending submission in April 2016. This paper evaluated the risk hay fever prevalence that is associated with extreme heat events. This thesis ends in Chapter 6 with a summary of the poignant conclusions that can be drawn from this body of research, discussion future research directions, and data needs in order to continue research advancement.

Chapter 2: Background

This background was completed through a comprehensive review of published literature as of 2012.

Need for Extreme Heat Event Indicators

The major challenge in quantifying the impact of extreme weather events—ascribed to climate variability and change—on chronic disease outcomes is the lack of a suitable exposure metric that appropriately captures the subtle variability in temperature with requisite spatial resolution while incorporating the long-term climate instead of short-term weather phenomenon. Additionally, since chronic health outcomes are very diverse, the metric used to quantify "exposure" should have malleability. Some metrics throughout the published literature are a simple measure of meteorological parameters (i.e., precipitation, ambient temperature, apparent temperature, etc.) and others aim to address some aspect of climate change itself.

Research that has widely used daily maximum, minimum, and mean temperature to show the relationship between weather and human health outcomes. Also the available research has compared short periods of time prior to a time frame of interest, or, throughout a series of years. Moreover, the differences in measures used throughout publications do pose a significant challenge in synthesizing findings across studies and is limited for gauging the chronic human health effects. In view of these short comings, there is an urgent need for

exposure metrics that can quantify exposure to extreme weather events encountered under climate change that will enable researchers to investigate the impact of subtle changes in climatic patterns and adverse chronic health effects.

<u>*Approaches to Create a Climate Sensitive Extreme Heat Event Indicator*</u>

The measurement of exposure to extreme temperatures is cumbersome and difficult because temperature may vary due to an individual's location, specific exposure time, or behavior (Moya et al., 2011; Harrison, 2004; Paustenbach, 2000). Furthermore, even if all of the exposure factors were constant across a set of individuals, variability in response ensues because of variability in susceptibilities such as health status and genetic composition (Harrison, 2004; Paustenbach, 2000; Nieuwenhuijsen et al., 2003). There are likely differences in exposure that are due to geographic location. In the case of climate change, spatial variability (due to geographic location) to prolonged changes may vary between people that live within the city center versus rural areas, or between people that live in the western region versus those living in the southern region of the country. Generally, residents in urban areas may experience increased exposure to higher and more prolonged warm temperatures, due to the urban heat island effect (Tomlinson, Chapman, Thornes, & Baker, 2012). Similarly, the effects of extreme temperature will be different across populations warranting the necessity of studying the chronic effects across all populations exhaustibly.

Following the principles of exposure science, the assessment of exposure to extreme heat events for an individual may involve the estimation or measurement of the magnitude,

frequency, and duration of exposure to the temperature of an environment (Moya et al., 2011; Nieuwenhuijsen et al., 2003). In the case of temperature as an exposure, the total personal exposure will reflect the time spent in particular environments and at the respective temperatures during that timeframe (Basu & Samet, 2002). Exposure to ambient temperature can be measured both directly and indirectly (Basu & Samet, 2002). Direct exposure assessment is tabulated with personal exposure monitoring devices that are placed on the person of each individual for a given time period. Whereas, indirect assessments rely on information provided by questionnaires, time–activity diaries, and environmental measurements made in the respective environments (Basu & Samet, 2002). In the case of indirect exposure assessment to temperature, ambient temperature measured at certain spatial areas and then assigned to a subject can serve as a viable surrogate to determine heat exposure (Basu & Samet, 2002; Moya et al., 2011) and is a plausible metric for quantifying weather anomalies, not climate events. Nonetheless, accounting for all possible variable factors, because individual exposure is differential, requires personal monitoring for every subject in the study would be costly and infeasible. These reasons explain the inability of the conventional approaches of exposure assessment to capture the attributes of a changing climate.

Using personal monitoring such as infrared technology in large studies that aim to assess exposure among entire populations is impractical and increases the cost of individual sampling over the long period of time necessary in the case of climate change. Therefore, a cost effective and strategically desirable alternative to quantifying personal exposure measurements based on the proxy of ambient temperature is a common and widely accepted method (Moya et al., 2011). Acceptable approaches include assuming a single value for a

given exposure level—mean and median—and the quantification of exposure at high levels are often expressed in percentiles, 99th, 95th, and 90th (Moya et al., 2011). Future studies on climate change and human health can use the meteorological indicators that are computed at varying spatial and temporal resolutions to match the resolution of the health survey data. The use of a baseline to identify temperature anomalies is also necessary to accurately compare the variability of present exposure compared to historical norms. Additional focus should be placed on exposure to the frequencies of temperature anomalies and not solely variations in the mean temperature; since small changes in the mean of a variable result in larger changes in their extreme and will not accurately quantify the type of exposure that affects the chronic diseased population (T. Karl, 2008). Moreover, measuring personal exposure for long-term climate is impractical; therefore, future research will have to use ambient data.

Exposure metrics created from ambient data can be used to assess the positive and negative environmental determinants of health in order to identify areas for intervention and prevention. In addition, the metrics can be interchangeably used as important communication tools for making environmental health information available to stakeholders, including environmental health practitioners, partners, policy makers, and the general public. A place-based metric that has spatial coordinates and altitude is one essential attribute for an indicator that aims to measure the attributes of changing climate. Given the variability of weather from place-to-place, climate is also variable on a larger-scale, therefore, the measurement has to have a location identifier such as a Zip Code and/or FIPS code. The exposure measure would also need to be calculated both directly and indirectly to quantify the likelihood, magnitude, and route of exposure—all factors that are used to identify the populations at risk.

Chapter 3: Frequency of Extreme Heat Event as a Surrogate Exposure Metric for Examining the Human Health Effects of Climate Change

Acknowledgements

Abstract

Epidemiological investigation of the impact of climate change on human health, particularly chronic diseases, is hindered by the lack of exposure metrics that can be used as a marker of climate change that are compatible with health data. Here, we present a surrogate exposure metric created using a 30-year baseline (1960-1989) that allows users to quantify long-term changes in exposure to frequency of extreme heat events with near unabridged spatial coverage in a scale that is compatible with national/state health outcome data. We evaluate the exposure metric by decade, seasonality, area of the country, and its ability to

capture long-term changes in weather (climate), including natural climate modes. Our findings show that this generic exposure metric is potentially useful to monitor trends in the frequency of extreme heat events across varying regions because it captures long-term changes; is sensitive to the natural climate modes (e.g., El Niño-Southern Oscillation (ENSO) events); responds well to spatial variability, and; is amenable to spatial/temporal aggregation, making it useful for epidemiological studies.

Introduction

Climate change is expected to cause approximately 250,000 deaths per year between 2030 and 2050 with direct damage costs totaling 2-4 billion USD per year by 2030 (WHO, 2015). Chronic diseases, that may be exacerbated by climate change, disproportionately affect more vulnerable populations—including children, older adults, the socially isolated, and those with mental health issues (G Luber et al., 2014). Epidemiological investigation of the impact of climate change on human health is hindered by the differing temporal scale of the primary exposure of interest (climate change: decadal scale) and health outcomes that have varying sensitive time windows (days to years) in epidemiological studies that are based on a few years of data (Haines & McMichael, 1997; McMichael, 2001). There is a need for a set of suitable exposure metrics that can capture the subtle attributes of changing climate (e.g., frequency, duration, and intensity of extreme events that are expected to rise), and would allow for comparisons across different geographical locations and time periods. Such an exposure metric should have enough flexibility for temporal aggregation to meet the needs of different types of epidemiological studies. Furthermore, for national health studies, there is

a need for spatial compatibility, as meteorological data are often available at station level or a specific grid, whereas, national health data (e.g., behavioral risk factor surveillance system (BRFSS), Centers for Medicare and Medicaid Services (CMS), healthcare cost and utilization project (HCUP), CDC's Public Health Tracking data) are commonly available at zip code, county or state levels, often with a non-uniform spatial resolution.

Public health researchers are increasingly using temperature measures (maximum, minimum, heat index, and apparent temperature), and heat wave episodes to identify the acute health outcomes associated with weather. While the linkage of frequency and intensity of heat waves with acute health outcomes provide important information about long-term climate trends and health, heat waves are still relatively uncommon in most locations in the US ("Climate Communication | Heat Waves," n.d.; Gutowski et al., 2008), limiting the generalizability of study results across locations and over time. Moreover, heat wave measurements are designed to capture physical phenomenon: most common definitions include a certain number of consecutive days exceeding a location-specific threshold (Perkins & Alexander, 2013). Hence, by definition, heat wave does not capture isolated days where temperatures may have been high and, possibly, affecting health. Extreme heat events, on the contrary, will capture such isolated event.

For chronic health outcomes, the meaningful window of exposure may vary from months to several years. Not surprisingly, the relationships between climate change and chronic health outcomes are less understood than acute health outcomes, such as mortality or an emergency department (ED) visit, owing to the difficulty in defining appropriate exposure metrics that characterize underlying and long-term climate change at varying temporal and

spatial resolutions and that are appropriate for chronic health outcomes (Costello et al., 2009; Frumkin, Hess, Luber, Malilay, & McGeehin, 2008).

In this paper we describe an indicator designed to capture exposure to climate variability and change at a spatial scale that is consistent with publically available county-level health outcome data. This indicator, henceforth referred to as an exposure metric or "*extreme heat event*", captures positive anomaly derived using distributions of county- and month-specific climatology using a 30-year reference period (1960-1989). Although both extreme heat and extreme cold are important, this manuscript focuses exclusively on extreme heat because warmer temperature is associated with etiology of many infectious (higher rates of pathogen replication) as well as chronic diseases (increases in concentration of pollutant such as ozone). The exposure metric enables users to look at spatial and temporal changes over time using location specific baselines and serves as an additional resource to investigate the potential relationships between climate change and human health. We tabulate this exposure metric by time period, season, census division, and 2006 urban-rural classification, documenting how the exposure metric is amenable to spatial and temporal aggregation across factors that are known to be associated with variability in temperature. Finally, we evaluate this exposure metric by assessing its correspondence to the different phases of El Niño-Southern Oscillation (ENSO), a natural oscillation patterns that affect the weather phenomenon in the continental US and other parts of the world.

Methodology

Meteorological data were acquired from the National Climatic Data Center (NCDC) branch of the National Oceanic and Atmospheric Association (NOAA) that maintains the

world's largest archive of meteorological data from the past 150 years. The data used to develop the metric are archived in two broad categories: DSI-3200 and DSI-3210. The DSI-3210 network is a smaller subset of DSI-3200 stations that collect several additional weather variables besides temperature and precipitation (e.g., barometric pressure, wind speed, wind direction), but has a poor spatial coverage. Therefore we chose the DSI-3200 database that contains approximately 8,000 active stations, with up to 23,000 stations for various years. The stations cover all 50 states plus Puerto Rico, US Virgin Islands and Pacific Island territories. Each dataset underwent quality control measures through both automated and manual edits by the NCDC, which consisted of internal consistency checks and evaluation against adjacent stations (U.S. NOAA, 2016). To develop and evaluate the metric, we used climate data for the 48 contiguous states and the District of Columbia. The county boundaries used for all years were defined by the 2000 Federal Processing Standards (FIPS) codes.

For *Urban-Rural* status, we used the 2006 county level NCHS Urban-Rural Classification Scheme. The 2006 NCHS urban-rural classification scheme was developed for use in studying and monitoring health disparities across the urban-rural continuum. The 2006 scheme consists of four levels of metropolitan counties (large central, large fringe, medium and small metro) and two levels of nonmetropolitan counties (micropolitan and non-core). This scheme is based on the December 2005 Office of Management and Budget delineations of county classification, Metropolitan Statistical Area (MSA) and principal city, MSA population-size cut points, and classification rules formulated by NCHS (Ingram & Franco, 2012). In congruence with other studies (Barnett, Strogatz, Armstrong, & Wing, 1996; Ingram & Gillum, 1989; Knobeloch & Imm, 2007; Savitz, Stein, Ye, Kellerman, & Silverman, 2011; Savitz, Danilack, Engel, Elston, & Lipkind, 2014; Rossen, Khan, &

Warner, 2013), we opted to use this relatively recent classification scheme for the complete 51 years of data (1960-2010). However, because the 2006 scheme is not as accurate for earlier time periods as it is for more recent time periods (Ingram & Franco, 2012), we also tabulated the extreme heat events using a 1990 urban rural classification ("Data Access - Urban Rural Classification Scheme for Counties," n.d.) to conduct a sensitivity analysis.

The census division classification used in this study consists of groups of contiguous states as defined by the US Bureau of the Census (as: New England – CT, ME, MA, NH, RI, VT; Middle Atlantic – NJ, NY, PA; South Atlantic – DE, DC, FL, GA, MD, NC, SC, VA, WV; East South Central – AL, KY, MS, TN; West South Central –AR, LA, OK, TX; East North Central- Il, IN, MI, OH, WI; West North Central – IA, KS, MN, MO, NE, ND, SD; Mountain – AZ, CO, ID, MT, NV, NM, UT, WY; and Pacific – CA, WA, OR). Seasons were defined as: Winter – December, January, and February; Spring – March, April, and May; Summer – June, July, and August; and Autumn – September, October, and November.

ENSO indicator data—Oceanic Niño Index (ONI)—were obtained from the National Oceanic and Atmospheric Administration (NOAA), National Weather Service Climate Prediction Center. The Climate Prediction Center is a coordinated program that monitors, assesses and predicts climate phenomena and their linkage to weather events. Warm and cold episodes are based on a threshold of +/- 0.5°C for the Oceanic Niño Index (ONI)—a 3-month running median anomalies in the sea surface temperature in the Niño 3.4 region (5°N-5°S, 120°-170°W). The threshold values are based on centered 30-year base periods and are updated every 5 years. El Niño and La Niña episodes are defined when the threshold is met for a minimum of 5 consecutive over-lapping 3-month periods. This ENSO indices data were

used to categorize the months as La Niña, El Niño and Neutral months ("Climate Prediction Center - Global ENSO Temperature Linear Regressions Information," n.d.).

Extreme Heat Events

We assigned daily maximum temperature for all counties using the following rules: 1) average of daily maximum temperatures from all stations within the county, 2) if no station data were available from the county, the daily maximum temperature used was from the closest available station within a 20 km radius of the county boundary, and 3) a missing value was assigned if the previous two criteria were not met. In the complete dataset of observations, 99% of all counties had less than 1.5% missing data and there was no spatial pattern to the location of missing data. To compute extreme heat events, we used 1960-1989 as a *reference period*. This time period was chosen because the weather data were recorded consistently with current methods of NCDC measurement and the 30-year time period is generally accepted as the epoch (per the IPCC report) to represent the standardization of a climate regime (Solomon et al., 2007). For each county within the continental US, we compiled daily maximum temperatures (T_{max}) by calendar months (e.g., Jan 1st to Jan 31st). For the 30-year reference period with no missing data, the total number of values would be approximately 900 observations (30 years by ~30 days in a month) for each county and calendar month. Using this distribution of daily T_{max}, we calculated the month specific 95th percentile thresholds for each county. Using this cutoff value, we computed the calendar month and year specific extreme heat events for each county as:

$$E_{jk} = \sum_i I_{ijk} \; where \; I_{ijk} = \begin{cases} 1, & if \; T_{ijk-max} > T_{jk-95} \\ 0, & if \; T_{ijk-max} \leq T_{jk-95} \end{cases}$$

1)

where E_{jk} is the total number of extreme heat events for county j in calendar

month k ; $T_{ijk-max}$ is the daily maximum temperature (T_{max}) in county j for day i of calendar

month k; T_{jk-95} is the 95th percentile T_{max} value for county j for calendar month k for the

1960-1989 period; and I_{ijk} represents the indicator of whether or not $T_{ijk-max}$ is greater

than T_{jk-95}.

Evaluation

The units of analysis for our evaluation of the indicator were the annual and monthly

total number of events; these are the metrics that are referenced throughout the paper. All

covariates of interest were defined at the county, year and month levels. We computed

descriptive statistics of the spatial (2006 urban-rural classification, Census division) and

temporal (seasonal, decadal) characteristics. Additional descriptive statistics were calculated

for ENSO periods. After checking the normality assumption, comparisons of means were

performed using one-way analysis of variance (ANOVA) and post-hoc Tukey's honest

significant difference (HSD) tests (Abdi & Williams, 2010). We further investigated the

temporal and spatial dependency of the exposure metric using negative binomial generalized

estimation equation (GEE) models (Byers, Allore, Gill, & Peduzzi, 2003; Greene, 1994). The

year and monthly total extreme heat event anomalies in each county were modeled as a

function of seasonality, ENSO, 2006 urban-rural classification, and census division. We

identified findings as statistically significant with a p-value <0.05. Most statistical analyses were performed using SAS 9.3 (SAS Institute, Cary, NC). In particular, PROC GENMOD was used to fit the negative binomial GEE models using a first-order autoregressive covariance structure. The exponent of the estimated regression coefficients was calculated to estimate the percent change in the mean response (number of extreme heat events) associated with changes in the covariates. Regression maps were created using ArcGIS 10 (esri, Redlands, CA) to display the county level regression parameter estimate for the impact of ENSO on the number of extreme heat events after adjusting for seasonal and 2006 urban-rural classification.

Results

The final extreme heat event dataset consisted of 3,109 counties over 51 years (1960 to 2010) located in the continental US (

Table 1). In general, we observed significantly higher frequency of extreme heat events during the 1990s and 2000s compared to the reference period (1960-1989). This trend was consistent across season, 2006 urban-rural classifications and most Census divisions, with few exceptions. Within the two time periods (1990s and 2000s) the large central metro areas observed higher number extreme heat events compared to small metro and micropolitan areas. We also found an increasing trend in extreme heat events that varied considerably by area of the country, with the most pronounced trend observed for the New England, Middle Atlantic and Mountain divisions with lesser increases in the East and West North Central divisions (Figure 1). Interactions between time periods and census divisions, ENSO, and seasons were found to be highly significant and justified the stratification of the analysis by time period.

Table 1. County-level annual frequency of extreme heat events (mean (standard deviation, SD)), excluding Alaska and Hawaii.

	No. Counties	Time Period		
		1960-1989	1990-1999	2000-2010
Contiguous United States	3109	15.2 (1.2)	16.5 (6.2)[+]	18. 2 (7.7)[+]
Season				
Autumn	3109	3.7 (0.4)	4.1 (1.7)[+]	4.9 (2.0)[+]
Winter	3109	3.9 (0.4)	5.1 (1.6)[+]	4.5 (1.6)[+]
Spring	3109	3.8 (0.4)	3.6 (1.6)[‡]	4.4 (2.2)[+]
Summer	3109	3.6 (0.4)	3.8 (2.7)[+]	4.4 (3.4)[+]
County Urban-Rural Classification				
Large central metro	63	15.2 (1.4)	20.9 (6.2)[+]	19.7 (6.8)[+]
Large fringe metro	354	15.1 (1.4)	17.8 (6.2)[+]	18.5 (8.0)[+]
Medium metro	329	15.2 (1.2)	17.7 (7.4)[+]	19.2 (8.8)[+]
Small metro	340	15.0 (1.2)	17.0 (6.2)[+]	18.0 (9.0)[+]
Micropolitan	688	15.1 (1.2)	16.1 (6.3)[+]	18.0 (7.3)[+]
Non-core	1335	15.2 (1.2)	15.8 (5.6)[+]	18.0 (7.3)[+]
Census Division				
New England	67	16.3 (0.5)	19.9 (5.8)[+]	21.6 (8.4)[+]
Middle Atlantic	150	16.1 (0.5)	21.4 (5.2)[+]	21.7 (6.0)[+]
South Atlantic	589	14.5 (1.4)	18.3 (7.8)[+]	17.9 (10.6)[+]
East South Central	364	14.7 (1.0)	14.6 (5.0)	17.2 (6.2)[+]
West South Central	470	14.1 (1.2)	15.7 (6.7)[+]	18.4 (7.8)[+]
East North Central	437	15.6 (1.0)	16.3 (3.6)[+]	17.4 (4.4)[+]
West North Central	618	15.9 (0.8)	14.2 (3.3)[‡]	16.7 (4.2)[+]
Mountain	281	15.4 (0.8)	18.0 (8.1)[+]	21.5 (11.0)[+]
Pacific	133	15.8 (0.7)	18.2 (5.7)[+]	18.2 (6.1)[+]

[+]Significantly higher than the baseline (1960-1989) period (Pvalue <0.05).
[‡] Significantly lower than the baseline (1960-1989) period (Pvalue <0.05)

Figure 1.Temporal trend in extreme heat events across census division for the 1960-2010 periods.
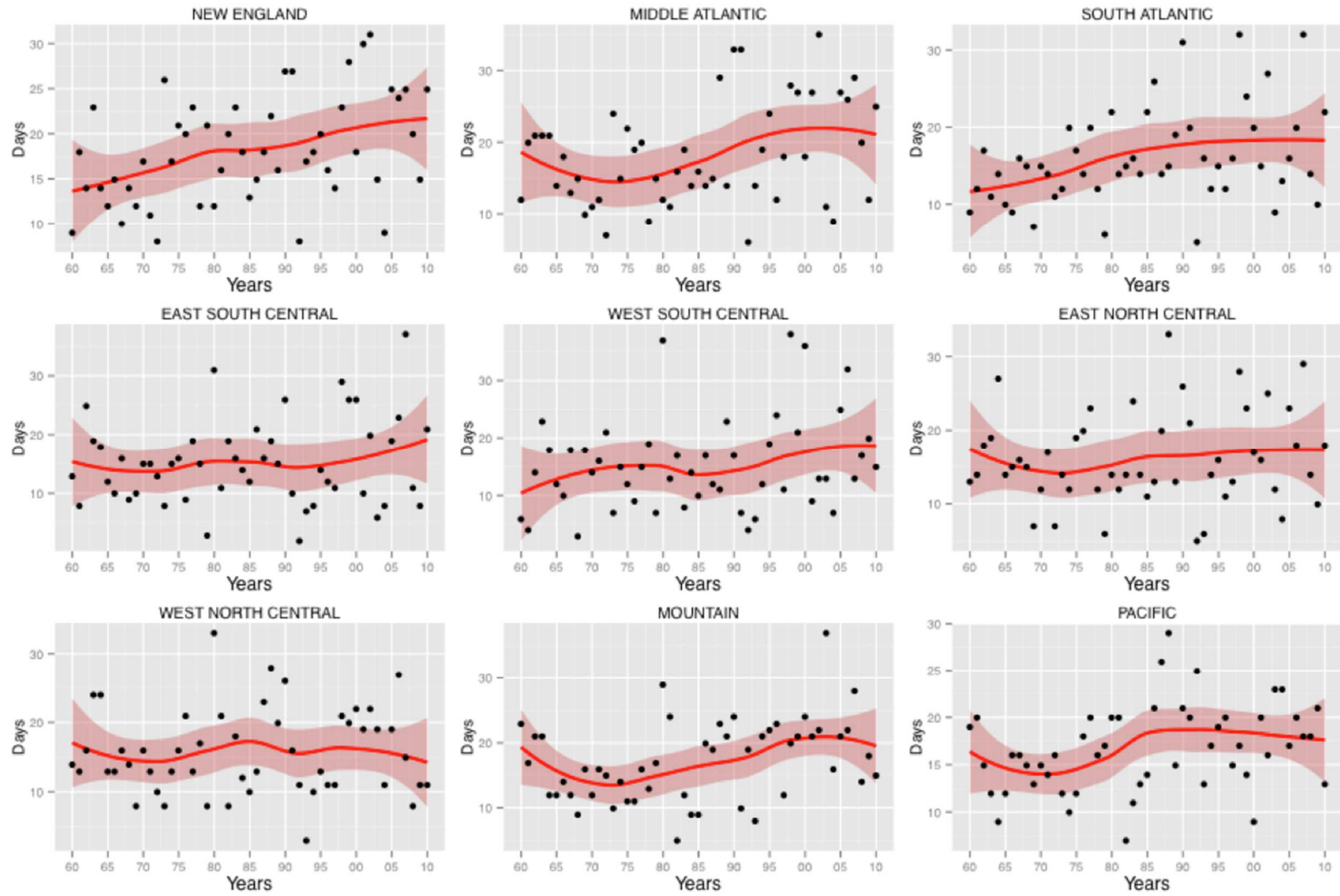
Table 2 provides the frequency of extreme heat events stratified by phases of ENSO for the 3 time periods (1960-1989, 1990-1999, and 2000-2010), across season, 2006 urban rural classification, and census division. In general, La Niña periods were characterized by significantly higher frequency of extreme heat events while El Niño periods showed significantly lower frequency of extreme heat events for all seasons, 2006 urban-rural classifications, and most census divisions when compared to the ENSO Neutral years. A noted exception to this pattern appeared in the 1990-1999 when the frequency of extreme heat events during El Niño were not lower than those observed during the ENSO neutral period, with some census divisions such as New England, Middle Atlantic, East/West North Central, Mountain and Pacific regions observing higher frequency of extreme heat events. Exceptions were also noted for winter of 1990s and 2000s, as well as summer of 1990s.

Table 3 presents the results from three negative binomial GEE models of monthly frequency of extreme heat events stratified by three time periods: 1960-1989, 1990-1999, and 2000-2010. Compared to ENSO neutral periods, El Niño periods were associated with significantly fewer events at the national scale, ranging from 9% fewer (estimated e^β =0.91, p<0.001) during the 1990s to 24% fewer (estimated e^β =0.76, p<0.001) during the 2000s, after adjusting for season, 2006 urban-rural classification and census division (Table 3). By comparison, La Niña periods were associated with as much as 29% higher frequency of extreme heat events at the national level (estimated e^β = 1.29, p<0.001 for 1990-1999 & 2000-2010). For the 1990s and 2000s, counties that were large metropolitan areas based on the 2006 urban-rural classification tended to have a higher frequency of extreme heat events (estimated e^β >1.0) compared to non-core counties; although, this urban-rural difference was statistically significant only during the 1990s (p<0.05). Compared to New England, the other

census divisions of the country had significantly fewer differences in the extreme heat events

for each of the three time periods (estimated e^β for all census divisions <1.0), with the

exception of the Middle Atlantic division.

Table 2. County-level annual frequency of extreme heat events (mean (SD)) overall and by season, urbanization and Census Division, across decades and ENSO periods.

	No. Counties	Time Periods								
		1960-1989 (Baseline)			1990-1999			2000-2010		
		Neutral	La Niña	El Niño	Neutral	La Niña	El Niño	Neutral	La Niña	El Niño
Contiguous US	3109	15.1 (2.3)	17.8 (3.0)[+]	12.6 (2.1)[‡]	14.7 (6.2)	22.8 (11.0)[+]	15.3(7.3)[+]	17.8 (8.9)	22.3 (9.1)[+]	13.0 (7.6)[‡]
Season										
Autumn	3109	16.0 (3.8)	16.0 (4.3)	13.0 (3.1)[‡]	13.9 (7.2)	21.6 (11.4)[+]	14.1 (8.6)	19.4 (12.2)	24.6 (11.0)[+]	11.8 (6.9)[‡]
Winter	3109	15.5 (2.6)	16.2 (3.8)[+]	14.1 (4.9)[‡]	15.6 (7.1)	9.0 (11.1)[‡]	13.7 (9.0)[‡]	18.2 (9.1)	15.1 (12.0)[‡]	19.0 (13.0)
Spring	3109	13.6 (3.2)	19.0 (6.8)[+]	12.1 (4.3)[‡]	12.5 (10.0)	26.7 (24.3)[+]	9.8 (11.4)[‡]	15.6 (14.5)	25.4 (23.1)[+]	14.8 (13.8)
Summer	3109	15.6 (3.7)	20.1 (6.0)[+]	11.5 (3.4)[‡]	16.4 (8.3)	27.2 (11.5)[+]	22.2 (8.9)[+]	18.7 (8.6)	21.1 (8.9)[+]	9.4 (8.1)[‡]
County Urban-Rural Classification										
Large central metro	63	15.0 (2.1)	18.0 (2.9)[+]	12.7 (2.1)[‡]	19.8 (6.7)	25.0 (10.0)[+]	20.0 (8.1)	19.6 (7.8)	22.8 (7.7)[+]	15.2 (7.4)[‡]
Large fringe metro	354	14.6 (2.3)	18.7 (3.0)[+]	12.3 (2.0)[‡]	15.9 (5.8)	23.1 (11.2)[+]	17.6 (8.0)[+]	17.6 (9.0)	23.3 (9.2)[+]	13.1 (7.2)[‡]
Medium metro	329	15.0 (2.1)	18.2 (3.1)[+]	12.6 (2.1)[‡]	16.2 (7.8)	24.1 (11.8)[+]	15.7 (7.9)	18.2 (9.6)	23.8 (10.1)[+]	14.2 (8.7)[‡]
Small metro	340	14.8 (2.3)	17.9 (3.1)[+]	12.6 (2.2)[‡]	15.0 (5.8)	23.4 (12.3)[+]	15.9 (7.4)	17.6 (10.2)	22.0 (10.2)[+]	12.7 (8.7)[‡]
Micropolitan	688	15.1 (2.3)	17.7 (3.1)[+]	12.6 (2.2)[‡]	14.2 (6.3)	22.5 (11.0)[+]	14.7 (7.2)	17.5 (8.4)	22.2 (8.8)[+]	12.8 (7.4)[‡]
Non-core	1335	15.4 (2.3)	17.5 (2.8)[+]	12.6 (2.1)[‡]	13.9 (5.7)	22.4 (10.3)[+]	14.5 (6.6)	17.9 (8.6)	21.7 (8.6)[+]	12.7 (7.3)[‡]
Census Division										
New England	67	15.4 (0.9)	18.9 (1.9)[+]	15.4 (1.4)	17.9 (5.2)	22.7 (8.4)[+]	21.5 (6.9)[+]	22.1 (9.5)	24.1 (8.7)[+]	16.9 (6.5)[‡]
Middle Atlantic	150	15.0 (1.1)	20.5 (1.6)[+]	13.6 (1.1)[‡]	18.9 (4.8)	23.4 (8.3)[+]	24.4 (6.2)[+]	21.9 (6.8)	25.6 (6.6)[+]	15.5 (5.0)[‡]
South Atlantic	589	13.8 (2.0)	19.3 (2.4)[+]	11.2 (1.9)[‡]	17.4 (7.7)	24.2 (12.8)[+]	15.4 (9.2)[‡]	16.3 (11.1)	22.6 (12.0)[+]	14.2 (9.6)[‡]
East South Central	364	14.5 (1.9)	17.9 (3.0)[+]	11.9 (2.0)[‡]	12.0 (5.0)	25.4 (9.7)[+]	11.3 (5.3)	13.3 (5.9)	26.5 (8.9)[+]	11.0 (5.3)[‡]
West South Central	470	13.7 (2.2)	14.9 (2.2)[+]	14.1 (2.2)[+]	13.0 (6.4)	30.3 (14.0)[+]	9.9 (4.9)[‡]	15.6 (7.8)	25.1 (9.0)[+]	13.7 (8.3)[‡]
East North Central	437	14.6 (1.8)	20.1 (1.9)[+]	12.9 (1.7)[‡]	14.2 (3.7)	19.9 (6.1)[+]	17.5 (4.1)[+]	17.6 (6.0)	21.6 (4.9)[+]	10.8 (4.4)[‡]
West North Central	618	16.7 (1.5)	18.0 (1.9)[+]	12.3 (1.5)[‡]	12.4 (3.2)	17.5 (5.6)[+]	15.2 (4.4)[+]	17.8 (5.7)	19.7 (4.8)[+]	10.2 (4.0)[‡]
Mountain	281	17.6 (1.9)	14.9 (2.5)[‡]	11.8 (1.8)[‡]	16.1 (7.8)	23.1 (12.0)[+]	17.8 (8.1)[+]	24.7 (12.3)	20.0 (11.2)[‡]	17.3 (11.4)[‡]
Pacific	133	17.2 (1.4)	15.0 (2.3)[‡]	14.0 (2.3)[‡]	18.1 (6.6)	16.6 (7.0)[‡]	19.6 (5.7)[+]	22.9 (7.4)	13.7 (7.1)[‡]	15.9 (6.6)[‡]

[+]Significantly higher than the ENSO Neutral period (P$_{value}$ <0.05).

[‡] Significantly lower than the ENSO Neutral period (P$_{value}$ <0.05)

Table 3. Relative percent change in extreme heat events, by time period, for the continental United States, excluding Alaska and Hawaii.

Factors	1960-1989	1990-1999	2000-2010
ENSO			
Neutral		Reference	
El Niño	0.85‡	0.91‡	0.76‡
La Niña	1.17‡	1.29‡	1.29‡
Season			
Autumn		Reference	
Winter	1.04‡	1.28‡	0.88
Spring	1.03‡	1.01	1.00
Summer	0.98‡	0.91‡	1.00
Urbanization			
Large central metro	0.99	1.22‡	1.05
Large fringe metro	0.99	1.06‡	1.01
Medium metro	1.00	1.06‡	1.04**
Micropolitan	0.99	0.99	0.99
Small metro	0.99	1.04**	1.00
Non-core		Reference	
Census Division			
New England		Reference	
Middle Atlantic	0.98	1.07*	1.00
South Atlantic	0.88‡	0.92‡	0.83‡
East South Central	0.90‡	0.72‡	0.77‡
West South Central	0.87‡	0.77‡	0.84‡
East North Central	0.95‡	0.82‡	0.80‡
West North Central	0.97**	0.72‡	0.78‡
Mountain	0.94‡	0.91‡	0.99
Pacific	0.97	0.92**	0.85‡

Note: *p<.05 ** p<.005 ‡ p<.001
The coefficients are from the negative binomial GEE model described in the text.

The analysis for continental US were further broken down by Census division (Table 4). Overall, the Census division results agreed with the country level analysis presented in Table 3 with few noted exceptions. For example, compared to ENSO neutral periods, El Niño years were associated with significantly lower frequency of extreme heat events across census divisions during 1960-1989 and 2000-2010 period. However, during 1990-1999, El Niño years were associated with increased frequency of extreme heat events compared to ENSO neutral years in several Census divisions (New England, Mid Atlantic and the Pacific divisions). La Niña periods were associated with a higher frequency of extreme heat events than ENSO neutral periods across most Census divisions; with the largest effect (75%) observed for the West South Central division during the 1990-1999 time periods. An exception to this pattern was in the Pacific division, where the La Niña period was associated with 15% lower frequency of extreme heat events compared to the ENSO neutral period during 2000-2010 (estimated e^{β}=0.85, p<0.001). Spatial heterogeneity in these findings was further investigated using the county level regression coefficients (Figure 2). The findings presented in Figure 2 are in agreement with the results of the divisional model (Table 4), but the finer county level resolution allows for the identification of additional counties whose results were masked in the divisional level analysis (e.g., selected counties in TX and ME experienced larger percent changes in frequency of extreme heat events during El Niño periods). We conducted sensitivity analysis using 1990 NCHS Urban-Rural Classification Scheme for Counties instead of the 2006 schemes; however this did not change our conclusions.

Figure 2. Relative percent change in monthly total extreme heat events for La Niña and El Niño months in 1960-2010 compared to ENSO Neutral months, adjusted for seasonal and 2006 land-use classification type.
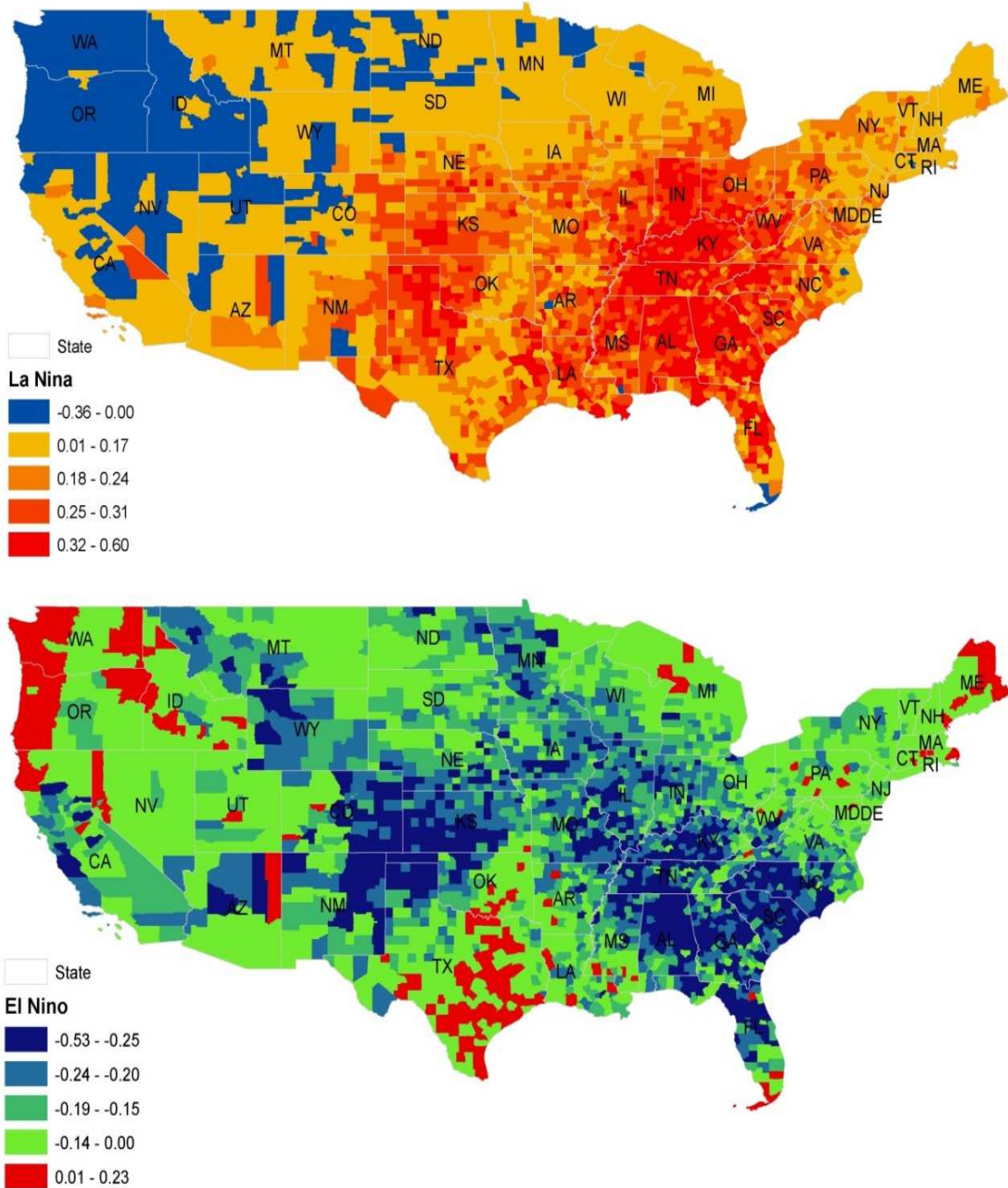
Table 4. Relative percent change in count of extreme heat events, by Census Division (excluding Alaska and Hawaii).

Period	Factors	New England	Middle Atlantic	South Atlantic	East South Central	West South Central	East North Central	West North Central	Mountain	Pacific
1960-1989 (Baseline)										
	ENSO									
	Neutral[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	El Niño	0.94**	0.86‡	0.8‡	0.82‡	1.02**	0.82‡	0.81‡	0.81‡	0.90‡
	La Niña	1.13‡	1.24‡	1.31‡	1.23‡	1.04‡	1.27‡	1.15‡	1.04‡	0.99
	Season									
	Autumn[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Winter	1.02	1.06**	1.05‡	1.04**	1.05‡	1.06‡	1.03**	1.01	0.96*
	Spring	1.05	1.08‡	1.06‡	1.03*	1.04*	1.05‡	1.01	1.02	1.01
	Summer	0.96	0.95*	1.03**	1.00	0.98	0.95‡	0.97**	0.92‡	0.97
	Urbanization									
	Large central metro	1.00	1.02	1.00	0.95	0.95	0.97	0.95	0.98	1.00
	Large fringe metro	1.01	1.00	1.02	0.98	0.94*	0.97	1.01	0.98	0.98
	Medium metro	0.99	1.01	1.01	0.98	1.01	1.01	1.00	0.99	1.00
	Micropolitan	1.00	1.00	1.00	0.99	1.00	0.99	0.99	0.98	0.99
	Small metro	0.99	0.99	1.01	0.98	0.97	0.97	1.01	0.98	0.98
	Non-core[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1990-1999										
	ENSO									
	Neutral[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	El Niño	1.10**	1.15‡	0.89‡	0.81‡	0.71‡	1.01	1.01	1.00	1.08‡
	La Niña	1.07*	1.04	1.23‡	1.57‡	1.75‡	1.19‡	1.12‡	1.17‡	0.91
	Season									
	Autumn[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Winter	1.63‡	1.68‡	1.29‡	1.13‡	1.30‡	1.64‡	1.32‡	0.87‡	0.86‡
	Spring	1.16**	1.20‡	1.04*	0.94*	1.32‡	1.11‡	0.80‡	0.86‡	0.94
	Summer	1.2‡	1.29‡	1.21‡	0.87‡	1.17‡	0.89‡	0.42‡	0.76‡	0.84‡
	Urbanization									
	Large central metro	1.05	1.14*	1.39‡	1.31*	1.34**	1.13	1.01	1.2*	1.15*
	Large fringe metro	1.11	1.03	1.15‡	1.08	1.09	0.99	0.93	0.99	1.08
	Medium metro	1.08	1.02	1.11**	1.10*	0.90*	1.06*	0.97	1.33‡	1.00
	Micropolitan	0.89*	1.06	0.9**	1.03	0.97	1.00	1.00	1.05	1.09*
	Small metro	0.91	1.07	1.02	1.07	1.08*	1.03	0.99	1.05	1.09

Non-core[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

2000-2010

ENSO									
Neutral[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
El Niño	0.82‡	0.74‡	0.79‡	0.70‡	0.87‡	0.69‡	0.69‡	0.9‡	0.97
La Niña	1.20‡	1.27‡	1.27‡	1.65‡	1.37‡	1.30‡	1.21‡	1.02	0.85‡
Season									
Autumn[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Winter	1.14‡	1.21‡	0.96*	0.8‡	1.07‡	0.85‡	0.82‡	0.64‡	0.71‡
Spring	1.25‡	1.09**	1.01	0.96*	1.39‡	0.82‡	0.72‡	1.15‡	1.30‡
Summer	1.27‡	1.35‡	1.25‡	1.16‡	1.18‡	0.70‡	0.54‡	1.22‡	1.05
Urbanization									
Large central metro	0.98	1.13*	1.01	1.01	1.28*	0.91	1.00	0.85*	1.19**
Large fringe metro	1.10	1.08	1.02	1.04	1.04	0.91**	0.89**	1.27‡	0.98
Medium metro	1.02	1.10*	1.01	0.98	1.03	0.97	0.99	1.45‡	1.11
Micropolitan	0.94	1.08	0.91**	1.03	0.97	0.99	0.98	1.07*	1.09
Small metro	0.93	1.14*	0.98	1.01	1.06	0.93**	0.96	0.93*	1.12*
Non-core[#]	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

*p<.05   ** p<.005   ‡ p<.001   [#]Reference Category

Discussion

We developed a generic surrogate exposure metric (extreme heat events) based on climatology that has a broad spatial coverage for the contiguous US with a county level geographic resolution. This exposure metric can correspond to county-level end-points, including many health outcome data such as Behavioral Risk Factor Surveillance System (BRFSS), Centers for Medicare and Medicaid Services (CMS), Healthcare Cost and Utilization Project (HCUP), CDC's Public Health Tracking data and others. We assessed the exposure metric for its ability to capture the ENSO events, while controlling for other temporal, seasonal, divisional, and urban-rural classification influences. The results showed the ability of the exposure metric to capture salient features of climate variability and change (long term change in the frequency of extreme heat events) including the effect of natural variability such as El Niño-Southern Oscillation (ENSO) patterns that have distinct heterogeneous effects across geographical regions. We also demonstrated how the exposure metric could provide flexibility in spatial and temporal aggregation of exposure—an ideal attribute for epidemiological studies. Our county level approach enables a straightforward linkage of the exposure metric to many publicly available national health outcome data collected at the county level, facilitating investigations of the possible impacts of climate change on chronic health outcomes (Akinbami, Lynch, Parker, & Woodruff, 2010; Parker, Akinbami, & Woodruff, 2009; Parker, Kravets, & Woodruff, 2008).

The threshold method we used has been used for defining extremes in studies looking at temperature and precipitation extremes; however, exceedences have not been quantified on a county level for the entire US (Zhai & Pan, 2003; Alexander et al., 2006; Beniston, 2009;

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Hao, AghaKouchak, & Phillips, 2013). The metric we developed captured the local impacts of ENSO. This oscillation between warm (El Niño) and cold (La Niña) conditions in the equatorial Pacific Ocean can alter weather patterns and latent heat release into the atmosphere. Such changes lead to widespread remodeling in atmospheric circulation patterns far removed from the Pacific Ocean (McPhaden, Zebiak, & Glantz, 2006). ENSO events have been linked to droughts, rainfall and the alteration of temperature and sunlight availability across the globe (Nils C. Stenseth et al., 2002; Nils Chr Stenseth et al., 2003; Wolff et al., 2011). In North America, the statistically significant relationships between ENSO and seasonal temperature extremes have occurred mostly in winter (Wolter, Dole, & Smith, 1999). In some divisions and times of year, El Niño and La Niña conditions modify the probabilities of very warm or very cold seasons (Wolter et al., 1999). The effects of climate change can manifest through natural forcing systems such as ENSO (Corti, Molteni, & Palmer, 1999). Globally, ENSO impacts are largely symmetric. The warm state (El Niño) is generally associated with increased precipitation and cooler temperature anomalies and the cold state (La Niña) changes the sign of the anomalies, to a decrease in precipitation and increase in temperature ("Climate Prediction Center - Global ENSO Temperature Linear Regressions Information," n.d.). The known temperature-related impacts of ENSO were expressed in the results of our analysis. Though it should be noted that the surface expressions of the ENSO anomalies in the tropical Pacific are alleged to have changed since 2000 (albeit with similar onsets (Ramesh & Murtugudde, 2012)) and the interconnectedness of these events (teleconnections) over the US appear to have changed (Larkin & Harrison, 2005). On a continental scale, we found that La Niña periods were consistently associated with an increase in extreme heat events and El Niño periods led to a decrease in extreme heat

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events. In certain region of the country, the magnitude as well as direction of the associations between ENSO periods and extreme heat events differed from this trend. In this context, the effects of climate change may be local for health endpoints that may manifest via local weather changes (Murtugudde, 2009; Patz, Campbell-Lendrum, Holloway, & Foley, 2005).

Land use factors are an important contributor to divisional climate. Urbanization affects divisional climates through changes in surface energy and water balance. The change in land use can alter the effects of net radiation through the division of energy into sensible and latent heat, and the partitioning of precipitation into soil water, evapotranspiration and runoff (Ramesh & Murtugudde, 2012). The urban "heat island" effect is an extreme case of how land use modifies divisional climate (Ganeshan, Murtugudde, & Imhoff, n.d.; George Luber & McGeehin, 2008). Previous studies have suggested that a major portion of the reduction in diurnal temperature range observed during the last several decades to urbanization and other land use changes (Kalnay & Cai, 2003; Zhou et al., 2004). In congruence with available literature, using the 2006 urban-rural classification, we found that more urbanized areas generally experienced relatively high proportional change in extreme heat events compared to the less urbanized areas. However, this pattern was not consistent across Census divisions and was only present during the latter 2 decades. These results may be due, in part, to the classification scheme used in this analysis. This scheme was developed based on the 2006 census statistics and applied in our study for time periods that span more than 4 decades prior. However, sensitivity analyses using the 1990 census scheme produced similar results.

More attention has been paid to the effects of extreme heat events in the summer and spring particularly because these changes can have an impact on biotic factors (e.g., pollen) and industrial air pollution along with heat waves (Cayan, Dettinger, Kammerdiener, Caprio, & Peterson, 2001; Leung & Gustafson, 2005; Menzel & Fabian, 1999; Westerling, Hidalgo, Cayan, & Swetnam, 2006; L. H. Ziska & Beggs, 2012). Using the metric, we identified larger differences in extreme heat events occurring during the winter, spring and summer months on a continental scale. Yet, at the divisional level, the patterns differ considerably, with the New England and Middle Atlantic divisions experiencing the largest differences in extreme heat events during winter and lowest level during autumn. In the Mountain and Pacific divisions, the largest differences in extreme heat events were observed during spring and lowest level observed during winter season.

Overall, the exposure metric captured subtle variability across geographic division, season, and urban-rural categorization. More importantly, the exposure metric was sensitive to large-scale phenomenon such as ENSO that are known to govern local weather patterns. As stated previously, the flexibility of this exposure metric lends itself to epidemiological studies of both infectious and chronic diseases. For example, in a recent study investigating the link between changing climate and Salmonellosis, Jiang et al. (2015) showed that the frequency of extreme heat and precipitation event was directly related to increased risk of Salmonellosis in Maryland, and that the risk was more pronounced among the coastal communities compared to inland communities (Jiang et al., 2015). Since the precise date of disease onset in the Jiang et al. (2015) was not known, the authors linked monthly count of Salmonellosis with number of extreme heat and precipitation event on the same month and employed negative binomial regression for the statistical analysis. In the instances where the

precise date of onset is known (e.g., hospitalization for asthma, or stroke), investigators can use case-crossover approach looking at presence/absence of extreme events in the case period compared to control period with adequate lag structure that are determined based on current knowledge about the disease etiology. In addition, the frequency of extreme heat events can also be used to investigate the spatio-temporal pattern of vector borne diseases (e.g., Lyme disease) that are sensitive to temperature changes. Previous studies have shown that the frequency as well as intensity of extreme events will continue to rise in the near future (D. R. Easterling et al., 2000; McCarthy, 2001). The exposure metric we have presented in this manuscript allows investigators to document how increases in the frequency of extreme heat event impacts human health.

Conclusion

We report on the development of a novel temperature-related exposure metric and quantify its ability to capture small and large changes in climatic variability across the US and over time. Findings from this study suggest that natural modes of forcing, seasonality, urban-rural classification, and division of country have an impact on the number extreme heat events recorded. We observed that the increases in frequency of extreme heat events differ across the geographical region and time periods. Likewise, we observed higher frequency of extreme heat events during La Niña period and lower frequencies during the El Niño. At regional level, exceptions to this trend were noted for El Niño years in selected geographical areas. This county level exposure metric generated based on location specific climatology data are versatile and can be easily extended to developing metrics for different

time periods and county based geographic aggregations. To facilitate research in this area, we will make this exposure metric freely available to potential users through a web portal.

Chapter 4: Geographic and Demographic Variability in County Level Exposure to Extreme Heat Events Using National Data Sets, 2010-2013

Abstract

The aims of this paper are to characterize the US population in counties that have experienced extreme heat events and thus identify population groups likely to experience future events. This study evaluated exposure to anomalous hot weather, *"extreme heat events"* (EHEs), across the United States from 2010-2013. Approximately 120,000 adults were eligible for this study through the National Health Interview Survey. Climate data from the National Climatic Data Center was used to create the exposure metric (number of days with temperature above 95th percentile value for monthly baseline from 1960-1989) by county of residence. We described the respondents in the top quartile and top decile of exposure. The results show similar demographic patterns and prevalence of chronic diseases for areas with higher numbers of annual extreme heat events compared to the general population. The areas affected by extreme heat events have a variety of vulnerable populations including women of childbearing age, people who are poor, and seniors. The percentages of chronic health conditions in top decile for suburban and rural areas were larger compared to the population in the top quartile. These measures show that decision makers should look at chronic health outcomes along with the demographic and geographic

compositions of their jurisdictions in order to prepare for changes that may occur and in order to properly plan for the expansion of public health responses.

Introduction

Studies suggest that certain populations may experience illness or death from exposure to high temperature days (Semenza et al., 1996a; Dhainaut, Claessens, Ginsburg, & Riou, 2003; Braga, Zanobetti, & Schwartz, 2002; Vanhems, Gambotti, & Fabry, 2003; Lim, Hong, & Kim, 2012; Anderson et al., 2013; Bobb, Obermeyer, Wang, & Dominici, 2014). Other small-scale investigations show that living alone, low socioeconomic status, lack of air conditioning, high body mass index, and some chronic diseases (i.e., diabetes (J. Schwartz, 2005), chronic obstructive pulmonary diseases (COPD) (Monteiro, Carvalho, Oliveira, & Sousa, 2012), depression and psychiatric disorders (Stafoggia et al., 2006), heart condition (J. Schwartz, Samet, & Patz, 2004), and cerebrovascular disease (Fuhrmann, Sugg, Konrad, & Waller, 2016)) are associated with the highest vulnerability of death or hospitalization due to exposure to high temperature days (Naughton et al., 2002; Davis et al., 2003; O'Neill, Zanobetti, & Schwartz, 2003; Stafoggia et al., 2006; Kovats & Hajat, 2008; Yang et al., 2016; Semenza et al., 1996b; Curriero et al., 2002). For hypertension, the clinical impact during heat exposure is unknown and its ubiquity as a chronic disease is cause for further investigation(Kenny, Yardley, Brown, Sigal, & Jay, 2010). Additionally, physiological susceptibility to extreme heat events can arise for those on medication for a chronic illness (Bouchama & Knochel, 2002; Sharma & Hoopes, 2003; Maughan, Shirreffs, & Watson, 2007; Childs, Jones, & Tyrrell, 2008; Kenny et al., 2010; Health Canada, 2011) and there is a

likely risk of preterm delivery during extreme heat events for pregnant women (Lajinian, Hudson, Applewhite, Feldman, & Minkoff, 1997; Strand, Barnett, & Tong, 2012). In the US, about one half of all adults—117 million people—have one or more chronic health conditions (CDC, 2016), and an estimated 26.2% of adults suffer from a diagnosable mental disorder in a given year (The Kim Foundation, 2014). Overall, treating chronic diseases accounts for 86% of the US health care costs (CDC, 2015).

An increasing body of literature suggests that the frequency, intensity, and duration of extreme heat events will continue to rise in the near future (Edenhofer et al., 2014; Field, 2012; G Luber et al., 2014). This is a public health concern because extreme heat events may worsen chronic disease morbidity or create more favorable conditions for other exposures that pose health risks, such as air pollution and pollen levels (NRDC, 2014). From a vulnerability perspective (demographic and health status), for the entire US, it is unknown whether adults living in areas that are experiencing the most impact from extreme heat days differ from those who are living in other areas. Presently and into the future, extreme heat events are an added concern for governments and public health responders because of their planning and prevention aims; typically, plans to prevent the onset of a health outcome, control the worsening of pre-existing illnesses. Local public health responders have the new challenge of strengthening their adaptive capacity for the health impacts of future excessive heat events (Health Canada, 2011; Marinucci & Luber, 2011; Hess, McDowell, & Luber, 2012). A range of public health interventions—on health education about prevention and identification of heat stress—is likely needed to address the risk that extreme heat events pose. Moreover, these responses to extreme heat events will likely vary by geography and demographics.

Given the challenges of adapting the public health response to future excessive heat events, the goal of this study is to characterize the demographic and health characteristics of US adults living in counties that have experienced relatively higher numbers of extreme heat days. This study used data from the 2010-2013 NHIS, a representative sample of the civilian, noninstitutionalized population of the US, merged with weather data obtained from the National Climatic Data Center (NCDC) to answer the following questions: 2) what is the proportion of adults living in counties that have experienced a high number of extreme heat days have chronic health conditions?; and, 2) do profiles of adult exposure to extreme heat days differ by geography (coastal vs. non-coastal, region, urban rural classification)? As adults with chronic diseases may require different services during extreme heat days, this study may help local planners with an improved understanding of likely resource needs when preparing for heat events.

Methodology

Meteorological Data

Daily weather data was obtained from two systems within the National Climatic Data Center (NCDC) (National Climatic Data Center, n.d.) for the 1960-2013 period, including daily maximum temperature (TMAX). Data for the years 1960-2010 were extracted from the DSI-3200 data set. The DSI-3200 data set was discontinued in 2010 and replaced with the Global Historical Climatology Network (GHCN) data set that consists of additional stations

that are not part of the original DSI-3200 network. Therefore, for the 2011-2013 period, we identified the DSI3200 stations within the GHCN network using unique station identification and extracted information from this subset of stations to maintain consistency.

Exposure Metric

Using daily TMAX for the 1960-1989 reference period, county-specific 30-year baselines for each calendar month were computed. Based on the distribution of this data, we identified the 95th percentile values of TMAX, referred to as Extreme Temperature Threshold 95th percentile (ETT_{95}) as previously described(Romeo Upperman et al., 2015). Daily TMAX values for each county were compared to their respective calendar-month-specific ETT_{95} and assigned a value of "1" if they exceeded the thresholds, and "0" otherwise. The ETT_{95} exceedences —referred to as *extreme heat events (EHE_{95})*— were summed over each calendar month for each county during the 2010-2013 period which the NHIS chronic disease prevalence data was available (Romeo Upperman et al., 2015).

National Health Interview Survey (NHIS), 2010-2013 data

We combined NHIS data for 2010-2013 for this analysis. The NHIS is a nationally representative cross-sectional household interview survey of the civilian non-institutionalized population of the United States that has been conducted since 1957, although the survey design and questionnaire have changed over time (U.S. CDC, 2015). The NHIS is conducted

continuously throughout the year. In 2010-2013, about 40,000 households were sampled each year, with some households having multiple families. In each family, a sample adult is selected for detailed questions on health and health care (U.S. CDC, 2015). During the 4-year period, the response rate for the household component of the survey ranged from 75.7% to 82.0% and the unconditional sample adult response rates ranged from 60.8% to 66.3%.

We used restricted-use NHIS files geocoded to county FIPS. These files are available through the NCHS Research Data Center (RDC). There are 137,008 sample adults 18 years of age or older in the 2010-2013 NHIS. A total of 17,299 (12.63%) of respondents were excluded from the analysis based on residence in a county that had less than 12 months of extreme heat data, had at least one non-valid month for the development of the baseline, resided outside the 48 contiguous states at the time of the, and had having missing data for any of the variables used in the analysis.

Psychological distress was measured in the NHIS using the Kessler-6 (K6) scale (Weissman, Pratt, Miller, & Parker, 2015). The K6 measures psychological distress with six questions (e.g., How often did you feel nervous? How often did you feel hopeless? How often did you feel sad that nothing could cheer you up? How often did you feel restless or fidgety? How often did you feel that every thing was an effort? How often did you feel worthless?) scored on a five-point Likert scale ranging from "none of the time" to "all of the time." Respondents with a score of 13 or greater on the K6 scale are identified as having serious psychological distress (SPD). Only participants who answered all six questions were included.

Heart disease is based on self-reported responses to survey questions about whether the respondent had ever been told by a doctor or other health professional that they had coronary heart disease, angina (angina pectoris), a heart attack (myocardial infarction), and any other kind of heart disease or heart condition. *Stroke* is based on responses to the question: "In the past 12 months have you been told by a doctor other health professional that you had a stroke?" *Hypertension* is based on responses to the question: "In the past 12 months, have you ever been told by a doctor or other health professional that you had hypertension or high blood pressure?" *Diabetes* is based on self-reported responses to survey questions about whether the respondents have ever been told by a doctor or other health professional that they had diabetes or sugar diabetes. *Chronic Obstructive Pulmonary Disease* (COPD) is based on separate self-reported responses to survey questions about whether the respondents had been told by a doctor or other health professional that they had chronic bronchitis in the past 12 months or ever had emphysema.

Demographic characteristics considered included age (18-34, 35-49, 50-64, 65+ years), race/ethnicity (Hispanic, non-Hispanic black, non-Hispanic white, all other races and ethnicities), sex (female, male), education level (less than high school/GED, high school/GED, some college, Bachelor's degree, Graduate degree), family income relative to poverty threshold (US Census Bureau, n.d.) (less than 100%, 100% to less than 200%, 200% to less than 400%, 400% or above the poverty threshold), and body mass index (BMI) is calculated using the formula weight in kilograms/height in meters (underweight=<18.5; normal weight=18.5 -<25; Overweight = BMI 25 - <30; Obese = BMI $\geq$ 30). Race/ethnicity was coded based on responses to separate questions for race and ethnicity; available responses for these variables differed across survey years. Hispanics were assigned to the

Hispanic category, regardless of reported race; among non-Hispanics, multiple race responses were assigned to non-Hispanic black or non-Hispanic white, if provided as a primary race, and to the all other races and ethnicities category when primary race was not provided. We used the NHIS multiple-imputed income data to assign poverty status level to records with missing values (percent missing ranged from 4.50% to 10.01% over 1997-2013) using NCHS-recommended methods (NCHS, 2010).

We also included a county-level geographical covariate describing urban-rural classification with four urban and two rural categories (urban: large central, large fringe, medium and small metro; rural: micropolitan and non-core) (Deborah D Ingram, 2012). Large central metro counties are counties in Metropolitan Statistical Areas (MSAs) of 1 million or more population that contain the largest principal city of the MSA, are contained within the MSA's largest principal city, or contain at least 250,000 residents of any principal city. Large fringe metro counties are counties in MSAs of 1 million or more population that do not qualify as large central metro. They are considered to be "suburbs" of large cities. Medium and small metro counties are counties in MSAs of 250,000–999,999 and less than 250,000 population, respectively. Micropolitan and noncore counties are nonmetropolitan counties that are not in MSAs. Coastal classification is adpated from the National Oceanic and Atmospheric Administration's list of coastal counties (U.S. NOAA / U.S. Census, n.d.).

Evaluation

Weighted percent was calculated in SUDAAN which accounts for the complex clustered sample design of the NHIS (RTI International, 2014). The quartiles and deciles for exposure were based on the distribution of extreme heat events for all 3,109 counties in the continental United States. Approximate, rather than actual, quartiles by season were used for comparability of cut-points across season. Maps were created using ArcGIS 10 (esri, Redlands, CA) to display the annual average number of extreme heat events.

Linkage of Extreme Heat Events and NHIS

Extreme heat event values were assigned to individual NHIS records, from 2010 to 2013, for each survey year by the cumulative number of *extreme heat events* for the county of residence in a 12-month window, which include the month of interview and the preceding 11 months. We looked at the characteristics of counties that had 25 or more (top quartile) and 38 or more (top decile) annual extreme heat events.

Demographics of Population with Top Quartile Annual Extreme Heat Events

Close to one half (*41.6%*) of the US population resided in locations in the highest quartile of annual exposure of extreme heat events (see Table 5). The demographic distribution for those living in counties in the highest quartile of exposure for annual extreme heat events was similar to the demographics for the entire population of the continental United States. In the highest exposed counties, 66.1% were non-Hispanic white, 15.8% were Hispanic, 12.6% were non-Hispanic black and 5.5% were all other races and ethnicities. Among young adults (18-34 years of age), in counties with the highest annual exposure to annual extreme heat events, psychological distress was the leading chronic disease (Appendix B). Among adults 35 years and older, hypertension was the leading heat-sensitive chronic illness.

The proportion of US adults living in the top decile of annual exposure to extreme heat was 18.8%. The demographic prevalence was similar to the entire study population and those of the top quartile of annual extreme heat events.

Geographic Location of Top Quartile Annual Extreme Heat Events

Nationally, those living in counties with the largest number of extreme heat events were disproportionality living in Southern states (40%), followed by the Northeast (21.4%),

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Midwest (21.3%), and West (16.8%). Urban areas (large central metro, 30.49%; large fringe metro 24.2%; and, medium metro, 21.4%) made up the majority of counties that have 25 or more annual extreme heat events in the past year (see Table 6). Moreover, while noncoastal counties were the majority of high exposed counties (51.7%), the proportion of coastal counties was also substantial (48.3%). Over the four-year period, 1320 (42.5%) counties averaged 25 or more EHE$_{95}$ (Figure 3).

Preexisting Heat-Related Chronic Health Conditions of Populations with Top Quartile Annual Extreme Heat Events

Among the counties with the largest annual exposure to extreme heat events, prevalence of preexisting chronic health conditions were similar to proportions nationally (Table 7). People living in counties with the top quartile of annual exposure of extreme heat events had hypertension (29.5%), heart disease (14.1%), and serious psychological distress (13.5%) at similar prevalence to levels nationally. The proportion of adults with diabetes, COPD and stroke were similar for those in the largest exposed group compared to the rest of the population.

Among those living in counties with 25 or more (top quartile) extreme heat events annually, the South had a disproportionately high proportion of people with pre-existing chronic health conditions (42.0%). The South also had the largest proportion of people with hypertension, heart disease, diabetes, and stroke among people living in counties with 25 or more annual extreme heat events (see Table 8). However, the West had the largest

proportions of people with serious physiological distress (15.61%) among those living in counties that have 25 more extreme heat events annually.

Table 8 shows the distribution of chronic health outcomes among the largest exposed quartile by the urban/rural classification of the county. While the majority of people with chronic health outcomes resided in urban areas, the proportions of chronic diseases were largest in the Noncore, Micropolitan and Small Metro. The proportions of chronic diseases were also higher in non-coastal counties, but not by much (see Table 8).

Comparison of Characteristics Between the Populations with Top Quartile (25+) Versus Top Decile (38+) Annual Extreme Heat Days

A total of 18.8% of the population lives in counties in top decile of annual extreme heat events (Table 5). The population characteristics of those living in counties in top decile of annual extreme heat events were also similar to the general population. However, these places may need to be more consistently prepared for extreme heat events. Again, the South made up the larger population portion of those exposed to the largest decile of heat events. One new revelation is that the nonmetropolitan and coastal areas made up a larger portion of the exposed population in the top decile of extreme heat events.

Table 5. Percent by demographic characteristics overall and in counties in top quartile of heat events, National Health Interview Survey 2010-2013.

	All (n=119,709; 100%[1])		Top Quartile (n=51,570; 41.6%[1])	Top Decile (n=23,549; 18.8%[1])
	N	%[1]	%(SE)[1]	%(SE)[1]
Race/Ethnicity				
non-Hispanic white	71,717	68	66.1 (0.5)	64.5 (0.7)
non-Hispanic black	18,612	11.8	12.6 (0.4)	12.8 (0.5)
Hispanic	21,313	14.5	15.8 (0.3)	17.5 (0.5)
All other races and ethnicities	8,067	5.75	5.5 (0.2)	5.1 (0.2)
Age (years)				
18-34	34,374	31.2	31.2 (0.4)	31.4 (0.6)
35-49	30,689	26.4	26.4 (0.3)	26.3 (0.4)
50-64	29,760	25.2	25.3 (0.3)	25 (0.4)
65 and older	24,886	17.2	17.1 (0.3)	17.3 (0.4)
Sex				
Male	54,268	49.2	49.1 (0.3)	48.8 (0.4)
Female	65,441	50.8	50.9 (0.3)	51.2 (0.4)
Marital status				
Singe	67,303	46.5	47 (0.4)	46.7 (0.6)
Married	52,406	53.5	53 (0.4)	53.3 (0.6)
Women of Childbearing Age				
No	35,956	52.9	53.1(0.4)	52.9(0.6)
Yes	29,485	47.2	46.9 (0.4)	47.1 (0.4)
Body Mass Index				
Underweight	2,171	1.74	1.7 (0.1)	1.7 (0.1)
Normal weight	41,949	35.5	35 (0.3)	34.3 (0.4)
Overweight	41,425	34.7	34.6 (0.3)	34.9 (0.4)
Obese	34,164	28.1	28.8 (0.3)	29.1 (0.4)
Education				
<High school/GED	16,494	11.7	11.9 (0.2)	12.3 (0.3)
High school/GED	33,928	28.6	28.8 (0.3)	28.7 (0.5)
Some college	36,408	31	30.8 (0.3)	31.4 (0.4)
Bachelor's degree	21,102	18.6	18.5 (0.3)	18.1 (0.4)
Graduate degree	11,777	10.1	10 (0.3)	9.5 (0.3)
Poverty status				
<100% FPL	21,530	13.5	13.8 (0.3)	13.9 (0.4)
100-<200% FPL	25,477	19.1	19.1 (0.3)	20 (0.4)
200-<400% FPL	35,053	30.1	30.1 (0.3)	30.1 (0.4)
>400% FPL	37,649	37.3	37.1 (0.5)	36.1 (0.6)

[1] Weighted Percent: All percentages were weighted using NHIS survey weights.
Body Mass Index (BMI) is calculated using the formula weight in kilograms/height in meters: underweight=<18.5; normal weight=18.5 -<25; Overweight = BMI 25 - <30; Obese = BMI $\geq$ 30.
Note: FLP=federal poverty level
Women of Childbearing Age: women between the ages of 18 and 45.

Annual Top Quartile=25 days or more EHE_{95}
Annual Top Decile=38 days or more EHE_{95}

Table 6. Percent by residential characteristics overall and in counties in top quartile of heat event, National Health Interview Survey 2010-2013.

	All (n=119,709; 100%[1])		Top Quartile (n=51,570; 41.6%[1])	Top Decile (n=23,549; 18.8%[1])
	N	%[1]	% (SE)[1]	% (SE)[1]
Region				
Northeast	19,630	17.7	21.4 (0.5)	15.2 (0.7)
Midwest	26,084	23.2	21.3 (0.6)	23.2 (1.1)
South	44,278	36.3	40.6 (0.8)	48.6 (1.3)
West	29,717	22.7	16.8 (0.6)	13.1 (1)
Urban-rural classification				
Large central metro	37,694	29.4	30.5 (0.7)	29.2 (1)
Large fringe metro	24,031	24.6	24.2 (0.8)	21.5 (1.1)
Medium metro	24,548	20.8	21.4 (1.1)	22.7 (1.6)
Small metro	12,274	9.7	8.8 (0.9)	9.2 (1.3)
Micropolitan	12,017	9.2	9.5 (1.1)	10.9 (1.6)
Non-core	9,145	6.3	5.5 (0.8)	6.5 (1.1)
Coastal classification				
Noncoastal	60,605	49.3	51.7 (1)	59 (1.4)
Coastal	59,104	50.7	48.3 (1)	41 (1.4)

[1] Weighted Percent: All percentages were weighted using NHIS survey weights.
SE: Standard Error
Annual Top Quartile=25 days or more EHE$_{95}$ | Annual Top Decile=38 days or more EHE$_{95}$

Table 7. Percent by residential characteristics overall and in counties in top quartile of heat event, National Health Interview Survey 2010-2013.

Chronic Disease	All (n=119,709; 100%[1])		Top Quartile (n=51,570; 41.6%[1])	Top Decile (n=23,549; 18.8%[1])
	N	%[1]	% (SE)[1]	% (SE)[1]
SPD	17,821	14.1	13.5 (0.2)	13.4 (0.3)
Heart disease	18,255	14.2	14.1 (0.2)	14.6 (0.3)
Stroke	3,722	2.7	2.7 (0.1)	2.8 (0.1)
Hypertension	38,245	29.3	29.5 (0.3)	29.7 (0.4)
Diabetes	12,278	9.2	9.4 (0.2)	9.4 (0.3)
COPD	6,506	5.1	5.1 (0.1)	5.1 (0.2)

[1] Weighted Percent: All percentages were weighted using NHIS survey weights.
SE: Standard Error | SPD: Serious psychological distress | COPD: Chronic Obstructive Pulmonary Disease
Annual Top Quartile=25 days or more EHE_{95} | Annual Top Decile=38 days or more EHE_{95}

Table 8. Percent by chronic health outcomes among population residing in counties with quartile top and top decile of annual extreme heat events with National Health Interview Survey 2010-2013.

Annual	SPD	Heart Disease	Stroke	Hypertension	Diabetes	COPD
Top Quartile				%(SE)[1]		
Region						
Northeast	12.3 (0.4)	12.9 (0.4)	2.3 (0.2)	27.3 (0.6)	8.3 (0.3)	4.3 (0.3)
Midwest	14.3 (0.5)	15.1 (0.5)	2.6 (0.2)	29.5 (0.7)	9 (0.4)	5.7 (0.3)
South	12.9 (0.3)	15.5 (0.4)	3.1 (0.2)	32.2 (0.5)	10.6 (0.3)	5.7 (0.2)
West	15.6 (0.5)	11.3 (0.3)	2.3 (0.2)	25.8 (0.6)	8 (0.4)	3.7 (0.3)
Urban-rural classification						
Large central metro	13.5 (0.4)	11.7 (0.3)	2.2 (0.1)	26.4 (0.5)	8.6 (0.3)	4.5 (0.2)
Large fringe metro	12.8 (0.5)	13.7 (0.4)	2.3 (0.2)	28 (0.6)	8.2 (0.4)	4.5 (0.3)
Medium metro	13.5 (0.4)	14.2 (0.4)	2.6 (0.2)	29.3 (0.6)	9.2 (0.3)	4.8 (0.2)
Small metro	13.6 (0.8)	16.2 (0.9)	3.5 (0.3)	32.3 (1.2)	10.3 (0.6)	6.1 (0.5)
Micropolitan	14.2 (0.7)	18 (0.8)	3.4 (0.4)	35.7 (1.1)	11.8 (0.5)	6.7 (0.5)
Non-core	15.6 (1)	19.9 (1.1)	4.5 (0.5)	38.8 (1.2)	12.8 (0.7)	8 (0.7)
Coastal classification						
Non-coastal	14.1 (0.3)	15.5 (0.3)	3.1 (0.1)	31 (0.4)	10 (0.3)	5.8 (0.2)
Coastal	12.9 (0.3)	12.6 (0.3)	2.2 (0.1)	27.9 (0.4)	8.7 (0.2)	4.3 (0.2)
Annual	**SPD**	**Heart Disease**	**Stroke**	**Hypertension**	**Diabetes**	**COPD**
Top Decile				%(SE)[1]		
Region						
Northeast	11.3 (0.7)	12.2 (0.8)	2 (0.3)	25.6 (1)	7.8 (0.5)	4.2 (0.6)
Midwest	14.3 (0.6)	14.9 (0.8)	2.4 (0.3)	28.1 (0.9)	8.4 (0.6)	5.6 (0.5)
South	13.3 (0.5)	15.8 (0.5)	3.2 (0.2)	32.5 (0.7)	10.8 (0.4)	5.6 (0.3)
West	14.9 (0.7)	12.2 (0.6)	2.8 (0.4)	26.9 (0.8)	7.9 (0.6)	3.6 (0.4)
Urban-rural classification						
Large central metro	13.5 (0.5)	11.9 (0.5)	2.1 (0.2)	26.5 (0.7)	8.6 (0.5)	4.5 (0.3)
Large fringe metro	12.4 (0.8)	14.1 (0.8)	2.5 (0.3)	28.1 (1)	8.2 (0.7)	4.4 (0.5)
Medium metro	13.2 (0.6)	14.6 (0.5)	3 (0.2)	29.3 (0.9)	10 (0.5)	5.2 (0.4)
Small metro	13.4 (1)	16.2 (1.3)	3.1 (0.4)	31.6 (1.5)	8.9 (0.7)	5.8 (0.6)
Micropolitan	14.3 (0.8)	18.5 (1.1)	3.7 (0.6)	35.4 (1.6)	10.9 (0.8)	6.4 (0.7)
Non-core	16.2 (1.2)	19.6 (1.2)	4.5 (0.6)	38.9 (1.2)	12.8 (1)	7.5 (0.9)
Coastal classification						
Non-coastal	14.1 (0.4)	15.6 (0.5)	3.2 (0.2)	31 (0.6)	9.6 (0.4)	5.7 (0.3)
Coastal	12.5 (0.5)	13 (0.5)	2.3 (0.2)	27.8 (0.7)	9.1 (0.4)	4.3 (0.3)

[1] Weighted Percent: All percentages were weighted using NHIS survey weights.
SE: Standard Error | SPD: Serious psychological distress | COPD: Chronic Obstructive Pulmonary Disease
Annual Top Quartile=25 days or more EHE$_{95}$ | Annual Top Decile=38 days or more EHE$_{95}$

Figure 3. 2010-2014 annual average extreme heat events (EHE$_{95}$) for counties in the continental US
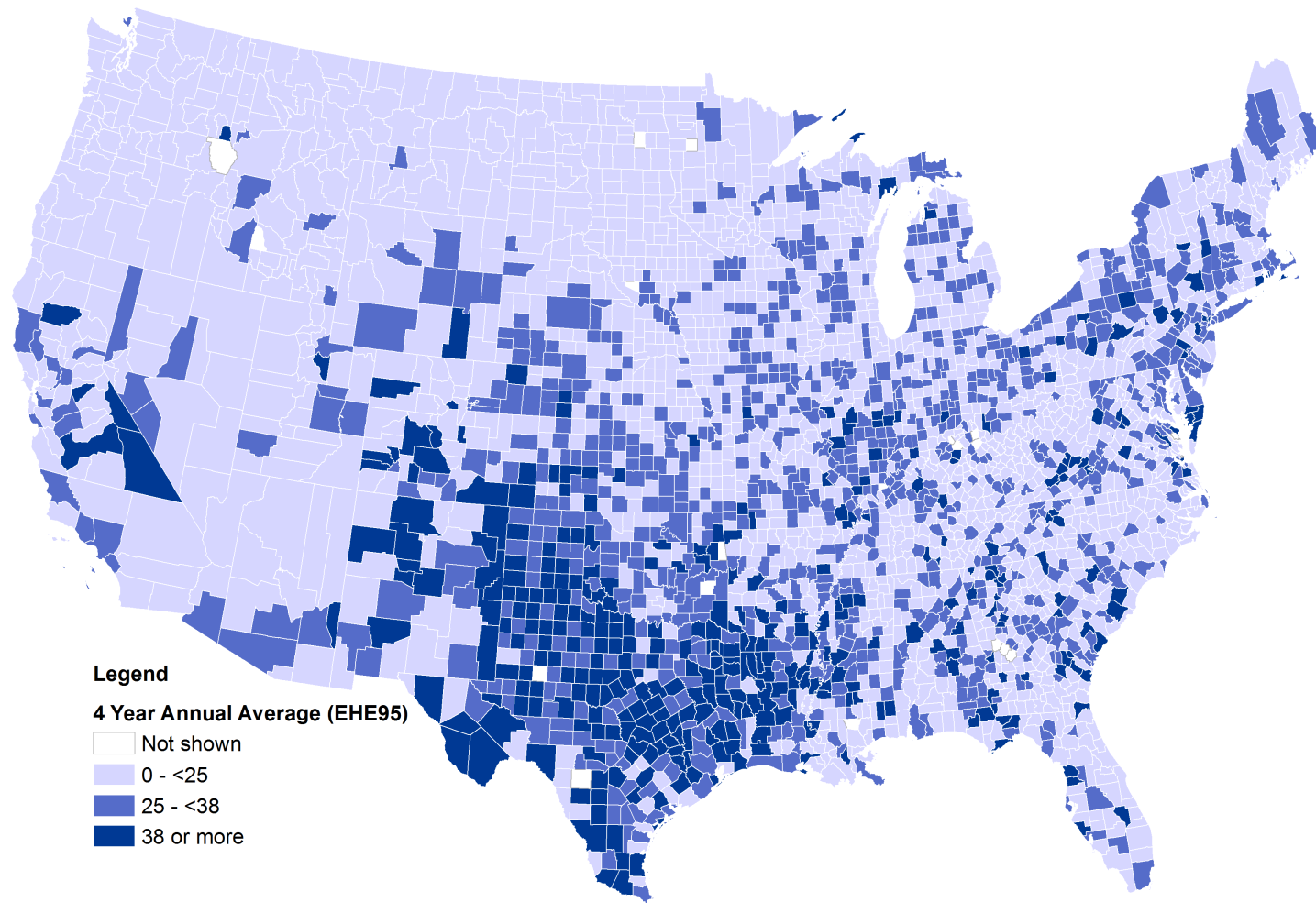
Not shown counties were excluded because of incomplete monthly data for the 4-year period.

EHE$_{95}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Discussion

The results show that demographic patterns for areas affected by extreme heat events are similar to the overall population. This is not surprising, however, given that 42% of the population lived in the counties with the top quartile of heat events in 2010-2013. The areas most affected by extreme heat events have a variety of vulnerable populations including women of childbearing age, people who are poor, and seniors. Also, there seems to be similar health patterns for areas affected by the largest numbers of extreme heat days when compared to the general population. Areas that are affected by extreme heat events show to have people with a variety of chronic conditions that could likely be exacerbated by heat, including COP, heart disease, hypertension, SPD, stroke, and diabetes. This remains true for all regions, levels of urbanizations, and coastal classifications.

Past work on heat-related deaths from 1999-2003 showed that 70% of deaths that occurred were among persons with chronic ischemic heart disease, 3.2% on those with endocrine, nutritional and metabolic disorders, 3.1% on those respiratory disorders, and 2.4% on persons with metal and behavioral disorders (U.S. CDC, 2006). During this same time period, exposure to heat was higher for men, and persons 65 years of age and older (U.S. CDC, 2006). The associations between cardiovascular disease, diabetes, respiratory diseases and adverse events related to heat events are well established. In light of our results, there is a suggested need for additional investigations on hypertension, mental distress, stroke, and COPD (U.S. CDC, 2006; Wainwright, Buchanan, Mainzer, Parrish, & Sinks, 1999). Nationally, we see that the majority of high exposed populations do live in the southern counties. These southern counties are also leaders for the highest prevalence of heat-

susceptible chronic diseases. Moreover, many of these southern counties also have some of the most rural populations that tend to lack access to care. Nationally, even though rural areas consist of about 20% of the United States' population, less than 10% of physicians practice in these areas, and the majority of first responders in these areas are volunteers (Bull, Krout, Rathbone-McCuan, & Shreffler, 2001; Stanford University School of Medicine, 2016).

This paper aims to be descriptive; we make no inference on the relationship between the exposure and each respective health outcome or the demographic and geographic variables. Instead, we focus on assessing the distribution of characteristics, at the population-level, that can describe those in the largest exposed groups. We used the most recent years of data because they are the most relevant data that can inform national agencies on how to deal and prioritize resource allocation. Also, the county level measure of temperature to assign possible extreme heat exposure is another limitation of this study. Due to limited availability of data we are not able to account for the likelihood that people are protected by adequate housing and proper cooling measures or are likely spending most of their time indoors, rather than outdoors. There are limitations that abound due to the sampling structure of the NHIS, which typically only changes its sample design approximately every 10 years. The questionnaire of the NHIS is subject to recall bias, however, many of the chronic health outcomes used are not likely to have such heavy bias as they reference diagnosis by a medical professional.

Despite these caveats, we have described the national exposure of extreme heat events for the continental US. The results could mean that with the widespread exposure, that preparedness is needed in many places (e.g., 42% of the population live in areas with

frequent extreme heat events, coastal and noncoastal areas are involved, and rural areas may have more vulnerable people). The analysis suggests that future studies are needed for hypertension and psychological distress, which is missing in the national dialogue. These results may be used to initiate planning and preparedness of national and local public health entities.

Chapter 5: Frequency of Extreme Heat Events and Hay Fever Prevalence in the United States, 1997-2013

Abstract

Increasing temperature affects concentration as well as seasonality of pollen, and may impact allergic diseases. Hay fever affects 7.5% of US adults and costs ~$11.2 billion/year in medical expenses. It remains unclear if extreme heat events—expected to increase in frequency and intensity—are associated with hay fever burden. To investigate this association, we analyzed the National Health Interview Survey data (1997-2013) together with extreme heat event data, defined as days when the daily maximum temperature (TMAX) exceeded the 95th percentile values of TMAX for a 30-year (1960-1989) reference period. We show that adults in the highest quartile of exposure to extreme heat events had a 7% increased odds of hay fever compared to those in the lowest quartile. Our data suggest that exposure to extreme heat events increases risk of hay fever among US adults.

Introduction

Hay fever affects 17.6 million (7.5%) adults in the United States (US) annually (Blackwell, Lucas, & Clarke, 2014) and can have an impact on their quality of life (Schoenwetter, Dupclay, Appajosyula, Botteman, & Pashos, 2004). In 2005, hay fever

medical expenses amounted to $11.2 billion (The Lancet, 2008; Blaiss, 2010). Hay fever—a form of allergic rhinitis—is a chronic condition caused by an inflammatory response to allergens, and is characterized by nasal congestion, clear rhinorrhea (runny nose), sneezing, and itching (Bousquet et al., 2008; US EPA, 2008; Seidman et al., 2015; "WHO | Allergic rhinitis and sinusitis," n.d.). The causes and triggers of hay fever are both outdoor (e.g., mold or trees, grass and weed pollens) and indoor allergens (e.g., animal dander, indoor mold, and house dust mites) (Bousquet et al., 2008; US EPA, 2008; Seidman et al., 2015; "WHO | Allergic rhinitis and sinusitis," n.d.). Previous studies have linked rise ambient temperature with increases in respiratory diseases (Braga et al., 2002; Basu & Samet, 2002; Lin et al., 2009; Michelozzi et al., 2009; Bhattacharyya, 2009; P. J. Beggs, 2010; Lim et al., 2012; D'amato et al., 2010), but no studies to date have investigated the role of extreme heat events on respiratory outcomes such as hay fever on a national scale.

An increasing body of literature suggests that the frequency, intensity, and duration of extreme weather events will continue to rise in the near future (Edenhofer et al., 2014; Field, 2012; G Luber et al., 2014). The potential impact of these increases on allergic diseases is a growing concern that has not been empirically assessed for the contiguous US. Prior studies have shown that increases in temperature and CO_2 concentrations affect plant phenology as well as concentration, distribution and allerginicity of pollen (Bortenschlager & Bortenschlager, 2005; Emberlin, Smith, Close, & Adams-Groom, 2007; Frumkin et al., 2008; L. Ziska et al., 2011; L. H. Ziska & Beggs, 2012; D'amato et al., 2010). This dynamic threatens to exacerbate the burden of hay fever by increasing both the window of exposure to pollen and the potency of pollen (Bortenschlager & Bortenschlager, 2005; Emberlin et al., 2007; Frumkin et al., 2008; L. Ziska et al., 2011; L. H. Ziska & Beggs, 2012; D'amato et al.,

2010). An increased burden may differentially impact people living in urban versus rural areas, and those of low socioeconomic status, children, and older adults (G Luber et al., 2014)—because of the urban heat island effect (Patz et al., 2005), poor housing conditions with lower rates of access to air conditioning (Klein Rosenthal, Kinney, & Metzger, 2014) and limited adaptive responses (Basu & Samet, 2002).

Using 17 years of health outcome data (NHIS 1997-2013), we explored the association between exposures to increased frequency of extreme heat events and hay fever among a nationally representative sample of the adult civilian non-institutionalized US population aged 18 years and older. We hypothesized that residents of counties with higher number of extreme heat events would have higher odds of hay fever and that the odds will vary by season.

Methodology

Meteorological Data

Daily weather data was obtained from two systems within the National Centers For Environmental Information (NCEI)—formerly known as the National Climatic Data Center)—for the 1960-2013 period, including daily maximum temperature (TMAX) (U.S. NOAA, 2016). Data for the years 1960-2010 were extracted from the DSI-3200 data set. The DSI-3200 data set was discontinued in 2010 and replaced with the Global Historical

Climatology Network (GHCN) data set that consists of additional stations that are not part of

the original DSI-3200 network. Therefore, for the 2011-2013 period, we identified the

DSI3200 stations within the GHCN network using unique station identification and extracted

information from this subset of stations to maintain consistency.

Exposure Metric

Using daily TMAX for the 1960-1989 reference period, county-specific 30-year

baselines for each calendar month were computed. Based on the distribution of this data, we

identified the 95th percentile values of TMAX, referred to as Extreme Temperature Threshold

95th percentile (ETT_{95}) as previously described (Romeo Upperman et al., 2015). Daily

TMAX values for each county were compared to their respective calendar-month-specific

ETT_{95} and assigned a value of "1" if they exceeded the thresholds, and "0" otherwise. The

ETT_{95} exceedences —referred to as *extreme heat events (EHE$_{95}$)*— were summed over each

calendar month for each county during the 1997-2013 period for which NHIS hay fever

prevalence data was available (Romeo Upperman et al., 2015).

Extreme heat event values were assigned to individual NHIS records for each survey

year in two ways: 1) the cumulative number of *extreme heat events* for the county of

residence in a 12 month window, which include the month of interview and the preceding 11

months; and, 2) the cumulative number of *extreme heat events* for the county of residence in

each of the four complete seasons over the 12-month window preceding the month of

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interview. Seasons were categorized as: Winter – December, January, February; Spring –

March, April, May; Summer – June, July, August; Fall – September, October, November.

National Health Interview Survey (NHIS), 1997-2013 Data

We combined NHIS data for 1997-2013 for this analysis. The NHIS is a nationally

representative cross-sectional household interview survey of the civilian non-institutionalized

population of the United States that has been conducted since 1957, although the survey

design and questionnaire have changed over (U.S. CDC, 2015). The NHIS is conducted

continuously throughout the year. In 1997-2013, about 40,000 households were sampled each

year, with some households having multiple families. In each family, a sample adult is

selected for detailed questions on health and health care (U.S. CDC, 2015). During the 17-

year period, the response rate for the household component of the survey ranged from 75.7%

to 91.8% and the unconditional sample adult response rates ranged from 60.8% to 80.4%.

We used the restricted-use NHIS files geocoded to county FIPS. These files are

available through the NCHS Research Data Center (RDC). There are 516,140 sample adults

18 years of age or older in the 1997-2013 NHIS. Respondents were excluded from the

analysis if they: 1) resided in a county that had less than 12 months of extreme heat data and

had at least one non-valid month for the development of the baseline (n=1,185); 2) resided

outside the 48 contiguous states at the time of the interview (n=5,334); or, 3) had missing

data for any of the variables used in the analysis (n=4,235), for a total of 10,754 (2%)

excluded respondents.

Hay fever was identified using responses to the question: "During the past 12 months, have you been told by a doctor or other health professional that you had hay fever?" Demographic characteristics considered included age (18-34, 35-49, 50-64, 65+ years), race/ethnicity (Hispanic, non-Hispanic black, non-Hispanic white, all other races and ethnicities), sex (female, male), education level (less than high school/GED, high school/GED, some college, Bachelor's degree, Graduate degree), and family income relative to poverty threshold (US Census Bureau, n.d.) (less than 100%, 100% to less than 200%, 200% to less than 400%, 400% or above the poverty threshold (K. D. Jackson, Howie, & Akinbami, 2013). We used the NHIS multiple-imputed income data to assign poverty status level to records with missing values (percent missing ranged from 4.5% to 10.0% over 1997-2013) using NCHS-recommended methods (NCHS, 2010).

We also included a county-level geographical covariate describing urban-rural classification with four urban and two rural categories (urban: large central, large fringe, medium and small metro; rural: micropolitan and non-core) (Deborah D Ingram, 2012). Large central metro counties are counties in Metropolitan Statistical Areas (MSAs) of 1 million or more population that contain the largest principal city of the MSA, are contained within the MSA's largest principal city, or contain at least 250,000 residents of any principal city. Large fringe metro counties are counties in MSAs of 1 million or more population that do not qualify as large central metro. They are considered to be "suburbs" of large cities. Medium and small metro counties are counties in MSAs of 250,000–999,999 and less than 250,000 population, respectively.

Statistical Analysis

Micropolitan and noncore counties are nonmetropolitan counties that are not in MSAs. Associations between annual and seasonal total extreme heat events and adult hay fever were evaluated using logistic regression models in SUDAAN which accounts for the complex clustered sample design of the NHIS (RTI International, 2014). Unadjusted and adjusted models were fitted separately for each overall annual cumulative lag and seasonal cumulative lag of extreme heat events. We fitted additional models for seasonal extreme heat events separately based on interview season defined in the description of the survey (see Figure 4). The quartiles for exposure overall and season were based on the distribution of extreme heat events for all 3,109 counties in the continental United States. Approximate, rather than actual, quartiles by season were used for comparability of cut-points across season.

Figure 4. Flow chart of data analysis procedure
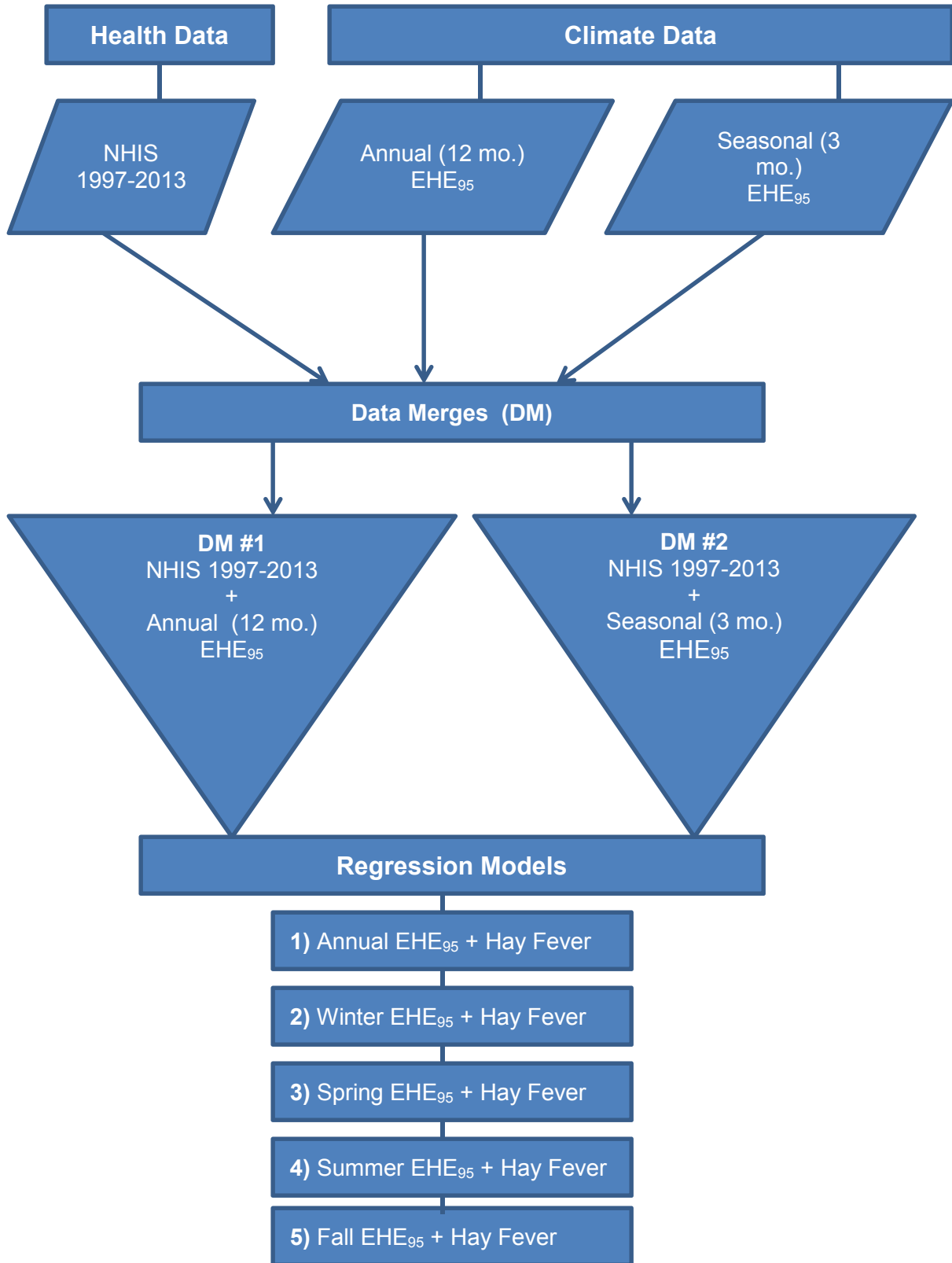
Results

Among adults aged 18 and older, 8.43% (n=42,601) reported being told they had hay fever within the previous 12 months for the period 1997 to 2013 (Table 9). All characteristics shown in Table 9 except urban-rural classification, were significantly associated with hay fever status.

Annual extreme heat events (approximate quartiles of the cumulative number of *extreme heat events* in the 12 months preceding the survey) were significantly associated with hay fever prevalence in an unadjusted analysis (Table 10, Model 1). When adjusting for demographic characteristics (Table 10, Model 2), the association between extreme heat events and hay fever persisted, i.e., compared to adults in the lowest quartile of exposure to extreme heat events (0 to 10 events), adults in the higher quartiles of exposures had higher odds of reporting a diagnosis of hay fever in the previous 12 months. This increase in odds ranged from 5% (OR 1.05, 95% CI: 1.01-1.09) for adults in the 2nd quartile to 7% (OR 1.07, 95% CI: 1.03-1.11) for adults in the 4th quartile. Additional adjustment for urbanicity did not change the observed association (Table 10, Model 3).

When we analyzed by timing (season) of extreme heat events, we observed a clear exposure-response relationship for associations between spring and winter extreme heat events and odds of hay fever ($P_{trend} <0.01$, Table 11). For springtime extreme heat events, the increases in odds of hay fever ranged from 2% (OR 1.02, 95% CI: 0.98-1.06) for adults in the 2nd quartile to 7% (OR 1.07, 95% CI: 1.03-1.12) for adults in the 4th quartile (Table 11). For extreme heat events that occurred during summer, the increase in the odds of hay fever was

significant only among those in the highest quartile of exposure (Table 11). Such associations were not observed for extreme heat events that occurred during fall.

Sensitivity analyses using both more liberal and more conservative exposure metrics using the 90th and 99th percentiles of distribution as cutoff thresholds for defining extreme heat events (EHE_{90} and EHE_{99}) showed a positive association between exposure to extreme heat events and hay fever (see Table 12, Table 13, and Table 14). Seasonal extreme heat events for EHE_{90} and EHE_{99} showed similar trends in the relationship for hay fever although the quartile definitions contrasted between the three measures of exposure (i.e., there were fewer extreme heat events measure when using ETT_{99} cutoff). The effects of extreme heat events remained significantly associated with hay fever when all models were adjusted for the month or year of interview.

Table 9. Characteristics of adults 18 years and older[*], NHIS 1997-2013

Variables	Categories	All	Hay Fever	EHE₉₅ Quartiles[§]			
				0-10 days	**11-16 days**	**17-24 days**	**25 days or more**
		(*n*=505,386)	(*n*= 42,601)	(*n*=111,524)	(*n*=113,255)	(*n*=123,998)	(*n*=156,609)
Total Percent Hay Fever		100	8.43	21.91	22.49	24.65	30.94
	No	91.57	-----	21.99	22.47	24.66	30.88
	Yes	8.43	-----	21.05	22.72	24.61	31.61
Race/ethnicity							
	non-Hispanic white	71.28	9.20	22.46	23.07	24.33	30.14
	non-Hispanic black	11.50	6.78	22.55	20.99	24.81	31.66
	Hispanic	12.52	5.73	18.98	20.65	25.81	34.56
	All other races and ethnicities	4.70	8.05	19.78	22.33	26.17	31.71
Sex							
	Male	48.13	7.45	21.89	22.54	24.77	30.80
	Female	51.87	9.35	21.93	22.45	24.55	31.08
Age							
	18-34 years	31.27	6.21	21.69	22.58	25.04	30.69
	35-49 years	29.40	10.34	21.86	22.50	24.76	30.88
	50-64 years	22.86	10.07	21.66	22.59	24.31	31.43
	65 years and older	16.48	6.98	22.78	22.16	24.21	30.85
Education							
	<High school/GED	16.24	6.00	21.92	22.12	25.19	30.77
	High school/GED	28.65	6.89	22.65	22.52	24.47	30.36
	Some college	29.48	9.19	22.11	22.57	24.55	30.78
	Bachelor's degree	16.83	10.29	21.11	22.56	24.59	31.74
	Graduate degree	8.79	11.88	20.36	22.7	24.75	32.19
Poverty Status^							
	Less than 100%	12.33	6.92	21.99	21.92	24.88	31.22
	100 to less than 200%	18.40	6.96	22.79	21.91	24.70	30.60

	200 to less than 400%	31.17	7.99	22.55	22.48	24.51	30.46
	400% or greater	38.09	10.00	20.94	22.97	24.67	31.42
Urban-rural classification+							
	Large central metro	28.22	8.09	17.93	22.68	27.43	31.97
	Large fringe metro	24.00	9.08	23.10	22.94	23.39	30.57
	Medium metro	20.99	8.63	22.27	21.85	23.37	32.51
	Small metro	10.13	8.56	23.00	23.26	24.63	29.12
	Micropolitan	10.20	7.86	25.52	20.43	23.83	30.22
	Non-core	6.46	7.55	26.34	24.14	22.76	26.75

All percentages were weighted using NHIS survey weights.

Poverty status is the poverty threshold percent is an imputed value

* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.

§The categories of days represent the quartiles of exposure based on county of residence

+ Counties were classified into urbanization levels based on the 2006 NCHS Urban-Rural Classification Scheme for Counties.

^Family income as a percent of Poverty Threshold

EHE_{95}= Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using 30 year of baseline data.

Table 10. Unadjusted (Model 1) and adjusted (Models 2 and 3) odds ratios for hay fever among US adults[*], NHIS 1997-2013.

Variables	Categories	Model 1	Model 2	Model 3
		OR (95% CI)	OR (95% CI)	OR (95% CI)
EHE$_{95}$		P_{trend} <0.001	P_{trend} <0.05	P_{trend} <0.05
	Q1 (0-10 days)[#]	1.00	1.00	1.00
	Q2 (11-16 days)	1.06 (1.02-1.10)	1.05 (1.01-1.09)	1.05 (1.00-1.09)
	Q3 (17-24 days)	1.04 (1.00-1.08)	1.05 (1.00-1.09)	1.04 (1.00-1.09)
	Q4 (≥25 days)	1.07 (1.03-1.11)	1.07 (1.03-1.11)	1.07 (1.02-1.11)
Sex			P_{trend} <0.001	P_{trend} <0.001
	Male[#]		1.00	1.00
	Female		1.30 (1.27-1.33)	1.30 (1.27-1.33)
Race/ethnicity			P_{trend} <0.001	P_{trend} <0.001
	non-Hispanic white		1.42 (1.35-1.49)	1.44 (1.37-1.51)
	non-Hispanic black		1.09 (1.03-1.15)	1.09 (1.03-1.15)
	Hispanic[#]		1.00	1.00
	All other races and ethnicities		1.19 (1.10-1.28)	1.19 (1.10-1.29)
Age			P_{trend} <0.001	P_{trend} <0.001
	18-34 years[#]		1.00	1.00
	35-49 years		1.66 (1.61-1.72)	1.67 (1.61-1.73)
	50-64 years		1.59 (1.53-1.65)	1.59 (1.53-1.65)
	65 years and older		1.12 (1.08-1.17)	1.13 (1.08-1.18)
Education			P_{trend} <0.001	P_{trend} <0.001
	<High school/GED[#]		1.00	1.00
	High school/GED		1.02 (0.98-1.07)	1.02 (0.98-1.07)
	Some college		1.40 (1.33-1.46)	1.39 (1.33-1.45)
	Bachelor's degree		1.50 (1.42-1.57)	1.48 (1.41-1.56)
	Graduate degree		1.68 (1.59-1.78)	1.67 (1.57-1.77)
Poverty Status			P_{trend} <0.001	P_{trend} <0.001
	Less than 100%[#]		1.00	1.00
	100 to less than 200%		0.96 (0.92-1.00)	0.96 (0.92-1.00)
	200 to less than 400%		0.98 (0.94-1.02)	0.98 (0.94-1.02)
	400% or greater		1.05 (1.01-1.10)	1.04 (1.00-1.09)
Urban-rural				P_{trend} <0.1

classification+	
Large central metro	0.99 (0.94-1.03)
Large fringe metro	1.00 (0.96-1.05)
Medium metro[#]	1.00
Small metro	0.99 (0.91-1.08)
Micropolitan	0.92 (0.85-1.00)
Non-core	0.89 (0.82-0.98)

[#] Reference Category

Poverty status is the percent of poverty threshold is an imputed value.

* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.

Model 1: Unadjusted model.

Model 2: adjusted for gender, race/ethnicity, age, education and poverty threshold.

Model 3: adjusted for gender, race/ethnicity, age, education, poverty threshold, and urban-rural classification.

+ Counties were classified into urbanization levels based on the 2006 NCHS Urban-Rural Classification Scheme for Counties.

The confidence intervals were calculated using standard methods to account for the survey design.

EHE_{95}=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using 30 year of baseline data.

Table 11. Adjusted odds ratios [AORs (95% CIs)] for hay fever in adults[*], NHIS 1997-2013, by season

Season	EHE$_{95}$ Categories	P$_{trend}$	AOR (95% CI)	Percent
Spring		<0.01		
	Q1 (0-2 days)[#]		1.00	32.19
	Q2 (3-4 days)		1.02 (0.98-1.06)	20.49
	Q3 (5-8 days)		1.04 (1.00-1.07)	28.25
	Q4 (≥ 9 days)		1.07 (1.03-1.12)	19.07
Summer		>0.05		
	Q1 (0-2 days)[#]		1.00	41.46
	Q2 (3-4 days)		1.01 (0.97-1.05)	14.51
	Q3 (5-8 days)		1.02 (0.99-1.06)	21.09
	Q4 (≥9 days)		1.04 (1.00-1.07)	22.94
Fall		>0.05		
	Q1 (0-2 days)[#]		1.00	35.14
	Q2 (3-4 days)		1.01 (0.97-1.04)	19.99
	Q3 (5-8 days)		1.00 (0.97-1.04)	29.63
	Q4 (≥9 days)		1.02 (0.98-1.07)	15.24
Winter		<0.01		
	Q1 (0-2 days)[#]		1.00	32.72
	Q2 (3-4 days)		0.95 (0.92-0.99)	18.55
	Q3 (5-8 days)		0.98 (0.94-1.01)	28.84
	Q4 (≥9 days)		1.05 (1.01-1.09)	19.88

Adjusted for sex, age, race/ethnicity, education, family income as percent of poverty threshold, urban-rural classification, and month of interview.
[#] Reference Category
* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.
The confidence intervals were calculated using NCHS standard methods to account for the survey design.
All percentages were weighted using NHIS survey weights.
EHE$_{95}$=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using 30 year of baseline data.

Table 12. Unadjusted (Model 1) and adjusted (Models 2 and 3) [AORs (95% CIs] for hay fever in adults[*], NHIS 1997-2013, sensitivity analysis for EHE$_{90}$

EHE$_{90}$	Model 1	Model 2	Model 3
Categories	OR (95% CI)	OR (95% CI)	OR (95% CI)
	P$_{trend}$ <0.05	*P$_{trend}$ <0.05*	*P$_{trend}$ <0.05*
Q1 (0-23 days)[#]	1.00	1.00	1.00
Q2 (24-34 days)	1.04 (1.00-1.09)	1.04 (1.00-1.09)	1.04 (1.00-1.08)
Q3 (35-46 days)	1.06 (1.02-1.10)	1.06 (1.02-1.10)	1.06 (1.01-1.10)
Q4 (≥47 days)	1.05 (1.01-1.10)	1.06 (1.01-1.10)	1.05 (1.01-1.10)

[#] Reference Category
Adjusted for sex, age, race/ethnicity, education, family income as percent of poverty threshold, and urban-rural classification.
* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.
The confidence intervals were calculated using standard methods to account for the survey design.
EHE$_{90}$=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using 30 year of baseline data.

Table 13. Unadjusted (Model 1) and adjusted (Models 2 and 3) [AORs (95% CIs)] for hay fever in adults[*], NHIS 1997-2013 merged with meteorological data, sensitivity analysis for EHE$_{99}$

EHE$_{99}$	Model 1	Model 2	Model 3
Categories	OR (95% CI)	OR (95% CI)	OR (95% CI)
	P$_{trend}$ <0.001	*P$_{trend}$ <0.001*	*P$_{trend}$ <0.001*
Q1 (0 days)[#]	1.00	1.00	1.00
Q2 (1-2 days)	1.05 (1.00-1.10)	1.03 (0.98-1.08)	1.03 (0.98-1.08)
Q3 (3-6 days)	1.11 (1.06-1.16)	1.09 (1.05-1.14)	1.09 (1.04-1.14)
Q4 (≥7 days)	1.09 (1.04-1.14)	1.08 (1.03-1.13)	1.08 (1.03-1.13)

[#] Reference Category
Adjusted for sex, age, race/ethnicity, education, family income as percent of poverty threshold, and urban-rural classification.
The confidence intervals were calculated using NCHS standard methods to account for the survey design.
* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.
The confidence intervals were calculated using standard methods to account for the survey design.
EHE$_{99}$=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 99th percentile threshold calculated using 30 year of baseline data.

Table 14. Adjusted odds ratios [AORs (95% CIs)] for hay fever in adults[*], NHIS 1997-2013, sensitivity analyses for EHE_{90} and EHE_{99} by season

	Quartiles	Hay Fever AOR (95% CI)			
		Winter	Spring	Summer	Fall
EHE_{90}		P_{trend} <0.001	P_{trend} <0.01	P_{trend} <0.5	P_{trend} <0.05
	Q1 (0-4 days)[#]	1.00	1.00	1.00	1.00
	Q2 (5-6 days)	0.98 (0.93-1.02)	1.05 (1.01-1.10)	1.02 (0.97-1.06)	1.03 (0.99-1.07)
	Q3 (7-13 days)	0.97 (0.93-1.00)	1.03 (0.99-1.06)	1.02 (0.99-1.06)	1.01 (0.98-1.05)
	Q4 (≥14 days)	1.04 (1.00-1.08)	1.08 (1.04-1.12)	1.03 (1.00-1.07)	1.06 (1.02-1.11)
EHE_{99}		P_{trend} <0.5	P_{trend} <0.01	P_{trend} <0.05	P_{trend} <0.5
	Q1 (0 days)[#]	1.00	1.00	1.00	1.00
	Q2 (1 days)	1.02 (0.99-1.05)	1.00 (0.97-1.04)	1.01 (0.97-1.06)	1.01 (0.97-1.05)
	Q3 (2 days)	1.00 (0.96-1.05)	1.02 (0.98-1.07)	1.04 (0.99-1.09)	1.00 (0.95-1.05)
	Q4 (≥3 days)	1.04 (1.00-1.08)	1.07 (1.04-1.11)	1.05 (1.02-1.09)	0.97 (0.94-1.01)

[#] Reference Category

Adjusted for sex, age, race/ethnicity, education, family income as percent of poverty threshold, and urban-rural classification.

* Includes sample adults 18 years and older with complete data for analytic covariates and who resided within the 48 contiguous states and within a county with complete exceedence and baseline data for daily maximum temperature.

The confidence intervals were calculated using NCHS standard methods to account for the survey design.

EHE_{90}=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using 30 year of baseline data.

EHE_{99}=Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 99th percentile threshold calculated using 30 year of baseline data.

Discussion

We evaluated the relationship between exposures to annual and seasonal extreme heat events and the prevalence of hay fever among a nationally representative sample of civilian non-institutionalized US adults during 1997-2013. This analysis builds upon previous work that has shown an association between increasing temperature and longer pollen seasons for important allergens such as ragweed (L. Ziska et al., 2011; L. H. Ziska & Beggs, 2012; L. H. Ziska, Epstein, & Schlesinger, 2009).

The present study found a modest positive association between exposures to extreme heat events, particularly during spring, and the prevalence of hay fever. For the extreme heat events during summer and fall, only counties in the highest quartile of extreme heat events showed a significant associated between extreme heat events and hay fever. Our findings regarding exposures to extreme heat events and hay fever prevalence were not substantially affected by adjustment for demographic factors and county urbanicity. The exact mechanism by which long-term exposures to extreme heat events increase the risk of hay fever remains unclear. One potential explanation is changes in plant phenology. Higher frequency of extreme heat events, particularly those occurring in winter and spring season lead to earlier onset of greening and flowering of plants including trees that are major sources of pollen; similarly, extreme heat events in the summer could potentially affect the fall weed pollen season (L. Ziska et al., 2011). Likewise, historically, the spring flowering taxa has shown an increasing trend for producing more pollen than any other season (Zhang et al., 2015).

This earlier onset of spring effectively increases the duration of exposure to pollen, which is an important risk factor for hay fever (Emberlin et al., 2007; L. Ziska et al., 2011; L.

H. Ziska & Beggs, 2012). Others have shown higher pollen production associated with warmer temperatures (P. Beggs, 2004; Rogers et al., 2006). Increased frequency of extreme heat events may lead to higher concentration of pollen in the environment—in addition to increasing the possible duration of exposure (P. Beggs, 2004; D'amato & Cecchi, 2008; D'Amato, Cecchi, D'Amato, & Liccardi, 2010). Our findings that show a positive association between extreme heat events during winter and spring seasons and hay fever prevalence support the aforementioned two hypotheses of longer duration and greater concentration of pollen exposure. When temperatures in winter and spring are unusually warm, individuals may spend more time outdoors, bringing them in closer contact with outdoor pollen as well as other pollutants; however, national patterns of time spent outdoors are unknown. From the winter analysis, when there are fewer extreme heat events, a protective impact on hay fever is shown; however, this association is lost when the number of extreme heat events exceeds 9 days.

Regardless of the exact underlying mechanism, our study is the first to link exposures to extreme heat events and increased odds of hay fever in the continental US. Previous studies have shown that the frequency and intensity of such extreme events are increasing and will continue to do so in the coming decades (Edenhofer et al., 2014). Our study relied on a large (n=505,386) nationally representative sample of the civilian non-institutionalized US population. Our county-specific and calendar month-specific exposure metric generated using the 30-year of baseline data (1960-1989) enabled us to focus on changes in frequency of extreme events relative to 30-year baseline rather than short-term weather phenomena. Furthermore, we were able to control for several socioeconomic characteristics including educational level, family income relative to the poverty threshold, and the urban-rural

classification of the county; but they were not sensitive to further adjustment for region. Finally, we performed several sensitivity analyses, which established the robustness of our findings.

This study also has several limitations. The NHIS is a multipurpose health survey, and as such, lacked information needed to more fully examine the effects of extreme heat events on hay fever. For instance, the NHIS survey does not collect exact date of onset of outcomes, or degree of hay fever symptoms. In addition, we have no information on local pollen levels, which may have improved our understanding of the association between extreme heat events and reported allergies. From the cross-sectional design of the NHIS we cannot establish a clear temporality in exposure to extreme heat event and hay fever, and our results may be affected by the length of time between exposure to extreme heat events and the recall of hay fever (Rothman, Greenland, & Lash, 2008). Moreover, hay fever may not capture the full spectrum of allergic rhinitis—a more complete account of respiratory allergies could result in a different observed association. Another limitation is the use of county of residence to define exposure for the NHIS respondents. Ideally, exposure measures would be available for each adult, either from personal monitoring or from finer spatial scales, which would minimize potential exposure misclassification.

Conclusion

In summary, this study investigated the impact of extreme heat events on the prevalence of hay fever among a nationally representative sample of the civilian non-

institutionalized US population from 1997 to 2013. We observed a modest, but significant, association between exposures to extreme heat events and hay fever prevalence. The findings were more pronounced for spring extreme heat events. A extreme heat events will continue to rise in the near future in response to our changing climate (Edenhofer et al., 2014; Field, 2012; G Luber et al., 2014), these results can be an informative guide for policy, future epidemiological investigations, and efforts to understand the effects on chronic health outcomes.

Chapter 6: Conclusions

This study set out to develop empirical models that can quantify the risks and vulnerability that the attributes of a changing climate may pose on the state of chronic diseases (particularly respiratory diseases) among US adults—using a 17-year time-period (1997-2013) on adults (18 years of age and older) linked to a novel county-level extreme heat event exposure metric. The general literature on this subject in the context of the US has grown in the recent decade. This study sought to create and verify an extreme heat event exposure metric; assess and describe the populations that are most susceptible to the highest levels of exposure in the US; and delineate the impact of exposure to extreme heat on chronic respiratory diseases.

Major Findings

The main empirical findings are chapter specific and were summarized within the respective experimental chapters: "*Frequency of Extreme Heat Event as a Surrogate Exposure Metric for Examining the Human Health Effects of Climate Change*," "*Geographic and Demographic Variability in County Level Exposure to Extreme Heat Events Using National Data Sets, 2010-2013*," and "*Frequency of Extreme Heat Events and Hay Fever Prevalence in the United States, 1997-2013*." This section will summarize the observed findings to answer the study's main research questions. The most interesting results from this research are:

Aim 1 Conclusion: Extreme Heat Exposure Metric

In this study an extreme heat event exposure metric was created and showed the ability to capture salient features of climate variability and change, including the effect of natural variability such as ENSO patterns that have distinct heterogeneous effects across geographical regions. This research confirmed that the natural modes of forcing, seasonality, urban-rural classification, and division of country have an impact on the number of extreme heat events recorded. In addition, the data showed increases in the frequency of extreme heat events that differ across the geographical region and time periods. The metric also showed the ability to capture the dynamics between the higher frequency of extreme heat events during La Niña months and lower frequencies during the El Niño months. However, there are exceptions to the impact of ENSO on lowering and increasing the frequencies of extreme heat events in select geographical areas that were also shown with this metric.

Aim 2 Conclusion: Extreme Heat Event Exposure Characterization

In this study we saw that there are similar demographic patterns and prevalences of chronic diseases for areas with higher numbers of annual extreme heat events compared to the general population. Many of the areas affected by extreme heat events do have a variety of vulnerable populations including women of childbearing age, people who are poor, and older adults. Moreover, high chronic disease rates in rural communities that are in the top quartile, and top decile showed to be larger than any other urban-rural category.

Aim 3 Conclusion: Impact of Extreme Heat Events on Hay Fever

This research showed that adults in the highest quartile of exposure to extreme heat events had a 7% significant increased odd of hay fever compared to those in the lowest quartile. The results of the research suggest that exposure to extreme heat events increases risk of hay fever among US adults.

Theoretical Implication

Extreme Heat Exposure Metric

Environmental indicators are increasingly being used for the formulation of policy because they can simplify, describe, and analyze otherwise complicated environmental problems—allowing for the identification of trends and patterns and can drive policy action (U.S. EPA, 2016; Weber, Sadoff, Zell, & de Sherbinin, 2015). The indictors in this research showcase the value of ground-level metrological observations for the advancement of the national priorities on climate change. The United States National Climate Assessment (NCA), the United States Environmental Protection Agency (U.S. EPA), and the National Institute for Environmental Health Sciences (NIEHS) are a few of the governing bodies that have identified the need for a national system of indictors for physical exposure and ecological and societal impacts to help communicate aspects of the changing environment, call attention to vulnerabilities, and inform decision making at the local, state and national

levels. The results of the second chapter of this research bolster the unanimous support for exposure indictors. The exposure metric created and verified in this work is an answer to the national call for indicators to measure physical exposure to extreme heat as a means to identify the impact of climate change on human health outcomes. This work supports the use of ambient temperature measures as a good proxy for creating indictors for temperature exposure. These indictors can be used in all sectors to find out how historical climate shifts have impacted various outcomes of interest. Moreover, it adds to literature that has verified the impact of the ENSO on maximum temperatures across the US—which is work that has been done by the National Oceanic and Atmospheric Administration (NOAA) (U.S. NOAA, 2012) .

Extreme Heat Event Exposure Characterization

Researchers and governmental entities have commented on the paucity of knowledge available to inform the extent to which populations in the US are being exposed to heat events that are related to climate change and variability. Existing studies have focused on select urban populations and have not looked at the entire US population. Those existing studies on smaller populations have identified older adults (and children), and those with heat sensitive chronic diseases, and outdoor workers, among others to be most vulnerable to heat episodes. This research supports the notion that there are vulnerable populations all across the US and not solely in urban areas. The results showed that vulnerability is not only a factor of being exposed but also the prevalence of disease in the base populations (along with adaptive capacity which is not discussed).

Impact of Extreme Heat Events on Hay Fever

There is a mounting concern for the impact that extreme heat events (from climate change) is expected to have on air quality, on the increase of pollen production and allergenicity of allergens, and the increase in regional concentrations of ozone, fine particulate matter, and dust. Some of these pollutants can cause respiratory disease or exacerbate conditions in susceptible populations (National Institute of, 2013). Researchers have attempted to summarize the relationship between climate changes and the phenology of allergenic plants and pollen distribution that it leads to an:

1) Increase in faster plant growth;

2) Increase in the amount of pollen produced;

3) Increase in the amount of allergenic proteins contained in pollen;

4) Increase in the start time of plant growth and therefore the start of pollen production; and,

5) Earlier and longer growing pollen seasons (D'amato & Cecchi, 2008; L. H. Ziska & Beggs, 2012; D'Amato et al., 2013).

It is thought that meteorological factors, including temperature, along with warming climate regimes can affect the biological components of the interaction between climate change, increased warming, and allergic respiratory diseases. This work supports the aforementioned notion and shows the likely effect that warming can have on pollen season and production, subsequently leading to more hay fever. We were able to see a positive

relationship between extreme heat events during the spring and summer on hay fever prevalence nationally. In view of this, there are still gaping holes as to the mechanism behind this interaction.

The methods developed in this research are applicable to future studies linking other attributes of a changing climate (extreme precipitation, etc.) to other diseases of concern—an added contribution to science that can lead to robust information to inform future policies. The nuanced impact of climate change identified in this research adds to the current literature on the impact of climate extremes. The logistic regression model provides a predictive equation for use in climate prediction and economic models to quantify the effects and costs of anthropogenic climate change.

The *extreme heat event* metric serves as a human impact indicator to help provide a clue into the matter of climate variability and change in a way that makes the significance more perceptible and show trends that are not immediately tangible. Researchers in climate risk communication have shown that the most salient point of communicating climate change risk to the general public is though the identification of human health impacts (K. Akerlof et al., 2010; DeBono, Vincenti, & Calleja, 2012; K. L. Akerlof, Delamater, Boules, Upperman, & Mitchell, 2015). This metric is a significant addition to fill the void of national-level indictors that can be used to assess the attributes of a changing and its impacts on health outcomes at national, state, and local levels. This indicator does not serve as an end, but

rather a tool to be utilized with guidance and restraint in order to build support for policy changes. The extreme heat event indictor and the ensuing analyses is a product of observed data collected by the United States Federal Government and shows the utility of federal data for research purposes.

This research highlights the characteristics of counties that have shown to have higher numbers of *extreme heat events*. This characterization of populations in counties with high exposure to *extreme heat events* show that there are a myriad of heat sensitive health outcomes that should be included the local and national emergency response and preparedness. Public officials should pay attention to this characterization to inform their future planning and implementation of adaptation and mitigation. The impact shown on hay fever is novel and is the first of its kind to support the educated assumptions of the impact of climate change on allergic diseases.

Recommendation for Future Research

A few future steps can progress the findings of this work. The first would be to verify that the results of this work are also valid at the local level. Being an ecological level analysis, future work can look at the variability between ambient temperature and actual exposure. This will help to assess direct exposure to extreme temperature.

Future work should also consider homogeneity-adjusted metrics that can provide a better understanding of weather and climate anomaly's variability and impacts on human health without the effects of non-climatic changes. Moreover, the impact of atmospheric

circulation on warm temperature events should be accounted for when calculating extreme weather and climate events. Future versions of this exposure metric should aim to account for the impact of natural modes of climate variability such as the El Niño-Southern Oscillation, the Pacific Decadal Oscillation, and the Northern Annular Mode circulation patterns (Gutowski et al., 2008).

Another possibility for future work is to identify which biological process (air pollution, pollen, etc.) is most robust for many of the heat-sensitive health outcomes. This can support further targeted policies for air pollution and climate change. In this research, we do not show causality. It would be beneficial for future work to tighten this connection which can be done by adding a probability-based function employing the recommendations of Hannart *et al.,* (Hannart, Pearl, Otto, Naveau, & Ghil, 2015).

The preliminary work was not able to capture an association between 1 year of exposure to *extreme heat events* and other chronic respiratory diseases such as asthma; however, a five-year aggregate of this metric and these health outcomes showed a positive association. Future work should try to decipher the logic behind this association. With differing etiology and the possible lag in the genesis of these and other respiratory diseases, maybe the 5-year aggregate of the extreme heat exposure metric defines some unknown environmental dynamic that warrants future evaluation (see Appendix C).

An investigation into the variability of counties in the NHIS can help to determine the consistency of warming at those locations. This will give some idea into the notion of locales that are experiencing continued warming versus those that are not. Another natural course for future work is to extend the use of the exposure metric to other heat-sensitive health

outcomes to further inform the need for public health preparedness and response. The results seen in the hay fever analysis can be expanded with additional data. Using the network of pollen monitoring data to re-evaluate this analysis can provide useful information. However, there is a paucity of pollen data due to the limited monitoring and funding of existing monitoring stations across the US. To fix this, funding of existing pollen monitoring stations and an expansion of pollen monitoring at existing National Ambient Air Quality Standards stations should be a future consideration. This can provide widespread data on pollen and its distribution. With this, such as in the case of air pollution, dispersion modeling can be done to fill in the gaps at locations without data. For the health data of the NHIS, having additional questions regarding length of time at residence would be useful in assuring that the analysis assigns exposure with less misclassification.

Limitation of the Study

This research had several limitations. First, in Chapter 2, the use of ambient temperature to create the metric is not the best measure due to the classical principles of exposure science; however, in this case it is the best available given the historical availability and measurement quality assurance. The exposure metric created relies on data from weather networks, changes in station locations, land use, instrument changes, and observing practices should be accounted for through proper adjustment to yield homogeneity-adjusted exposure metrics (Lead & Easterling, 2008).

The cross-sectional design of the National Health Interview survey is another limitation because the questioning precludes establishing a temporal relationship or inferring causality. Another limitation associated with the survey is that we are assuming that the person resided and spent the majority of time in their county of survey for the entire duration of the calculated exposure metric that is assigned.

Conclusion

Climate change will lead to a rise in extreme heat events across all seasons affecting the many atmospheric and biological processes that lead to environmental exposures to air pollution and pollen. This dissertation provides, for the first time, a comprehensive assessment of the impact of historical measures of extreme heat events and its impact on hay fever among the US population.

Appendices

Appendix A. Supplemental Table for Chapter 3.

Table 15. Relative percent change in extreme heat events with climate regions, by time period, for the continental United States, excluding Alaska and Hawaii.

Parameter	$e^{(\beta)}$ 1960-1989	1990-1999	2000-2010
Intercept	1.33‡	1.68‡	1.79‡
ENSO			
Neutral		Reference	
El Niño	0.83‡	0.88‡	0.73‡
La Niña	1.2‡	1.33‡	1.31‡
Season			
Autumn		Reference	
Winter	1.03‡	1.31‡	0.89‡
Spring	1.01**	1.00	0.93‡
Summer	0.96‡	0.93‡	0.96‡
County Urban-Rural Classification			
Large central metro	0.98	1.24‡	1.04
Large fringe metro	0.99	1.08‡	1.02
Medium metro	1.00	1.08‡	1.05**
Micropolitan	0.99	1.00**	0.99
Small metro	0.99	1.05	1.00
Non-core		Reference	
Climate Regions			
Northeast		Reference	
Central	0.94‡	0.70‡	0.73
East North Central	1.00	0.75‡	0.83‡
Northwest	0.99	0.95*	0.87‡
South	0.91‡	0.72‡	0.84‡
Southeast	0.89‡	0.84‡	0.81‡
Southwest	0.94‡	0.88‡	1.10‡
West	0.97*	0.81‡	0.95*
West North Central	0.98**	0.76‡	0.83‡

*p<.05 ** p<.005 ‡ p<.001

Appendix B. Supplemental Tables for Chapter 4

Table 16. Weighted percent and standard error of chronic health conditions for highest quartile and decile of annual extreme heat events by age group, National Health Interview Survey 2010-2013.

	Age in years			
Annual	**18 to 34**	**35 to 49**	**50 to 64**	**65 and older**
Top Quartile *(n=51,570; 41.61%[1])*				
25 days or more EHE$_{95}$	*(n=14,894; 31.2%[1])*	*(n=13,193; 26.4%[1])*	*(n=12,865; 25.3%[1])*	*(n=10,618; 17.1%[1])*
SPD	13.2 (0.4)	14.1 (0.4)	14.8 (0.4)	11.4 (0.4)
Heart disease	5.3 (0.3)	9.1 (0.4)	17.7 (0.5)	32.8 (0.6)
Stroke	0.2 (0.1)	1.3 (0.1)	3.3 (0.2)	8.4 (0.4)
Hypertension	8 (0.3)	21.8 (0.5)	42.5 (0.6)	61.5 (0.7)
Diabetes	1.5 (0.1)	6.1 (0.3)	14.4 (0.4)	21.2 (0.5)
COPD	2.5 (0.2)	3.8 (0.2)	7 (0.3)	8.9 (0.4)
Top Decile *(n=23,549; 18.78%[1])*				
38 days or more EHE$_{95}$	*(n= 6,879; 31.4%[1])*	*(n= 5,980;26.3%[1])*	*(n= 5,865; 25%[1])*	*(n= 4,825;17.3%[1])*
SPD	12.9 (0.6)	14.4 (0.6)	14.3 (0.6)	11.8 (0.6)
Heart disease	5.6 (0.4)	9.2 (0.5)	17.9 (0.7)	34.2 (0.9)
Stroke	0.2 (0.1)	1.5 (0.2)	3.3 (0.3)	8.8 (0.5)
Hypertension	8.4 (0.4)	22.4 (0.7)	42.6 (0.9)	60.9 (0.9)
Diabetes	1.5 (0.2)	6.2 (0.4)	14.2 (0.6)	21.5 (0.8)
COPD	2.6 (0.3)	4.1 (0.3)	6.7 (0.5)	9.1 (0.5)

SE: Standard Error

SPD: Serious psychological distress

COPD: Chronic Obstructive Pulmonary Disease

EHE$_{95}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Table 17. Percent by demographic characteristics overall and in counties in top quartile and top decile of summer extreme heat events, National Health Interview Survey 2010-2013.

	All		Summer	
	(n=119,709; 100%[1])		Top Quartile *(n=44,613; 36.5%[1])*	Top Decile *(n=26,565; 21.36 %[1])*
	n	*%[1]*	%(SE)[1]	
Race/Ethnicity				
non-Hispanic white	71,717	68.0	64.9 (0.5)	63.3 (0.7)
non-Hispanic black	18,612	11.8	13.9 (0.4)	13.9 (0.5)
Hispanic	21,313	14.5	16 (0.4)	17.8 (0.5)
All other races and ethnicities	8,067	5.8	5.1 (0.2)	5 (0.2)
Age (years)				
18-34	34,374	31.2	31.2 (0.4)	32.4 (0.5)
35-49	30,689	26.4	26.4 (0.3)	26.1 (0.4)
50-64	29,760	25.2	25.2 (0.3)	24.8 (0.4)
65 and older	24,886	17.2	17.2 (0.3)	16.7 (0.3)
Sex				
Male	54,268	49.2	49.2 (0.3)	49.1 (0.4)
Female	65,441	50.8	50.8 (0.3)	50.9 (0.4)
Marital status				
Singe	67,303	46.5	46.5 (0.4)	47.2 (0.5)
Married	52,406	53.5	53.5 (0.4)	52.8 (0.5)
Women of Childbearing Age				
No	35,956	52.9	52.1 (0.5)	51.7(0.6)
Yes	29,485	47.2	47.9 (0.5)	48.3 (0.6)
Body Mass Index				
Underweight	2,171	1.7	1.7 (0.1)	1.8 (0.1)
Normal weight	41,949	35.5	35.5 (0.3)	34.2 (0.4)
Overweight	41,425	34.7	34.7 (0.3)	35 (0.4)
Obese	34,164	28.1	28.1 (0.3)	29.1 (0.4)
Education				
<High school/GED	16,494	11.7	11.7 (0.3)	12.7 (0.3)
High school/GED	33,928	28.6	28.6 (0.4)	28.5 (0.4)
Some college	36,408	31.0	31 (0.3)	30.7 (0.4)
Bachelor's degree	21,102	18.6	18.6 (0.3)	18.5 (0.4)
Graduate degree	11,777	10.1	10.1 (0.3)	9.7 (0.3)
Poverty status				
<100% FPL	21,530	13.5	13.5 (0.3)	14.3 (0.4)
100-<200% FPL	25,477	19.1	19.1 (0.3)	19.9 (0.4)

200-<400% FPL	35,053	30.1	30.1 (0.3)	30.1 (0.4)
>400% FPL	37,649	37.3	37.3 (0.5)	35.8 (0.6)

[1] Weighted Percent: all percentages were weighted using NHIS survey weights.

Body Mass Index (BMI) is calculated using the formula weight in kilograms/height in meters: underweight=<18.5; normal weight=18.5 -<25; Overweight = BMI 25 - <30; Obese = BMI ≥ 30.

Note: FLP=federal poverty level

Women of Childbearing Age: women between the ages of 18 and 45.

Summer Top Quartile = 9 days or more EHE_{95}; Summer (June, July, August)

Summer Top Decile = 14 days or more EHE_{95}; Summer (June, July, August)

EHE_{95} = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Table 18. Percent by residential characteristics overall and in counties in top quartile and top decile of summer extreme heat event, National Health Interview Survey 2010-2013.

	All (n=119,709; 100%)		Summer	
			Top Quartile (n=44,613; 36.5%)	Top Decile (n=26,565; 21.4%)
	n	%[1]	%(SE)[1]	%(SE)[1]
Region				
Northeast	19,630	17.74	19 (0.6)	12.4 (0.7)
Midwest	26,084	23.23	18.9 (0.7)	19.8 (1)
South	44,278	36.29	48.3 (0.9)	54.8 (1.2)
West	29,717	22.74	13.9 (0.6)	13 (0.8)
Urban-rural classification				
Large central metro	37,694	29.38	30.7 (0.7)	33 (1)
Large fringe metro	24,031	24.63	23.6 (0.9)	21.4 (1.1)
Medium metro	24,548	20.88	23.2 (1.2)	22.5 (1.4)
Small metro	12,274	9.65	7.8 (1)	8.1 (1.1)
Micropolitan	12,017	9.16	9.4 (1.1)	9.7 (1.4)
Non-core	9,145	6.31	5.4 (0.8)	5.3 (1)
Coastal classification				
Noncoastal	60,605	49.27	53.1 (1)	57.5 (1.3)
Coastal	59,104	50.73	46.9 (1)	42.5 (1.3)

[1] Weighted Percent: all percentages were weighted using NHIS survey weights.
SE: Standard Error
Summer Top Quartile = 9 days or more EHE_{95}; Summer (June, July, August)
Summer Top Decile = 14 days or more EHE_{95}; Summer (June, July, August)
EHE_{95} = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Table 19. Percent by residential characteristics overall and in counties in top quartile and top decile of summer extreme heat event, National Health Interview Survey 2010-2013.

Chronic Disease	**All** (n=119,709; 100%)		**Top Quartile** (n=44,613; 36.5%)	**Top Decile** (n=26,565; 21.4%)
	n	*%*	%(SE)[1]	%(SE)[1]
SPD	17,821	14.05	13.3 (0.2)	13.1 (0.3)
Heart disease	18,255	14.21	14.2 (0.2)	14.3 (0.3)
Stroke	3,722	2.67	2.8 (0.1)	2.8 (0.1)
Hypertension	38,245	29.28	29.6 (0.3)	29.6 (0.4)
Diabetes	12,278	9.18	9.5 (0.2)	9.7 (0.2)
COPD	6,506	5.05	5.2 (0.2)	5.1 (0.2)

[1] Weighted Percent: all percentages were weighted using NHIS survey weights.
SE: Standard Error
SPD: Serious psychological distress
COPD: Chronic Obstructive Pulmonary Disease
Summer Top Quartile = 9 days or more EHE_{95}; Summer (June, July, August)
Summer Top Decile = 14 days or more EHE_{95}; Summer (June, July, August)
EHE_{95} = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Table 20. Weighted percent and standard error of chronic health outcomes and demographic factors for top quartile and top decile of summer extreme heat event by geographic descriptors, climate data merged with National Health Interview Survey 2010-2013.

Annual			SPD	Heart Disease	Stroke	Hypertension	Diabetes	COPD
Top Quartile (*n*=51,570)								
Region								
Northeast	7,548	19 (0.6)	12.6 (0.6)	12.9 (0.5)	2.5 (0.2)	27 (0.6)	8.8 (0.4)	4.5 (0.4)
Midwest	7,721	18.9 (0.7)	14.4 (0.5)	15.3 (0.6)	2.7 (0.2)	29.6 (0.9)	9.3 (0.4)	5.9 (0.3)
South	22,338	48.3 (0.9)	12.6 (0.3)	15.2 (0.3)	3.1 (0.1)	31.9 (0.5)	10.3 (0.2)	5.6 (0.2)
West	7,006	13.9 (0.6)	15.3 (0.5)	11.4 (0.4)	2.5 (0.2)	25.4 (0.6)	7.8 (0.4)	3.7 (0.4)
Urban-rural classification								
Large central metro	14,849	30.7 (0.7)	13.5 (0.4)	12 (0.4)	2.3 (0.1)	26.3 (0.5)	8.6 (0.3)	4.6 (0.3)
Large fringe metro	8,370	23.6 (0.9)	12.4 (0.5)	13.5 (0.4)	2.6 (0.2)	28.3 (0.7)	8.7 (0.4)	4.3 (0.3)
Medium metro	10,387	23.2 (1.2)	13.4 (0.5)	14.4 (0.4)	2.7 (0.2)	29.3 (0.6)	9.2 (0.3)	5.1 (0.3)
Small metro	3,881	7.8 (1)	13.4 (0.8)	15.6 (1)	3.6 (0.4)	33.5 (1.2)	10.2 (0.7)	5.8 (0.6)
Micropolitan	4,436	9.4 (1.1)	13.4 (0.7)	19 (0.9)	3.6 (0.4)	36 (1.3)	12.1 (0.6)	7.2 (0.6)
Non-core	2,690	5.4 (0.8)	15.6 (1)	19.5 (1.1)	4.6 (0.5)	39.2 (1.4)	13.5 (0.8)	7.8 (0.7)
Coastal classification								
Non-coastal	24,179	53.1 (1)	13.7 (0.3)	15.5 (0.3)	3.1 (0.1)	31.2 (0.5)	10.1 (0.3)	5.9 (0.2)
Coastal	20,434	46.9 (1)	12.9 (0.3)	12.8 (0.3)	2.4 (0.1)	27.8 (0.4)	8.7 (0.2)	4.4 (0.2)
Top Decile (*n*=23,549)								
Region								
Northeast	2,717	12.4 (0.7)	11.3 (0.8)	10.9 (0.6)	2.1 (0.3)	25.7 (0.8)	8.9 (0.5)	4.2 (0.6)
Midwest	4,774	19.8 (1)	14.4 (0.6)	15.5 (0.8)	2.4 (0.3)	28.3 (1)	8.7 (0.5)	5.7 (0.5)
South	14,981	54.8 (1.2)	12.6 (0.4)	15.1 (0.4)	3.1 (0.2)	31.6 (0.6)	10.6 (0.3)	5.5 (0.3)
West	4,093	13 (0.8)	14.6 (0.6)	12.1 (0.6)	2.7 (0.3)	26.7 (0.7)	8.2 (0.6)	3.5 (0.4)
Urban-rural classification								
Large central metro	9,693	33 (1)	13.2 (0.5)	12.2 (0.5)	2.3 (0.2)	26.9 (0.7)	8.8 (0.4)	4.6 (0.3)

Large fringe metro	4,332	21.4 (1.1)	11.3 (0.7)	13.4 (0.7)	2.5 (0.3)	27.8 (0.8)	8.8 (0.5)	4 (0.4)
Medium metro	6,009	22.5 (1.4)	13.3 (0.5)	13.5 (0.5)	2.8 (0.2)	29.3 (0.8)	9.9 (0.4)	4.8 (0.3)
Small metro	2,271	8.1 (1.1)	13.3 (1)	16.6 (1.3)	3.6 (0.4)	31.7 (1.3)	9.7 (0.8)	6.4 (0.7)
Micropolitan	2,704	9.7 (1.4)	13.8 (1)	18.9 (1.1)	3.4 (0.5)	36.4 (1.7)	12 (0.8)	7.4 (0.8)
Non-core	1,556	5.3 (1)	16.4 (1.4)	21.6 (1.2)	4.9 (0.6)	38.9 (1.4)	13.3 (1.1)	8.9 (1.1)
Coastal classification								
Non-coastal	15,484	57.5 (1.3)	13.5 (0.4)	15.5 (0.4)	3.1 (0.2)	30.7 (0.6)	9.9 (0.3)	5.8 (0.3)
Coastal	11,081	42.5 (1.3)	12.4 (0.4)	12.6 (0.4)	2.4 (0.2)	28 (0.6)	9.5 (0.3)	4.3 (0.3)

SPD: Serious psychological distress

COPD: Chronic Obstructive Pulmonary Disease

Summer Top Quartile = 9 days or more EHE_{95}; Summer (June, July, August)

Summer Top Decile = 14 days or more EHE_{95}; Summer (June, July, August)

EHE_{95} = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Table 21. Weighted percent and standard error of chronic health conditions for highest quartile and decile of summer extreme heat events by age group, National Health Interview Survey 2010-2013.

Summer	Age in years			
	18 to 34	35 to 49	50 to 64	65 and older
Top Quartile				
9 days or more EHE$_{95}$	*(n=44,613; 31.9%)*	*(n=13,063; 26.4%)*	*(n=11,474; 24.8%)*	*(n=11,022; 17%)*
SPD	13.2 (0.4)	14.1 (0.4)	14.8 (0.4)	11.4 (0.4)
Heart disease	5.3 (0.3)	9.1 (0.4)	17.7 (0.5)	32.8 (0.6)
Stroke	0.2 (0.1)	1.3 (0.1)	3.3 (0.2)	8.4 (0.4)
Hypertension	8 (0.3)	21.8 (0.5)	42.5 (0.6)	61.5 (0.7)
Diabetes	1.5 (0.1)	6.1 (0.3)	14.4 (0.4)	21.2 (0.5)
COPD	2.5 (0.2)	3.8 (0.2)	7 (0.3)	8.9 (0.4)
Top Decile				
14 days or more EHE$_{95}$	*(n= 8,026; 32.4%)*	*(n=6,770; 26.1%)*	*(n= 6,507; 24.8%)*	*(n= 5,262; 16.7%)*
SPD	12.9 (0.6)	14.4 (0.6)	14.3 (0.6)	11.8 (0.6)
Heart disease	5.6 (0.4)	9.2 (0.5)	17.9 (0.7)	34.2 (0.9)
Stroke	0.2 (0.1)	1.5 (0.2)	3.3 (0.3)	8.8 (0.5)
Hypertension	8.4 (0.4)	22.4 (0.7)	42.6 (0.9)	60.9 (0.9)
Diabetes	1.5 (0.2)	6.2 (0.4)	14.2 (0.6)	21.5 (0.8)
COPD	2.6 (0.3)	4.1 (0.3)	6.7 (0.5)	9.1 (0.5)

SE: Standard Error

SPD: Serious psychological distress

COPD: Chronic Obstructive Pulmonary Disease

EHE$_{95}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 95th percentile threshold calculated using a 30 year of baseline data.

Appendix C. Supplemental Tables for Extreme Heat Events and Other Chronic Respiratory Health Outcomes.

Table 22. Weighted percent of respondents by demographic characteristics, NHIS 1997-2010 merged with Climate Data.

Characteristic	All eligible adults (*n* = 411,493; 100%)	By Race Ethnicity			
		NH White (*n* = 263,802; 72.0%)	NH Black (*n* = 59,684; 11.5%)	Hispanic (*n* = 70,807; 12.1%)	NH Other (*n* = 17,200; 4.4%)
Sex					
Male	48.1	48.2	44.5	50.9	49.0
Female	51.9	51.8	55.5	49.1	51.0
Age					
18-34	31.3	27.8	36.7	44.5	38.4
35-49	30.2	29.7	31.3	31.5	32.5
50-64	22.2	23.8	20.1	15.5	19.4
65+	16.3	18.7	11.9	8.5	9.7
Education					
≤High School/GED	46.0	42.2	52.8	67.5	32.3
>High School/GED	54.0	57.8	47.2	32.5	67.7
Poverty Threshold[b]					
Less than 100%	11.8	8.3	22.5	22.3	14.0
100- <200%	17.6	14.9	23.0	29.2	17.5
200- <4000%	31.3	31.9	30.8	29.8	27.1
400% or greater	39.3	45.0	23.8	18.7	41.5
Insurance Coverage					
Not covered	13.7	10.1	15.2	33.2	15.2
Covered	86.3	89.9	84.8	66.8	84.8
Smoking Status					
Never Smoker	56.2	51.9	63.6	69.8	70.9
Current/Past smoker	43.8	48.1	36.4	30.2	29.1
Level of urbanization					
Large central metro	27.9	20.6	42.4	51.0	47.0
Large fringe metro	23.8	25.3	21.1	17.1	24.8

Medium metro	21.0	22.3	18.0	18.3	14.4
Small metro	10.2	11.7	7.2	6.0	5.8
Micropolitan	10.5	12.3	7.0	5.3	5.1
Non-core	6.5	7.8	4.2	2.3	2.9
Division					
New England	5.0	6.0	2.4	2.4	3.7
Middle Atlantic	13.7	13.7	14.3	12.1	15.3
South Atlantic	19.3	18.1	33.3	15.2	13.3
East South Central	6.3	6.8	10.2	0.9	1.8
West South Central	10.9	9.2	13.6	19.4	8.7
East North Central	16.7	19.0	15.0	6.7	10.4
West North Central	7.9	9.7	3.6	2.1	5.5
Mountain	6.6	6.7	1.5	10.3	7.0
Pacific	13.7	10.7	6.1	30.8	34.5

All percentages were weighted using NHIS survey weights.

Table 23. Characteristics of health outcome for top quartile of extreme heat events (47.5 or more EHE_{90} days) of exposed, by Race/Ethnicity, NHIS 1997-2010 merged with Climate Data.

	Race/Ethnicity				
	ALL Percent[1]	NH White Percent[1]	NH Black Percent[1]	Hispanic Percent[1]	Other Percent[1]
Asthma	5.5	5.6	0.8	4.4	4.6
ED Visit for Asthma	0.5	0.4	0.8	0.5	0.4
ED Visit for Asthma (Asthma=Yes)	4.2	3.5	7.3	6.1	4.6
Hay Fever	4.5	4.8	3.8	3.3	4.2
Chronic Bronchitis	2.2	2.4	2.2	1.3	1.3

[1]Weigthed percent: all percentages were weighted using NHIS survey weights.

NH= non-Hispanic

Other: All other races and ethnicities

Table 24. Crude and adjusted odds ratios for the impact of extreme heat events by quartile of exposure and asthma, 1997-2013.

| EHE$_{90}$ | Asthma | |
	Crude OR (95% CI)	Adjusted OR* (95% CI)
1 Year Lag Sum		
0 - ≤23.94	Reference	Reference
23.95 - 34.40	1.01 (0.97-1.04)	0.95 (0.91-1.00)
34.41 - 47.5	0.99 (0.95-1.03)	0.95 (0.91-1.00)
>47.5	1.00 (0.96-1.04)	0.96 (0.91-1.01)
2 Year Lag Sum		
0 - ≤44.23	Reference	Reference
44.24 - 59.31	0.98 (0.95-1.02)	0.94 (0.89-0.99)
59.32 - 76.63	1.02 (0.98-1.06)	0.98 (0.93-1.03)
>76.63	1.01 (0.97-1.05)	0.97 (0.92-1.03)
3 Year Lag Sum		
0 - ≤70.06	Reference	Reference
70.07 - 90.4	1.03 (0.99-1.07)	1.01 (0.96-1.07)
90.41 - 111.9	1.04 (1.00-1.08)	1.02 (0.97-1.07)
>111.9	1.03 (0.99-1.08)	1.01 (0.95-1.06)
5 Year Lag Sum		
0 - ≤145.88	Reference	Reference
145.89 - 177.3	1.07 (1.03-1.12)	1.05 (1.00-1.10)
177.31 - 211.82	1.10 (1.05-1.14)	1.06 (1.01-1.11)
>211.82	1.11 (1.06-1.16)	1.08 (1.02-1.14)

*Adjusted for age, sex, race/ethnicity, education, poverty status, health insurance coverage, smoking status, urban/rural classification, climate region.
EHE$_{90}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using a 30 year of baseline data.

Table 25. Crude and adjusted odds ratios for the impact of extreme heat events by quartile of exposure and asthma attack, 1997-2013.

| EHE$_{90}$ | Asthma Attack | |
	Crude OR (95% CI)	Adjusted OR* (95% CI)
1 Year Lag Sum		
0 - ≤23.94	Reference	Reference
23.95 - 34.40	1.02 (0.97-1.08)	0.96 (0.89-1.03)
34.41 - 47.5	0.98 (0.93-1.04)	0.95 (0.87-1.03)
>47.5	0.98 (0.92-1.04)	0.96 (0.89-1.05)
2 Year Lag Sum		
0 - ≤44.23	Reference	Reference
44.24 - ≤59.31	1.01 (0.96-1.07)	0.95 (0.88-1.03)
59.32 - ≤76.63	1.05 (0.99-1.11)	1.04 (0.96-1.12)
>76.63	1.00 (0.95-1.07)	0.99 (0.91-1.07)
3 Year Lag Sum		
0 - ≤70.06	Reference	Reference
70.07 - ≤90.4	1.05 (0.99-1.11)	1.05 (0.97-1.14)
90.41 - ≤111.9	1.09 (1.03-1.16)	1.08 (0.99-1.17)
>111.9	1.01 (0.95-1.08)	1.02 (0.94-1.11)
5 Year Lag Sum		
0 - ≤145.88	Reference	Reference
145.89 - 177.3	1.11 (1.04-1.18)	1.07 (0.99-1.16)
177.31 - 211.82	1.10 (1.03-1.18)	1.07 (0.99-1.16)
>211.82	1.09 (1.02-1.16)	1.08 (1.00-1.18)

*Adjusted for age, sex, race/ethnicity, education, poverty status, health insurance coverage, smoking status, urban/rural classification, climate region.

EHE$_{90}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using a 30 year of baseline data.

Table 26. Crude and adjusted odds ratios for the impact of extreme heat events by quartile of exposure and asthma attack among asthmatics, 1997-2013.

EHE$_{90}$	Asthma Attack (Asthmatics)	
	Crude OR (95% CI)	Adjusted OR* (95% CI)
1 Year Lag Sum		
0 - ≤23.94	Reference	Reference
23.95 - ≤34.40	1.02 (0.95-1.10)	1.00 (0.91-1.09)
34.41 - ≤47.5	0.99 (0.92-1.07)	0.98 (0.89-1.08)
>47.5	0.97 (0.90-1.05)	1.01 (0.92-1.12)
2 Year Lag Sum		
0 - ≤44.23	Reference	Reference
44.24 - ≤59.31	1.04 (0.97-1.11)	0.99 (0.90-1.09)
59.32 - ≤76.63	1.04 (0.97-1.12)	1.08 (0.98-1.19)
>76.63	1.00 (0.93-1.07)	1.01 (0.92-1.12)
3 Year Lag Sum		
0 - ≤70.06	Reference	Reference
70.07 - ≤90.4	1.04 (0.96-1.12)	1.06 (0.96-1.17)
90.41 - ≤111.9	1.08 (1.00-1.16)	1.07 (0.97-1.19)
>111.9	0.98 (0.91-1.05)	1.03 (0.93-1.14)
5 Year Lag Sum		
0 - ≤145.88	Reference	Reference
145.89 - ≤177.3	1.05 (0.98-1.13)	1.02 (0.92-1.12)
177.31 - ≤211.82	1.02 (0.95-1.10)	1.01 (0.91-1.11)
>211.82	0.99 (0.91-1.07)	1.02 (0.93-1.13)

*Adjusted for age, sex, race/ethnicity, education, poverty status, health insurance coverage, smoking status, urban/rural classification, climate region.
EHE$_{90}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using a 30 year of baseline data.

Table 27. Crude and adjusted odds ratios for the impact of extreme heat events by quartile of exposure and emergency department visit for asthma, 1997-2013.

EHE$_{90}$	ED Visit for Asthma	
	Crude OR (95% CI)	Adjusted OR* (95% CI)
1 Year Lag Sum		
0 - ≤23.94	Reference	Reference
23.95 - ≤34.40	1.03 (0.92-1.15)	0.92 (0.76-1.10)
34.41 - ≤47.5	0.92 (0.82-1.03)	0.87 (0.74-1.03)
>47.5	0.93 (0.83-1.05)	0.83 (0.70-0.99)
2 Year Lag Sum		
0 - ≤44.23	Reference	Reference
44.24 - ≤59.31	0.98 (0.88-1.09)	0.93 (0.79-1.1)
59.32 - ≤76.63	1.03 (0.92-1.16)	1.01 (0.85-1.2)
>76.63	0.94 (0.84-1.05)	0.85 (0.71-1.01)
3 Year Lag Sum		
0 - ≤70.06	Reference	Reference
70.07 - ≤90.4	1.05 (0.94-1.17)	1.08 (0.91-1.28)
90.41 - ≤111.9	1.02 (0.91-1.15)	0.94 (0.79-1.11)
>111.9	0.93 (0.83-1.05)	0.86 (0.73-1.02)
5 Year Lag Sum		
0 - ≤145.88	Reference	Reference
145.89 - ≤177.3	0.95 (0.85-1.06)	0.83 (0.71-0.98)
177.31 - ≤211.82	1.04 (0.92-1.17)	0.94 (0.79-1.12)
>211.82	0.97 (0.86-1.09)	0.84 (0.71-0.99)

*Adjusted for age, sex, race/ethnicity, education, poverty status, health insurance coverage, smoking status, urban/rural classification, climate region.

EHE$_{90}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using a 30 year of baseline data.

Table 28. Crude and adjusted odds ratios for the impact of extreme heat events by quartile of exposure and emergency department visit for asthma among asthmatics, 1997-2013.

EHE$_{90}$	ED Visit for Asthma (Asthmatics)	
	Crude OR (95% CI)	Adjusted OR* (95% CI)
1 Year Lag Sum		
0 - ≤23.94	Reference	Reference
23.95 - ≤34.40	1.13 (1.00-1.28)	1.08 (0.88-1.32)
34.41 - ≤47.5	1.09 (0.96-1.25)	1.09 (0.90-1.31)
>47.5	1.14 (1.00-1.31)	1.04 (0.85-1.28)
2 Year Lag Sum		
0 - ≤44.23	Reference	Reference
44.24 - ≤59.31	1.00 (1.00-1.00)	1.08 (0.89-1.30)
59.32 - ≤76.63	1.16 (1.01-1.33)	1.21 (1.00-1.47)
>76.63	1.10 (0.97-1.26)	1.03 (0.84-1.26)
3 Year Lag Sum		
0 - ≤70.07	Reference	Reference
70.07 - ≤90.4	1.13 (1.00-1.29)	1.25 (1.03-1.52)
90.41 - ≤111.9	1.13 (0.99-1.28)	1.07 (0.88-1.29)
>111.9	1.10 (0.96-1.26)	1.04 (0.85-1.26)
5 Year Lag Sum		
0 - ≤145.88	Reference	Reference
145.89 - ≤177.3	0.85 (0.75-0.97)	0.75 (0.62-0.91)
177.31 - ≤211.82	0.96 (0.84-1.09)	0.87 (0.72-1.06)
>211.82	0.82 (0.72-0.94)	0.70 (0.58-0.85)

*Adjusted for age, sex, race/ethnicity, education, poverty status, health insurance coverage, smoking status, urban/rural classification, climate region.
EHE$_{90}$ = Extreme heat events – days where the daily TMAX value exceeded the county and calendar month specific 90th percentile threshold calculated using a 30 year of baseline data.

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    known as National Climatic Data Center (NCDC) | NCEI offers access to the most

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    mapping the vulnerability of urban populations to extreme heat events: A case study

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    pollen season in central North America. *Proceedings of the National Academy of*

    Sciences, *108*(10), 4248–4251. http://doi.org/10.1073/pnas.1014107108

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EDUCATION

University of Maryland   *College Park, MD*
Ph.D. Marine Estuarine Environmental Sciences   January 2011 – May 2016
Advisor: Amir Sapkota, Ph.D.
"Exposure to Extreme Heat Events and Chronic Respiratory Diseases Among A Nationally
Representative Sample of the United States Population." doctoral dissertation

Kennesaw State University   *Kennesaw, GA*
M.P.A., Nonprofit Administration (Graduate Honors)   August 2008 – May 2010
Advisor: Andrew Ewoh, Ph.D.
"A Comparative Study of Intergovernmental Relations of two Federal Districts: The Case of the U.S.
District of Columbia and Brasília, Brazil." masters thesis

Spelman College   *Atlanta, GA*
B.S., Environmental Science (Departmental Honors)   August 2002 – May 2006
Advisor: Victor Ibeanusi, Ph.D.
"The bioremediation of heavy metals in wastewater using metal resistant bacteria strains." honors
thesis

HONORS AND AWARDS

U.S. EPA Science to Achieve Results (STAR) Fellowship, 2014 – 2016   (US$ 84,000)
UMD Council on the Environment (ConE) Green Fellowship, 2014   (US$ 10,000)
UMD, Graduate Research Interaction Day (1st Place)–Poster, 2012   (US$ 500)
Emerging Researchers Network (AAAS) Travel Award, 2012   (US$ 1,000)
National Science Foundation PROMISE Travel Award, 2011   (US$ 1,000)
National Science Foundation, LSAMP Fellowship, 2011 – 2012   (US$ 106,000)
U.S. Department of Energy, Mickey Leland Energy Fellowship, 2005   (US$ 4,000)

PROFESSIONAL EXPERIENCE

Maryland Department of Health and Mental Hygiene   *Baltimore, MD*
Program Manager, CDC Building Resilience Against Climate Effects (B.R.A.C.E.)
Environmental Health Bureau   01/2013 – 05/2016
U.S. Centers for Disease Control and Prevention (CDC)   *Hyattsville, MD*
Guest/Student Researcher
Office of Analysis and Epidemiology   05/2012 – 09/2015
Division of Health and Nutrition Examination Surveys   09/2015 - 05/2016

District of Columbia Department of Health   *Washington, D.C.*

Environmental Specialist/Health Physicists
Radiation Protection   08/2010 – 01/2011

Georgia Department of Natural Resources   *Atlanta, GA*
Environmental Specialist III
Environmental Protection Division, Ambient Air Monitoring   09/2007 – 08/2010

New Jersey Department of Environmental Protection   *Trenton, NJ*
Environmental Specialist I
Site Remediation Program   03/2007 – 09/2007

BASF Corporation   *Iselin, NJ*
Laboratory Technician I
Environmental Technology   06/2006 – 03/2007

U.S. Department of Energy   *New Orleans, LA*
Environmental Health and Safety Intern
Strategic Petroleum Reserve   06/2005 – 08/2005

RESEARCH INTERNSHIPS

Kennesaw State University, Political Science Department   *Kennesaw, GA*
Graduate Research Assistant   01/2010 – 05/2010

Model Institutions of Excellence: Spelman College   *Atlanta, GA*
Research Intern   08/2004 – 05/2005
Conducted laboratory research on the bioremediation of RDX, ammunition waste, in soil.

U.S. Department of Energy & Savannah State University   *Savannah, GA*
Research Intern   06/2004 – 08/2004
Conducted laboratory research on plants grown on soil amended with fly ash and sewage sludge.

Environmental Science Program: Spelman College   *Atlanta, GA*
Research Intern   08/2003 – 05/ 2004
Researched the bioremediation of toxic metals in wastewater using metal resistant bacteria strains.

SERVICE AND LEADERSHIP

International Society for Exposure Science
Student Councilor   2016 – 2017
Student and New Researcher Committee   2014 – present
Diversity Committee   2015 – present

University of Maryland
Vice President of Committee Affairs, Graduate Student Government   2015 – 2016
University Committee for the Review of Student Fees   2015 – 2016
University Facilities Review Committee   2015 – 2016
Nyumburu Cultural Center Advisory Committee   2015 – 2016
Search Committee Member, Clark School of Engineering   Spring 2013

Faculty Affairs Senate Member   2012 – 2013

PROFESSIONAL AFFILIATIONS

International Society for Exposure Science   2011 – present
American Public Health Association   2014 – present

PUBLICATIONS

Upperman, C.R., Parker, J., Jiang, C., He, X., Murtugudde, R. and Sapkota, A., 2014. Frequency of Extreme Heat Event as a Surrogate Exposure Metric for Examining the Human Health Effects of Climate Change. *PloS one*, *10*(12), pp.e0144202-e0144202.

Jiang, C., Shaw, K.S., **Upperman, C.R.,** Blythe, D., Mitchell, C., Murtugudde, R., Sapkota, A.R. and Sapkota, A., 2015. Climate change, extreme events and increased risk of salmonellosis in Maryland, USA: Evidence for coastal vulnerability. *Environment International*, *83*, pp.58-62.

Akerlof, K.L., Delamater, P.L., Boules, C.R., **Upperman, C.R.** and Mitchell, C.S., 2015. Vulnerable Populations Perceive Their Health as at Risk from Climate Change. *International Journal of Environmental Research and Public Health*, *12*(12), pp.15419-15433.

Soneja, S., Jiang, C., Fisher, J., **Upperman, C.R.,** Mitchell, C., Sapkota, A., Extreme Heat and Precipitation Events Associated with Increased Risk of Hospitalization for Asthma in Maryland, U.S.A. *Journal of Environmental Health.* Under Review.

LaKind, J.S., Overpeck, J., Breysse, P.N, Backer, L., Richardson, S., Sobus, J., Sapkota, A., **Upperman, C.R.,** Jiang, C., Beard, C.B., Brunkard, J.M. Bell, J., Harris, M.R., Chretien, J., Peltier, R.E., Chew, G.L. Ben Blount, B. Exposure science in an age of rapidly changing climate: Challenges and opportunities. *Journal Of Exposure Science And Environmental Epidemiology.* Under Review.

Upperman C.R., Parker, J., Akinbami, L., Jiang, C., He, X., Murtugudde, R., Curriero, F., Ziska, L., Sapkota, A. Frequency of Extreme Heat Events and Hay Fever Prevalence in the Continental United States, 1997-2013. *Environmental Health Perspectives.* Under Review.

In Preparation:
Upperman C.R., Parker, J., Akinbami, L., Jiang, C., He, X., Murtugudde, R., Sapkota, A. Geographic and Demographic Variability in County Level Exposure to Extreme Heat Events Using National Data Sets, 2010-2013.

SCIENTIFIC PRESENTATIONS (Conferences as of 2009)

Upperman, C.R., Parker, J., Akinbami, L., Jiang, C., He, X., Murtugudde, R., Curriero, F., Ziska, L., Sapkota A. "The Risk of Exposure to Climate Specific Extreme Heat and Hay Fever Prevalence among Adults in the Continental United States: Linkage of the National Health Interview Survey " Oral presentation at the University of Maryland Graduate Student Research Appreciation Day, College Park, Maryland, April 6, 2016.

Upperman, C.R., Parker, J., Akinbami, L., Jiang, C., He, X., Murtugudde, R., Curriero, F., Ziska, L., Sapkota A. "The Risk of Exposure to Climate Specific Extreme Heat and Hay Fever Prevalence among Adults in the Continental United States: Linkage of the National Health Interview Survey "

Oral presentation at the International Society of Exposure Science 25th Annual Meeting, Henderson, Nevada, October 18-22, 2015.

Romeo, C., Parker, J., Jiang, C., He, X., Murtugudde, R., Sapkota A. "Exposure Indicators for Examining the Potential Human Health Effects of Climate Change." Abstract accepted for poster presentation at the International Society of Exposure Science 24th Annual Meeting, Cincinnati, Ohio, October 12-16, 2014.

Romeo, C., Sapkota A. "Exposure to an Aggregate Climate Change Metric and Respiratory Health Outcomes in the Continental US." 013 Environment and health – Basel | Abstract Number: 5411 | ID: P2-2-12-13.

Romeo, C., Mehta, S., Parker, JD., Sapkota, A. "Indicators for Examining the Potential Chronic Respiratory
Effects of Climate Change." University of Maryland, Graduate Student Research Interaction Day, College Park, Maryland, April 11, 2012.

Romeo, C., Mehta, S., Parker, JD., Sapkota, A. "Indicators for Examining the Potential Chronic Respiratory Effects of Climate Change." Abstract accepted for poster presentation at the International Society of Exposure Science 21st Annual Meeting, Baltimore, Maryland, October 24-28, 2011.

Romeo, C., Mehta, S., Parker, JD., Sapkota, A. "Indicators for Examining the Potential Chronic Respiratory Effects of Climate Change." Abstract accepted for poster presentation at the NSF LSAMP Bridge to the Doctorate Research Symposium, College Park, Maryland, December 3, 2011.

Romeo, C., Mehta, S., Parker, JD., Sapkota, A. "Indicators for Examining the Potential Chronic Respiratory Effects of Climate Change." Abstract accepted for poster presentation at the NSF/AAAS Emerging Researchers National (ERN) Conference in STEM 2nd Annual Meeting, Atlanta, Georgia, February 23-26, 2011.

Aldredge, J., Smith, W., **Romeo, C.** "Georgia EPD Ambient Air Monitoring Network Assessment." Oral presentation at the Georgia Air Policy Symposium (GAPS) 2nd Annual Meeting, Atlanta Georgia, August 4, 2009.

OUTREACH

University of Maryland, College Park
Honors Seminar: Global Health Colloquium (February 2011, November 2013, & November 2014)
- Lectured on the global health effects of climate change.

Princeton Plasma Physics Laboratory & Princeton University, Princeton, New Jersey
Exhibitor: Young Women's Conference (March 2012)
- Displayed research and discussed research experiences for 8th–10th grade girls.

Science Mentors 1to1, Princeton, New Jersey
- *Honorary Guest Speaker* (May 2011)
- *Honorary Guest Speaker* (April 2016)

SKILLS

Programming Languages	SAS, SUDAAN, STATA, R, C++
Software	Microsoft Office (Word, Excel, PowerPoint), ArcGIS
Operating Systems	Microsoft, Macintosh

OTHER

Citizenship: United States of America
Language: English (native), Spanish (intermediate), Portuguese (beginner)