IMPACTS OF HIGH TEMPERATURES ON CAUSE-SPECIFIC EMERGENCY DEPARTMENT VISITS IN NORTH CAROLINA

Steven J. Lippmann

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Approved by:

David B. Richardson

Charles E. Konrad

Charles Poole

Scott K. Proescholdbell

Anna E. Waller

ABSTRACT

Steven J. Lippmann: Impacts of High Temperatures on Cause-Specific
Emergency Department Visits in North Carolina
(Under the direction of David B. Richardson)

Background: High ambient temperature is associated with a number of physiological and psychological responses that may influence the occurrence of emergency department visits. This dissertation project uses a cause-specific approach to assess the exposure-response associations between high ambient temperature and a wide range of disease and injury types, with the aim of more fully describing the impact of heat on emergency department visits in North Carolina. The first aim of this dissertation focuses on temperature and injury-related emergency visits. The second aim focuses on temperature and a nearly comprehensive set of diagnosis groups.

Methods: Data on emergency department visits in North Carolina between April 1st and October 31st in 2008-2013 were ascertained from a statewide surveillance system. County-specific daily mean temperature data were obtained from meteorological archives. For Aim 1, injury visits were classified by intent and mechanism using external cause of injury codes. For Aim 2, visits were categorized into diagnosis groups using the Clinical Classification Software system. Age- and sex-stratified exposure-response trends for the associations between temperature and emergency department visits were quantified using Poisson regression

Results: Over 13 million emergency department visits were categorized. In the first aim, unintentional injuries due to drowning among children were positively associated with temperature, as were bites and stings and excessive heat in all age groups. Adverse medical effects increased markedly with temperature among older adults. Intentional assault among adolescents and young adults was positively associated with temperature. In the second aim, Injury/Poisoning and Symptoms/Signs were leading causes of ED visits in all ages, and Circulatory diagnoses ranked highest in patients ≥65 years old. The exposure-response patterns for nearly all age and diagnosis combinations were reasonably well described by a linear function of temperature and most of these associations were positive. Mental illness was the only diagnosis group that was inversely associated with temperature in all age groups.

Conclusions: This study offers strong evidence of positive associations between daily mean temperatures and wide range of conditions resulting in emergency care, and highlights the importance of injury morbidity as a contributor to the overall population health impact of heat.

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LIST OF ABBREVIATIONS

CCS	Clinical Classification Software
CDC	Centers for Disease Control and Prevention
CI	Confidence interval
DPH	Division of Public Health
ED	Emergency Department
F	Fahrenheit
ICD-9-CM	International Classification of Diseases, 9th Revision, Clinical Modification
IRR	Incidence rate ratio
NC	North Carolina
NC DETECT	North Carolina Disease Event Tracking and Epidemiologic Collection Tool

CHAPTER 1. SPECIFIC AIMS

As climate change awareness increases and governmental agencies develop plans to minimize potential health effects of warmer temperatures, it is important to have comprehensive, research-based information about the public health impacts of heat. While there is a substantial literature on associations between ambient temperature and mortality, primarily among older adults residing in urban areas, with a focus on deaths due to cardiovascular and respiratory causes, recent studies have found temperature effects across a wider spectrum of causes. This study examined the effects of heat exposure on people of all age groups and examined heat effects on emergency department visits for a wide range of diseases and injuries. The results of this study improve our understanding of the effects of temperature on injury and disease among residents of North Carolina of all ages.

This study utilized state-wide surveillance data for 2008-2013 from the North Carolina Disease Event Tracking and Epidemiologic Collection Tool (NC DETECT) system, which has captured data on over 99% of all emergency department visits throughout the state of North Carolina since 2008. Emergency department visits were categorized into ICD-9-CM diagnosis groups using the Clinical Classifications Software, a widely-used standardized diagnosis clustering tool developed by the Agency for Healthcare Research and Quality. Injury-related emergency department visits were grouped by intent and mechanism based on ICD-9-CM external cause of injury codes. These data were merged with ecological data at the county level, including daily meteorological data from the North Carolina State Climate Office and annual population estimates from the U.S. Census Bureau to form a time-series analytical database with daily emergency department visit counts for each diagnosis and injury group.

The specific aims addressed by this study were:

> Aim 1: Describe associations between county-level daily average ambient temperature and warm-season (April-October) injury-related emergency department visits, with detailed attention to variation by injury intent and mechanism, as well as by demographic factors including sex and age.
>
> Aim 2: Examine the association between warm season daily average ambient temperature and emergency department visits for a comprehensive set of diagnosis groups, assessing the relative and absolute contributions of different diagnosis groups to the overall burden of heat and emergency department morbidity.

CHAPTER 2. BACKGROUND

2.1. Overview

Like all species, humans can thrive in only a relatively narrow band of the temperature spectrum. Exposure to temperatures beyond tolerable thresholds can result in illness, injury, and death as our body's natural ability to thermoregulate increasingly fails, resulting in multi-organ dysfunction.[1,2,3(chap3)] Concern about the impact of extreme temperatures on human health is growing, especially in light of mass casualties during major recent heat waves [4–9] and projected global climate change [10–12]. Many governmental agencies are currently developing or refining their heat advisory and preparedness strategies.[13–17] More effective emergency preparedness policies and programs may be developed if we understand more completely the impact of heat on human health outcomes.

Epidemiological research has consistently found U- or J-shaped curvilinear associations between temperature and mortality and morbidity outcomes, with the lowest risk in an optimal central range of temperatures and increasingly higher risk at the extremes.[18–22] The exact shape and inflection points of these curves differ depending on cause of death/morbidity, geographic location, population distribution, acclimatization, and availability of technologies such as air-conditioning, but the basic form remains. This study focused on heat effects, though cold effects are equally concerning, especially in cooler climates.[23,24]

While there is now a large body of literature on temperature effects on health, several important research gaps exist. First, most studies have examined all-cause mortality or cause-specific mortality limited to cardiovascular, respiratory, or cerebrovascular fatalities.[18–20,22]

Comparatively little research has been conducted on temperature and morbidity, in part because morbidity surveillance data are less available than vital statistics and death certificate data.[21] Even within the temperature-morbidity literature, most studies have focused on hospital admissions rather than emergency department visits and thus may only capture the most severe non-fatal outcomes.[25] Addressing this gap is important because studies have shown that the heat-morbidity patterns can differ considerably from those observed for mortality.[26,27] Second, many studies have focused exclusively on the impact of specific heat wave episodes using heat-wave period versus non-heat-wave period comparisons rather than using time-series or case-crossover designs that allow estimation of the effects of temperature over broader time intervals and temperature ranges.[21] Third, in both the mortality and morbidity literature, researchers have usually chosen a limited set of diseases or health outcomes of interest. This practice leaves open the possibility that there are unstudied diseases that are, in fact, affected by temperature. Major recent studies have all tended to use similar small sets of disease groupings (primarily cardiovascular and respiratory diseases), which were selected based on outcomes that were historically used in heat-wave-specific studies of mortality. More specifically, nearly all studies have *excluded* health outcomes that are due to external causes, such as injury and poisoning [28–31], though the rationale for this exclusion is rarely discussed.

Recent papers that have cast a wider net are notable exceptions, and have found heat is associated with many types of disease and injury.[32–34] Additional studies which have focused on individual diseases have found temperature is associated with conditions as disparate as renal disease [35], gout attacks [36], and preterm birth [37]. Together, these findings suggest that temperature-disease associations may extend beyond the cardiorespiratory outcomes that are typically studied, and provide support for this study's aims of taking a comprehensive, cause-specific approach that includes both disease and injury causes to evaluating the full public health impact of high temperatures on emergency department morbidity in North Carolina.

2.2. Temperature and Injury and other External Causes

2.2.1 Introduction

Historically, the possible effect of high temperatures on injury has received little epidemiological attention. In fact, many of the largest epidemiologic studies of heat and mortality have specifically *excluded* deaths due to injury and external causes**,** and focused instead on “non-accidental” all-cause, cardiovascular, or respiratory mortality.[24,28–31] While this exclusion is likely founded on the known excess of cardiovascular and respiratory deaths during heat waves, it precludes an investigation of potential associations between temperature and injuries..

2.2.2 Epidemiological Studies

Two recent heat-mortality studies have suggested that the effects of heat may include external causes.[32,33] Both studies found evidence of heat effects on external cause / injury deaths. In fact, in both studies the relative effect estimates for some injury causes of death were of similar magnitude to those for cardiovascular or respiratory sub-types.[32,33] Similarly, a recent study of meteorological effects on emergency department visits for nine different diagnosis groups in Taipei, Taiwan found that higher temperatures were associated with increased emergency department visits categorized into the catch-all group for “accidents” that included all ICD-9-CM codes in the range 800-999.[38]

Other epidemiological studies have also found evidence of associations between temperature and injuries. Higher temperatures have been associated with higher trauma admission volumes [39–42] and with work-related injuries [43,44] In an Australian heatwave-focused mortality and morbidity study that incorporated ambulance call-outs, however, there were more mixed results. While assault- and work-related ambulance calls increased during heat waves, some other injury categories, including sports and falls, had inverse or null associations with temperature.[45] Weak temperature associations were also reported in a study evaluating the usefulness of several weather variables in predicting pediatric injury-related emergency department volumes.[46]

Interpretation of temperature-injury association findings has been complicated by the fact that some prior studies have combined all injuries together [38]; this can be problematic because it combines heat-related illness (ICD-9-CM code 992.x, which includes heat exhaustion, heat stroke, and heat syncope) with other injuries. By not disaggregating injuries, these studies preclude estimation of temperature effects on specific types of injuries. Other studies include *only* heat-related illness and do not include any other injury types.[45,47] In these studies, and in studies that focus exclusively on heat-related illness, the effect sizes for this diagnosis group have been very large.[47–49]

2.2.3 Studies from Related Fields

Studies in fields such as ergonomics and occupational hygiene, military medicine, and environmental/social psychology provide support for considering the associations between temperature and injury. From the 1950's to the 1990's, researchers in the fields of occupational health and ergonomics conducted many experimental and observational studies on the effects of heat on human work. In fact, in 1972 and again in 1986, the National Institute of Occupational

Safety and Health tried, unsuccessfully, to persuade the Occupational Safety and Health Administration to mandate upper limits on occupational heat exposure.[50,51] These efforts were reinvigorated recently, and a new draft criteria for occupational exposure to hot environments, updated with additional research findings, was distributed for public comment in 2013.[13] Although this NIOSH document primarily focuses on physiological mechanisms such as inadequate heat balance that can result in heat illness, it also discusses the cognitive and performance effects of heat, which can result in an increased likelihood of injury.[13(pp3, 51)]

Some of these cognitive and psychomotor performance effects have been directly studied in ergonomic laboratory tests. Performance tasks used in these studies have included measures of reaction time; attention/perceptual skill; mathematical processing; and reasoning, learning, and memory. Overall, increased temperature has been associated with performance decrements, but the results have been somewhat mixed, with some studies finding no effect and others finding performance increments with increased temperature.[52,53] Some researchers have argued that these differences are related to the type of tasks used in the experiments or the type of heat exposure.[53–56]

In additional to experimental data, the fields of ergonomics and occupational health have also provided some observational evidence for potential heat effects on injury. One such study examined the effects of workplace temperature on unsafe work behaviors.[57] After observing over 17,000 observations of worker behavior and directly measuring proximal heat exposures, a U-shaped curve emerged in adjusted models, with the lowest unsafe behavior index measures occurring when the temperature was in the range 17°C to 23°C wet-bulb globe temperature [57] In a more recent study, Morabito et al. found an association between apparent temperature and hospital-admission due to workplace injuries in Tuscany, Italy; interestingly, this study found that workplace injury peaked at high, but not extremely high temperatures, possibly due to changes in work behaviors at those extremes.[44]

Many of the early findings about heat stress and the physiology of heat-related illness emerged from studies conducted by military researchers.[58–62] Military studies have also provided a mechanism for evaluating whether findings from laboratory observations hold true under real-world conditions. One such study, conducted by researchers from the Israeli Air Force, examined records for 500 randomly selected warm-season helicopter incidents due to pilot error and compared the temperature on the day of those events to the temperature on 1000 other days during the same period.[63] Notably, this study design is similar to a case-crossover design, though the authors do not refer to the study as using that method and do not appear to have used conditional statistical methods. Again, a curvilinear J-shaped dose-response curve was found, with increasing temperatures being associated with more pilot-error-related incidents.[63]

Seasonal variations have also been linked to injury rates during military trainings, with warmer season training sessions resulting in higher injury rates.[64,65] Since military training is standardized and runs throughout the year, potential confounding by season-varying task activities, a limitation of most sports-related studies, is reduced. In the 2002 study, injuries were categorized into overuse (e.g. strains, stress fractures, and tendinitis) or traumatic (e.g. sprains, dislocations, lacerations). Interestingly, the risk of injury in summer for both overuse and traumatic injury was about twice that in fall, even after controlling for difference in physical characteristics of the four training groups.[64]

2.2.4 Heat and Violence

Another way that temperature might affect injury rates is through heat effects on aggression and violence. Even our language forms these connections; phrases like “hot under the collar", "hot tempered", and "in the heat of the moment" capture the commonly held connection between heat and aggression.[66]

Heat acts as both a physiological and psychological stressor. Researchers in the field of environmental and social psychology have linked temperature with increased aggression or violent crime.[66–75] There has been considerable debate, however, about whether this relationship is linear and monotonically increasing; non-monotonic (with some researchers finding a decrease in violence at the highest end of the temperature spectrum); or even a real effect at all.[67,70,76–79] Some researchers have even expanded this potential connection from interpersonal violence to climate effects on global inter- and intra-national conflicts.[80,81]

2.3. Temperature and Cause-Specific Mortality/Morbidity

In the heat-health literature, researchers have typically created *ad hoc* diagnosis groups of diseases of interest for each study. Tracing the history of these groupings in many recent papers leads back to findings from a seminal paper describing excess hospital admissions during the 1995 heat wave in Chicago.[82] Over time, these groupings have been replicated and augmented by other researchers, though much of the focus has remained on cardiovascular and respiratory diseases.

Semenza et al. considered nearly all ICD-9-CM diagnosis categories in their study of excess hospital admissions during the catastrophic 1995 heat wave in Chicago. Both primary and secondary discharge diagnoses were evaluated. The conditions that exhibited an excess as primary diagnoses during the heat wave were related to dehydration, heat-related illness, or renal failure. However, when considering primary discharge diagnoses together with secondary diagnoses, which were thought to represent comorbidities and existing conditions, cardiovascular, cerebrovascular, respiratory, renal, and endocrine diseases were highlighted as important underlying conditions that elevated risk of hospital admission during the heat wave. Semenza et al. are careful to note that by using admission data, they may be not be adequately representing illnesses that are treatable in the emergency department or another outpatient provider.[82(p276)] They also point to incomplete E-coding as potentially limiting their ability to detect excesses in external cause admissions.[82(p276)] Unfortunately the details of these limitations have seemingly been lost over time and the implicit exclusion of external causes and certain other diagnoses, justified on the basis of a lack of evidence of an excess in injury admissions in this paper, continues to propagate.

Several recent heat-health studies have taken a different approach, however. These studies have focused on systematically and consistently modeling the cause-specific associations between heat and various diseases, both by widening the set of disease groups under study and by disaggregating sub-types of major disease categories such as cardiovascular and respiratory disease. Together, these studies serve as models for our approach to assess the heat effects on cause-specific emergency department visit morbidity.

Two of these studies investigated cause-specific mortality.[32,33] Using a shared modeling strategy for each cause of death, these studies provided evidence on the relative contribution of each cause to the total health impact of heat. Gasparrini et al. examined cause-specific temperature-mortality relationship across 33 different cause of death categories and included groups for “all external causes”, “accidents/injuries”, and “intentional self-harm”.[32] Basagaña et al. studied 66 cause-of-death groups, including eight external cause of injury subgroups.[33]

This approach has also been used in two studies of hospital admissions: one in Australia[34] and another among Medicare patients in the United States[83]. In the Medicare study, the researchers used the same Clinical Classification Software diagnosis grouping system that we employ in Aim 2 of this dissertation project.

Since mortality and hospital admission research involve only the most serious cases, disproportionate emphasis may be placed on certain diseases that are either more fatal or require greater medical intervention, or populations whose health may already be compromised, such as older adults. Prior research has already found important differences between mortality and hospital admissions resulting from heat [26,27] and it is likely that emergency department visit patterns will differ from both deaths and hospital admissions. The literature on ambient temperature and emergency department visits is very limited. Two studies in California have also looked at cause-specific effects across many disease categories, first in a study of hospital admissions and emergency department visits focused on a 2006 heatwave, in which 11 groups were used [25], and a case-crossover study of temperature effects on hospital admissions in nine California counties, in which 16 groups were formed.[84]

Only a few studies have looked at cause-specific associations at the emergency department level. Two studies in California, one focused on heat waves [25] and the other a case-crossover design [47] examined cardiovascular and respiratory diseases (each disaggregated into sub-types in the Basu et al. paper), as well as electrolyte imbalance, cerebrovascular disease, renal failure, diabetes, and heat-related illness. A recent study of emergency department visits in Taipei, Taiwan, examined temperature effects on nine different diagnosis groups.[38] In these studies, however, the outcomes of interest do not comprehensively encompass the different types of diseases or injuries that are treated in the emergency department.

CHAPTER 3. METHODS

3.1. Study Design

3.1.1 Study Designs in Existing Literature

Three main study designs have been used in the temperature-health literature: 1) case series studies, such as those enumerating the impact of specific heat wave events[5,82,85]; 2) time-series studies, which model the temporal associations between heat exposures and health effects[32,86]; and 3) case-crossover studies, which compare heat exposures at the time of the event (case) to those during a sample of other time points (crossover).[31,47] Case series studies of heat wave mortality have been informative in revealing risk factors and vulnerable populations including being elderly, lower socio-economic status, having a mental illness, African-Americans, and having co-morbid conditions such as cardiovascular or respiratory disease.[19,87] Protective factors included air-conditioning and access to transportation.[19,88–90] Methodological research has demonstrated the equivalence of rate ratios obtained from time-series and case-crossover designs in the special case where exposures are shared by the population and are measured at the ecological level, such as air pollution or temperature.[91–93]

Many heat-health studies have focused on comparing “heatwave” periods to “non-heatwave” periods.[25,33,45] This approach can be problematic, however, because heat wave definitions vary widely in temperature thresholds and duration requirements[94], and different definitions can yield disparate effect estimates.[24,95] Despite these challenges, there has also been interest in assessing whether there is an added effect of a heat wave above and beyond the effects of high temperature itself.[23,96–98]

3.1.2 Study Design for this Project

This study linked emergency department visit data from a state-wide surveillance system with meteorological observations and population estimates to estimate the associations between daily county-level temperatures and county-level emergency department visit rates for a large set of disease and injury groups. The study used a time-series design with outcomes and potential confounders or modifiers measured at the individual level and exposures shared at the geographical level. The combined data were analyzed using Poisson generalized linear regression models.[91,99–101]

3.2. Study Setting and Population

The source population was all residents of the state of North Carolina in the years 2008-2013. North Carolina residency was determined by the patient's recorded county of residence. Since NC DETECT, the source of emergency department visit data, captures nearly all emergency department visits in North Carolina, we considered the full state as the catchment area and calculated rates using Census population denominators.

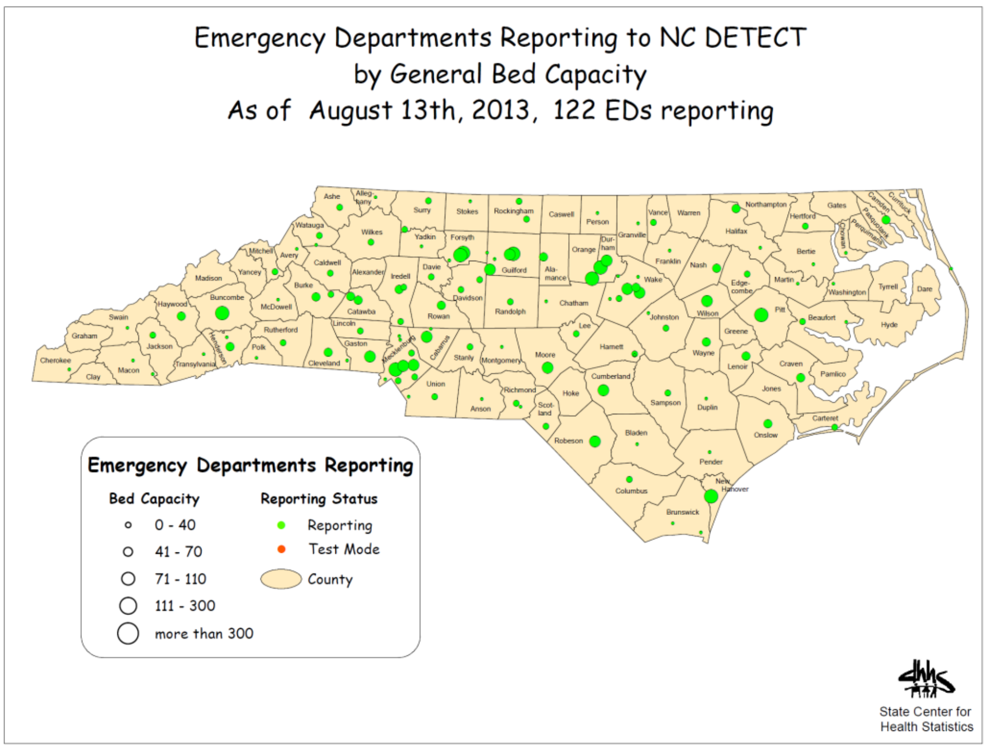
North Carolina is a large and growing Southeastern state with a 2010 population of approximately 9.5 million people, making it the 10th most populous US state [102]. North Carolina is divided into 100 counties, with Census 2010 total populations ranging from 4,400 (Tyrell county) to 920,000 (Mecklenburg county) and land areas ranging from 172.5 (Chowan county) to 949.2 (Robeson county) square miles. The state has a varied topography and is geographically divided into three main regions: the Coastal Plains abutting the Atlantic Ocean and extending westward to Interstate 95 and beyond to a natural fall line running from Halifax County southwest to Scotland County; the Piedmont, in the center of the state, containing the fast-growing population centers connected by Interstates 85 and 40--Charlotte-Mecklenburg, Greensboro-Winston-Salem-High Point (the "Triad"), and Raleigh-Durham-Chapel Hill (the "Triangle"); and the Appalachian Mountains region in the western portion of the state, containing the Blue Ridge and Smoky Mountain ranges. The topography of these geographic regions also produces distinct climates, with the Coastal Plains typically having a warmer and moister climate due to its proximity to the Atlantic Ocean, and the Mountains experiencing cooler temperatures throughout the year as a result of its higher elevation.

3.3. Data Sources and Acquisition

3.3.1 Outcome Data: Emergency Department Visit Data

The NC DETECT surveillance data system has been collecting data on emergency department visits in North Carolina since the early 2000's, but it expanded into a comprehensive, statewide system after the NC legislature mandated that all hospitals with 24-hour acute care emergency departments must provide their data for public health surveillance purposes, effective January 1, 2005. Hospitals now report de-identified visit data to NC DETECT electronically, in near real time, via the North Carolina Hospital Emergency Surveillance System. By 2008, nearly all hospitals contributed data, with only a few small, rural hospitals as temporary holdouts. Psychiatric, military and veteran's hospitals are not included in the data available for research. As of August 13th, 2013, there were 122 active hospitals reporting to the system, though this number fluctuates as new hospitals come online and others either close or have gaps in data such as when electronic medical record systems are upgraded. Figure 1 displays the geographic distribution of the EDs that report to NC DETECT. An estimated 99.5% of all emergency department visits statewide in 2008 were captured in NC DETECT [103]; with essentially all hospitals reporting, the effective catchment area for this surveillance system encompasses the whole state, allowing us to calculate population-based rates using Census denominators. Over 4 million emergency department visits are recorded in the NC DETECT system each year.

Figure 3.1 Map of participating hospitals contributing data to NC DETECT, 2013.[104]



For this dissertation project, I obtained state-wide visit-level data for all emergency department visits made by North Carolina residents to civilian 24/7 acute-care hospital-affiliated emergency departments during the period between January 1st, 2008 and December 31st, 2013 under a data use agreement with the NC Public Health Data Group and NC DETECT data oversight committee. The following data elements from NC DETECT were used to develop the analysis dataset: age, sex, discharge diagnosis codes (up to 11 ICD-9-CM diagnoses), coded cause of injury (up to 5 ICD-9-CM E-codes), date and time of visit, and patient's county of residence. Demographic information other than age and sex are unavailable in the NC DETECT system; race and ethnicity data were not collected prior to June 2015.

3.3.1.1. Categorization of Injury Types (Aim 1)

Injury-related emergency department visits were categorized using both ICD-9-CM diagnosis codes and external cause of injury codes, also known as E-codes. Each injury-related visit record in the NC DETECT data includes up to five ICD-9-CM external cause of injury codes, or "E-codes". These codes provide additional information about the precipitating event that resulted in the patient being injured and needing emergency care.

In the language of the ICD-9-CM codebook, the term "external causes", and their corresponding "E-codes", refers to an additional classification scheme that was developed to describe the circumstances under which an injury, poisoning, or adverse effects event occurred.[105] E-codes are prefixed with an "E" followed by a 3-5 digit number, and range from E800-E999.xx. A fully-coded data record for a patient treated for an injury, poisoning, or adverse effect at the emergency department should receive both diagnosis code(s) and E-code(s). For example, a patient who falls on a set of stairs and breaks her ankle would receive a diagnosis code reflecting the ankle fracture itself (such as 824.8) and an E-code reflecting the fact that the fracture was the result of a fall from stairs (such as E880.9).

Emergency department visits were identified as "injury-related" if they contained either an ICD-9-CM diagnosis code in the 800-999 range, or an ICD-9-CM external cause of injury code (E-code) in the E800-E999 range. Injury-related visits were further disaggregated into groups using the CDC's injury matrix framework for ascribing E-codes to different types of injury.[106,107] Due to the more complex meteorological effects on motor vehicle crashes, such as the effects of precipitation and fog, and the lack of driving exposure metrics and detailed crash data, we chose to exclude motor vehicle crashes from this study.

There are two primary axes by which injuries are categorized: Intent and Mechanism [106]. Intent is divided into six groups: 1) *Self-Inflicted*, which includes suicide and other self-harm; 2) *Assault*, which includes injuries intentionally inflicted by others; 3) *Unintentional*, which includes "accidental" injuries such as falls; 4) *Undetermined*, including injuries for which intent could not be adequately discerned; 5) *Adverse Effects*, which includes adverse reactions to medications and medical misadventures; and 6) *Other*, which includes legal intervention (injuries resulting from legal police actions) and operations of war. Mechanism of injury describes the physical causes of the injury, such as falls, poisoning, cutting/piercing, fight/brawl, fire, natural and environmental factors, firearms, or suffocation.

In addition to intent and mechanism, E-codes can also be used to describe the place of occurrence. Place codes are listed in the E849.0-E849.9 range, and include the following categories: Home, Farm, Mine and quarry, Industrial place and premises, Place for recreation and sport, Street and highway, Public building, Residential institution, Other specified place, or Unspecified place. In 2010, two new sets of E-codes were introduced into the ICD-9-CM to describe the *status* and *activity* of the patient at the time of the injury. *Status* codes are useful for differentiating between occupational, military, and recreational injuries. Status categories include: civilian activity done for income or pay, military activity, other external cause status, and unspecified. *Activity* codes describe the type of activity that the patient was doing at the time of the injury. They are particularly useful for identifying sports and recreational activities that resulted in injury, since each sport has its own code.

Despite their utility in providing additional details about injury events, these *place*, *status*, and *activity* E-codes are not consistently coded by hospitals. This is particularly true for activity and status codes because these codes were introduced in the middle of the study period and are still being adopted by hospitals in North Carolina. As a result, the data for this study did not have sufficient inclusion of place, status, and activity codes to use them for categorizing injury-related emergency department visits.

For the Aim 1 analyses, we assigned visits to injury groups based on the first-listed E-code that represents intent and mechanism. Since place, activity, and status codes can be present amongst the five possible E-code positions, I developed data management routines to scan through each set of E-codes and skip over E-codes that indicate only the place, activity, or status of the injury event. While the second- or lower-listed E-codes may provide additional information, researchers commonly focus on the first-listed code both for practicality given the quantity of data and because the first-listed E-code is supposed to represent the primary intent and mechanism of injury which resulted in the emergency department visit.[108] Furthermore, it has been reported that in the NC DETECT system more than 50% of injury-related emergency department visits in 2010 received only one E-code [108], limiting the possible gains from also considering the 2^{nd}-5^{th} codes.

3.3.1.2. Categorization of ICD-9-CM Diagnosis Codes (Aim 2)

With the proliferation of electronic medical records and health surveillance systems, the vast magnitude of health data accentuates the need for standardized classification schemes. Standardized categorizations allow for comparability across studies, and, when developed with physicians, help to ensure that the disease groupings are clinically relevant. Taking a health informatics approach, we used a standardized classification algorithm for grouping the thousands of illnesses and other conditions codified in the ICD-9-CM into a more manageable set of clinically-related diagnosis groups.[109]

Emergency department visits were categorized into diagnosis groups based on ICD-9-CM diagnosis codes using the Clinical Classification Software (CCS) diagnosis clustering system.[109] The CCS is actively maintained by the Healthcare Cost and Utilization Project and sponsored by the Agency for Healthcare Research and Quality. Also referred to as a “clinical grouper”, the CCS is a diagnosis categorization scheme that condenses the more than 14,000 individual ICD-9-CM diagnosis codes into 285 clinically-meaningful diagnosis groups.[109] Although other diagnosis clustering tools are available, the CCS was previously found to have the best coverage for the types of diagnoses that are typically encountered in the emergency department [110] and has been used successfully with NC DETECT data in earlier studies.[111]

There are two forms of the CCS system: a single-level version with 285 clusters and a multi-level version that hierarchically positions the single-level groups into larger super-groups and also provides even finer sub-groups for some conditions.[109] For example, the ICD-9-CM diagnosis code “493.02 Extrinsic asthma with acute exacerbation” is labeled in the single-level version as group “128 (Asthma)”. In the multi-level version, however, it is labeled as group “8.3.2.3”, where each digit represents a different level in the hierarchy: “8 (Diseases of the respiratory system)” > “8.3 (Asthma)” > “8.3.2 (Other and unspecified asthma)” > “8.3.2.3 (Other asthma with acute exacerbation)”. Note that in this case, the single-level CCS group corresponds to the 2nd level in the multi-level version. This is the most common pattern for bridging the two versions, but some single-level groups correspond instead to the 1st, 3rd or 4th levels.

While the 285 single-level CCS groups are far more manageable than the thousands of individual ICD-9-CM codes, it is still impractical to estimate effects for all 285 groups. In order to reduce the number of groups but still retain a comprehensive and exhaustive approach, we used the highest level of the multi-level form of the CCS as the basis for grouping diagnoses.

3.3.2 Exposure Data: Meteorological Data

3.3.2.1. Temperature Metrics

Several metrics are available to characterize meteorological exposure; some are directly measured, such as ambient temperature, while others combine multiple variables algorithmically to incorporate both temperature and the potential effects of other factors such as humidity, dew point temperature, wind speed, or solar radiation [112–114]. These algorithmic “biometeorological” measures, such as heat index and apparent temperature, were originally developed to characterize human thermal comfort and are often presented alongside temperature forecasts in media outlets because they are informative for choosing weather-appropriate apparel, but they have also been used extensively in heat-health research.[19,87]

The question of which of these metrics to use in heat-health research has been an active area of deliberation. Further complicating this decision, each of these measures can also be summarized at the daily level with many different statistics, including daily mean, median, maximum, or minimum. Several comparison studies have tested various metrics against each other to determine which performs best at predicting health outcomes, but no clear winner has emerged. The optimal predictive metric has varied by disease, by location, or by age group.[115–120]

Furthermore, for epidemiological studies, where less emphasis is placed on the purely predictive quality of models, it has been concluded that these metrics tend to produce similar exposure-response patterns, largely due to the fact that these metrics are highly correlated.[116,120,121] For practical purposes, these studies have suggested that these metrics are largely interchangeable [121] and have advocated selecting a metric for which the available data are most spatially and temporally complete[116] and which is most easily measured and interpreted to aid effective communication in heat-warning systems.[121] In North Carolina, like elsewhere, average daily ambient temperature data are most spatially and temporally complete; and, it is for these reasons that I will use this temperature metric in my dissertation analyses.

3.3.2.2. Meteorology Data

Meteorological data, including the daily maximums, minimums, and means for ambient, dewpoint, and heat index temperatures (where available), were obtained from the NC Climate Retrieval and Observations Network Of the Southeast (NC CRONOS) system via a data request to the State Climate Office of North Carolina.

Weather conditions throughout the state of North Carolina are continually monitored at first order automated weather stations, including Automated Weather Observing System (AWOS), Automated Surface Observing System (ASOS), Agricultural Weather Network (AgNet), and North Carolina Environment and Climate Observing Network (NC ECONet) stations maintained by the Federal Aviation Administration (AWOS and ASOS), the National Weather Service (ASOS), the Department of Defense (ASOS), the NC Agricultural Research Service (AgNet), and the NC State Climate Office (AgNet and NC ECONet). These first order monitoring stations record ambient and dewpoint temperature observations on an hourly basis year-round and also provide daily summary statistics for each midnight-to-midnight 24 hour period. In addition to the first order stations, there is also an additional network of non-automated Cooperative Observing Program (COOP) monitoring stations, maintained by a network of volunteers and contractors organized by the National Weather Service, in areas of NC where first order stations are not available. These COOP stations record 24-hour-period minimum and maximum ambient temperatures, though the time of observation varies from station to station and is typically not midnight-to-midnight as with the first order stations. Data from both the first order and COOP monitoring stations are aggregated in NC CRONOS and made available to researchers through data requests to the NC State Climate Office.

Meteorological exposures were assigned by county and day, by linking the patient's county of residence and the visit date recorded in the NC DETECT system to measurements taken at monitoring stations within that county. If more than one monitoring station was situated in a given county, the stations' values were averaged. If one or more of the monitoring stations in a county had missing or invalid data for a given day, the average of the remaining functioning monitors was used.

One limitation of using the patient's county of residence is that we cannot guarantee that the precipitating events that led to the emergency department visit occurred in that same county or in another county. For example, if a Wake County resident went to the emergency department while vacationing in New Hanover County, it is possible to introduce exposure misclassification by assigning the temperature in Wake County to that emergency department visit. An alternative approach would be to use the county in which the emergency department facility is located, with the presumption that patients are usually brought to the nearest emergency department. However, due to restrictions in NC DETECT data use agreements, we were prohibited from identifying individual hospital facilities; since many counties have only one emergency department, we were also restricted from obtaining facility's county because that information would identify the facility itself. To address this concern empirically, we created larger *regional* clusters of counties; instead of identifying the location of each facility at the county level, we were able to identify which *region* it was in. With this information, we compared the region of the facility to that of the patient's county of residence to evaluate the extent to which travel outside of the county of residence might affect our results.

Exposure assessment at the individual-level was neither available nor practical for this study. Exposure misclassification may occur as a result of the use of ecologic, rather than personal, ambient temperature. However, an exposure assessment study conducted in Baltimore with a small group of elderly subjects using personal ambient temperature monitors found that personal ambient temperatures were well correlated with temperatures measured in downtown and at Baltimore Washington International airport, though the personal ambient temperatures were slightly lower than those measured by weather stations.[122] Another concern is that outdoor temperatures may not reflect the actual exposures that the population experiences; for example, office workers may typically experience lower temperatures during work hours due to the cooling effects of air conditioning. This potential misclassification can go in the opposite direction, too; a study of the homes of older adults in Detroit found that indoor temperatures often *exceeded* outdoor ambient temperatures.[123] The correlation between outdoor ambient temperature and personal ambient temperatures, however, is likely to vary by factors such as geography (for example, microclimate differences, such as elevation or forestation, between where an outdoor temperature is measured and where a person resides) or occupation (for example, outdoor workers versus workers in air-conditioned office settings.) Although air conditioning prevalence is likely to be appreciably higher in North Carolina than in the cooler climate of Detroit, actual usage is highly dependent on economic factors.

3.3.3 Population Estimates

Age-group and sex-specific county-level mid-year population estimates for each study year were obtained from the U.S. Census Bureau's Intercensal Population Estimates (2008-2009) and Current Estimates (2010-2013). These data serve in the current analysis as population denominators in calculations of incidence rates.[124,125] These data were available with five-year age groups. To match the breakpoints in the Census population data, we used the following six groups: 0-9, 10-19, 20-44, 45-64, 65-74, and 75 and older.

3.4. Data Examination and Quality Assurance

Several data quality steps were performed to address the presence of incomplete or erroneous data points in the input datasets.

Meteorology: Data in the NC CRONOS system are the raw measurements taken by weather monitoring stations and are not processed through data quality checks prior to inclusion or dissemination. When monitoring stations malfunction, the data contributed to NC CRONOS can contain implausible values, such as midsummer temperatures of -40°F; if the malfunction persists, there can be long strings of unusual values in the time series. Potentially erroneous meteorological values were identified using range checks based on climate normals for North Carolina. Values that fell outside of the expected range were vetted by comparing them to values from nearby stations for the same time period. When we determined that a value was likely to be the result of monitor malfunctions, the erroneous values was set to null. These checks were run on a monitor-level prior to the calculation of county-level daily averages; since we were averaging monitor values when 2 or more monitors were situated in a given county, we could still generate an average from the remaining monitors after removal of the erroneous values stemming from a malfunctioning monitor.

NC DETECT: When new hospital electronic medical records systems are deployed or when existing systems experience technical problems, there can be temporal discontinuities in the data feeds that are aggregated into the NC DETECT system. In many instances, these discontinuities are able to be repaired with data updates at a later time, but in other cases, the NC DETECT data remain incomplete. This may affect all data elements coming from a given hospital, or can be specific to one or more variables. The duration of these gaps can be as short as a day or as long as several months.

Additionally, some hospital data feeds into NC DETECT are more systematically missing certain elements, such as diagnosis codes or E-codes, for a substantial proportion of visits. For example, some hospitals' data are regularly missing diagnosis codes for approximately 40-50% of their visits. Since these codes are necessary for categorizing emergency department visits into disease or injury groups, this under-coding can affect our ability to accurately enumerate diagnosis- or injury-specific visit counts and may result in underestimates of rates and outcome misclassification in the time-series analyses.

To address this issue, we examined the emergency department visit data; since the data use agreement did not include hospital identifiers, these data quality checks were performed at the county level. Temporal discontinuities were identified through visual inspection of county-specific time-series plots for each variable of interest. Systematic data incompleteness was assessed by calculating the proportion of all visits made in a given county on a given day that contained only missing values for the variable of interest.

We developed a threshold for missing diagnosis codes or E-codes after considering both the need to remove from the analysis those county-days that lacked adequate data with which to generate accurate visit counts and the cost of removing county-days in terms of reduced power and rate stability. When the data completeness in a given county on a given day crossed that threshold, both the visit count numerators and the corresponding person-time were removed prior to the calculation of rates and regression analyses.

3.5. Statistical methods

3.5.1 Data Transformations

NC DETECT data were structured as a line-listing with each row consisting of a single emergency department visit. Data elements in the NC DETECT, meteorological, and population data were categorical or continuous, and some of these data values were transformed for analysis (Table 3.1). The emergency department visit data were grouped by county, day, age group, and sex. Next, these data were linked to meteorological data by county and day, and to population data by county, age group, sex, and year to form a grouped data table.

Table 3.1. Description of data elements, sources, and transformations.

Variable	Data Sources	Original data type	Data Transformation(s)	Ecological Level
Outcome				
Age	NC DETECT	Continuous	Six age groups: 0-9, 10-19, 20-44, 45-64, 65-74, and ≥75	Individual Visit
Patient’s county of residence	NC DETECT	Categorical	100 NC counties	Individual Visit
Diagnosis code (ICD-9-CM)	NC DETECT	Categorical	Grouped by Clinical Classification Software	Individual Visit

Injury E-code (ICD-9-CM)	NC DETECT	Categorical	Grouped by Intent and Mechanism	Individual Visit
Exposure				
Ambient temperature	NC CRONOS	Continuous	Daily mean: Either mean of minimum and maximum temperatures or mean of hourly temperature values, based on weather station type. Parameterizations: Categorical (approx. 5°F increments); linear; natural cubic spline	County
Population				
Age group specific mid-year population estimates	U.S. Census Bureau	Categorical	Six age groups: 0-9, 10-19, 20-44, 45-64, 65-74, and ≥75	County
Day of year	NC DETECT (visit date); NC CRONOS (date of temperature observation)	Integer (April 1=1 to October 31=214)	Smoothing function for longer term time trends (spline)	N/A
Day of week	NC DETECT (visit date); NC CRONOS (date of temperature observation)	Integer (1-7)	Indicator term for weekday vs weekend	N/A
Year	NC DETECT (visit date); NC CRONOS (date of temperature observation)	Integer (2008-2013)	Indicator for year	N/A

The analysis dataset was a matrix constructed from the cross-classification groups of county, day, sex (Aim 1 only) and age, with additional variables for each diagnosis/injury group. In this dataset, there was one data row for every cross-classification of county (n=100), day (n=214*6=1284, for the 214 days between April 1 and October 31, and 6 data years from 2008-2013, inclusive), age group (n=6), and sex (n=2) for a total of 1,540,800 possible rows. This data structure also included the spatio-temporally linked meteorological and population data corresponding to each county-day-age-sex group. Additional variables indexed the selected diagnosis/injury groupings, and contained the daily disease/injury-specific emergency department visit counts enumerated for each county-day-age-sex group combination.

3.5.2 Statistical Analysis

Descriptive statistics included cause-specific emergency department visit counts and rates, as well as cross-tabulations by age, sex, and temperature intervals. Cells sized >0 and <10 were suppressed in compliance with the NC DETECT data use agreement with NC DPH. Distributional plots and statistics for ambient temperature such as mean, median, and range were also generated.

In both aims, count-based Poisson generalized linear regression models were used to estimate the exposure-response patterns for the associations between temperature and cause-specific emergency department visit rates, and to adjust for potential confounders.[99,100] The natural logarithm of the population estimate for the relevant age group, sex, county, and year strata was used as an offset term for incorporating the population denominator into the Poisson model in order to model the log-rate instead of the log-count as the dependent variable.[126]

We modeled the exposure-response curve for the association between warm-season county-level average daily mean temperature and emergency department visits for each disease or injury group separately, using a series of generalized linear models of the form:

$$\ln\left(count_{ijkl}\right) = \alpha + f\left(\beta; t_{ij},\right) + \gamma YEAR_j + \gamma DOW_j + f\left(\gamma; \mathrm{DOY}_j,\right)$$
$$+ \ln(personyears_{ijkl}/100{,}000)$$

where:

i	indexes county;
j	indexes calendar day;
k	indexes age group;
l	indexes sex;
$\ln(count_{ijkl})$	is the natural logarithm of the daily emergency department visit count for county *i*, day *j*, age group *k*, and sex *l*;
α	represents the intercept;
$f\left(\beta; t_{ij}, s\right)$	is a set of beta coefficients representing the functional form of the parameterization of the county-specific daily mean ambient temperature (and optionally, including product interaction terms for potential effect measure modifiers *s*);
$\gamma YEAR_j$	Represents the coefficients for the indicator term for calendar year;
γDOW_j	represents the coefficients for the indicator term for day of week (weekday vs weekend);
$f\left(\gamma; \mathrm{DOY}_j,\right)$	is the set of coefficients representing the functional form of the smoothing function for day of year; and
$\ln(person - years_{ijkl} /100{,}000)$	is the population denominator offset term: the natural logarithm of the county-year-age-sex-specific population estimate represented as person-years divided by 100,000.

To evaluate the shape of the exposure-response relationship, our modelling approach explored several parameterizations for temperature. Modelling of ambient temperature started with a simple categorical parameterization of this variable, with indicator terms for each 5°F interval, and then proceed to more flexible natural cubic spline parameterizations. Some recent papers consider lagged effects of temperature on morbidity or mortality, examining for example the association between the rate of disease on day *j* and average daily ambient temperature on day *j*, *j*-1, *j*-2,…*j*-*n*.[127] The current analysis examines only unlagged associations. To account for longer term time trends, we included in the model a smoothing function for day of year, a term for day of week (weekend vs weekday), and a term for calendar year, with no regression model adjustment for sex or age. Some heat-health studies have considered air pollution as a potential confounder; this is particularly true for heat studies that are offshoots of air pollution – health studies. However, recent methodological commentaries have called this practice into question using directed acyclic graphs, on the grounds that air quality is a causal intermediate of the heat-health association and not a confounder of this relationship. [128,129] For this reason, we did not adjust for air pollution concentrations in this study.

While age and sex were not considered important potential confounders a priori, we were interested in modification of ambient temperature-disease associations by sex and age. To examine heterogeneity in these associations, we repeated the analysis using interaction terms for sex and age group. Figures depicting the stratified exposure-response curves on the log-rate scale were produced for each diagnosis or injury group, including 95% confidence bands. Where summarization with simpler models was possible, we also produced tables and forest plots with estimates of the incidence rate ratios and 95% confidence intervals.

CHAPTER 4. TEMPERATURE, INJURIES, AND ADVERSE EFFECTS

4.1. Introduction

Despite the extensive literature on the effects of high temperatures on human mortality[18–20,22,130] and morbidity[21,25,34,38,48,83,84,131,132], few epidemiological studies have quantified the effects of temperature on injuries[39–43,45,46,133,134]. In fact, many of the largest recent heat-health studies have specifically excluded external cause outcomes *a priori*.[24,29,30,135]

Such exclusions are noteworthy since research in fields such as ergonomics, psychology, and criminology provides support for considering the associations between temperature and injury generally, and not just the patent increased risk of heat-related illnesses such as heat exhaustion and heat stroke, which are also classified as external cause of injury events.[48] Heat acts as both a physiological and psychological stressor, and can lead to increased cognitive and psychomotor fatigue, decreased concentration, or other performance decrements[53,55] that may increase the risk of unintentional injury to self or others. High temperature has also been posited to affect intentional injury rates through heat effects on aggression, violence, or mental health. Researchers in the field of environmental and social psychology have linked temperature with increased aggression and violent crime.[66–70,72,74,75]

The current study examines associations between county-level average daily mean temperature and the leading causes of injury-related emergency department visits in North Carolina in 2008-2013 using state-wide surveillance data from the North Carolina Disease Event Detection and Epidemiologic Collection Tool (NC DETECT), including detailed analyses of variations in the exposure-response patterns by injury intent and mechanism, as well as modification by age and sex.

4.2. Methods

4.2.1 Study Setting

This study examines associations between heat and injury-related emergency department visits among residents of North Carolina, the 10th most populous US state in 2010[136], during the warm months (April through October) in the years 2008-2013. Seven of the 100 counties in North Carolina had no weather stations during this period and were excluded from this study (Alleghany, Camden, Catawba, Clay, Greene, Jones, Perquimans counties); these are counties with relatively small populations and contain only 2.4% of the 2010 state population.

4.2.2 Meteorological Data

Daily mean ambient temperature data were obtained from the NC Climate Retrieval and Observations Network of the Southeast (NC CRONOS), a large meteorological database developed and maintained by the NC State Climate Office. This system aggregates observed values from over 300 weather stations throughout the state, and includes both automated and non-automated stations. Automated stations record temperature observations on an hourly basis year-round and also provide daily summary statistics for each midnight-to-midnight 24 hour period. In addition to the automated stations, there is also an additional network of non-automated Cooperative Observing Program (COOP) monitoring stations, maintained by a network of volunteers and contractors organized by the National Weather Service, in areas of NC where automated stations are not available. These COOP stations record 24-hour-period minimum and maximum ambient temperatures, though the time of observation varies from station to station and is typically not midnight-to-midnight as with the automated stations. Daily mean values for each station were calculated as the average of the 24 hourly observations for automated stations, and the average of the 24-hour minimum and maximum values for non-automated stations. Non-automated stations do not capture heat index, apparent temperature, or other humidity-related metrics; by choosing daily mean temperature as our exposure metric, we were able to retain 16 counties that contained only non-automated stations.

Same-day meteorological exposures were assigned by county and day. If more than one monitoring station was situated in a county, the stations' values were averaged. If one or more of the monitoring stations in a county had missing or invalid data for a given day, the average of the remaining functioning monitors was used. The number of monitors contributing to each county-day's average ranged from 1 to 10 with a mode at 2 monitors; 67% of the county-days averages were composed from 1, 2, or 3 monitors.

Potentially erroneous meteorological values were identified using range checks based on typical temperature values for North Carolina. Monitor values were manually reviewed and compared to values from nearby stations for the same time period if the daily mean temperature was <25°F or >90.5°F; if the daily maximum temperature was <30°F or >110°F; or if the daily minimum temperature was <10°F or >90°F. 169 potentially implausible temperature values were identified and reviewed; 119 of these were excluded prior to the calculation of county-day average daily mean temperatures. In all 119 cases, however, other monitors in the same counties were functioning properly, so no county-days were lost due to implausible values. Additionally, six mountaintop research stations, all at elevations above 4,000 feet, were excluded since they do not reflect population exposures; other monitors in those counties were available for calculating daily averages. In order to focus on higher temperatures and attenuate potential non-linearity introduced by cold effects, we truncated the temperature range so that observations less than 40°F were excluded from the regression analyses. This truncation resulted in the removal of 266 county-days; these all occurred during April or October, at the tails of our study season, and were concentrated in mountainous counties in Western North Carolina.

4.2.3 Emergency Department Visit Data

Emergency department data from April 1st through October 31st for the years 2008 to 2013 were obtained from the North Carolina Disease Event Tracking and Epidemiologic Collection Tool (NC DETECT) system, a statewide public health syndromic surveillance system. EDs operating in 24/7 acute-care civilian hospitals electronically report de-identified emergency department visit data in near real time to this legislatively-mandated system; beginning in 2008, an estimated 99.5% of emergency department visits statewide have been captured in NC DETECT.[103] As of December 2013, 123 hospital EDs were actively submitting data to the system, though this number fluctuates as new hospitals come online and others either close or have temporary data feed gaps, such as when electronic medical record systems are upgraded. Residency in NC was confirmed by the patient's reported county of residence.

In addition to basic patient demographic information, NC DETECT data include up to eleven International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM)[105] diagnosis codes and up to five external cause of injury codes, also known as "E-codes". These E-codes provide additional information about the precipitating events that resulted in the patient being injured and needing emergency care.

4.2.4 Outcomes of interest

Our primary analyses focus on the three leading causes of injury-related emergency department visits: unintentional injuries, adverse medical effects, and intentional assault. Injury emergency department visits for which intent was categorized as intentional self-harm (n=36,096), undetermined (n=13,396), or “intentional - other” (n=2,592) are not reported here. In addition, unintentional injuries due to motor vehicle crashes (n=419,609) are not reported in this paper; we chose to exclude these due to the more complex meteorological effects involved in crashes and the unavailability of driving exposure metrics.

Emergency department visits were categorized as injury-related if they contained either an ICD-9-CM diagnosis code in the 800-999 range, or an ICD-9-CM E-code in the E800-E999 range. To classify each injury-related visit into a single intent and mechanism category, we identified the first-listed ICD-9-CM E-code recorded for each visit that encoded intent and mechanism of the injury event. We used this code to categorize the intent and mechanism of the precipitating event according to the Centers for Disease Control and Prevention’s injury matrix framework for ascribing E-codes to different types of injury.[106,107] Some records contained only E-codes that provided information *other than* intent or mechanism, such as place of occurrence, and could not be categorized. E-codes for excessive heat (E900.*) were separated from the CDC’s “Natural and Environmental Factors” mechanism group and assigned to their own group, “Excessive Heat”. The adverse medical effects category includes “Drugs, Medicinal and Biological Substances causing adverse effects in therapeutic use” (E930-E949), “Misadventures to patients during surgical and medical care” (E870-E876), and “Surgical and medical procedures as the cause of abnormal reaction of patient or later complications, without mention of misadventure at the time of the procedure” (E878-E879).[105]

Although hospitals are mandated to submit all diagnosis and E-codes that they record for administrative purposes, these data elements are missing for some emergency department visits. To account for these missing data, we calculated the proportion of missing data for each day in each county and established a threshold for inclusion. We dropped both the visit counts and the person-time contribution for any county-day where more than 50% of visits in that county-day were missing diagnosis codes, or if more than 50% of visits receiving an injury-related diagnosis code in a given county-day were missing E-codes.

4.2.5 Census data

Age-group and sex-specific county-level population estimates for were obtained from the U.S. Census Bureau's Intercensal Population Estimates (2008-2009) and Current Estimates (2010-2013) datasets for use as population denominators in calculations of incidence rates.[124,125] These annual, mid-year (July 1st) estimates were assigned to all study days within their respective years. These data were available with five-year age groups. To match the breakpoints in the Census population data, we used the following six groups in age-stratified analyses: 0-9, 10-19, 20-44, 45-64, and 65-74, and 75 and older.

4.2.6 Statistical Methods

Daily emergency department visit counts for each intent and mechanism category were enumerated for each level in the cross-classification of county, day, sex, and age (in six groups defined as 0-9, 10-19, 20-44, 45-64, and 65-74, and 75 and older), to form a grouped count data structure with no age adjustment within age groups. Visits where the patient's sex was missing, unknown, or other were excluded (n=164). These data were linked to meteorological data by county and day, and to population data by year, sex, and age group.

Adjusted and unadjusted Poisson regression models were fitted to evaluate the association between average daily temperature and each injury type, yielding estimated incidence rate ratios (IRR) and corresponding 95% confidence intervals (CI). To evaluate the shape of the exposure-response relationships, we evaluated several parameterizations for temperature, starting with simple linear and categorical parameterizations, and proceeding to cubic spline forms, which allow more flexibility but still restrict the tails where uncertainty is typically greatest, to be linear. We used only same day temperatures and did not evaluate lag functions; previous research has indicated the heat effects are usually apparent with very short lag periods, such as same day or previous day.[24,127] Modification was modeled using product interaction terms between the functional forms of temperature and a variable that indexed combinations of sex and age group to obtain our stratified log-rate temperature trend estimates. As in previous research focusing on short-term effects of ambient temperature on disease occurrence[99,100], our adjusted models included a smoothed function for day of year to adjust for longer-term intra-seasonal variation in emergency department visit rates, an indicator term for day of week (weekend vs. weekend) to account for differential usage of EDs on weekends, and an indicator term for calendar year to account for longer term secular trends in emergency department visit rates. The natural logarithm of the population estimates for the relevant age group, sex, county, and year strata were used as offset terms for incorporating the population denominator into the Poisson model in order to model the log-rate instead of the log-count as the dependent variable.[126] Figures depicting the spline-based exposure-response curves and 95% confidence bands from both the adjusted and unadjusted models, stratified by sex and age group combinations, were produced for each major injury intent group. The exposure-response patterns for age-sex-specific temperature-emergency department visit associations from the unadjusted models closely resembled those estimated from the adjusted models; results from the adjusted models are presented in the subsequent text except where specified and the unadjusted figures are presented in electronic appendix eFigures 2-4. All regression analyses were performed in SAS (SAS Institute, Cary, NC) version 9.4 using the GLIMMIX and PLM procedures.

4.3. Results

During the months of April through October in the years 2008 to 2013, there were 2,616,285 eligible emergency department visits for unintentional injury (excluding motor vehicle crashes), adverse medical effects, and intentional assault (Table 4.1), out of the 3,827,134 total visits that contained either an injury-related ICD-9-CM diagnosis code or E-code. A detailed summary of all inclusion/exclusion criteria and the number of visits and county-days affected is provided in Appendix eTable A.1. The final analysis dataset had temperature values for 103,391 county-days with a mean of 69.3°F and standard deviation of 9.4°F.

Table 4.1 provides a summary of the counts and rates of eligible injury-related emergency department visits by sex and age group. For both males and females, overall injury rates were highest in the ≥75 year old age group, reaching over 17,000 per 100,000 person-years for females and over 12,600 per 100,000 person-years for males. Males had higher rates than females in the 0-9, 10-19, and 20-44 year old age groups, but lower rates in the older age groups. Unintentional injuries made up the largest proportion of injury-related visits, accounting for over 2.2 million emergency department visits during the study period. Similar to overall injury rates, unintentional injury rates were higher for males than females up to age 64; female rates overtook male rates at ages 65 or older. Unintentional injury rates for females in the 75 and older age group were substantially higher than those for younger females and all male age groups, likely due to their greater propensity to fall-related injuries. Adverse effects made up the second largest group of external cause emergency department visits and increased with age for both sexes. Rates of intentional assault peaked in the 20-44 year old age group and were lower in the younger and older groups.

Table 4.2 reports crude incidence rates by injury intent and mechanism and by categories of average daily temperature. Overall, unintentional injury emergency department visit rates tended to increase with temperature to about 70°F and then diminish at higher temperatures; however, exposure-response trends differed by mechanism. Table 4.2 reports crude unintentional injury incidence rates for 4 selected mechanisms of unintentional injury; additional unintentional injury mechanisms are presented in Appendix eTable A.2. Incidence rates increased with increasing daily mean temperature for unintentional injuries with mechanisms including drowning, excessive heat, and bites and stings, while rates for injury due to overexertion increased with temperature until about 70 degrees and decreased with further increasing temperatures. Rates of emergency department visits for adverse effects, and for intentional assault increased with increasing daily mean temperature (Table 4.2); rates for specific mechanisms of intentional assault are presented in Appendix eTable A.2.

Exposure-response patterns for unintentional injury differed across injury mechanisms. The panels of Figure 4.1 depict temperature-response associations for 4 selected mechanisms of unintentional injury, stratified by age group and adjusting for day of year, calendar year, and weekday; associations for additional unintentional injury mechanisms are presented in eAppendix Figure A.1. Patterns were similar for males and females (results not shown). Emergency department visits for drowning (Panel A) increased sharply with higher temperatures in the youngest age group, but were flat for most other age groups. Visits for excessive heat increased exponentially in all age groups as temperatures increased (Panel B). Visits for bites and stings (Panel C) followed an inverted U-shaped curve with rates peaking between 70-80°F for all age groups, though the strongest effects were for children under 10. Temperature-emergency department visit rate patterns for overexertion (Panel D) were flat for the three oldest age groups, but decreased with increased temperature in the younger groups, with the steepest decrease in the 10-19 year old group. For most age groups, the rate of emergency department visits for unintentional injury due to falls (Appendix eFigure A.1 Panel A) appear to vary minimally with temperature over the range from about 40°F to 70°F and then slightly decrease at the highest temperatures; for the oldest age group, however, rates decreased monotonically over the whole temperature range. Visit rate patterns for unintentional injuries categorized as "struck by, against" (Appendix eFigure A.1 Panel B) were mostly flat or slightly increasing with temperature for young children and all adults, but dropped precipitously among children aged 10-19 years. In most age groups, visits for unintentional injuries resulting from cutting/piercing instruments (Appendix eFigure A.1 Panel C) were either flat or increased slightly from 40°F through 70°F and then receded at higher temperatures. Rates for unintentional injuries labeled with an "unspecified" mechanism (Appendix eFigure A.1 Panel D) increased substantially for adults aged 20 and older, but had a slightly inverse-U-shaped curve for the children and adolescents.

Visit rates for adverse medical effects increased with age for both males and females and reached over 3000 per 100,000 person-years in the ≥75 year old group (Figure 4.2). Adverse effects increased markedly with higher temperatures in the middle and older age groups, but were not as strongly associated with increased temperature in children and adolescents (Figure 4.2). These patterns were similar for males and females in each age group.

Figure 4.3 illustrates the association between temperature and emergency department visits for intentional assault by sex and age groups. The strongest positive associations between daily mean temperature and emergency department visits for intentional assault (Figure 4.3) were observed among adolescents and adults; rates were comparatively low and flat for children aged 0-9 years and adults 65 years old or older. Rates of intentional assault emergency department visits were highest among males 20-44 years old, followed by females of the same age group. Exposure-response curves for the association between intentional assault and temperature for females aged 10-19 and 20-44 had an inverted U-shape, with rates peaking between 60-70°F and around 80°F, respectively. For males aged 10-19, rates increased up to a temperature between 60-70°F and then fluctuated at higher temperatures. For males in the 20-44 year old age group, rates increased up to around 80°F, then plateaued. For both men and women in the 45-64 year old group, rates appear to increase monotonically with increasing temperatures.

4.4. Discussion

We found evidence of associations between high daily mean temperatures and rates of emergency department visits for some of the leading external causes of morbidity. We observed substantial differences in the magnitude of the rates and in the exposure-response trends, by injury type and by sex and age.

With regards to unintentional injuries, in our study there was considerable heterogeneity in the associations between temperature and unintentional injury by both injury mechanism and age group. The mechanisms that had the strongest positive associations with temperature were bites and stings, drowning, excessive heat, cutting/piercing instruments, and unspecified mechanism, although for some of these mechanisms, rates decreased at the highest temperature after peaking at more moderate temperatures (Appendix eFigure A.1). Since they are so common, emergency department visits for falls were very influential on the overall unintentional injury trends, especially for the older age groups. Emergency department visits for bites and stings also occurred in large numbers and appeared to be strongly associated with temperature; this is likely due to a combination of biological life-cycles and increased human outdoor exposure at moderately high, but not extremely high temperatures.

With regards to adverse effects or medical misadventures, we found substantial positive associations between temperature and rates of emergency department visits for adverse effects or medical misadventures. These associations were strongest in older adults. Although prior epidemiological studies have found temperature impacts related to illicit drug overdoses[137] and psychiatric medications[138,139], and pharmacological studies have identified certain classes of drugs that alter or inhibit thermoregulatory response[140], the impact of temperature on adverse effects is not frequently cited as a major component of heat-health effects. This may be because previous studies often have excluded mortality or morbidity due to external causes *a priori*. Not all of the adverse effects included in this category are related to medications; this category also includes adverse effects of medical or surgical care. Additional research is needed to further differentiate which sub-types of adverse effects are most impacted by temperature and to develop interventions targeted to those specific conditions.

Finally, with regards to intentional injuries, we found strong associations between temperature and intentional assault emergency department visits among adolescents and young adults. Research in social psychology and criminology has suggested that aggression and violent crime increase with heat.[66–68,70] Our study corroborates those findings and demonstrates that the heat-effects on violence can generate not only interpersonal strife, but also substantial increases in serious health outcomes such as emergency department visits. Interestingly, we found that the association between heat and assault-related emergency department visits was largely confined to the 10-19 and 20-44 year old age groups, and was present for both male and female victims. One area of debate in the psychological literature on heat and aggression has been whether this effect tapers or recedes at the most extreme temperatures.[75,76] Although there is considerable uncertainty at this tail, our models suggest a slight decrease in intentional assault emergency department visit rates at the highest temperatures.

This study draws upon a large, comprehensive database in NC of statewide emergency department visit data. Much of the prior literature on heat-related effects has relied upon either mortality or morbidity measured by hospital admissions. Since many injuries require only emergency care and do not result in hospitalization or death, examination of these relationships at this level of morbidity is crucial. Another strength of this study is that, by disaggregating injuries, we were able to distinguish the exposure-response patterns for different age groups and for different injury intents and mechanisms. Previous studies have either lumped all injuries together[32,38], or have grouped them by the physical type of injury (e.g. laceration, fracture, sprain)[133] rather than by the characteristics of the precipitating events leading up to the injury, which are captured in the E-codes we used to categorize injury-related emergency department visits in this study. Since falls make up such a large portion of injury-related emergency department visits, the relationship between temperature and falls dominates the overall heat-injury response pattern; separating visits by age group and sex and by injury intent and mechanisms provides insight into the heterogeneity in these responses and may also suggest potential areas for targeted public health interventions.

One limitation of using the patient's county of residence is that we cannot guarantee that the precipitating events that led to the emergency department visit occurred in that same county.

For example, if a resident of the centrally located Wake County went to the emergency department while vacationing in New Hanover County along the coast, exposure misclassification could potentially be introduced by assigning the temperature in Wake County to that emergency department visit. To address this limitation, we compared the region in which the patient resided (four regions, based on aggregation of North Carolina counties by climatic zones) to the region in which the emergency department was located. We found that only 4.4% of injury visits were made in regions that differed from the patient's home region. Furthermore, given the strong spatial correlations in daily temperatures within the state, we do not believe that this potential misclassification greatly affected our results. Another limitation is that we did not have humidity data with which to calculate biometeorological metrics such as heat index or apparent temperature from all counties. Previous research, however, has advocated using whichever temperature metric has the least missing data and the greatest spatial/temporal coverage since all of these metrics are highly correlated.[116]

Some prior studies have examined outcomes due to external causes, and have also suggested that the effects of heat may extend well beyond the cardiovascular and respiratory causes that are the typical heat-health concern. Two recent cause-specific heat-mortality studies that included external causes found evidence of heat effects on injury deaths; in both studies, the relative effect estimates for some injury causes were of similar magnitude to those for cardiovascular or respiratory sub-types.[32,33] Similarly, a recent study of meteorological effects on emergency department visits for nine different diagnosis groups in Taipei, Taiwan, found that higher temperatures were associated with increased emergency department visits categorized into a catch-all "accidents" group that included all ICD-9-CM codes in the range 800-999.[38] In a study in cities in South Korea, researchers categorized injury-related ambulance calls into traumatic and non-traumatic injuries; they found that increased temperature was positively associated with ambulance calls for non-traumatic injuries, but found a more complex non-linear exposure-response curve for traumatic injuries, wherein ambulance calls increased through the moderate temperature range but then decreased at the highest temperatures.[133] Other epidemiological studies have also found evidence of associations between temperature and injuries. Higher temperatures have been associated with higher trauma admission volumes[39–42] and with work-related injuries[43,44,134]. Mixed or weak associations have also been reported, however, in a study of ambulance calls[45] and another on pediatric injury-related emergency department volumes[46].

Like those prior studies cited above, our primary analyses adjust for temporal factors including day of year, calendar year, and day of week. Recent methodological discussions in the epidemiological literature have questioned some of the adjustment variables that have been standard in previous heat-health analyses. For example, in the past, adjustment for ozone levels had been considered essential; now, it has been suggested that such adjustment is contraindicated in most cases.[128,129] The current practice in heat-health studies is to adjust for long-term and intra-season time trends by including smoothing terms for day of year and indicator terms for year. In our study, we found little impact of adjustment for day of year, calendar year, or day of week on the estimated temperature-emergency department visit associations reported in eFigures B.1-B.3 (Appendix B); this may be due, in part, to several factors, such as the absence of any reason to suspect that ambient temperatures would differ between weekends and weekdays and the restriction of our analyses to relatively narrow ranges of calendar years (2008-2013), months within those years (April-October), and temperatures within those months (>40^0 F).

In summary, this study offers strong evidence of positive associations between average daily temperature and emergency department visits due to a variety of types of injury, including unintentional injuries among youth primarily due to heat, bites, and stings, intentional assault injuries among adolescents and younger adults, and adverse effects of medication and medical care. The latter is noteworthy both due to the magnitude of association, its evidence of substantial excess rates at older ages, and the sizable increase in visits observed on hot days among older adults. The findings suggest important directions for further research on heat in relation to injury.

4.5. Tables and Figures

Table 4.1 Summary statistics on injury-related emergency department visit counts and rates by sex and age group. North Carolina, April-October, 2008-2013.

	Intent (Count)				Person-time (person-years)	Overall incidence Rate (per 100,000 person-years)
	Unintentional[a]	Adverse Effects / Medical Misadventures	Intentional Assault	Total[b]		
Sex / Age Group						
Female						
0-9	142,427	5,532	940	148,899	1,834,781	8,115.4
10-19	130,032	6,155	8,305	144,492	1,866,106	7,743.0
20-44	381,423	37,959	35,436	454,818	4,846,575	9,384.3
45-64	229,420	40,599	7,678	277,697	3,863,749	7,187.2
65-74	74,327	19,693	476	94,496	1,160,767	8,140.8
75 or older	142,670	27,227	402	170,299	999,952	17,030.7
Male						
0-9	192,376	7,060	1,069	200,505	1,917,062	10,459.0
10-19	206,082	4,652	12,210	222,944	1,963,787	11,352.8
20-44	437,754	21,316	46,660	505,730	4,799,162	10,537.9
45-64	205,201	32,543	13,275	251,019	3,575,036	7,021.4
65-74	49,391	17,587	734	67,712	992,634	6,821.4
75 or older	58,464	18,846	364	77,674	615,880	12,611.9
Total	2,249,567	239,169	127,549	2,616,285	28,435,492	9,200.8

[a] Excludes motor vehicle crashes.

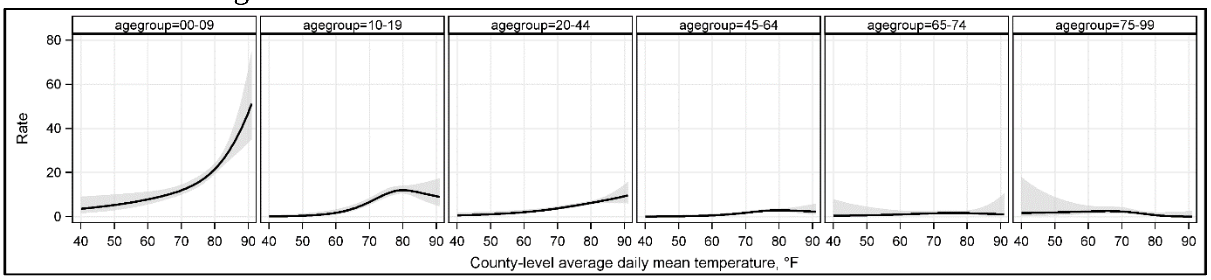
[b] Includes only injury intent categories listed.

Table 4.2 Select injury-related emergency department visit rates by county-level daily mean temperature (°F). North Carolina, April-October 2008-2013.

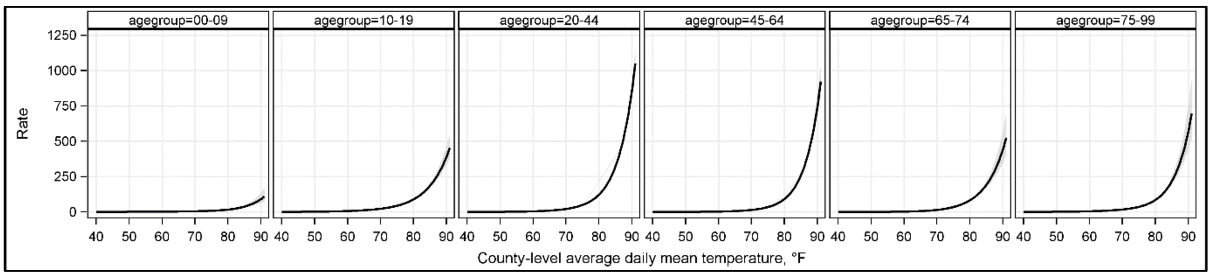
	Crude incidence rate per 100,000 person-years, by county-level daily mean temperature (°F)							
	40-<50	50-<55	55-<60	60-<65	65-<70	70-<75	75-<80	≥80
Person-years	851,226	1,361,312	2,433,709	3,495,886	4,148,380	5,790,587	6,726,151	3,628,241
Unintentional	6,815.7	7,422.5	7,480.0	7,618.0	8,050.0	8,210.9	8,107.9	7,921.1
Drowning	0.7	0.8	0.9	1.4	2.2	5.0	7.5	9.9
Excessive heat	1.1	0.8	2.3	4.2	9.5	22.7	51.8	153.3
Bites and Stings	270.6	355.6	387.1	465.9	590.4	713.8	799.5	817.9
Overexertion	806.8	893.4	892.4	897.2	920.0	908.8	873.8	837.7
Adverse Effects or Medical Misadventures	758.9	795.0	802.7	815.0	837.4	847.7	870.6	867.6
Intentional - Assault	361.7	398.4	413.9	428.2	444.7	456.5	469.4	483.7

Figure 4.1 Predicted incidence rates and 95% confidence bands for emergency department visits for selected unintentional injury types, by age group. North Carolina, April-October 2008-2013.

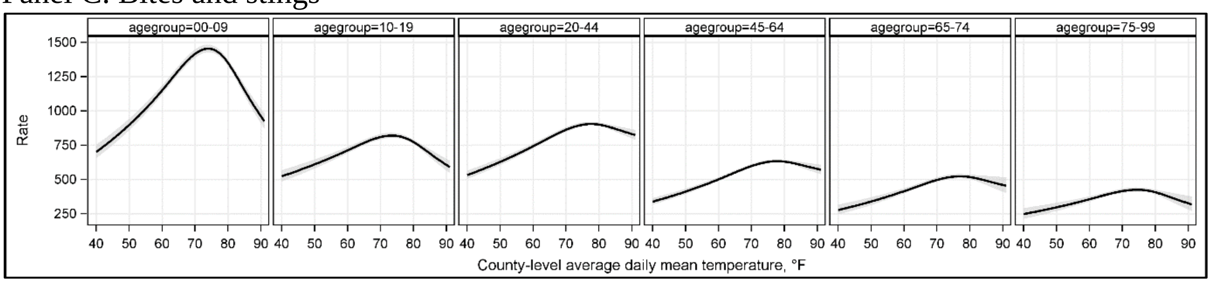
Panel A. Drowning



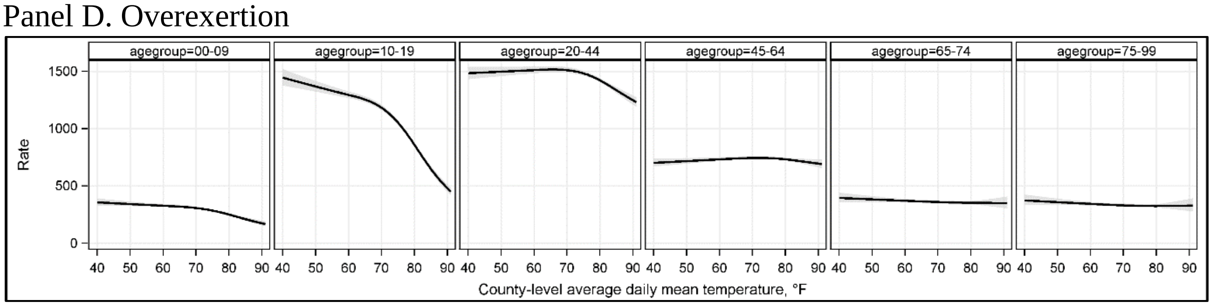
Panel B. Excessive heat



Panel C. Bites and stings



Panel D. Overexertion



Footnote to Figure 4.1. We used a natural cubic spline for daily mean temperature with the lowest knots set at 60.4°F (40%ile of the temperature range). Models are adjusted for calendar year, weekday, and day of year. Figures for additional injury types are presented in eFigure 1 in online appendix 1.

Figure 4.2 Predicted incidence rates and 95% confidence bands for emergency department visits for adverse effects and medical misadventures, by sex and age group. North Carolina, April-October 2008-2013.

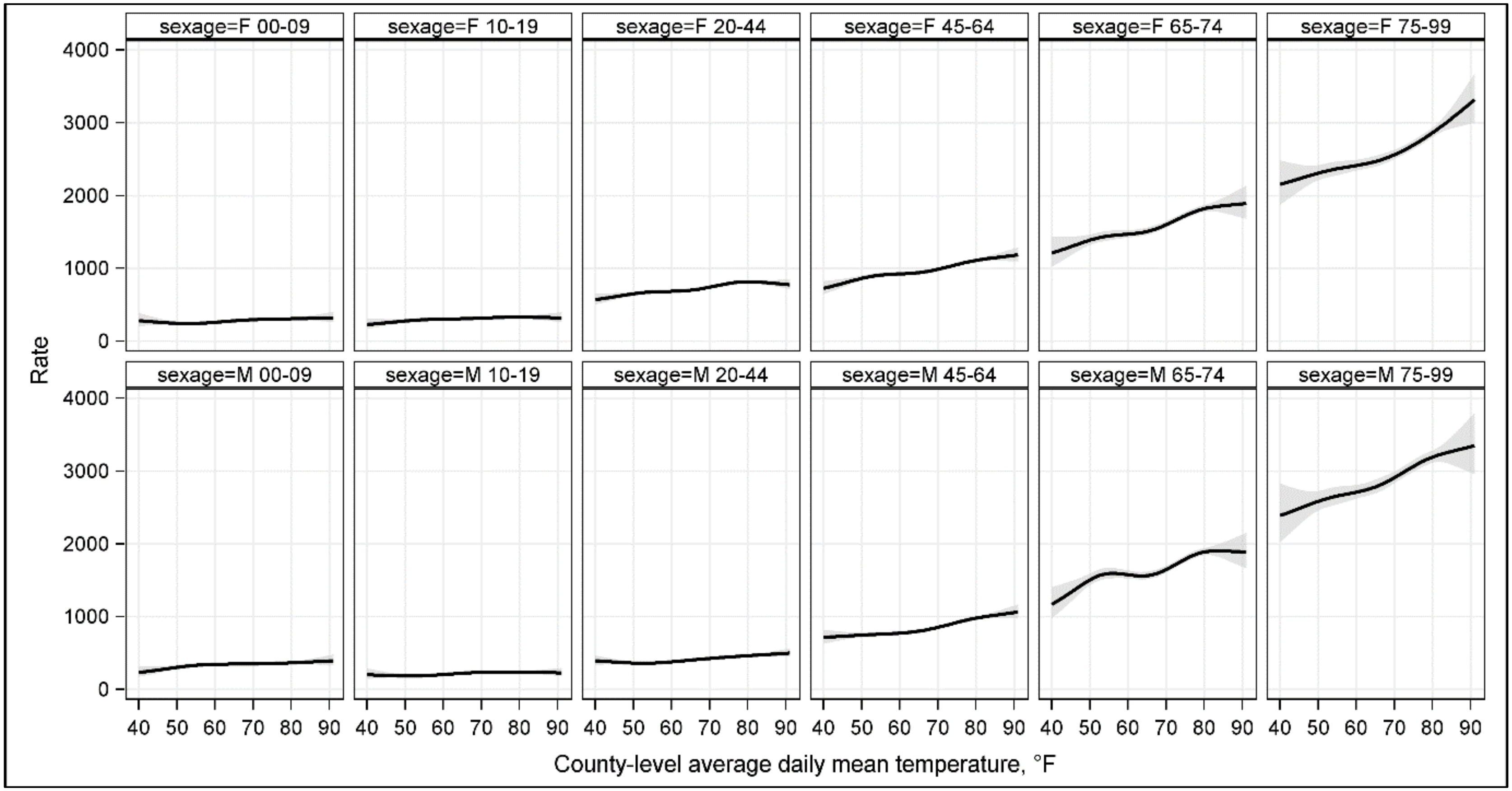
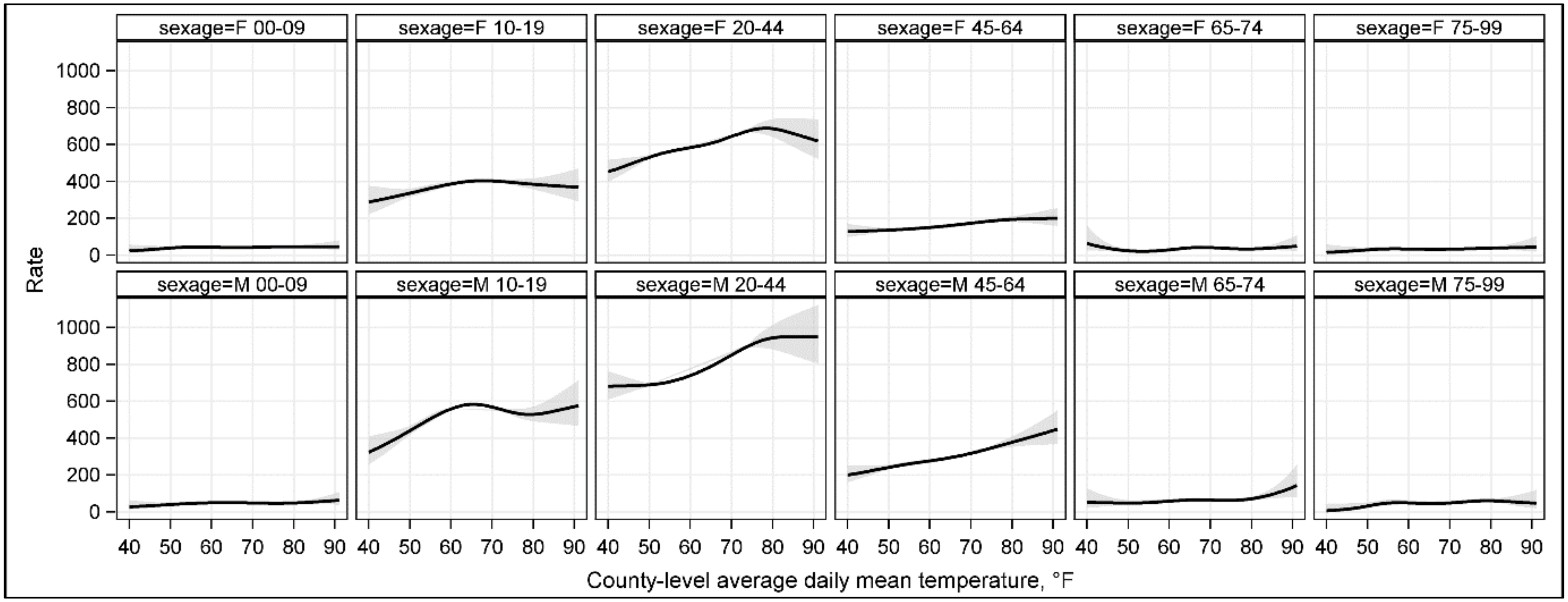


Figure 4.3 Predicted incidence rates and 95% confidence bands for emergency department visits for intentional assault, by sex and age group. North Carolina, April-October 2008-2013.



CHAPTER 5. TEMPERATURE AND CAUSE-SPECIFIC EMERGENCY DEPARTMENT VISITS

5.1. Introduction

Exposure to high ambient temperature has long been recognized as hazardous. Epidemiological studies have convincingly demonstrated excesses in all-cause mortality in the period during, and shortly after, exceptionally high temperatures.[18,20,24] More recently, associations between heat and human health have been the topic of more detailed study, examining morbidity as well as mortality, and the effects of ambient temperature not only on exceptionally hot days, but also across the range of temperatures experienced in a region.[21,47,84].

While prior studies have examined all-cause mortality or morbidity in aggregate, or focused narrowly on cardiovascular and respiratory effects, a few recent studies have used a cause-specific approach to systematically examine the impact of heat on mortality[32,33] and hospital admissions[34,83] across a broad array of disease groups. Findings from these cause-specific studies provide a fuller description of the health impact of ambient heat and the range of effects that can occur when our bodies' natural thermoregulatory systems are overtaxed.[1]

In the current study, we examine associations between temperature and a broad range of causes for emergency department visits. Prior research has found important differences between mortality and hospital admissions resulting from heat (Kovats, Hajat, and Wilkinson 2004; Linares and Diaz 2008); patterns relating heat to emergency department visits may differ still. In comparison to studies for those higher-severity outcomes, studies of emergency department visits can expose relationships between heat and less medically-intensive or fatal conditions, and draw conclusions that extend beyond already-compromised populations, such as older adults, who receive more emphasis based on their preponderance in research that relies only on mortality or admissions data.

In this study, we analyzed data from a state-wide surveillance system that captured all emergency department visits in North Carolina during the typically warm months of April through October in 2008-2013. Using an age-stratified and cause-specific approach, we examine the exposure-response relationships between county-level average daily mean temperature and emergency department visits for a comprehensive set of clinically-related diagnosis groups constructed using an existing validated diagnosis clustering system.

5.2. Methods

We obtained data on all emergency department visits recorded in the North Carolina Disease Event Tracking and Epidemiological Collection Tool (NC DETECT) during the months of April through October in 2008-2013. This statewide surveillance system includes visit-level administrative data from all civilian, 24/7 hospital-based emergency departments in North Carolina, including patients' age, sex, and county of residence as well as the visit date and selected clinical information such as chief complaint and discharge diagnoses. Emergency department visits by non-residents of North Carolina were excluded.

Up to 11 discharge diagnosis codes can be recorded for each emergency department visit in NC DETECT; we selected the first-listed diagnosis, coded according to the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM).[105] We then categorized these individual ICD-9-CM diagnosis codes into diagnosis groups using the multi-level version of the Agency for Healthcare Research and Quality's (AHRQ's) Clinical Classification Software (CCS) diagnosis clustering system.[109] Also referred to as a "clinical grouper", the CCS is a diagnosis categorization scheme that condenses the more than 14,000 individual ICD-9-CM diagnosis codes into a more manageable set of clinically-meaningful diagnosis groups.[109] Although other diagnosis clustering tools are available, the CCS was previously found to have the best coverage for the types of diagnoses that are typically encountered in the emergency department [110] and has been used successfully in previous studies with NC DETECT data.[111]

The multi-level version of the CCS assembles diagnosis groups hierarchically. We categorized emergency department visits into the 18 groups at the highest level of aggregation in the CCS and all groups were retained in the analyses of total emergency department visits and displayed in Table 1. Two groups, "Congenital anomalies" and "Residual Codes" were not reported separately elsewhere, however. The former are suppressed due to low numbers, while the latter are not displayed because this group is relatively non-specific compared to the others. Although the "Symptoms/signs" group is also relatively non-specific, we chose to keep it in our analyses because it includes many non-specific ailments, such as abdominal pain, fever, nausea/vomiting, and syncope, that commonly present in the emergency department. Although this group of codes does not point to specific disease diagnoses, it represents a major portion of emergency department utilization.

Annual mid-year population data for each county, stratified by age group and sex, were collated from the Intercensal Population Estimates (2008-2009) and the Current Estimates (2010-2013) databases from U.S. Census Bureau.[124,125] From these data, we assembled six age groups which are used as population denominators throughout the analysis: 0-9, 10-19, 20-44, 45-64, 65-74, and 75 or older, with no age adjustment within these categories.

Diagnosis codes were missing for some records. When the percentage of visits with zero recorded diagnosis codes exceeded 50% in a given county on a given day, we removed both the visit counts and the population person-time denominators for that county-day in the calculation of rates and in the grouped data used for the regression analyses.

5.2.1 Meteorological Data

Daily temperature observations were provided by the NC State Climate Office from their meteorological archive database, the NC Climate Retrieval and Observations Network of the Southeast (NC CRONOS). To maximize the spatial extent of our study, we queried both automated and non-automated monitoring stations throughout the state since some counties, particularly in rural areas, are equipped with only non-automated stations. Seven counties (Alleghany, Camden, Catawba, Clay, Greene, Jones, and Perquimans) had no monitoring stations and were excluded from the study.

To evaluate the meteorological data quality, we generated time series and distribution plots to identify potential data errors. Gross outliers were removed with range checks based on NC climate normals; more proximal outliers were manually reviewed by comparing them to values from nearby stations. Additionally, values from six monitors in sparsely populated high-elevation areas were excluded.

Daily mean values for each station were calculated either as the mean of the 24 hourly observations from automated stations, or as the average of the daily minimum and maximum temperatures recorded at non-automated stations. In counties with more than one monitor, we calculated a county-level average daily mean temperature by averaging all of the county’s non-missing station-level daily means. To focus on the effects of heat, observed temperatures less than 40°F were excluded.

5.2.2 Statistical Methods

We ascertained the number of emergency department visits for each of CCS diagnosis groups for every combination of county, age group, and sex for each study day. These grouped data were merged with temperature data at the county-day level and with population data at the year-sex-age level to assemble the final analysis dataset.

Using this grouped time-series data, we fit Poisson regression models, restricted by age group, to evaluate the age-specific exposure-response patterns for each CCS group. We evaluated both linear and non-linear (restricted cubic spline) parameterizations for temperature for each model. Covariates included indicator terms for calendar year, an indicator term for day of week (weekend vs. weekday), and a flexible B-spline smoothing function for day of year.[99,100] We also included the natural logarithm of the county-year-age-specific population estimates as an offset term. All regression analyses were performed in SAS (SAS Institute, Cary, NC) version 9.4 using the GLIMMIX and PLM procedures.

Age-group-specific incidence rate curves and 95% confidence bands from both spline and linear temperature parameterizations were plotted for each CCS diagnosis group. Each plot includes two lines: one based on a natural cubic spline parameterization of county-level daily mean temperature, shown with its corresponding 95% confidence band, and the other based on a model with temperature entered as a continuous term (dashed line). We also report the incidence rate ratio and 95% confidence interval for a 10°F increase, derived from the model with the linear parameterization of temperature, recognizing that such summarization to a linear trend is an oversimplification of more nuanced non-linear exposure-response associations.

While we focus on the leading causes of emergency department visits in reporting our results, electronic Appendix 1 provides the temperature-response for all major CCS diagnosis groups, by age group.

5.3. Results

A total of 13.2 million emergency department visits with diagnosis codes that matched categories in the CCS grouping system were recorded in NC DETECT during the months of April through October in 2008-2013 for the 93 counties with available meteorological data. Table 5.1 provides crude incidence rates of emergency department visits for each of the 18 top-level CCS diagnosis groups, stratified by age group, during the study period. Injury/Poisoning and Symptoms/Signs consistently ranked in the top three CCS groups with the highest incidence rates, though Circulatory diagnoses overtook them in the oldest three age groups. Figure 5.1 contains the exposure-response associations for the top three CCS groups by incidence rate in each age group, which we describe below. Graphs of the age-specific exposure-response association for the remaining CCS groups are presented in Appendix eFigures C.1-C.6.

The three leading diagnosis groups for emergency department visits among children age 0-9 years old were Injury/Poisoning, Symptoms/Signs, and Respiratory diagnoses, respectively (Table 5.1). The association between temperature and emergency department visits for Injury/Poisoning followed an inverted U-shaped curve (Figure 5.1, Row 1). Symptoms/Signs exhibited a hockey-stick shape, with a flat section at the lower tail of the temperature range followed by a shallow, but monotonically increasing trend at warmer temperatures. The curve for Respiratory diagnoses was U-shaped, with higher rates at the tails of the temperature range.

Among adolescents aged 10-19 years old, the top three causes of emergency department visits were Injury/Poisoning, Symptoms/Signs, and Nervous/Sense diagnoses, respectively

(Table 5.1). As in the younger children, the exposure-response curve for Injury/Poisoning followed an inverted U-shaped curve (Figures 5.1, Row 2) and the curve for Symptoms/Signs followed a hockey-stick shape, increasing steadily with temperature after a flatter section at the lowest temperatures. The rate for the Nervous/Sense group generally increased with temperature, though the slope was steeper at temperatures above 65-70°F.

Injury/Poisoning, Symptoms/Signs, and Musculoskeletal diagnoses were the leading three CCS group among 20-44 year olds (Table 5.1). For all three diagnosis groups, the incidence rates increased linearly to between 70-80°F, then tapered off at the highest temperatures (Figure 5.1, Row 3)

Injury/Poisoning and Symptoms/Signs ranked 1st and 3rd, respectively, for 45-64 year olds (Table 5.1). Circulatory diagnoses appeared among the top 6 groups for the first time in the 45-64 year old age group, where it ranked 2nd. Injury/Poisoning visits increased with temperature, though the slopes were flatter at the tails than in the central temperature range (Figure 5.1, Row 4). Circulatory diagnoses increased with temperature and had a steeper slope above an inflection point between 60-70°F. Symptoms/signs exhibited a non-monotonic step-like pattern, with increasing rates overall, but flat or slightly negative sections between 55-65°F and above 80°F.

The top three diagnosis groups for the 65-74 age group were Circulatory, Injury/Poisoning, and Symptoms/Signs (Table 5.1). Both Circulatory diagnoses and Injury/Poisoning increased linearly with temperature (Figures 5.1, Row 5). Symptoms/Signs generally increased with temperature, but had mild downturns at the tails.

Circulatory, Injury/Poisoning, and Symptoms/Signs were also the top three diagnosis groups for the oldest adults (Table 5.1). For Circulatory diseases, the rate increased with temperature, with a minor upturn in the exposure-response function at the very highest temperatures (Figure 5.1, Row 6). Injury/Poisoning had a slightly U-shaped curve, with the lowest rate between 60-70°F. Symptoms/Signs generally increased with temperature, but dipped at the tails.

Figure 5.2 provides a forest plot summarizing the exposure-response associations for each age group and for total emergency department visits and each of the CCS groups, derived from models where temperature is parameterized as a linear term. The values plotted represent the estimated incidence rate ratio and 95% confidence interval for a 10°F increase in county-level average daily mean temperature. The linear assumption gains simplification, but at the acknowledged expense of obscuring indications of threshold-like trends (e.g., pregnancy and birth related admissions age 10-19 and mental illness age 20-44 (Appendix eFigures C.2 and C.3), U-shaped trends (e.g., respiratory age 10-19 (Appendix eFigure C.2)), dome-shaped trends (e.g., genitourinary age 0-9 (Appendix eFigure C.1)) and other potential non-linearities.

Incidence rate ratios for total emergency department visits ranged from 1.022 (95%CI: 1.021, 1.024) for 20-44 year olds to 1.063 (95%CI: 1.061, 1.065) for 45-64 year olds (Figure 5.2). In each age group, the incidence rate ratios for nearly all disease groups were above the null and the 95% confidence intervals were narrow (Figure 5.2). As noted above, Mental Illness was an exception; the point estimate for the incidence rate ratio for this set of diagnoses was below the null in all age groups. Aside from Mental Illness, Digestive diagnoses among 20-44 year olds was the only combination in which both the point estimate and the upper 95% confidence limit were below the null.

5.4. Discussion

We found positive associations, with evidence of non-linearity in several cases, between county-level average daily mean temperature and emergency department visit rates for most of the major categories in the CCS diagnosis classification system in each age group, with relative increases in estimated incidence rates of up to 12% of their baseline values for each 10°F increment. The highest incidence rate ratios were for Pregnancy/birth diagnosis codes; among 10-19 and 20-44 year olds, rates of emergency department visits resulting in pregnancy-related diagnoses increased approximately 12% of their baseline values per 10°F increment.

When arranged by the absolute magnitude of the mean incidence rates in the observed temperature range, however, Injury/Poisonings and Symptoms/Signs rise to the forefront among the leading causes for all age groups, while Circulatory diseases predominated among the older age groups. Although the incidence rate ratios for these leading diagnosis groups appear modest, in the range of 1% to 7% of the baseline values per 10°F increment, they represent substantial numbers of excess emergency department visits as temperatures increase. Injury has received relatively little attention in the epidemiological literature in this area of research, but the few cause-specific studies that have included a category for injuries have noted positive associations.[32,33,38] Emergency department data is well-suited to studying injury, since approximately 9 out of 10 injury-related emergency department visits result in discharge to home and therefore would not appear in hospital admission records. More detailed study of the relationship between temperature and injury is warranted.

The Symptoms/signs diagnosis group, which was among the top 3 causes in all age groups, includes common ailments such as abdominal pain, fever, nausea, and vomiting. Relative excess rates for this group ranged from approximately 3% to 7%. Since these symptoms are generic and not tied to specific diseases, previous cause-specific studies may have overlooked these common, yet difficult-to-categorize, types of visits. Unfortunately, the non-specific nature of these diagnosis codes makes it difficult to draw any etiologic conclusions from them or develop potential prevention strategies to reduce them.

Cardiovascular and respiratory diseases have been a common focus in the heat-health literature.[38,141,142] In this study, rates for the Circulatory diagnosis group (which includes cardiovascular diseases) increased with temperature in all age groups, although the absolute magnitude of these increases was greatest in the older age groups where overall incidence rates for Circulatory diseases was highest. Interestingly, however, trends for Respiratory diseases were fairly flat in the 65-74 and 75 and older age groups where the overall rates were highest.

Our finding of an inverse relationship between temperature and emergency department visit rates for Mental Illness differs from some previous studies which have found increases in mental or psychiatric disorders. [32,34,143,144]

Strengths of this study include the large number of emergency department visits captured, the state-wide nature of the surveillance system, and the use of a standardized, validated method for grouping ICD-9-CM diagnoses. This study extends previous research into the effects of heat on cause-specific outcomes by using emergency department visits records instead of hospital admissions or mortality, and by examining these associations across all age groups. By doing so, we capture heat impacts on some conditions that do not typically necessitate admission or result in death, but are still important constituents of overall morbidity burden and healthcare utilization, such as Injury/Poisoning and Symptoms/Signs. Injury in particular has received little attention in the epidemiological literature on heat-health effects, but was found to be a major contributor to the overall impact of heat on emergency department visit rates in our study.

Several limitations apply to this study. First, we use only the first-listed diagnosis code to characterize each visit; while this code is presumed to describe the main reason for the visit, we cannot definitively confirm the primacy of this diagnosis over other assigned diagnoses. Second, by aggregating to the highest level of the CCS hierarchy, we may be masking intra-group heterogeneity. Third, we examine only same-day effects of temperature and do not consider lagged effects; previous research has found that heat effects tend to accrue quickly, within the same day or the first subsequent day. Finally, we did not have humidity or humidity-related metrics such as apparent temperature from many counties and did not evaluate humidity as a potential confounder or effect-measure modifier of the temperature-emergency department visit associations; however, previous research has indicated that since these alternate biometeorological metrics are typically highly correlated with temperature, the overall exposure-response patterns are often little-changed when different measures are used.[116,121]

5.5. Conclusions

This study contributes additional evidence supporting the impact of heat on a broad array of health conditions. By assessing the relative measures of effect in the context of the absolute magnitude of the incidence rates for each diagnosis group, we also shift the attention of previous research from cardiovascular and respiratory diseases to outcomes that are commonly seen in the emergency department, such as injury and general symptoms, especially among the younger age groups. Along with studies of mortality and hospital admissions, studies of emergency department morbidity are necessary for fully appreciating the full impacts of heat on human health.

5.6. Tables and Figures

Table 5.1 Crude incidence rates (per 100,000 person-years) of emergency department visits, grouped by discharge diagnosis using the multi-level version of the Clinical Classification Software, April-October 2008-2103, North Carolina.

Clinical Classification Software Group, Multi-level version	**Age Group (years)**					
	≤9	10-19	20-44	45-64	65-74	≥75
1. Infectious and parasitic diseases	1,673.7	667.1	846.0	552.7	659.0	1296.1
2. Neoplasms	17.0	17.2	78.4	224.5	452.0	653.4
3. Endocrine; nutritional; and metabolic diseases and immunity disorders	210.8	288.2	965.0	1,762.1	2,509.9	4,040.4
4. Diseases of the blood and blood-forming organs	88.2	96.7	248.8	202.5	349.5	785.6
5. Mental illness	166.4	1,552.1	3,465.6	2,192.5	1,160.0	1,968.9
6. Diseases of the nervous system and sense organs	3,902.3	2,317.0	4,385.2	2,884.1	2,274.2	3,282.2
7. Diseases of the circulatory system	173.0	702.5	2,818.1	5,102.3	7,316.7	12,842.5
8. Diseases of the respiratory system	7,783.2	3,589.3	4,179.1	3,259.7	4,098.9	6,560.1
9. Diseases of the digestive system	1,625.8	1,205.8	3,579.1	2,254.5	2,334.8	3,931.7
10. Diseases of the genitourinary system	866.27	1,813.1	3,615.7	1,753.8	2,331.5	4,714.8
11. Complications of pregnancy; childbirth; and the puerperium	[a]	858.0	1,661.8	[a]	[a]	[a]
12. Diseases of the skin and subcutaneous tissue	1,703.6	1,244.7	2,051.8	1,042.5	720.6	956.5
13. Diseases of the musculoskeletal system and connective tissue	784.1	2,063.48	4,845.7	4,094.5	3,031.5	4,258.1
14. Congenital anomalies	49.7	15.3	17.9	14.8	19.6	31.1
15. Certain conditions originating in the perinatal period	349.4	[a]	[a]	[a]	[a]	[a]
16. Injury and poisoning	8,317.4	8,852.2	8,508.2	5,229.2	4,706.1	9,298.6
17. Symptoms; signs; and ill-defined conditions and factors influencing health status	7,980.7	4,658.3	7,188.1	4,714.1	4,840.8	7,842.0
18. Residual codes; unclassified; all E codes[b]	417.6	326.5	727.7	721.7	862.2	1,810.5
Total	36,110.3	30,268.6	49,183.6	36,014.8	37,669.2	64,276.2

[a] Cells were suppressed where age group and disease/condition pairings are incongruous; visit counts from these cells were retained in the calculation of Total emergency department visit rates.
[b] E-codes are stored in a separate set of fields in the NC DETECT data; therefore this group is composed only of diagnosis codes in CCS group 18.

Figure 5.1 Predicted incidence rates of emergency department visits by county-level average daily mean temperature for the three highest-incidence Clinical Classification Software groups in each age group, North Carolina, April-October 2008-2013.
Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges are age-group specific. CCS group names are abbreviated; refer to Table 1 for full CCS group names. Not sorted by rank.

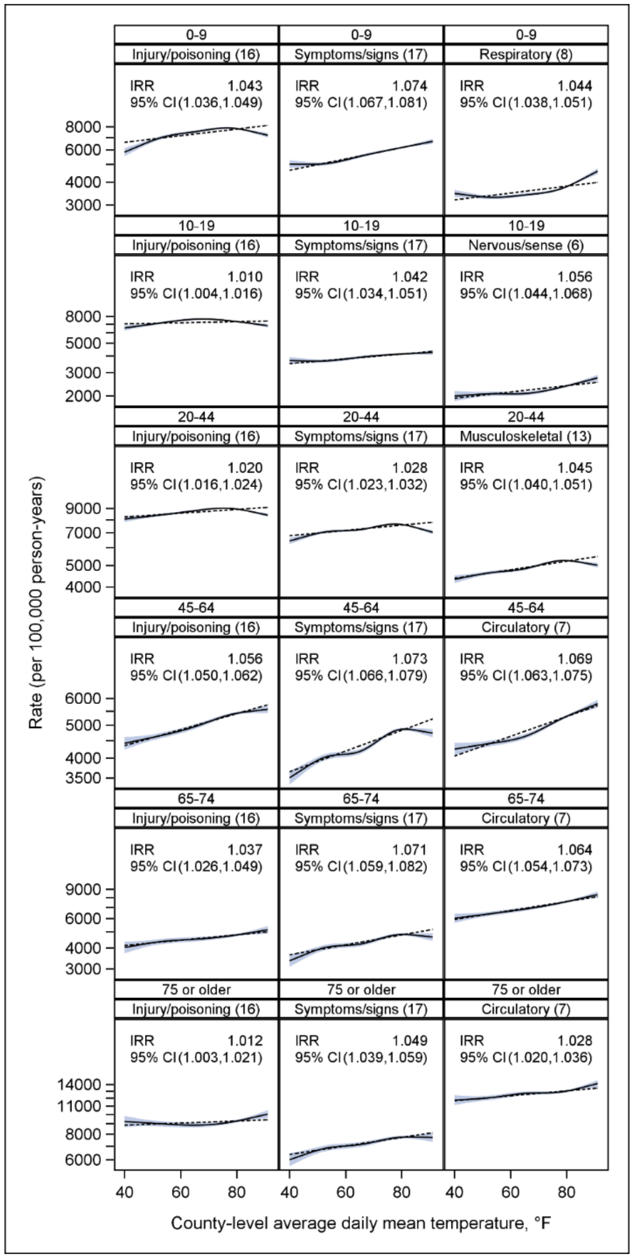
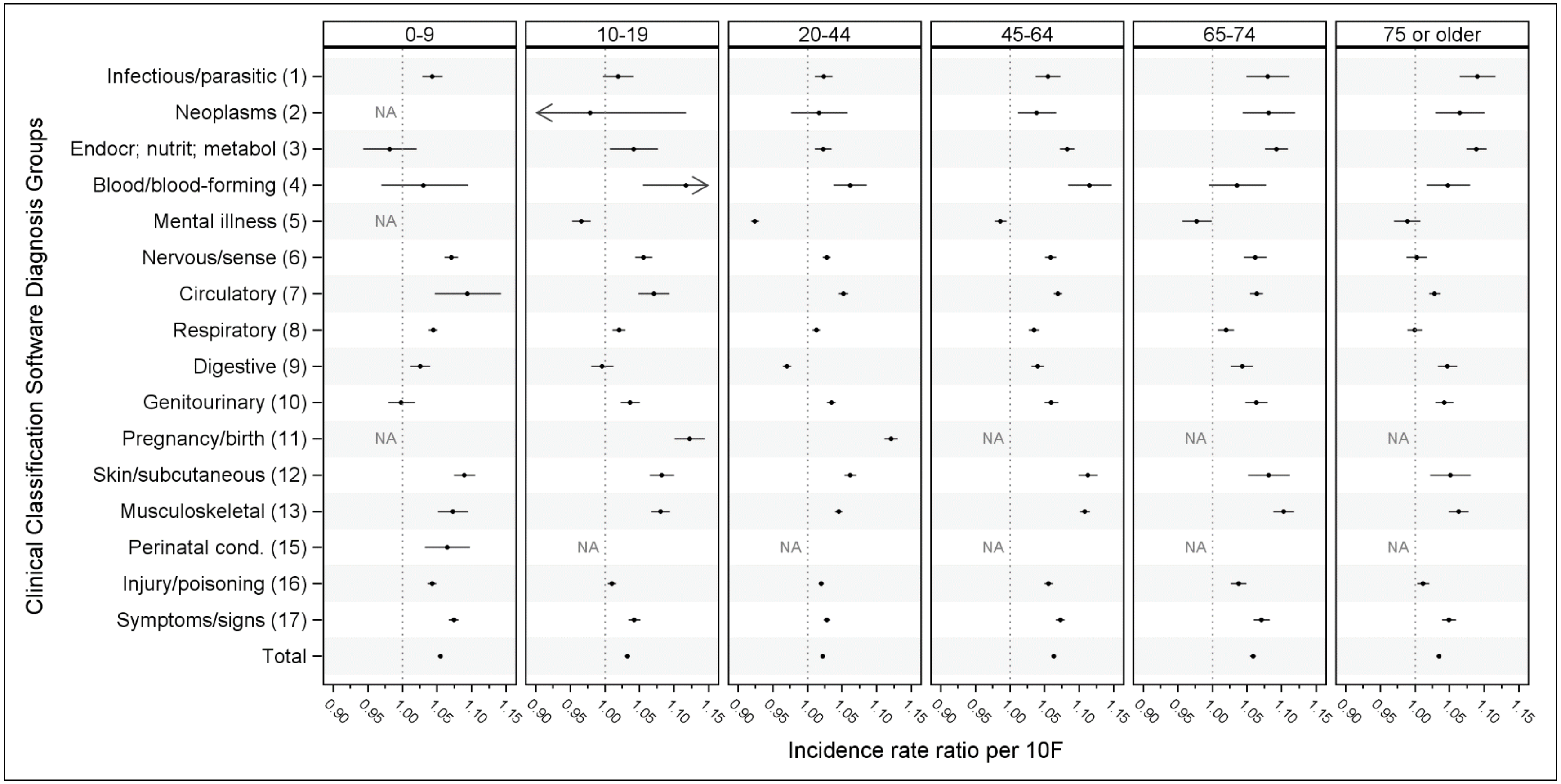


Figure 5.2 Cause-specific incidence rate ratios for a 10°F increase in county-level average daily mean temperature, by age group, in North Carolina, April-October 2008-2013, from a model with a linear parameterization of temperature.
CCS group names are abbreviated; refer to Table 5.1 for full CCS group names. Disease and age group combinations that are incongruous are displayed as “NA” (see also Table 5.1).



CHAPTER 6. CONCLUSIONS

6.1. Overview

This dissertation project aimed to describe the exposure-response associations between ambient temperature and a broad range of diseases and injuries resulting in emergency department visits among North Carolina residents. We used data for the months of April-October 2008-2013 from a state-wide surveillance system that captured all emergency department visits in North Carolina during that period, along with daily meteorological monitor data, to model these associations using Poisson regression.

6.2. Strengths

This dissertation project benefits from the strong surveillance capability of the NC DETECT system. With several years of data now accumulated, this system is a rich database for epidemiological research. We also benefit from the geographic coverage of meteorological monitoring stations in North Carolina, which is enhanced by the presence of the ECONET network of stations maintained by North Carolina State Climate Office. In both aims, we take advantage of existing, standardized categorization schemes for grouping emergency department visits into meaningful clusters. We also stratified by age and sex, allowing us to examine heterogeneity by these strata in the exposure-response associations.

By using emergency department visit data, we extend the heat-health literature beyond the level of mortality and hospital admissions that predominates our current understanding of the effects of heat on health outcomes. We also extend the current literature by examining injuries and other external causes, including adverse medical effects, which have been excluded from many previous studies. Since injuries requiring emergency care are very frequent but in most cases do not result in hospital admission or fatality, having information at this level of morbidity is essential for understanding the associations between temperature and injury. The same can be said for other diseases or conditions that have high rates of emergency department visits but are typically non-fatal and can be addressed effectively in the emergency department without admission—these simply would not be present in studies that include only the most serious outcomes of morbidity at the hospital admission level and mortality.

6.3. Limitations

Several general limitations apply to this dissertation project. As with any study where exposure is assessed at an aggregate level, exposure misclassification may have occurred if personal temperature exposures differ greatly from the temperatures reported from the monitoring stations; however, the spatial and temporal auto-correlation of temperature potentially ameliorates the degree to which this misclassification can influence our results. Incomplete, implausible, or missing data, both in the health data and the meteorological data, required us to exclude some data points. We did not assess lagged temperature effects and thus can only comment on the effects of same-day temperatures.

Although the use of existing categorization systems is beneficial, it also has the potential to mask sub-group heterogeneity in the exposure-response associations. In this project, for example, we did not investigate sub-types of cardiovascular disease as some previous researchers have, and instead emphasize the comprehensiveness of our approach.

One methodological tension in this type of research is finding the right balance between detail and summarization in the interpretation of exposure-response associations that exhibit some degree of non-linearity, as did many of the associations in this project. In Aim 2 of this project, we modeled temperature with both flexible and linear parameterizations, and we present both results graphically. We describe the shapes of the flexibly-modeled exposure-response associations, and also report incidence rate ratios derived from the linear parameterization of temperature. These two ways of representing the associations can be at odds with each other, however, when the exposure-response associations begin to deviate from a purely linear trend. The difficult task, then, is to arbitrate the conflicting priorities of adequately acknowledging any non-linearity while also providing useful numeric summarizations that capture the macro-level associations.

Previous cause-specific heat-health studies involving a large number of causes of morbidity or mortality have either modeled temperature as a continuous term or have dichotomously compared incidence during heat wave periods to that during non-heat wave periods.[32–34,83] By design, both of those approaches result in single, summarized effect estimates for the associations between heat and each cause, even when some of those relationships may, in fact, be non-linear over the temperature spectrum. While our approach yields more nuanced information, it also poses new challenges in interpreting both sets of results.

6.4. Summary of Findings and Conclusions

In our analyses addressing Aim 1, we examined injury-related emergency department visits and grouped these visits based on injury intent and mechanism, as coded with ICD-9-CM external cause of injury codes. We focused on the associations between temperature and the three leading causes of injury-related emergency department visits: unintentional injury, adverse medical effects, and intentional assault. We found heterogeneity in the associations between temperature and different mechanisms of unintentional injury; the strongest positive associations were for bites and stings, drowning, excessive heat, cutting/piercing instruments, and unspecified mechanism. We also found positive associations between temperature and adverse medical effects; these associations were strongest among older adults. Finally, we found that emergency department visits resulting from intentional assault increased with temperature among adolescents and young adults of both sexes.

In our analyses addressing Aim 2, we expanded our scope to examine age-stratified associations between temperature and a comprehensive set of diagnoses, grouped into clinically-meaningful clusters using the Clinical Classification Software system. Total emergency department visits increased with temperature in each age group. Temperature was also positively associated with most of the diagnosis groups in each age group, with incidence rate ratios of up to 1.12 for each 10°F increment when summarized with linear temperature trends. Ranked by absolute magnitude of mean incidence rates, Injury/Poisonings and Symptoms/Signs rose to the forefront as being among the top three causes in all age groups, while Circulatory diseases ranked highest among the older age groups. Even though the incidence rate ratios in these groups were relatively modest, they represent a large number of excess emergency department visits when temperatures rise. This study offers strong evidence of positive associations between daily mean temperatures and wide range of conditions resulting in emergency care, and highlights the importance of injury morbidity as a contributor to the overall population health impact of heat.

APPENDIX A. **CHAPTER 4 APPENDIX 1**

eTable A.1 Description of inclusion and exclusion criteria for injury-related emergency department visits.

	Visits Excluded	Visits Retained	County-days Excluded	County-days Retained
A. Visit-level exclusions				
1. Full dataset, all emergency department visits	-	26,116,073	-	219,200
2. Reduce to April-October	10,739,079	15,376,994	90,800	128,400
3. Identify injuries by diagnosis code or E-code	11,549,860	3,827,134	-	128,400
4. Exclude injury visits with no E-code	423,916	3,403,218	-	128,400
5. Include only visits with first-listed intent E-codes for: Unintentional (excluding motor vehicle crashes) Adverse effects/ medical misadventures Intentional assault	533,770	2,869,448	-	128,400
6. Exclude if sex was missing/other	164	2,869,284	-	128,400
B. County or county-day exclusions				
7. Exclude 7 counties that had zero meteorological stations	83,459	2,785,825	8,988	119,412
8. Exclude county-days where diagnosis or E-code missingness crossed 50% threshold	145,713	2,640,112	14,671	104,741
9. Exclude county-days based on meteorological data[a], where either: a) All monitors in a county were missing for daily mean temperatures (1234 county-days), or b) Calculated county-level average daily mean temperatures were <40°F (266 county-days)	23,827	2,616,285	1,350	103,391

[a] Note: Although 119 individual monitor observations were removed due to implausible values, none of these removals caused a whole county-day to be set to missing. In each case, other monitors in the county were still supplying valid temperature values and we could still calculate the county-level average daily mean temperature. There were 1500 county-days that met these meteorological exclusion criteria, but 150 of them were already excluded due to missing diagnosis or E-code data.

eTable A.2 Intent- and mechanism-specific injury-related emergency department visit rates by county-level daily mean temperature (°F). North Carolina, April-October 2008-2013.

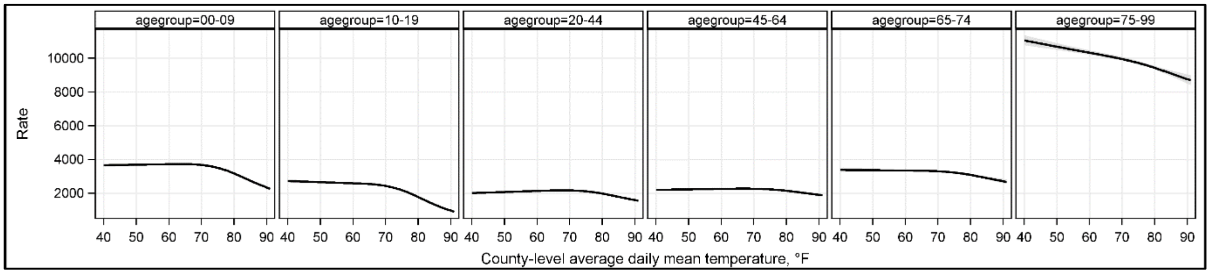
	Crude incidence rate per 100,000 person-years, by county-level daily mean temperature (°F)							
	40-<50	50-<55	55-<60	60-<65	65-<70	70-<75	75-<80	≥80
Person-years	851,226	1,361,312	2,433,709	3,495,886	4,148,380	5,790,587	6,726,151	3,628,241
Unintentional	6,815.7	7,422.5	7,480.0	7,618.0	8,050.0	8,210.9	8,107.9	7,921.1
Caught in/between objects	118.7	128.0	126.6	122.0	130.5	127.1	126.4	122.0
Cutting/piercing instruments	487.2	540.0	551.8	559.7	606.5	640.7	650.3	647.0
Drowning	0.7	0.8	0.9	1.4	2.2	5.0	7.5	9.9
Falls	2,640.7	2,796.1	2,772.2	2,774.6	2,871.7	2,849.3	2,703.7	2,509.1
Fire/burns	110.2	109.6	114.3	116.9	122.5	132.3	137.8	142.5
Firearms	30.7	37.3	35.3	31.9	32.3	36.1	33.0	31.5
Foreign body	146.7	169.5	171.1	173.1	179.5	181.6	189.9	189.6
Late effects of injury	54.9	49.6	48.8	50.2	52.6	52.2	52.8	49.7
Machinery	41.5	40.0	39.6	41.2	40.5	38.3	35.5	31.9
Excessive heat	1.1	0.8	2.3	4.2	9.5	22.7	51.8	153.3
Bites and Stings	270.6	355.6	387.1	465.9	590.4	713.8	799.5	817.9
Natural or environmental factors[a]	10.1	8.1	8.7	9.1	9.0	7.3	9.3	9.5
Other specified, NEC	213.3	231.0	221.6	224.2	244.7	250.4	243.4	222.6
Other transportation	92.7	121.3	132.5	141.1	150.4	164.2	153.3	138.2
Overexertion	806.8	893.4	892.4	897.2	920.0	908.8	873.8	837.7
Poisoning	132.6	148.5	148.2	146.9	158.5	166.4	165.7	162.0
Struck by, against	961.6	1,061.7	1,097.7	1,106.4	1,133.7	1,108.0	1,057.7	1,011.7
Suffocation	6.5	7.2	7.1	7.4	7.7	7.5	7.7	7.2
Unspecified	689.4	724.0	721.9	744.5	787.7	798.9	808.9	827.9

Adverse Effects / Medical Misadventures	758.9	795.0	802.7	815.0	837.4	847.7	870.6	867.6
Intentional - Assault[b]	361.7	398.4	413.9	428.2	444.7	456.5	469.4	483.7
Cutting/piercing instruments	24.4	28.9	27.9	31.2	31.3	33.0	36.6	37.8
Firearms	9.0	11.8	11.7	11.4	12.0	12.3	14.4	16.1
Late effects of injury	5.4	5.2	5.1	6.1	6.1	5.5	6.0	5.8
Other specified, NEC	81.3	86.2	96.8	96.8	99.8	106.2	106.2	108.1
Struck	188.7	208.8	215.0	219.7	227.0	230.5	235.7	246.1
Unspecified	51.3	56.2	55.9	61.3	67.0	67.5	69.0	68.4

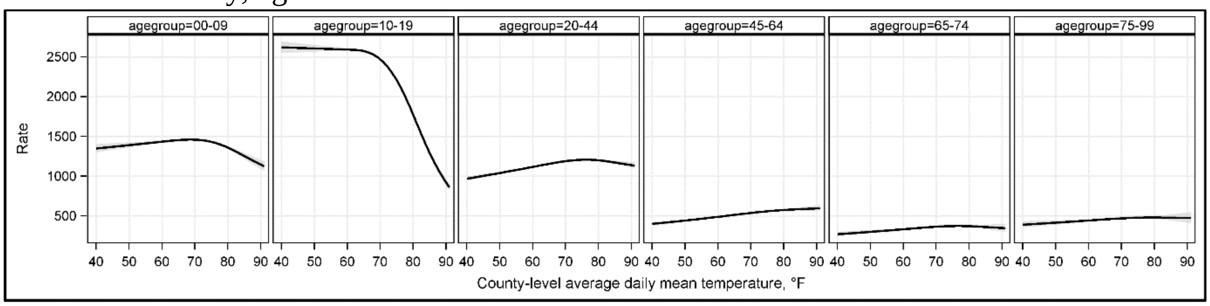
[a] Excluding excessive heat and bites/stings.
[b] Includes poisoning and suffocation, not shown due to small cell sizes.

eFigure A.1 Predicted incidence rates and 95% confidence bands for emergency department visits for additional selected unintentional injury types, by age group, in North Carolina, April-October 2008-2013, adjusted for calendar year, weekday, and day of year.

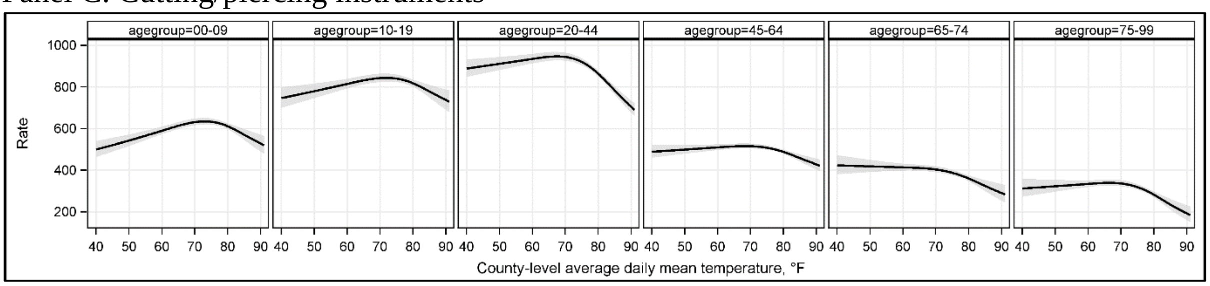
Panel A. Falls



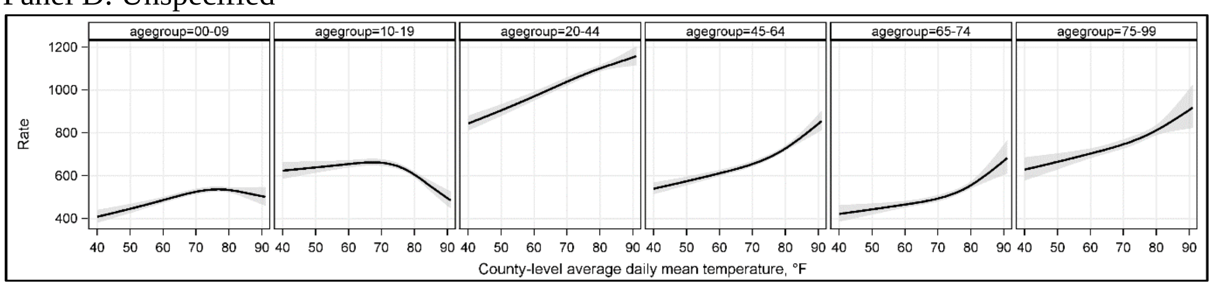
Panel B. Struck by, against



Panel C. Cutting/piercing instruments



Panel D. Unspecified



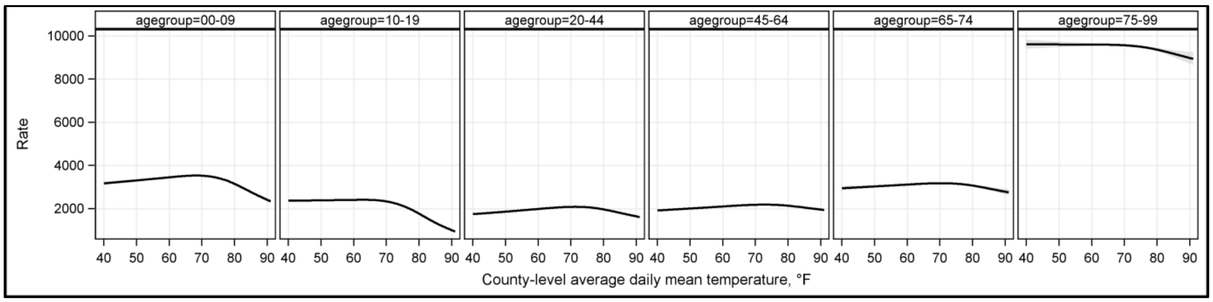
Footnote to eFigure A.1. For the models presented in eFigure A.1, we used a natural cubic spline for daily mean temperature with the lowest knots set at 60.4°F (40%ile of the temperature range) to restrict the slope below that temperature to be linear.

APPENDIX B. **CHAPTER 4 APPENDIX 2**

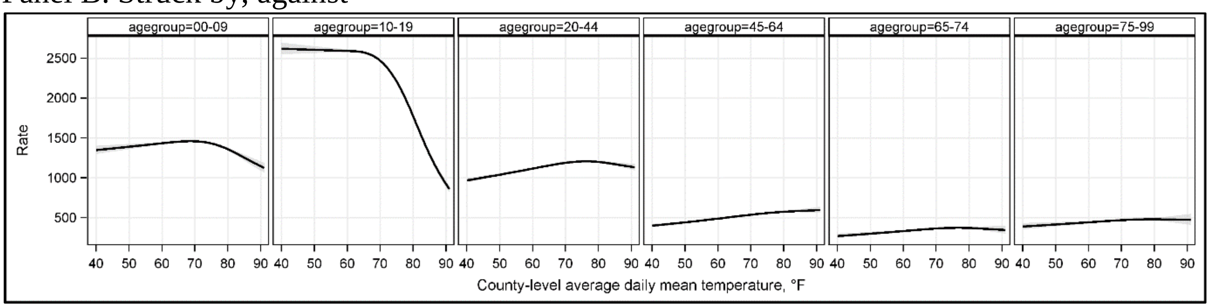
Unadjusted Models: Results below are for models that are not adjusted for calendar year, weekday, or day of year.

eFigure B.1 Predicted incidence rates and 95% confidence bands for emergency department visits for selected unintentional injury mechanisms, by age group. North Carolina, April-October 2008-2013. Unadjusted model.

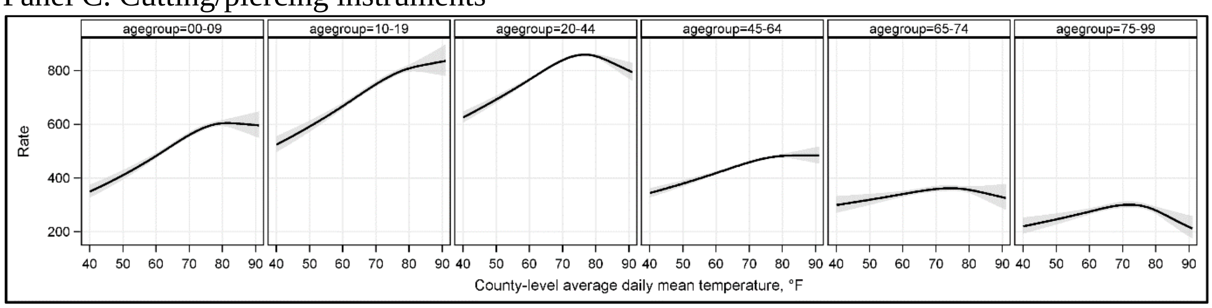
Panel A. Falls



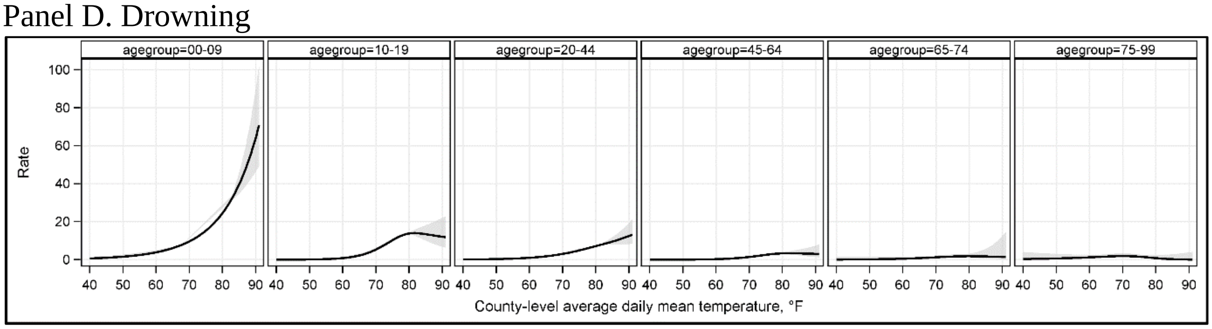
Panel B. Struck by, against



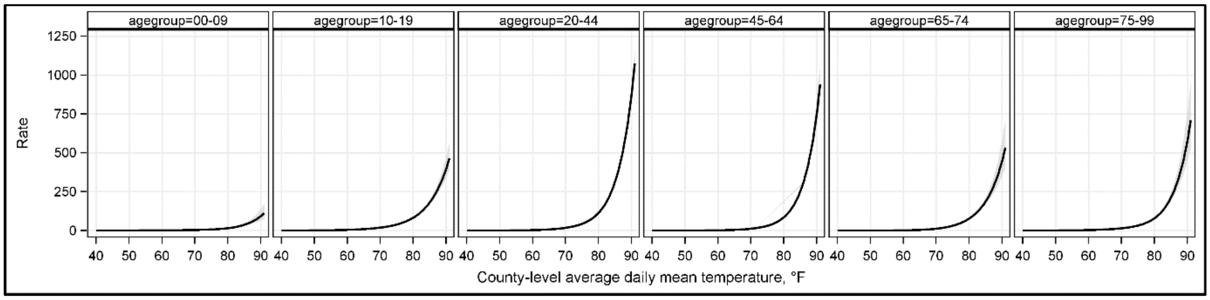
Panel C. Cutting/piercing instruments



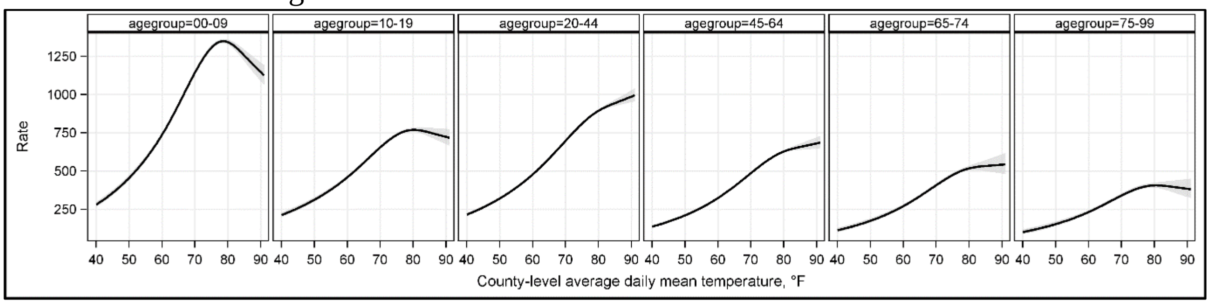
Panel D. Drowning



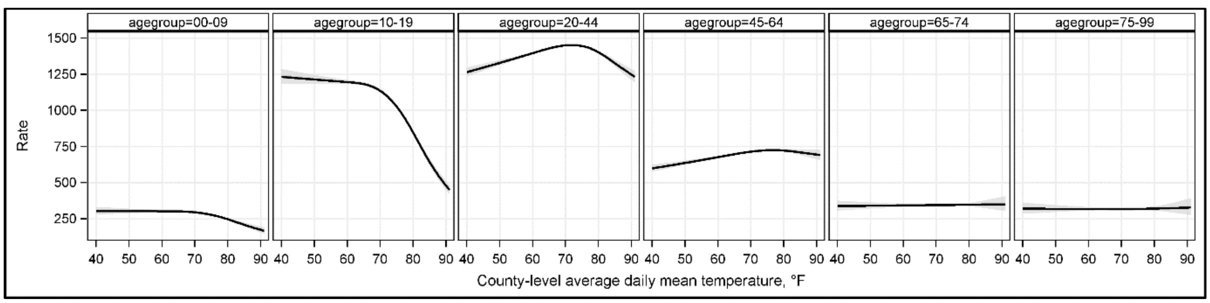
Panel E. Excessive heat



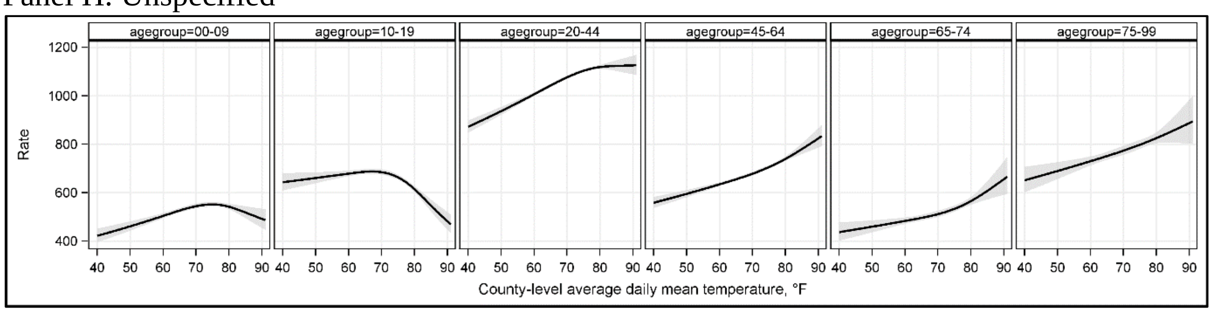
Panel F. Bites and stings



Panel G. Overexertion

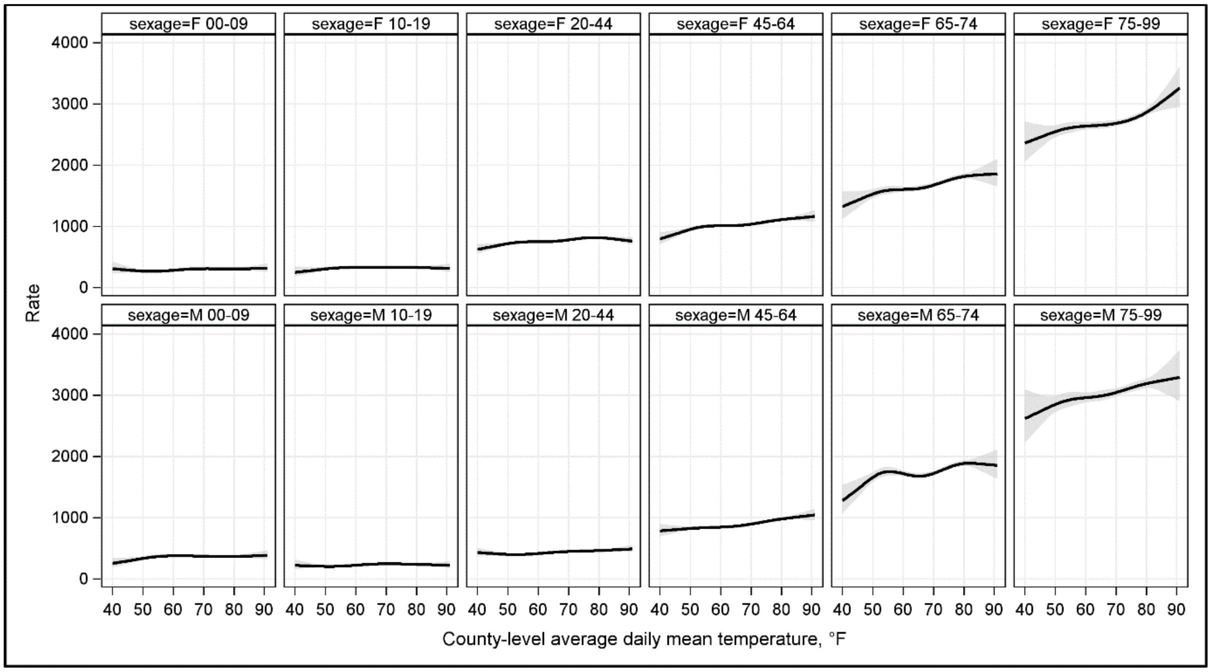


Panel H. Unspecified

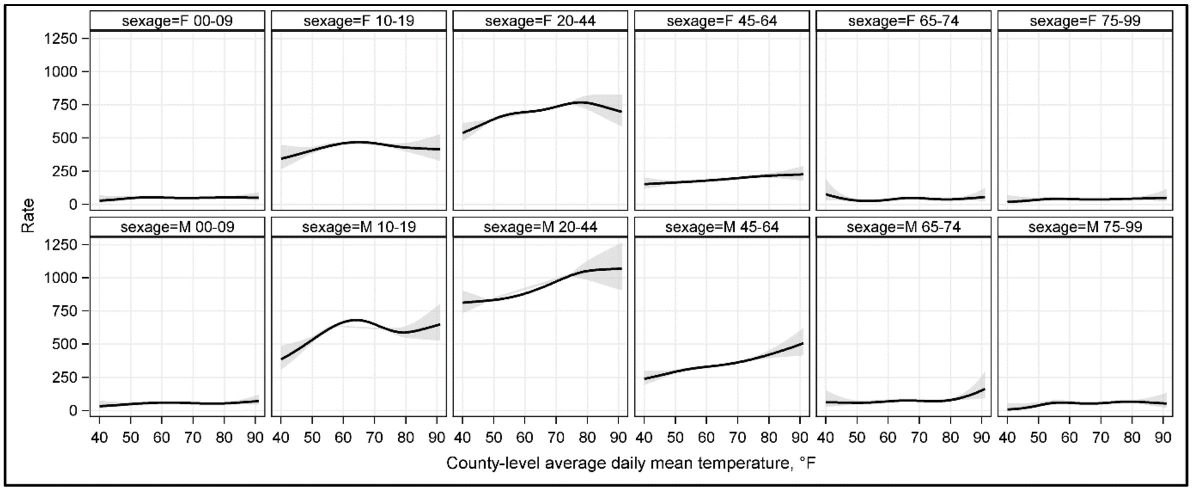


Footnote to eFigure B.1. For the models presented in eFigure B.1, we used a natural cubic spline for daily mean temperature with the lowest knots set at 60.4°F (40%ile of the temperature range) to restrict the slope below that temperature to be linear.

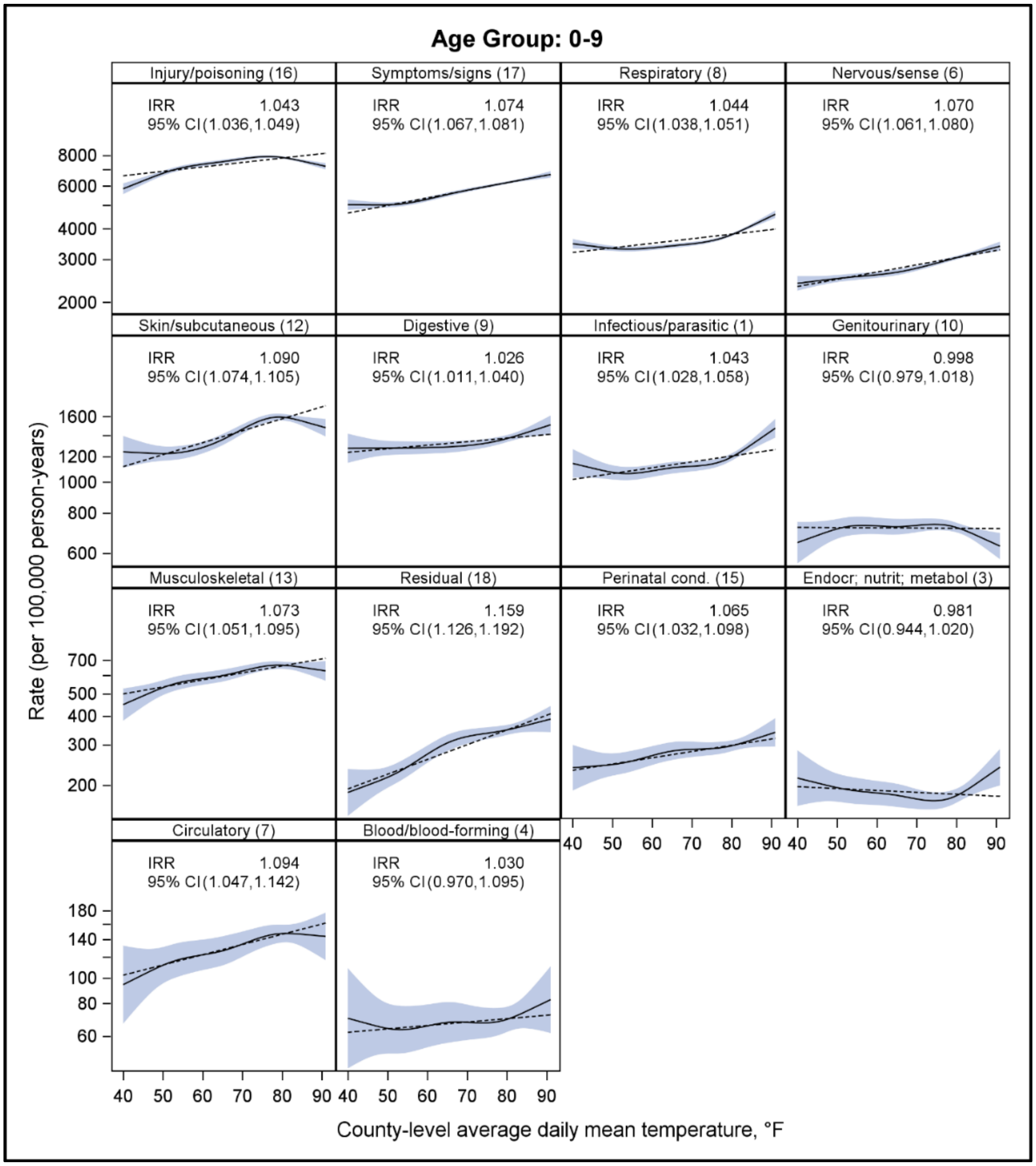
eFigure B.2 Predicted incidence rates and 95% confidence bands for emergency department visits for adverse effects and medical misadventures, by sex and age group, in North Carolina, April-October 2008-2013. Unadjusted model.



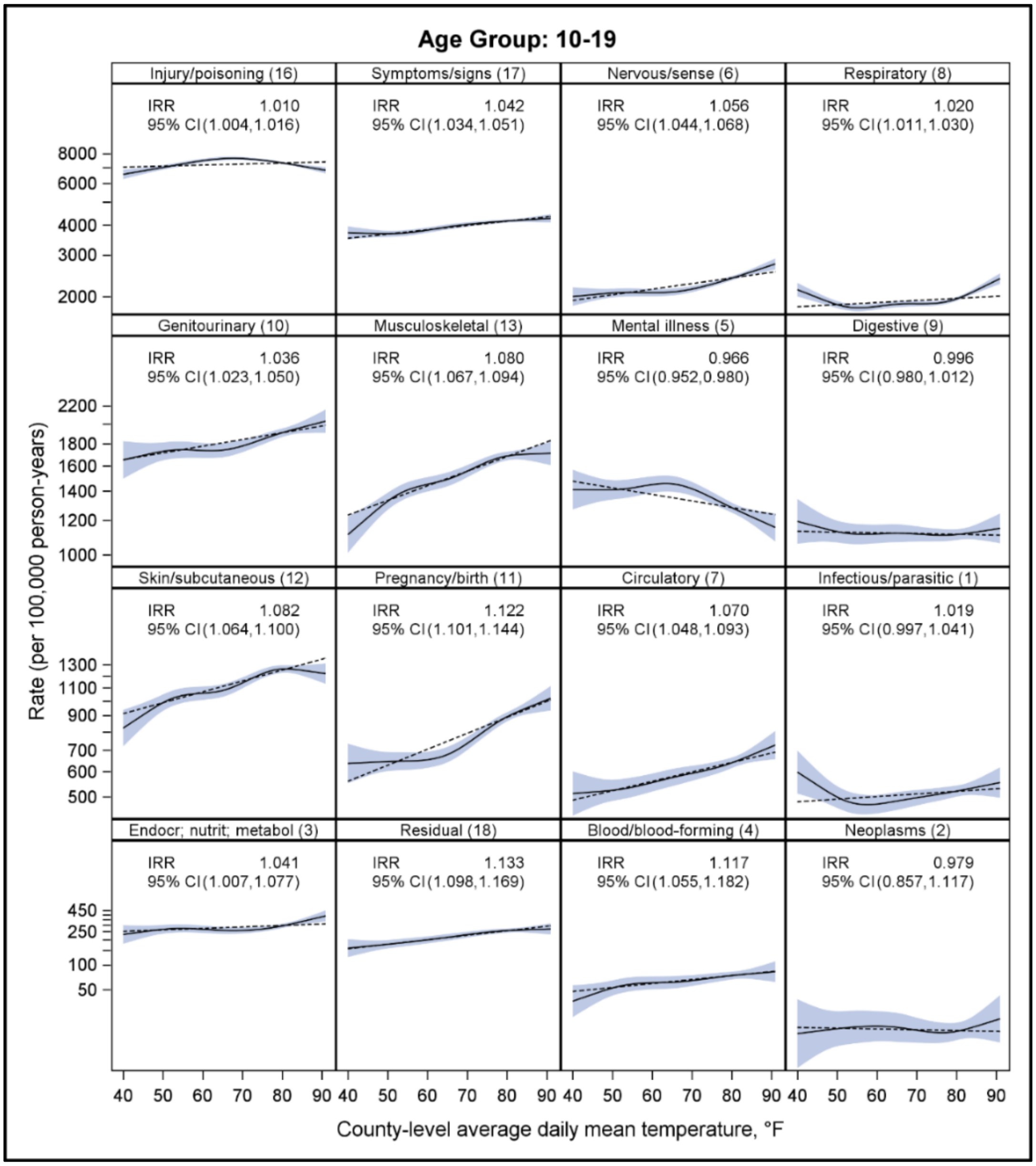
eFigure B.3 Predicted incidence rates and 95% confidence bands for emergency department visits for intentional assault, by sex and age group, in North Carolina, April-October 2008-2013. Unadjusted model.



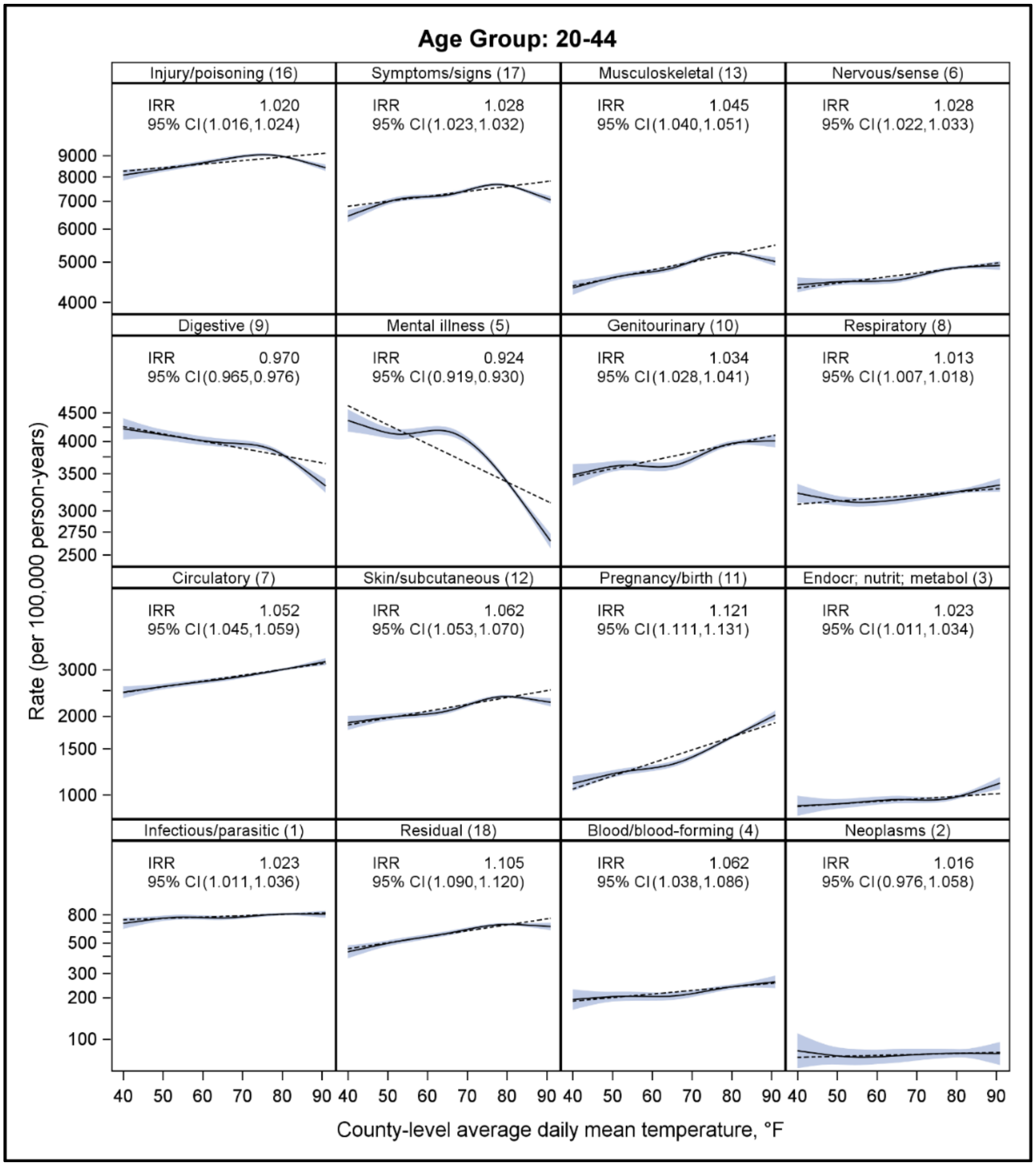
eFigure C.1 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages 0-9 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



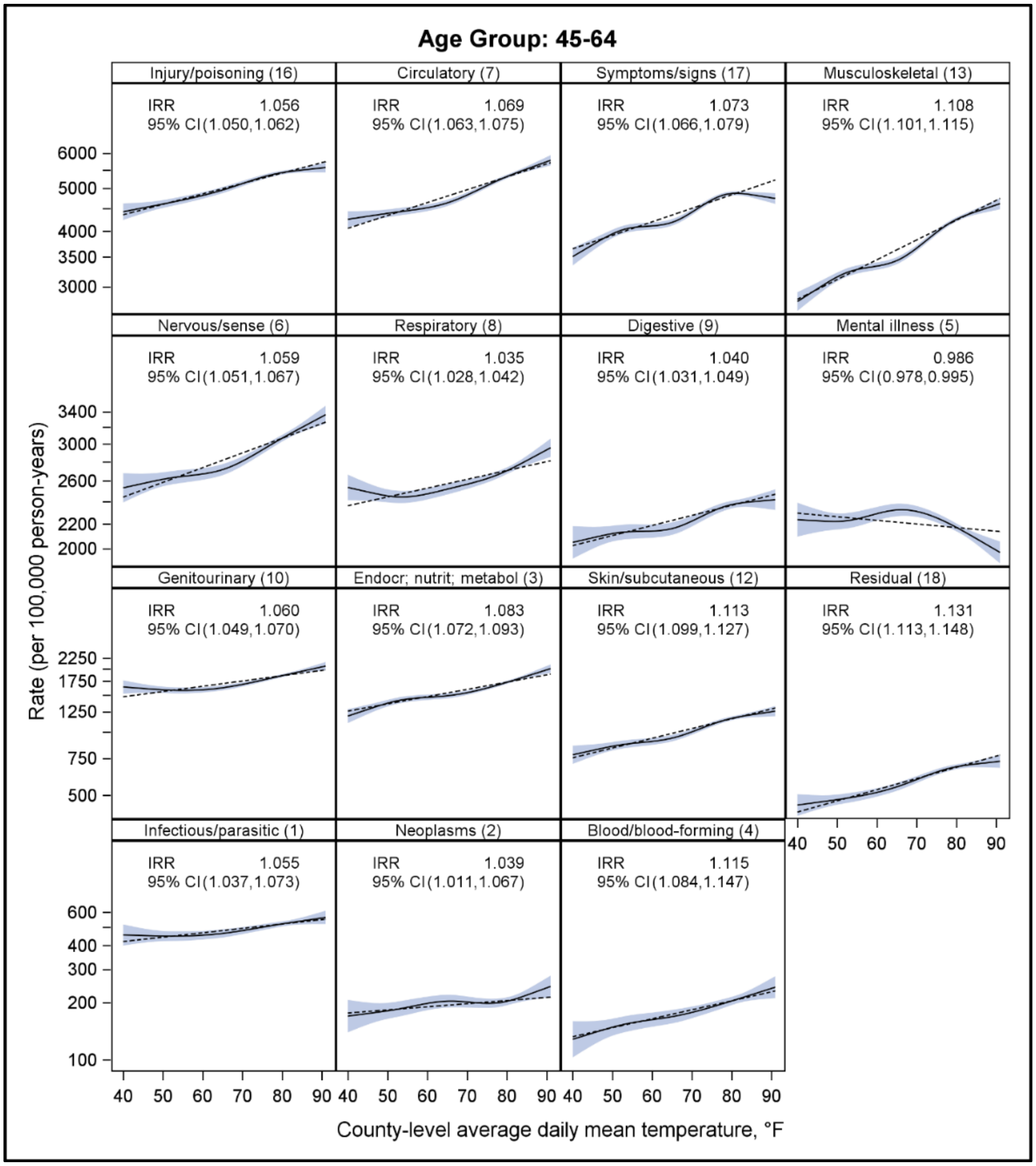
eFigure C.2 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages 10-19 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



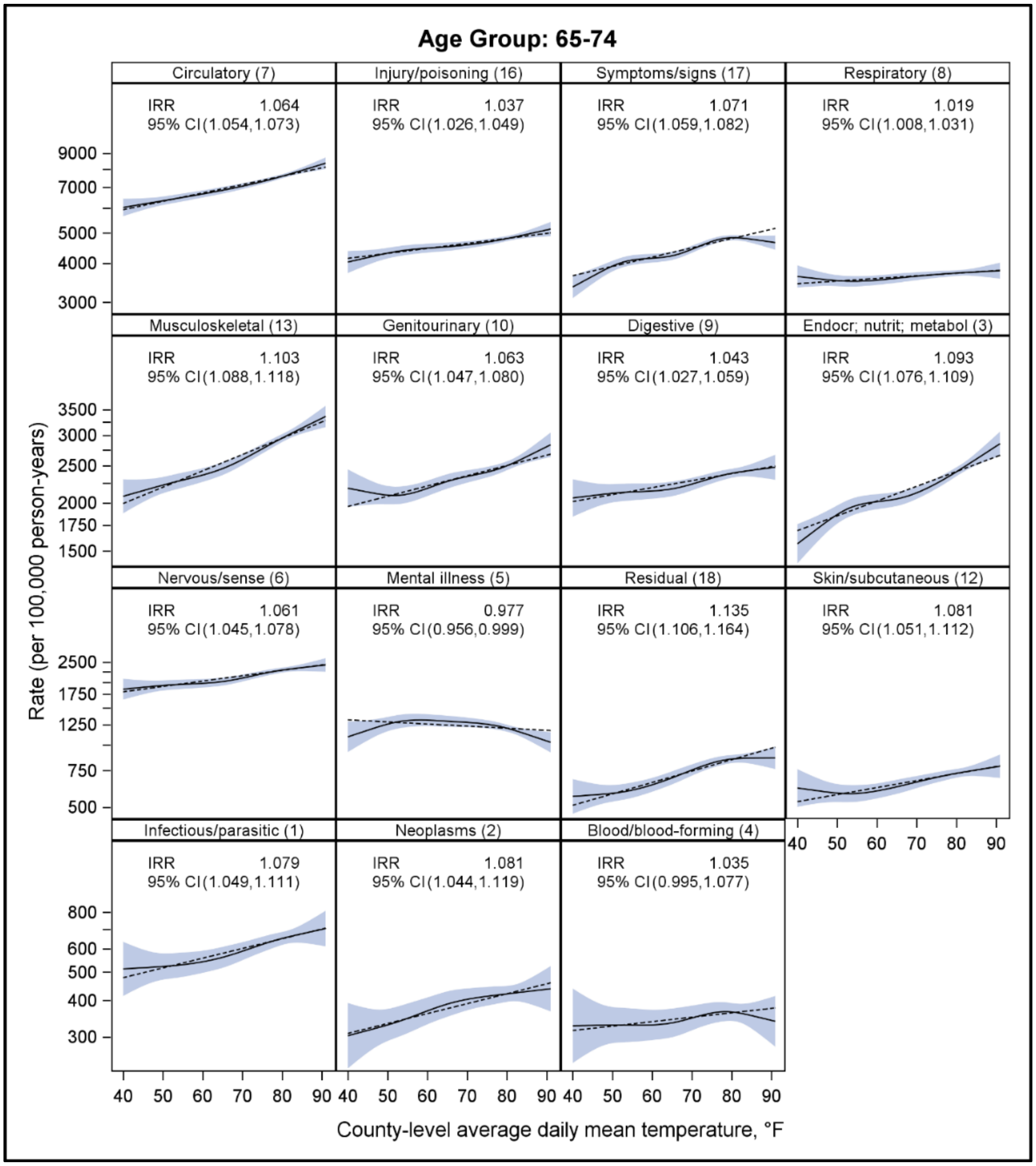
eFigure C.3 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages 20-44 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



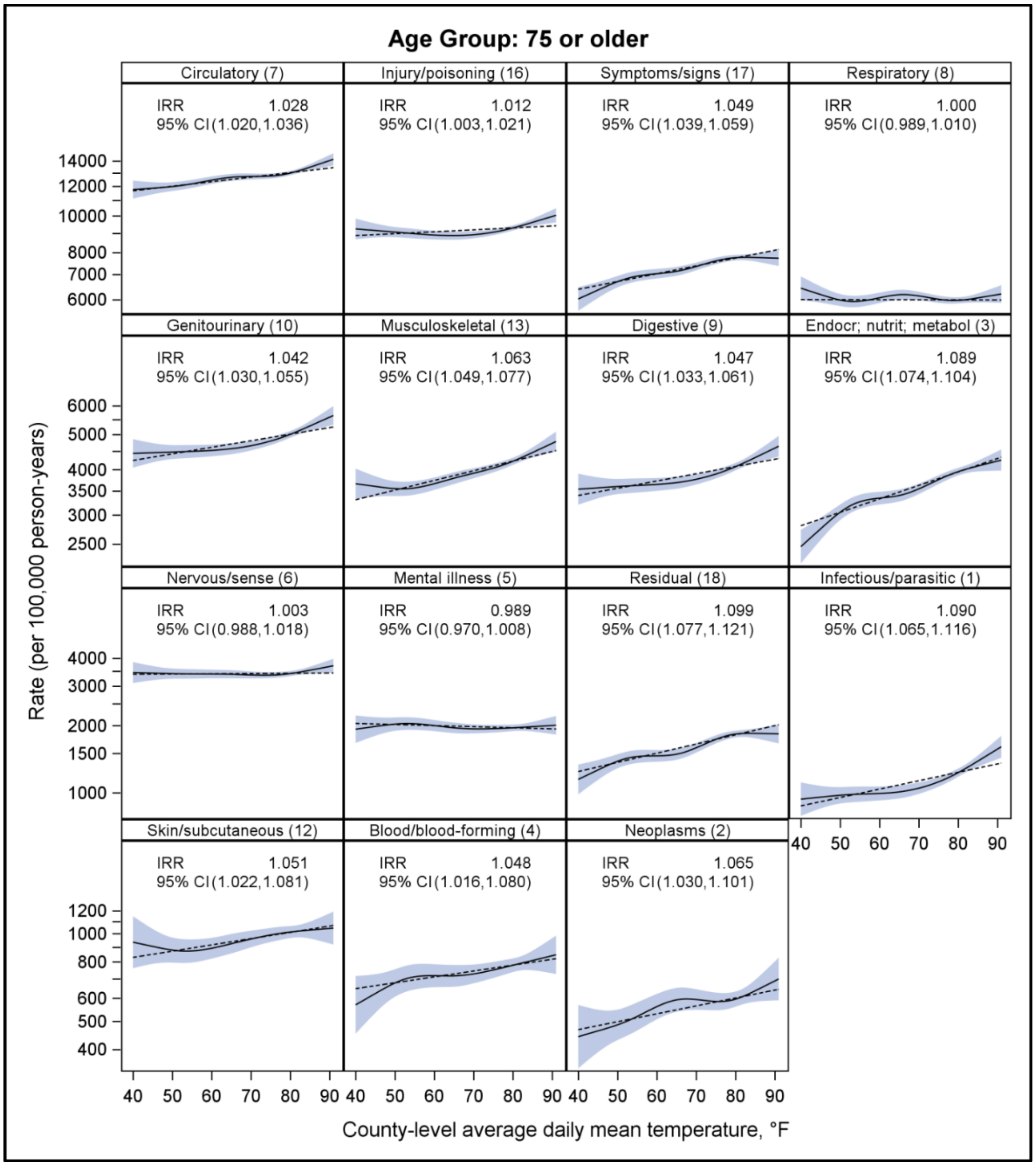
eFigure C.4 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages 45-64 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



eFigure C.5 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages 65-74 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



eFigure C.6 Predicted incidence rates of emergency department visits for the top-level Clinical Classification Software groups for ages ≥75 years, North Carolina, April-October 2008-2013. Solid line and 95% confidence band: Temperature as natural cubic spline. Dashed line: Temperature as linear term. Note: Y-axes are log-scaled and the ranges decrease with each row. CCS group names are abbreviated; refer to Table 1 for full CCS group names.



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