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IMPACTS OF COLD WEATHER ON HEALTH IN TEXAS

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IMPACTS OF COLD WEATHER ON HEALTH IN TEXAS

by

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2018

DEDICATION

To My Family

and

To My Dog, Jordi

IMPACTS OF COLD WEATHER ON HEALTH IN TEXAS

by

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BS, Taipei Medical University, 2007

MPH, Emory University Rollins School of Public Health, 2010

Presented to the Faculty of The University of Texas

School of Public Health

in Partial Fulfillment

of the Requirements

for the Degree of

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IMPACTS OF COLD WEATHER ON HEALTH IN TEXAS

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The University of Texas
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Recent events with recorded low temperature and unusual snow accumulation in the United States and Europe have raised the public awareness of the potential health impacts of extreme winter weather. Excessive cold was the leading cause of weather-related death during 2006-2010 in the U.S., accounting for 63% of weather related deaths. Several studies worldwide have demonstrated that, in general, mortality rates are higher in winter compared to summer. Studies have also shown that the association between cold temperature and death vary across cities, regions and countries and is especially relevant with decreasing latitude or in regions with mild winter climate. In addition to cold temperatures, higher mortality rates may be attributable to cold wave, an extended period of extreme cold temperature. However, due to global climate change, attention has focused on current and future heat waves on human health rather than cold waves. Despite the fact that climate change is expected to increase the intensity of winter storms, only a few studies have investigated cold wave-mortality association. Further, the results of these studies are inconsistent. In addition, most studies have focused on all-cause and cause-specific mortality, cold-related morbidity was less studied. The long-term goal of this study is to improve the understanding of how cold temperature and cold wave affect human health and to reduce adverse health effects of future cold events.

The dissertation used time-series data with Poisson regression model to quantify both cold temperature effect and cold wave effect in Texas, one of the most populous and largest states that covers a variety of demographical and geographical feature with a general mild winter climate as located in the southern USA. Daily counts of deaths/emergency hospital admissions were modeled with both temperature and different cold-wave definitions for 12 major Metropolitan Areas (MSAs). Moreover, considering winter weather patterns are anticipated to become more variable with increasing average global temperatures, we used downscaled global climate models with population projection to estimate future public health burden attributable to cold temperature.

The study showed that cold weather generally increases health risk significantly in Texas ranging from 0.1% to 5.0% for mortality and 0.1% to 3.8% for emergency hospital admissions with a 1⁰C decrease in temperature below the cold thresholds. The cold effects vary with age groups with highest risk in people over 75-year old. The strongest cold effects were associated with mortality in heart diseases and with emergency hospital admission in respiratory diseases. We found although the annual cold- mortality rates reduced with projected temperature under climate change, the number of deaths attributable to cold temperature increased largely with projected population through the end of the century.

The findings can improve the understanding of cold-related health impacts in southern U.S. regions, and help local governments allocate resources to the areas in greatest need. This study can provide evidence for local policy makers to design strategies in reducing future public health burden of temperature-related deaths.

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CHAPTER I

BACKGROUND

Introduction

Cold weather has been identified as a major cause of weather-related deaths in the U.S.² According to the National Health Statistics Reports from the Centers for Disease Control and Prevention (CDC), approximately 2,000 U.S. residents died from weather-related causes annually during 2006-2010.² Among these deaths, 63% were due to extreme cold, 31% were attributed to extreme heat and approximately 6% were attributed to floods, storms, tornadoes, hurricanes or lightning.² While cold-related mortality has been investigated extensively, publications on cold-related morbidity are less well studied. In the U.S., it was estimated that 15,574 emergency room visits were related to hypothermia and other cold-related morbidity during 1995-2004.¹³

Biological Mechanism

Exposure to extreme cold can lead to direct effects such as hypothermia, a core body temperature below 35 °C, and result in death, or indirect effects such as frostbite and infectious diseases.⁷ Moreover, extreme cold may also exacerbate pre-existing chronic conditions (cardiovascular and respiratory diseases) and lead to death.² The human body has thermoregulation system that maintains a constant core body temperature of around 37°C.¹⁴ A series of heat retention and production will be initiated upon cold exposure. First, the body will preserve heat by favoring the internal organs. Blood is shunted from the periphery to the

interior and vasoconstriction occurs at extremities. Involuntary shivering generates heat through increased muscle contractions and activity.¹⁴ Extreme temperatures have been associated with elevated cardiovascular risk; however, the underlying mechanisms were not fully studied yet.⁷ Studies show low temperature causes constriction of blood vessels, resulting in increased blood pressure (cold-induced hypertension) and increases the risk of cardiovascular events.⁷ Cardiovascular-related events were responsible for half of excess winter deaths and usually occurred shortly after exposure to extreme cold.⁷ Myocardial infarction and cardiac arrest were identified as the primary causes of death during extremely cold days.¹⁵ Bronchoconstriction may occur after inhalation of cold air.⁷ Respiratory illness was estimated to account for half of the remaining excess winter deaths¹⁶ and was generally associated with longer lags of extreme cold event.⁷ Respiratory deaths during winter were mostly attributed to infectious diseases, such as pneumonia and influenza.⁷

Cold Temperature Effect

Many studies have demonstrated an association between ambient temperature and mortality in the U.S.^{3,4,6,8,15,17,18} and worldwide.^{1,9-11} In general, higher mortality was observed at both high and low temperatures.^{1,3,4,6,8,11,15,17} Overall, mortality rates are higher in winter compared to summer; in fact, winter cold deaths are twice as common as heat deaths in the U.S.^{5,19}

Many studies have shown increased mortality with winter temperature worldwide. Few multi-city studies in the U.S. have investigated the cold-mortality/morbidity associations (Table 1). The results across studies were difficult to directly compare due to the fact that the

measures of the associations have been reported differently, such as relative risk, odds ratio, regression coefficient, percent change in mortality and excess mortality during winter. Furthermore, Braga et al.¹⁷ investigated the lagged structure of temperature-mortality in 12 U.S. cities and indicated that effects of cold temperature persisted for days while effects of hot temperature were more immediate. Different use of lagged days for cold temperature effects may also result in different estimates. Xiao et al.²⁰ reported the relative risk of all-cause mortality in 13 eastern U.S. cities was 1.012 [1.008-1.016] with 1 °C decrease in cold temperature threshold, using lag structure up to 27 days. Anderson and Bell³ found a 4.2% [3.2%-5.3%] increase in all-cause mortality risk using relative temperature comparison (1st vs. 10th percentile temperatures of the studied community) with lags up to 25 days. A stronger effect estimate of cold temperature was found in a study of seven U.S. cities with a 10.1% increase in mortality at -5 °C when compared with 15 °C using a 3-day lag.¹⁸ Moreover, the effects of cold temperature on mortality varied by geographic location with different temperature thresholds⁶ and some population demographic characteristics.⁸

Geographic location is strongly associated with cold weather mortality.⁷ Studies have shown that the association between cold temperature and death may vary across cities, regions and countries.^{3,7,15} Studies conducted in the U.S.,^{3,8} Europe¹⁰ and Asia⁹ reported increased mortality during cold periods and observed a higher cold-related mortality in mild winter climate regions or with decreasing latitude.^{8,9,20} This spatial variation of cold effects indicates that the cold-mortality association is specific to one area and may not be fitted to another area.³ Moreover, these findings implied how different acclimatization of the communities was associated to their local weather conditions.^{8,21}

In addition to spatial heterogeneity of cold temperature effect, several studies indicated that the most vulnerable populations in cold weather are the elderly, black or rural residents.^{3,8,15,18} Age is one of modifiers of the cold temperature effect. The cold-related mortality association was stronger in people over age 65 as their ability of thermoregulation was impaired.¹⁸ African Americans were associated with higher risk of cold related mortality.¹⁸ Difference in susceptibility related to urbanity was also found, and cold-related mortality was higher in smaller communities than in larger communities.³ However, socioeconomic indicators were not strongly related to mortality.³

In addition to cold temperature effect, excessive cold-mortality/morbidity may also be attributable to cold waves, an extended time period of cold temperature extremes.⁷ This sustained extreme of cold temperature over a number of consecutive days may have additional risks of mortality/morbidity due to extra strains on body's heating systems, and this is be defined as cold waves effect.⁴

Table 1. Evidence Table Multi-city studies conducted in U.S. investigated cold temperature/cold wave effect on all-cause mortality/morbidity.

Author	Year	Location	Study Period	Exposure	Outcome	Findings
Xiao et al.	2015	13 US cities	1987–2000	Cold temp	Morbidity Mortality	RR:1.012 [1.008, 1.016]
Zanobetti et al.	2013	135 US cities	1985–2006	Cold temp Cold wave	Medicare deaths	Precondition of dementia and disorder of the peripheral nervous system had a higher risk of mortality
Von Klot et al.	2012	48 US cities	1992-2000	Cold temp	Cardiac mortality morbidity	1.6% increase in risk with decrease temp (0 vs. -5 °C)
Barnett et al.	2012	99 US cities	1987-2000	Cold wave	mortality	No additional cold wave effect
Anderson and Bell	2009	107 US cities	1987-2000	Cold temp	Mortality	4.2% (3.2%, 5.3%) increase in risk (1st vs. 10th percentile)
Medina-Ramon Schwartz	2007	50 US cities	1989-2000	Cold temp Cold wave	Mortality	1.59% (0.56%, 2.63%) increase in risk with extreme cold days
O'Neill et al	2003	7 US cities	1986-1993	Cold temp	Mortality	10.1% increase in risk (-5 vs. 15 °C)
Curriero et al.	2002	11 US cities	1973-1994	Cold temp	Mortality	During the spring and fall, a slight increase in mortality risk occurred with colder temperatures
Larsen	1990	6 State	1921-1985	Cold temp	Mortality	A one degree drop in the mean temp is associated with a 3.5% increase in the February crude death rate

Cold Wave Effect

Cold wave effects may lead to a greater increased risk in deaths/illnesses than predicted by cold temperature effects alone.⁴ However, due to global climate change, more of the attention has focused on the impact of current and future heat waves on human health compared to cold waves.^{21,22} While the average winter temperatures in U.S. have risen in past decades, many areas continue to experience extremely low temperatures.²

Despite cold extremes continuing to be a significant health problem, only a few studies have investigated the cold-mortality associations during cold waves. Medina-Ramon and Schwartz¹⁵ examined the impact of cold wave on mortality in the 50 U.S. cities for a 12-year period and found a significant increase in mortality. Several studies conducted in other countries also reported increased mortality risks during cold waves.^{10,11} In contrast, Barnett et al.⁴ reported no additional cold wave effects above the known increased risk associated with cold temperatures in 99 U.S. cities for a 14-year period. This lack of consistency on cold-wave mortality may be due to different levels of controlling confounders, such as long term trend, seasonal variation, influenza, air pollutions etc. Moreover, effect estimates of cold waves depend on the choice of lag structure. Typically, heat-wave mortality is associated with a shorter lag (same day and previous day temperature); while cold-wave effect can last longer (can be weeks or up to a month).^{3,7} However, studies conducted prior to 2007 were mostly using a shorter lag structure for cold-wave effect.⁴

Climate Change and Acclimatization

Global average temperatures will continue to rise over the next few decades. Assessments of the health impacts of climate change worldwide have often concluded that a reduction in the severity and length of cold weather due to global warming would substantially reduce winter mortality deaths.²³ However, the accuracy of these predictions depends on how much of this winter mortality is directly dependent on cold temperatures alone. A recent study indicated that in UK and other temperate countries, with the greater awareness of the risks of cold, improved housing and health care, the link between winter temperature and cold-mortality may no longer be as strong as before.²⁴ This does not imply winter mortality will fall with climate warming, however, the severity of winter may not directly predict the number affected in those temperate countries. Projections of the health impact associated with climate change have not been conducted in other climate regions (e.g., subtropical) yet, and previous evidence has shown a stronger cold-related mortality in mild winter climate regions or with decreasing latitude.^{8,9,20} Thus, the association between winter temperature and cold mortality with future climate projection remain unsure in the Southern U.S.

PUBLIC HEALTH SIGNIFICANCE

In the U.S., most previous studies were conducted using data before the early 2000s; new studies with updated data including recent extreme cold winters should be performed. Current literature shows that despite cold extremes continuing to be a significant health problem, only a few studies have investigated the cold-mortality relationships during cold waves and results are inconsistent. In addition, further information on effect modifiers of the temperature and mortality association is needed. While temperature patterns are expected to change as a consequence of climate change, cold-mortality/morbidity associations and their

geographic variation are likely to be a growing concern. While most cold-related mortality or morbidity events are preventable, improving the understanding of how cold temperature and cold wave affects human health can provide insights for community leaders and policymakers to design better intervention strategies targeted towards reducing adverse health effects of future cold temperature events.

SPECIFIC AIMS

This dissertation is aiming to improve the understanding of cold temperature and cold wave association with mortality and morbidity. By looking at MSA level associations, the state government or regional leaders would be able to locate areas with excessive mortality and morbidity risk and help local governments allocate resources to the areas in greatest need. This dissertation also aiming to provide insights to aid community leaders and policymakers in the design of better intervention strategies targeted towards reducing adverse health effects of future cold events. Specifically, we propose to:

Aim 1: Investigate the associations between cold weather (cold temperature and cold wave) and all-cause/cause-specific mortality (1990-2011) including cardiovascular diseases (ischemic heart disease, myocardial infarction and stroke) and respiratory diseases (chronic obstructive pulmonary disease and pneumonia) in major Metropolitan Statistical Areas (MSAs) in Texas.

Based on the evidence from previous studies, we hypothesize that higher cold-related mortality rates are expected in Texas comparing to high latitude climate winter climate region. Distributed lag nonlinear models (DLNMs) will be applied to major MSAs in Texas to examine the cold-mortality association for the 22-year period. To determine if an extra cold wave effect

exist, models will be tested with and without a cold wave indicator. We will explore potential cold wave definitions with different intensity and durations.

Aim 2: Investigate the associations between cold weather (cold temperature and cold wave) and hospital admissions (2004-2013) in major MSAs in Texas.

We will apply the same research approach in Aim 1 to examine the cold-morbidity association for the 10-year period using hospital admission as our main outcome variable. Our working hypothesis is that the trend of higher cold-related mortality rates with mild winter climate regions will also show in hospital admissions.

Aim 3: Generate predictive model for future cold-related mortality impacts for Texas in the 2000s, 2050s and 2080s, using different global climate models and emission scenarios.

Future warming is expected as the consequence of global climate change, however, cold-related health impacts may not correspondently decrease. Along with the consideration of population projection, we estimate cold temperature-related deaths under different climate models and scenarios in Texas. With this strategy, we will be able to account for climate change in temperature-related health impacts for future.

CHAPTER II

JOURNAL ARTICLE I: IMPACTS OF COLD WEATHER ON ALL-CAUSE AND CAUSE-SPECIFIC MORTALITY IN TEXAS, 1990-2010

Title of Journal Article

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Impacts of Cold Weather on All-cause and Cause-specific Mortality in Texas, 1990-2011

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Abstract

Cold weather was estimated to account for more than half of weather-related deaths in the U.S. during 2006–2010. Studies have shown that cold-related excessive mortality is especially relevant with decreasing latitude or in regions with mild winter. However, only limited studies have been conducted in the southern U.S. The purpose of our study is to examine impacts of cold weather on mortality in 12 major Texas Metropolitan Areas (MSAs) for the 22-year period, 1990–2011. Our study used a two-stage approach to examine the cold-mortality association. We first applied distributed lag non-linear models (DLNM) to 12 major MSAs to estimate cold effects for each area. A random effects meta-analysis was then used to estimate pooled effects. Age-stratified and cause-specific mortalities were modeled separately for each MSA. Most of the MSAs were associated with an increased risk in mortality ranging from 0.1% to 5.0% with a 1 °C decrease in temperature below the cold thresholds. Higher increased mortality risks were generally observed in MSAs with higher average daily mean temperatures and lower latitudes. Pooled effect estimate was 1.58% (95% Confidence Interval (CI) [0.81, 2.37]) increase in all-cause mortality risk with a 1 °C decrease in temperature. Cold wave effects in Texas were also examined, and several MSAs along the Texas Gulf Coast showed statistically significant cold wave-mortality associations. Effects of cold on all-cause mortality were highest among people over 75 years old (1.86%, 95% CI [1.09, 2.63]). Pooled estimates for cause-specific mortality were strongest in myocardial infarction (4.30%, 95% CI [1.18, 7.51]), followed by respiratory diseases (3.17%, 95% CI [0.26, 6.17]) and ischemic heart diseases (2.54%, 95% CI [1.08, 4.02]). In conclusion, cold weather generally increases

mortality risk significantly in Texas, and the cold effects vary with MSAs, age groups, and cause-specific deaths.

Keywords

Cold weather; Heart disease; Mortality; Spatial heterogeneity; Temperature

Capsule

Cold weather generally increases mortality risk significantly in Texas, and the cold effects vary with region, age groups and cause-specific deaths.

Highlights

- Cold weather generally increases mortality risk significantly in Texas.
- Cold effects vary with geographic locations, age groups and mortality causes.
- Strong effect estimates were observed in heart diseases.

Introduction

Recent events with recorded extreme low temperature and unusual snow accumulation in the U.S. and Europe have raised the public awareness of the potential health impacts of extreme cold weather. Cold weather has been linked to significant levels of mortality and morbidity (Guo et al. 2014; O'Neill and Ebi 2009; Ye et al. 2012). In the U.S., excessive cold was the leading cause of weather-related deaths during 2006-2010, accounting for 63% of weather related deaths (Berko et al. 2014). Exposure to extreme cold can lead to direct effects such as hypothermia and result in death, moreover, extreme cold can exacerbate preexisting chronic conditions (Conlon et al. 2011). Larsen (1990) indicated that unusual cold winter temperature has strongest fatal effects on mortality, including deaths from infectious disease, heart diseases, cerebrovascular diseases, pneumonia, and influenza. In general, mortality rates are 10-20% higher in winter compared to summer (National Vital Statistics System (NVSS) 2014).

Studies worldwide have shown that the effects of cold temperature on mortality were varied by geographic location and some demographic characteristics of population (Conlon et al. 2011; Curriero et al. 2002). Cold-related excessive mortality is especially relevant with decreasing latitude or in mild winter climate region (Curriero et al. 2002; Ma et al. 2014). Spatial heterogeneity in cold effects indicates cold-mortality relationships from one community may not be applicable to another (Anderson and Bell 2009). Moreover, these findings implied how different acclimatization of the communities was associated to their local weather conditions (Curriero et al. 2002; Turner et al. 2012). Studies have observed that cold weather have a larger impact on health among the elderly compared to younger people (Yu et

al. 2012; Conlon et al. 2011). The cold-related mortality had a moderate increased for persons aged 15-75, and a substantial increase for person aged 75 and over (Berko et al. 2014).

In addition to cold temperatures, higher mortality rates may be attributable to cold waves. An extended period of extreme cold temperature, cold waves, may have additional risks of mortality due to extra strains on body's thermoregulation. However, due to global climate change, attention has focused on current and future heat waves on human health rather than cold waves. Few studies have investigated cold wave-mortality association; despite climate change is expected to increase the intensity of winter storms (Conlon et al. 2011; Barnett et al. 2012). Further, the results of these studies were inconsistent (Barnett et al. 2012; Medina-Ramon and Schwartz 2007; Montero et al. 2010; Huynen et al. 2001).

Despite cold extremes continuing to be a significant health problem, only a handful of multi-city studies have investigated the cold-mortality association in the U.S. (Ye et al. 2012). Studies investigated cold wave effects were even less common (Barnett et al. 2012). Moreover, detrimental effects of cold are especially profound in regions with mild winter climate. While temperature patterns are expected to change as a consequence of climate change, cold-mortality associations and their geographic variation are likely to be a growing concern. Texas covers an area of 267,339 square miles and is the largest of the conterminous states. Texas extends from 25°50'N to 36°30'N latitude and from 93°31'W to 106°38'W longitude; the elevation range is from sea level to 8,751 feet on Guadalupe Mountain. Because of this great variation in so many geographical features, it is ideal for studying spatial heterogeneity. In light of the spatial variation of cold effects and the lack of studies including recent cold extremes, this paper aims to examine impacts of cold weather on mortality in 12 major Texas Metropolitan Areas (MSAs) for the 22-year period, 1990-2011.

Material and methods

Study area

Texas is the largest of the 48 contiguous states and the second most populous state in the U.S. As of February 2013, 25 Texas Metropolitan Statistical Areas (MSAs) are delineated by the U.S. Office of Management and Budget (OMB) based on the 2010 Census Bureau data (U.S. Census 2013). Twelve Texas MSAs were selected based on population sizes that were consistently over 200,000 throughout the 22-year study period (1990-2011) and the availability of weather and air pollution data. Selected MSAs are shown in Figure 1. The climate of selected Texas MSAs varies widely ranging from hot-dry, mixed-dry in the west to hot-humid and mixed-humid in the east (U.S. Department of Energy 2010).

Data collection

Mortality data

Mortality data were obtained from the Texas Department of State Health Services and were aggregated on a daily basis at the MSA level. The International Classification of Disease (ICD) Ninth Revision (ICD-9) and Tenth Revision (ICD-10) (World Health Organization 1975, 1993) were used for diagnosis of primary mortality causes during the periods 1990-1998 and 1999-2011, respectively. Deaths were divided into all causes, cardiovascular disease (CVD, ICD-9 390-429; ICD-10 I01-I52), respiratory disease (RESP, ICD-9 460-519; ICD-10 J00-J99). We further classified CVDs into subtypes including ischemic heart disease (IHD, ICD-9 410-414; ICD-10 I20-I52), myocardial infarction disease (MI, ICD-9 410; ICD-10 I21,

I22) and stroke (ICD-9 430-438; ICD-10 I60-I69), and categorized RESPs into chronic obstructive pulmonary disease (COPD, ICD-9 490-496 except 493; ICD-10 J40-J44, J47), and pneumonia (PNEU, ICD-9 480-486; ICD-10 J12-J18). For age stratification, we used 65 of age as the cutoff point and further categorized older population with two subgroups (0-64, 65-74 and above 75 years old).

Weather data

Hourly weather data at weather stations were downloaded from the National Climate Data Center (NCDC) through the Integrated Surface Database (ISD) (NCDC 2014). For each MSA, we selected one weather station, which was considered the most representative of the population exposure at MSA-level (e.g., airport weather station and closest to the most populous city in the MSA). Daily mean, minimum, maximum temperatures and dew point temperature were then calculated. Previous studies indicated that there is no consensus in ‘the best’ temperature measure consistently predicting temperature-mortality association better than others (Barnett et al. 2010; Zhang et al. 2014). We used mean temperature as it represents the temperature exposure for both day and night (Guo et al. 2014). The ISD weather data have been checked for extreme values, consistency between parameters, and continuity between observations through a rigorous quality control procedure developed by NCDC (Lott 2004).

Cold wave definition

There is no consensus on the definition of cold waves. We explored three percentile-based cutoff points with two different durations. We first identified cold waves as daily mean temperatures below the 1st, 5th, or 10th percentiles of the entire study period of each MSA with periods of 2 or more consecutive days. Then we extended each cold wave seven days

beyond its last day below the threshold to capture delayed effects as described in Barnett et al. (2012).

Statistical analysis

The multi-city time-series analyses were performed in two stages: MSA-specific analysis on cold temperature-mortality association and meta-analysis. In the first stage, a Poisson regression allowing for over dispersion model was used to estimate the MSA-specific association. In the second stage, the estimated associations were then pooled at the entire state using meta-analysis. This two-stage approach is commonly used in multi-city studies (Guo et al. 2014; Gasparrini et al. 2012).

MSA-specific models

There are two steps in building up MSA-specific models. First, to determine whether a cold-temperature threshold exist, the association between temperature and daily count deaths was analyzed and plotted using the generalized additive model (GAM) with a spline function of temperature for each MSA separately. To account for the delayed effect of cold temperature, we used lag 0-25 (average the same day and previous 25 days temperature) as our main exposure in the GAM models. Confounding variables including day of the week, day of year and mean dew point temperature were also included in the models. Our initial analysis showed a V-, U- or hockey-stick shaped non-linear association between temperature and mortality, with potential cold thresholds (see Supplemental Figure 1). We decided that there were linear relationships below cold thresholds evident through visual inspection. Second, to quantify the risks of mortality, we applied single threshold distributed lag non-linear models (DLNMs).

Across-basis function can express exposure-response dependencies and delayed effects simultaneously. The MSA-specific associations were estimated through a Poisson regression model as:

$$\text{Log}[E(Y_t)] = \alpha + \mathbf{cb}(meTMP_{t,l}) + \boldsymbol{\gamma}CW_t + \boldsymbol{\delta}DOW_t + s(DOY_t, 7/year) + s(meDWP_t, 3) \quad [1]$$

Where Y_t is the number of deaths on day t ; α is the intercept; $cb()$ is a cross-basis function; $meTMP_{t,l}$ represents mean temperature on lag day l , and l was up to 25 days with 5 degree of freedom; CW_t is a dummy variable for cold waves (1 if day t was classified as part of a cold wave, 0 otherwise); DOW_t is a set of dummy variables for day of the week; $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are the vector of regression coefficients; $s()$ is a smooth function (natural cubic spline); DOY_t represents day of year with 7 degrees of freedom per year to account for seasonality and long-term trend; $meDWP_t$ represents mean dew point temperature with 3 degrees of freedom.

Cold thresholds used in equation [1] were determined by minimizing Akaike information criterion (Q-AIC) for regression models using quasi-Poisson distribution. We reported the estimated mortality relative risk as with a 1 °C decrease in temperature below the cold threshold. The associations between mean temperature and age-stratified and cause-specific mortality were also fitted using the same approach.

Meta-analysis

In the second stage, MSA-specific effect estimates obtained from the first-stage were then pooled through multivariate meta-analysis. A random effects model was used to obtain effect estimates in the entire state. For a set of $i = 1 \dots k \dots 12$ independent MSA, we assume

that $\hat{\theta}_i$ denote the observed value of the effect size or outcome measure in the i th MSA, the model can be expressed as follow:

$$\hat{\theta}_i \sim N(\theta_i, v_i + \tau^2) [2]$$

Where $\hat{\theta}_i$ is the effect estimate in MSA i , v_i is the variance within MSA i , θ_i is the true effect of cold temperature on mortality and τ^2 is the variance of the true effect among MSAs. We used restricted maximum likelihood (REML) to estimate the between-MSA variance τ^2 in our models. In the random-effect model, the k MSA, included in the meta-analysis is assumed to be a random selection from a larger population of MSAs. We assume that the true effects/outcomes in the population of MSAs are normally distributed with θ_i denoting the average true effect/outcome and τ^2 denoting the variance of the true effects/outcomes in the population.

All statistical analyses were performed in the R statistical software (R Development Core Team; <http://R-project.org>). GAMs were fitted using the “mgcv” package (version 1.8-5) (Wood 2006); DLNMs were fitted using “dlnm” package (version 2.0.6) (Gasparrini et al. 2010); and meta-analysis was performed using “metafor” package (version 1.9-7) (Viechtbauer 2010).

Sensitivity analysis

We performed sensitivity analysis to evaluate how effect estimates vary with and without adjustment for temperature effects. We compared the MSA-specific associations with and without adjustments for cold wave effects. All selected cold wave definitions (five percentile-based cutoff points with two different durations) were evaluated.

Results

Table 1 shows the summary of meteorology and population characteristics in the 12 MSAs, which included 62 Counties in Texas. The population sizes of Texas MSAs are varied. As of 2010, Houston-The Woodlands-Sugar Land was the most populous MSA with nearly 6 million residence followed by Dallas-Fort Worth-Arlington MSA with over 4 million population; and Waco was the least populous MSA with approximately 250,000 population (U.S. Census 2010). The average daily mean temperatures in Texas MSAs ranged from 16.2 to 24.3°C during the study period. McAllen-Edinburg-Mission and Brownsville-Harlingen MSAs located at the southernmost tip of Texas and had higher annual mean temperatures. The lowest annual mean temperature was observed in Lubbock MSA, the northernmost MSA included in this study. The average daily counts of all-cause deaths ranged from 5 to 77 with the highest daily counts observed in Houston-The Woodlands-Sugar Land MSA. There were over 2 million deaths between January 1990 and December 2011 with 65% of these deaths among elderly (age above 65). Additionally, MSA-specific cold thresholds for all-cause mortality varied between 10.6 and 20.0 °C (Table 1).

Table 2 shows the effect estimates of cold in each MSA using three different models: modeling for daily mean temperature only (temperature effects), modeling for cold waves only (overall cold wave effects), and modeling for both daily mean temperature (temperature effects) and cold waves (additional cold wave effects) simultaneously. The temperature effects were estimated with lags days (up to 25 days) in each MSA using single threshold DLNMs. All MSAs show statistically significant increase in all-cause mortality risk with a 1°C decrease

in temperature below the cold threshold except for Lubbock. A 1°C decrease in temperature below threshold was associated with 0.1-5.0% increase in mortality risk. Highest increased mortality risk was observed in McAllen-Edinburg-Mission (5.01% [95% CI: 4.96%, 5.06%]), which also had the highest average daily mean temperature (24.3 °C) among other MSAs. The cold temperature effects remained statistically significant when we included cold wave terms in the models simultaneously and the magnitude of increased mortality risk were similar. However, additional cold wave effects were not observed in any of the MSAs. Overall cold wave effects were observed in a few MSAs along the Texas Gulf Coast area in cold wave-mortality association without adjusting for temperature effects. Thus, we present the results of temperature effects only in the following paragraphs.

The pooled effect estimate between daily mean temperature and all-cause mortality was statistically significant at state level. A 1 °C decrease in temperature below threshold was associated with overall increase in all-cause mortality of 1.58% [95% CI: 0.81%, 2.37%] (Figure 2). Age-stratified and cause-specific mortality were performed in each MSA. Figure 3 shows the pooled age-stratified and cause-specific mortality in the entire state using random effects model. The cold temperature effect of all-cause mortality showed an increase trend among all age groups, with highest in people over 75 years old (1.86%, 95% CI [1.09, 2.63]). The pooled cause-specific mortality showed a 1 °C decrease in temperature below threshold was associated with 0.8%–7.0% increased risk across cause-specific mortalities, however, the highest association we found in pneumonia was not statistically significant (7.0%, 95% CI [−0.85, 15.46]). The statistically significant associations were found highest in MI, followed by RESP and IHD.

Discussion

Cold weather has been identified as a major cause of weather-related deaths in the U.S. Excessive cold-related mortality is especially relevant with decreasing latitude or in mild winter climate regions. In this multi-city time-series study, we examined the impacts of both cold temperatures and cold wave effects on all-cause and cause-specific mortality in 12 major MSAs in Texas. Our findings showed that cold temperature generally had significant effects in Texas and the effects varied with MSAs, age groups, and cause-specific deaths. To the best of our knowledge, this may be the first study that examined the association between both cold temperature and cold waves and mortality among multiple causes in U.S. general population.

Excess winter mortality during cold waves variations varied with region and the definition of cold waves. We calculated the percentage difference in mortality by comparing cold wave days to non-cold wave days using the similar approach described in Dimitriou et al, (2016). With the definition of cold waves defined as a period of at least 2 days below 5 percentile-based cutoff point of temperature then extended 7 days beyond its last day, a state-wide average in the percentage change of mortality is 12.1% ranging from 10.4% to 14.0%. With a stricter definition of cold waves (1st percentile), the average mortality change rate increased slightly. In general, our results showed a similar magnitude of percentage difference compared to a previous study conducted in UK (Dimitriou et al., 2016).

In general, the effect estimates of cold temperature on all-cause mortality were generally statistically significant in Texas. The strongest cold effect estimate was found in the McAllen-Edinburg-Mission MSA, where the average daily mean temperature during the study period was the highest (24.3 °C). We also found that the risk of all-cause mortality increased

as the MSAs' year-round average mean temperature increase (coefficient = 0.53, 95% CI [0.28, 0.78]), and the all-cause mortality increased as the latitude decrease (coefficient = -0.49 , 95% CI [-0.70 , -0.28]). Our findings were consistent with two previous studies. Curriero et al, (2002) reported the cold effect slope was steeper for the southern cities compared to the northern cities, and Gasparrini et al, (2012) showed the effect of cold temperature was larger in lower latitude cities. On the contrary, Braga et al, (2001) reported that no significant cold effects on deaths were found in hot cities (including Houston). The authors explained that the lack of association between cold temperature and mortality may be due to less chance of being exposed to extreme low temperatures. However, the study was conducted from 1986 through 1993, the global climate temperature patterns have been changed that extreme weather (winter storms) are expected to increase in intensity in the future (Conlon et al., 2011).

The random effects meta-analysis showed a statistically significant association between cold temperature and all-cause mortality (1.58%, 95%CI [0.81%, 2.37%]). The finding was consistent with many other previous studies. For example, Anderson and Bell (2009) reported a 4.2% (95%CI [3.2%, 5.3%]) increase in mortality risk when comparing the 1st and 10th percentile temperatures for the community while O'Neill et al. (2003) showed a 10.1% increase in total mortality when compared with absolute temperatures (-5°C to 15°C).

The pooled estimates showed cold effect estimates were strongest in MI, followed by RESP and IHD. CVDs have been reported to be the most common mortality causes among excess winter mortality. CVDs include a range of conditions involving heart and blood vessels. Thus, the associations between temperature and mortality may vary by subtypes of CVDs. Myocardial infarction and cardiac arrest were consistently reported as the primary causes of death during extreme cold days. The underlying mechanisms of increased cardiovascular

diseases during winter have been postulated (Schneider et al., 2008). As a result of exposures to cold, the body tries to reduce heat loss by decreasing peripheral blood circulation, which may increase systolic and diastolic blood pressure, blood viscosity, vasoconstriction, plasma cholesterol and plasma fibrinogen. These changes could trigger an acute cardiac event (Giang et al., 2014).

Similar to previous studies, cold weather is associated with increased risk of respiratory diseases. Respiratory diseases have long been accounted for nearly half of the remaining excess cold mortality other than CVDs (The Eurowinter Group, 1997) and are generally associated with longer lags of extreme cold events (Ebi and Mills, 2013). Our results were based on daily mortality counts that included deaths attributed to influenza while some studies controlled for influenza events. Pneumonia and influenza are commonly combined as an endpoint because many influenza-associated deaths occur from secondary complications when influenza viruses are no longer detectable (Davis et al., 2012). Many winter respiratory deaths are reported due to influenza (Thompson, 2010; Conlon et al., 2011). Although cold temperature can be linked to suppress mucociliary defenses and resulting in inflammation, cold temperature alone may not explain the infection rates. Influenza epidemic may play an important role in the winter mortality that mortality was significantly higher in season dominated by influenza A (H2N2) and A (H3N2) (Ebi and Mills, 2013).

Among the studies conducted in U.S., the effects of cold are more pronounced in elderly populations (Curriero et al., 2002, O'Neill et al., 2003). Cold effects were found strongest in people age above 75 as their ability to thermoregulation can be impaired (Conlon et al., 2011). Severe cold weather and mortality due to ischemic heart diseases were reported highest among males aged 35–49 years whereas females aged 65 and older experienced

increased mortality due to respiratory and cerebrovascular diseases (Gorjanc et al., 1999). Moreover, cardiac mortality among people over 55 years of age has been shown to have significant negative association with daily average temperature (Cagle and Hubbard, 2005).

Our study did not observe additional cold wave effects in Texas. Barnett et al. (2012) reported no additional cold wave effects above the known increased risk associated with cold temperatures in 99 U.S. cities for a 14-year period. In contrast, Medina-Ramon and Schwartz (2007) examined the impact of cold waves on mortality in the 50 U.S. cities for a 12-year period and found a significant increase in all-cause mortality. Several studies conducted in other countries also reported increased mortality risks during cold waves (Montero et al., 2010, Huynen et al., 2001). This inconsistency may be due to different levels of controlling confounders, such as long-term trends, seasonal variation, influenza, air pollution. Moreover, as cold temperature effect, the choice of lag structure for cold wave effect may differ in the results. Typically, heat-wave mortality is associated with a shorter lag (same day and previous day temperature), while cold-wave effect can last longer (can be weeks or up to a month) (Anderson and Bell, 2009, Conlon et al., 2011). However, studies conducted prior to 2007 were mostly using a shorter lag structure for cold-wave effect (Barnett et al., 2012). Although we did not observe additional cold wave effects in our study, it does not necessarily mean that cold waves did not increase mortality risks in Texas area.

Our sensitivity analysis indicated increasing risks of mortality among coastal MSAs when comparing cold wave days and non-cold wave days without adjusting temperatures (5.2%–12.1% or 2.8%–7.8% increase risk varied by cold wave definitions) (see Supplemental Table 1).

This study has two major limitations. The first limitation of this research is exposure misclassification. We assigned temperature exposures from a single weather station per MSA rather than using personal exposures. It is usually impractical for population-based epidemiological studies using personal exposure due to cost and logistic reasons. Another major limitation is ecologic fallacy (or aggregation bias). We did not explore individual characteristics such as social economic status (SES), education level, tobacco/alcohol use, housing quality and characteristics (heating/AC status), which may modify associations between cold temperature and health. Differences in thresholds, cold and cold-wave effects are likely explained by individual-level factors (e.g., elderly and acclimatization), neighborhood- and even regional-level factors (e.g., the prevalence of heating system). The contribution of these factors requires further studies to incorporate such information into data analysis. This will be examined in future studies beyond the scope of this work. However, we did consider age in our study as it is crucial indicator of vulnerable population.

Strengths of this study include the use of a population-based registry that covered all-age cases throughout the state of Texas for over two decades. Previous studies conducted in the U.S. primarily examined elderly or used data before the early 2000s. Our study not only included all age groups but also included more recent cold events. This appears to be the first multi-city study of the association between cold weather (cold temperature and cold waves) and mortality with over 20 years of study period in a mild winter region.

Conclusions

Cold weather has been the leading cause of the weather-related deaths in the U.S. Excessive cold mortality is especially relevant in mild climate regions. However, only limited studies have been conducted in the southern U.S. Our study showed that cold weather generally increases mortality risk significantly in Texas ranging from 0.1% to 5.0% with a 1⁰C decrease in temperature below the cold thresholds. The cold effects vary with age groups (highest in people over 75-year old) and cause-specific deaths (highest in pneumonia followed by MI and ISD).

Cold-related deaths and illnesses can be fatal but also preventable. People can easily reduce their risk of developing cold-related adverse health outcomes by keeping body warm (wearing clothes, stay indoors). Our findings can improve the understanding of cold temperature effect on mortality in southern regions, and help local governments allocate resources to the areas in greatest need. This study can provide insight for community leaders and policymakers to design better intervention strategies targeted towards reducing adverse health effects of future cold wave events.

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Table 1: Summary of the mean temperature distribution, daily count of all-cause deaths, population sizes and selected cold thresholds in 12 major Texas Metropolitan Areas, 1990-2011.

MSA	Daily mean temperature(^o C) ^a	Daily all-cause death	Population size ^b	Cold thresholds (^o C)	Percentage difference in mortality (%) ^c
	Mean (Min, Max)	Mean (Min, Max)			
Austin-Round Rock	20.4 (-6.4, 34.4)	18 (2, 40)	1,716,289	18.4	14.0
Beaumont-Port Arthur	20.8 (-2.2, 32.8)	11 (1, 26)	403,190	14.5	11.9
Brownsville-Harlingen	23.7 (0.0, 33.1)	5 (0, 17)	406,220	17.0	13.2
Corpus Christi	22.5 (-1.9, 33.1)	9 (0, 21)	428,185	16.7	10.7
Dallas-Fort Worth-Arlington	19.4 (-9.4, 36.7)	62 (28, 108)	4,230,520	20.0	11.0
El Paso	18.6 (-12.5, 36.4)	11 (0, 27)	804,123	10.6	13.5
Houston-The Woodlands-Sugar Land	21.0 (-3.1, 34.7)	77 (40, 137)	5,920,416	20.0	11.0
Killeen-Temple	20.2 (-8.6, 36.9)	6 (0, 19)	405,300	19.4	11.6
Lubbock	16.2 (-13.6, 35.6)	6 (0, 18)	290,805	20.0	10.4
McAllen-Edinburg-Mission	24.3 (-7.5, 35.0)	8 (0, 22)	774,769	12.0	14.0
San Antonio-New Braunfels	21.0 (-4.4, 35.6)	34 (7, 64)	2,142,508	20.0	12.3
Waco	19.7 (-8.3, 35.8)	6 (0, 35)	252,772	20.0	11.7

^aAverage daily mean temperature throughout the study period. ^bBased on 2010 U.S. Census data. ^cPercentage difference in mortality by comparing cold wave days to non-cold wave days.

Table 2. Estimates of cold effects using three different models in 12 Major Texas Metropolitan Areas, 1990-2011.

Texas MSA	Temperature model ^a	Cold wave model ^b	Temperature and Cold wave model ^c	
			Temperature	Cold wave
Austin-Round Rock	1.31 (1.30, 1.32)*	1.21 (-2.54, 5.12)	1.43 (1.42, 1.44)*	-2.39 (-6.37, 1.77)
Beaumont-Port Arthur	1.65 (1.63, 1.67)*	7.75 (2.66, 13.10)*	1.36 (1.34, 1.38)*	3.30 (-2.31, 9.24)
Brownsville-Harlingen	3.34 (3.31, 3.37)*	7.58 (0.32, 15.36)*	3.09 (3.06, 3.13)*	2.30 (-5.79, 11.09)
Corpus Christi	1.92 (1.90, 1.94)*	0.52 (-4.88, 6.22)	1.96 (1.94, 1.98)*	-0.59 (-6.63, 5.83)
Dallas-Fort Worth-Arlington	0.61 (0.61, 0.62)*	2.77 (0.83, 4.75)*	0.58 (0.58, 0.59)*	0.73 (-1.33, 2.83)
El Paso	1.33 (1.31, 1.35)*	3.11 (-1.67, 8.11)	1.12 (1.10, 1.13)*	2.35 (-3.23, 8.25)
Houston-The Woodlands-Sugar Land	1.56 (1.56, 1.56)*	4.08 (2.02, 6.17)*	1.54 (1.54, 1.55)*	0.43 (-1.68, 2.59)
Killeen-Temple	0.06 (0.05, 0.07)*	4.13 (-2.34, 11.02)	-0.04 (-0.05, -0.03)	2.17 (-4.81, 9.66)
Lubbock	-0.01 (-0.02, 0.00)	-0.93 (-7.69, 6.32)	0.04 (0.03, 0.05)*	-2.22 (-9.32, 5.44)
McAllen-Edinburg-Mission	5.01 (4.96, 5.06)*	7.27 (1.73, 13.10)*	4.43 (4.37, 4.49)*	2.07 (-5.45, 10.19)
San Antonio-New Braunfels	0.98 (0.97, 0.98)*	2.06 (-0.75, 4.96)	1.07 (1.06, 1.07)*	-1.79 (-4.77, 1.27)
Waco	1.37 (1.36, 1.38)*	1.65 (-4.72, 8.45)	1.46 (1.45, 1.48)*	-2.49 (-9.06, 4.55)

^a Model included a cross-basis function of daily mean temperature and did not include a cold wave indicator. ^b Model included a cold wave indicator and did not include daily mean temperature term. ^c Model included a cross-basis function of daily mean temperature and a cold wave indicator. * Statistically significant.

Figure 1. Twelve Texas Metropolitan Statistical Areas (MSAs) in the study. MSAs were selected based on the size of population and availability of weather and air pollution data during the 22-year study period.

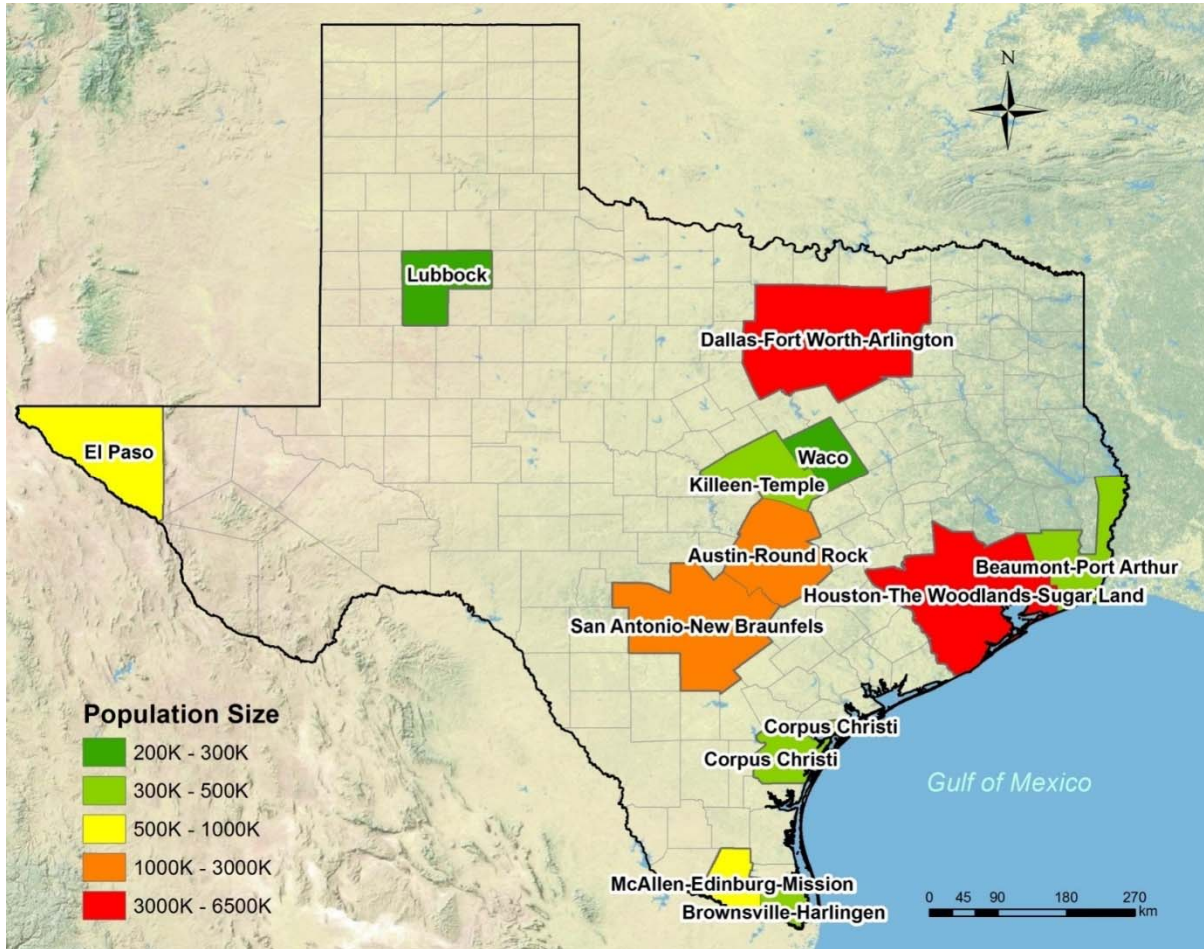


Figure 2. Meta-analysis for cold effects on all-cause mortality at lag 0-25 in 12 major Texas MSAs during 1990-2011.

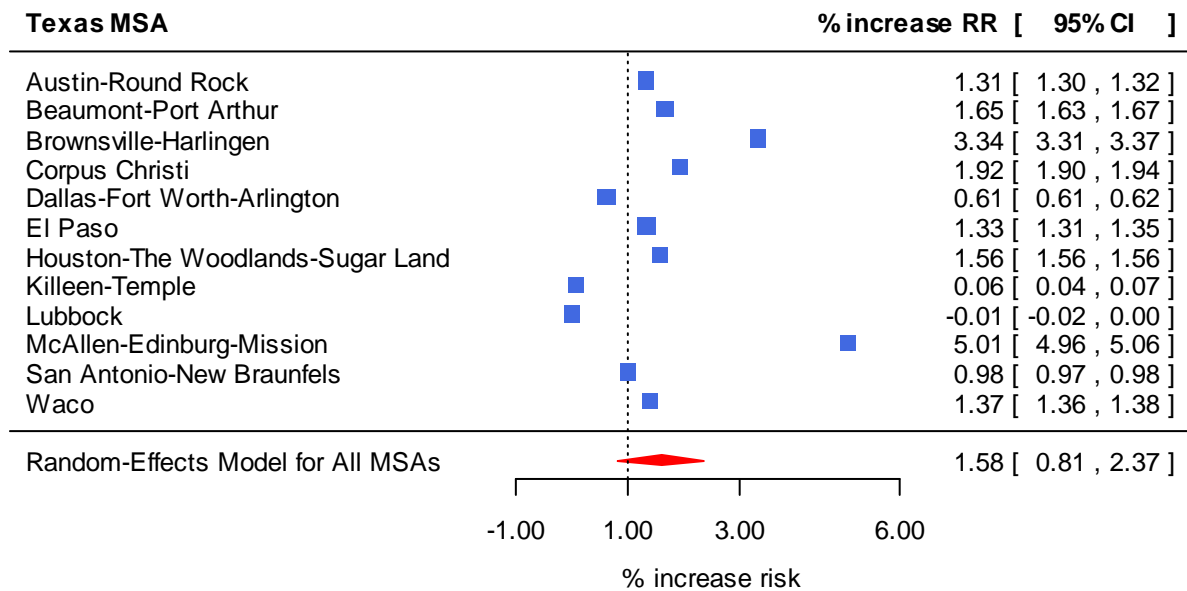
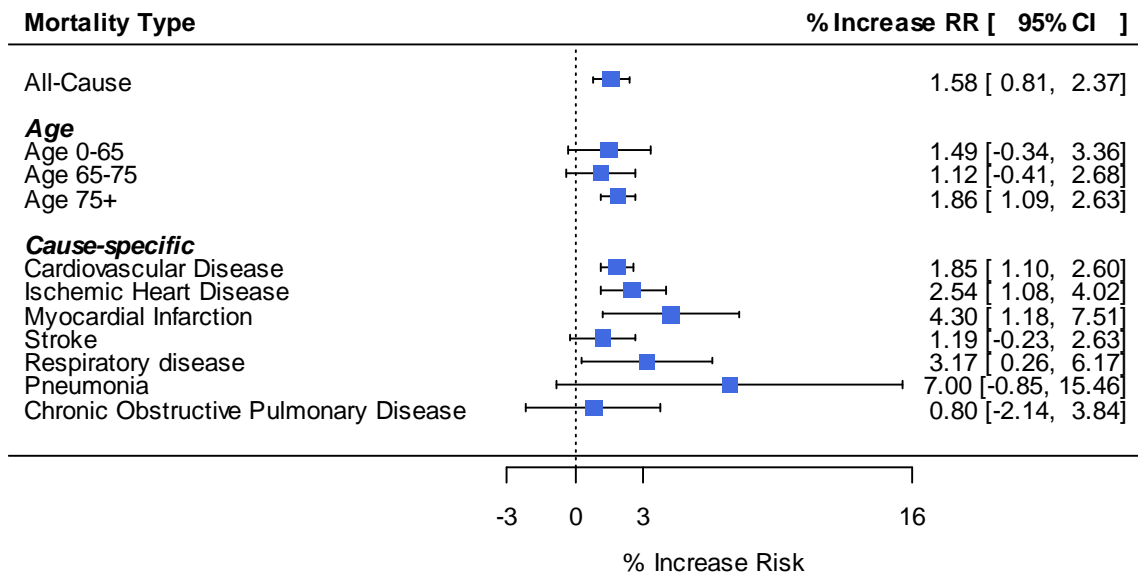


Figure 3. Pooled estimations of cold effect to age-stratified and cause-specific mortality at State-level in Texas.



Appendices

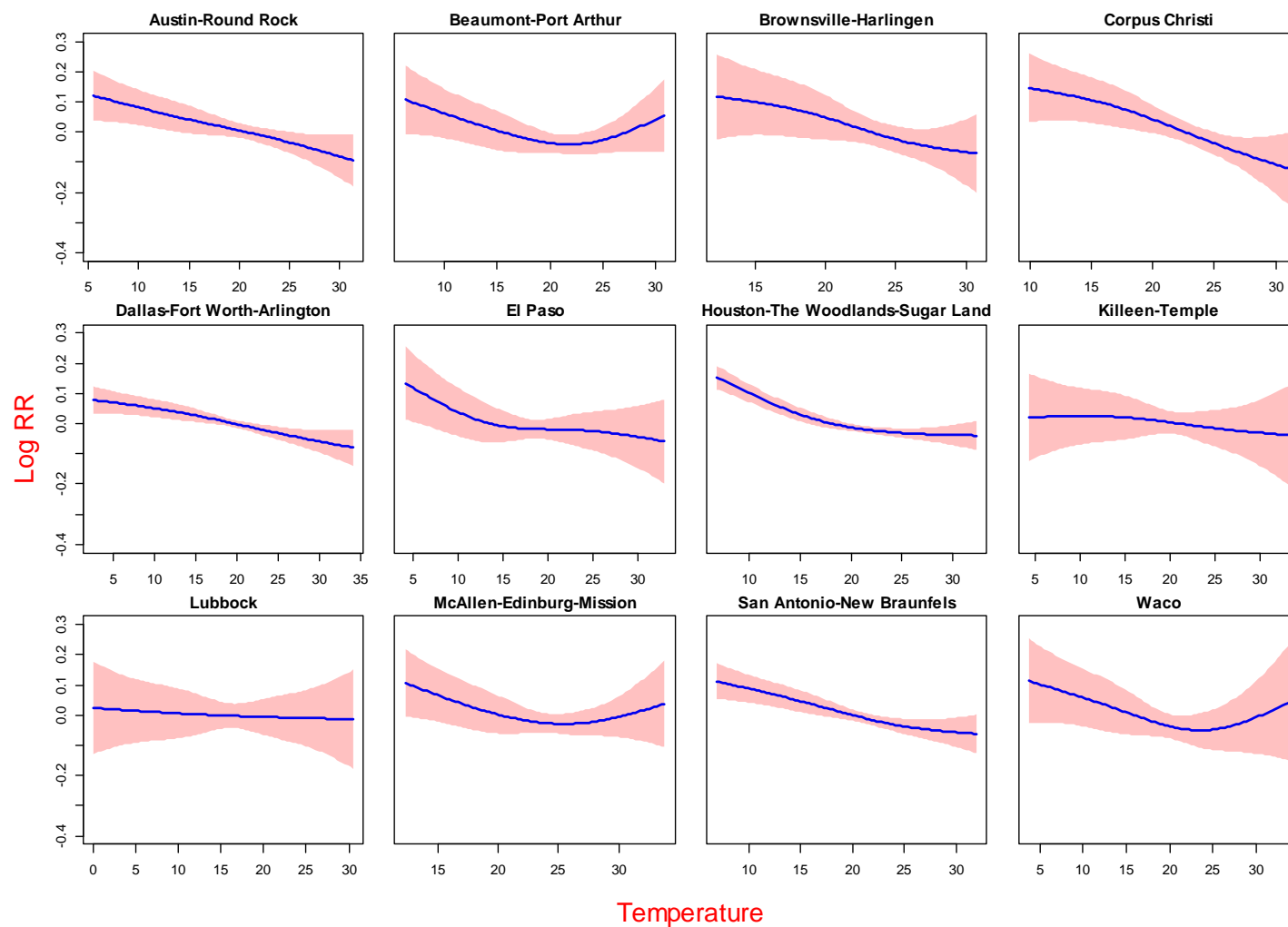
Appendix A: Journal Article I Supplemental Materials

Supplemental Table 1. Overall cold wave effects (modeling for cold wave only) using different cold wave definition for each MSA.

MSA	Duration	2 days ^a			Extended 7 days ^b		
	Cut off percentile	1st	5th	10th	1st	5th	10th
Austin-Round Rock		4.05 (-2.65, 11.20)	-0.90 (-3.97, 2.26)	0.33 (-2.23, 2.96)	1.21 (-2.54, 5.12)	2.23 (0.00, 4.51)	2.70 (0.49, 4.96)*
Beaumont-Port Arthur		8.82 (0.10, 18.31)*	0.33 (-4.02, 4.87)	1.06 (-2.37, 4.62)	7.75 (2.66, 13.10)*	1.25 (-1.70, 4.29)	2.88 (0.21, 5.62)*
Brownsville-Harlingen		11.39 (-1.67, 26.19)	4.29 (-1.67, 10.60)	3.80 (-1.13, 8.97)	7.58 (0.32, 15.36)*	4.39 (0.60, 8.31)*	2.26 (-1.48, 6.14)
Corpus Christi		-1.04 (-10.18, 9.03)	-2.30 (-6.65, 2.25)	-4.12 (-7.56, -0.54)	0.52 (-4.88, 6.22)	1.37 (-1.59, 4.42)	0.10 (-2.73, 3.01)
Dallas-Fort Worth-Arlington		1.98 (-1.48, 5.56)	-0.84 (-2.59, 0.95)	-0.25 (-1.58, 1.10)	2.77 (0.83, 4.75)*	1.47 (0.23, 2.73)*	1.48 (0.35, 2.62)*
El Paso		2.17 (-5.28, 10.22)	-1.14 (-4.76, 2.62)	-2.93 (-5.75, -0.03)	3.11 (-1.67, 8.11)	0.18 (-2.66, 3.09)	1.89 (-0.94, 4.81)
Houston-The Woodlands-Sugar Land		5.19 (1.71, 8.79)*	-0.37 (-1.98, 1.27)	-0.72 (-1.98, 0.56)	4.08 (2.02, 6.17)*	2.98 (1.90, 4.08)*	2.13 (1.11, 3.17)*
Killeen-Temple		-4.91 (-15.23, 6.65)	3.15 (-2.09, 8.68)	-2.94 (-6.80, 1.08)	4.13 (-2.34, 11.02)	0.80 (-2.77, 4.51)	-0.30 (-3.63, 3.15)
Lubbock		-6.24 (-17.54, 6.59)	-2.66 (-7.59, 2.53)	-4.00 (-7.64, -0.21)	-0.93 (-7.69, 6.32)	-0.09 (-3.58, 3.53)	1.89 (-1.55, 5.45)
McAllen-Edinburg-Mission		12.12 (2.00, 23.24)*	4.78 (0.00, 9.78)	-0.48 (-4.07, 3.24)	7.27 (1.73, 13.1)*	2.14 (-1.03, 5.41)	0.42 (-2.49, 3.41)
San Antonio-New Braunfels		-0.16 (-4.92, 4.84)	0.29 (-1.93, 2.56)	-0.01 (-1.77, 1.78)	2.06 (-0.75, 4.96)	2.30 (0.76, 3.87)*	2.55 (1.03, 4.09)*
Waco		-10.73 (-20.69, 0.48)	0.07 (-5.35, 5.79)	1.01 (-3.30, 5.51)	1.65 (-4.72, 8.45)	3.18 (-0.66, 7.16)	4.37 (0.83, 8.04)*

^a Cold wave duration defined as daily mean temperature below the cut off percentile for 2 or more consecutive days. ^b Cold wave duration defined as daily mean temperature below the cut off percentile for 2 or more consecutive days plus an extended 7 days beyond its last day below the threshold (Barnet et al. 2012).

Supplemental Figure 1. The MSA-specific linear-threshold exposure-response relationships. Relative risk of all-cause mortality was examined with daily mean temperature using single threshold distributed lag non-linear with lag up to 25 days.



CHAPTER III

JOURNAL ARTICLE II: IMPACTS OF COLD WEATHER ON EMERGENCY HOSPITAL ADMISSION IN TEXAS, 2004-2013

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Impacts of Cold Weather on Emergency Hospital Admission in Texas, 2004-2013

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Abstract

Cold weather has been identified as a major cause of weather-related deaths in the U.S. Although the effects of cold weather on mortality has been investigated extensively, studies on how cold weather affects hospital admissions are limited particularly in the Southern United States. This study aimed to examine impacts of cold weather on emergency hospital admissions (EHA) in 12 major Texas metropolitan statistical areas (MSAs) for the 10-year period, 2004-2013. A two-stage approach was employed to examine the associations between cold weather and EHA. First, the cold effects on each MSA were estimated using distributed lag non-linear models (DLNM). Then a random effects meta-analysis was applied to estimate pooled effects across all 12 MSAs. Percent increase in risk and corresponding 95% confidence intervals (CIs) were estimated as with a 1 degree Celsius ($^{\circ}\text{C}$) decrease in temperature below a MSA-specific threshold for cold effects. Age-stratified and cause-specific EHA were modeled separately. The majority of the 12 Texas MSAs were associated with an increased risk in EHA ranging from 0.1% to 3.8% with a 1°C decrease below cold thresholds. The pooled effect estimate was 1.6% (95% CI: 0.9%, 2.2%) increase in all-cause EHA risk with 1°C decrease in temperature. Cold wave effects were also observed in most eastern and southern Texas MSAs. Effects of cold on all-cause EHA were highest in the very elderly (2.4%, 95% CI: 1.2%, 3.6%). Pooled estimates for cause-specific EHA association were strongest in pneumonia (3.3%, 95% CI: 2.8%, 3.9%), followed by chronic obstructive pulmonary disease (3.3%, 95% CI: 2.1%, 4.5%) and respiratory diseases (2.8%, 95% CI: 1.9%, 3.7%). Cold weather generally increases EHA risk significantly in Texas, especially in respiratory diseases, and cold effects estimates increased by elderly population (aged over 75 years). Our findings provide insight into better

intervention strategy to reduce adverse health effects of cold weather among targeted vulnerable populations.

Keywords

Cold wave; Cold weather; Emergency hospital admission; Heart disease; Temperature

Highlights

- Cold weather generally increased hospital admission risk significantly in Texas.
- Strong effect estimates were observed in respiratory diseases.
- Cold effect estimates increased by elderly population.

1. Introduction

Extreme cold events in the U.S. have become a public health concern. The number of severe snowstorms that occurred in the eastern two-thirds of the contiguous U.S. was approximately twice in the second half of the twentieth century than the first (Kunkel et al. 2013). Cold weather has been identified as a major cause of weather-related deaths in the U.S., and during 2006-2010, over 60% of weather-related deaths were estimated to be attributable to cold weather (Berko et al. 2014). Numerous epidemiological studies have demonstrated there is an association between cold temperature and mortality which varied by geographic locations, regional climates, and demographic characteristics (Song et al. 2017; Conlon et al. 2011). However, while cold-related mortality has been investigated extensively, studies on cold-related morbidity such as hospital admissions or emergency room visits were less well studied.

Compared with other emergency department (ED) visits, cold-related morbidity ED visits have been reported to be more resource intensive. These cold-related morbidity patients are often admitted to the critical care units and require more medical attentions or transferring to other facilities (Baumgartner et al. 2008). However, few efforts have been made to examine the impact of cold temperature on patients admitted to hospital through ED, with most conducted outside the U.S. (Ye et al. 2012). One of the few cold-morbidity studies conducted in the U.S. estimated that 15,574 emergency room visits during 1995-2004 were related to hypothermia and external causes of reduced temperature (Baumgartner et al. 2008). However, exposure to cold weather can lead to not only direct effects such as hypothermia and frostbite, but also indirect effects such as pneumonia, and influenza (Conlon et al. 2011). Moreover,

under such circumstances, pre-existing chronic conditions could be exacerbated, which then are often coded as non- thermal-related causes in primary diagnoses (de Freitas and Grigorieva 2015). Thus, when the indirect effects are considered, the incidence of cold weather-related morbidity is likely to be tremendously higher. A systematic review reported 1 degree Celsius ($^{\circ}\text{C}$) decrease in temperature was associated with 6.89% and 4.96% increased risk of pneumonia and respiratory morbidity respectively in the elderly population (Bunker et al. 2016). Review studies on cold-related cardiovascular hospitalizations reported an elevated risk in the general population (2.8%, 95% CI: 2.1%, 3.5%) (Phung et al. 2016), but increased morbidity risk was not observed in studies focusing in the elderly population (0%, 95% CI: - 0.67%, -0.66%) (Bunker et al. 2016). However, previous studies have suggested that cold effects were most pronounced in the elderly due to their often impaired thermoregulation ability (Conlon et al. 2011). Given the different findings, it is necessary to assess cold effects on cause-specific morbidity in different age groups (Liu et al. 2015).

Few multi-city studies have shown cold-related adverse health impacts is especially relevant with decreasing latitude or in warmer winter climate regions (Curriero et al. 2002; Ma et al. 2014; Medina-Ramon and Schwartz 2007). This spatial variation of cold weather effects implies different acclimatization to communities' local weather conditions (Curriero et al. 2002; Medina-Ramon and Schwartz 2007). In other words, residents in warmer climate regions are well-adapted to heat but have less physical, social, and behavioral adaptations to cold temperature. Texas, one of the most populous and diverse states, is located in the Southern Central region of the U.S. and generally has a mild winter. Additionally, Texas encompasses different climates varying from arid desert in the west to humid subtropical in the east. The wide range of climate, geographical and demographic features in Texas makes it well suited to

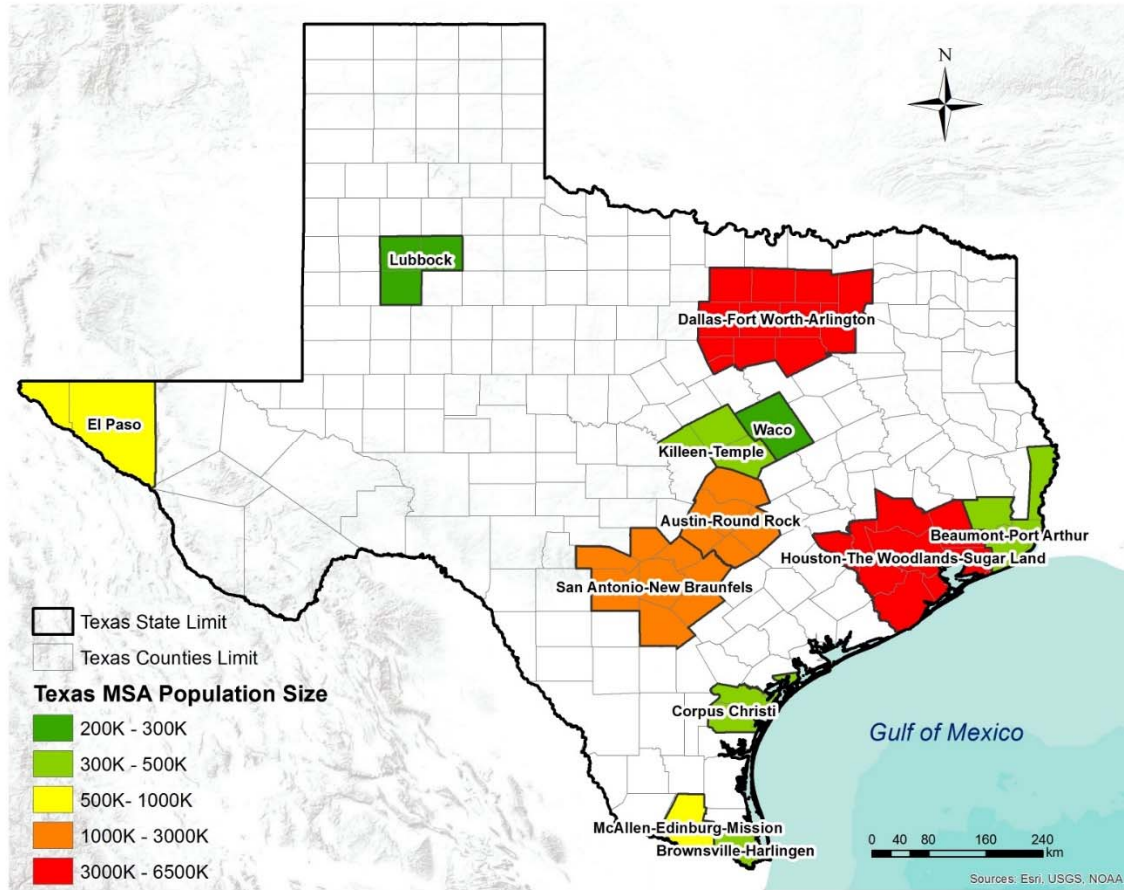
investigate the strength of the association between cold weather and morbidity. Despite evidence has shown that cold weather is related to significant levels of mortality in Texas, and the effects varied with cities, age groups, and cause-specific deaths (Chen et al. 2017), information on cold-morbidity in Texas is still lacking. In addition to cold temperature, cold waves, prolonged periods of extreme cold temperature may pose an extra risk of adverse health outcomes. Therefore, this paper aimed to evaluate the impacts of cold weather (both cold temperature and cold wave effects) on emergency hospital admissions (EHA) for a 10-year period, 2004-2013, in 12 major Texas Metropolitan Areas (MSAs).

2. Material and methods

2.1. Study area

Texas is the largest of the 48 contiguous states and one of the most populous state in the U.S. Based on the 2010 Census Bureau data, twenty-five Texas MSAs were delineated by the U.S. Office of Management and Budget (OMB) (U.S. Census 2013). In order to assure enough sample size for our data analysis, we selected twelve Texas MSAs for the present study based on quality and availability of the weather data and the population sizes that were constantly over 200,000 during the study period (Figure 1).

Figure 1. Twelve Texas Metropolitan Statistical Areas (MSAs) in the study. MSAs were selected based on the size of population and availability of weather and air pollution data during the 10-year study period.



2.2. Data sources

2.2.1. Emergency hospital admissions data

Emergency hospital admissions (EHA) data were obtained from the Texas Department of State Health Services (DSHS). We defined cases as inpatients with emergency admission and identified based on the type of admission. The number of patients admitted in to the hospital for care were aggregated daily totaling 3653 observations for the period 2004-2013 in each of 12 MSAs in Texas. As defined by the International Classification of Disease, Ninth Revision, Clinical Modification (ICD-9-CM), diagnosis of primary EHA from all causes (ICD-

9-CM 000-999, E and V codes), cardiovascular disease (CVD, ICD-9-CM 390-429), respiratory disease (RESP, ICD-9-CM 460-519), and stroke (ICD-9-CM 430-438) during the study period of 2004-2013 were compiled and used for analysis. We further looked into CVD subtypes including ischemic heart disease (IHD, ICD-9-CM 410-414), and myocardial infarction disease (MI, ICD-9-CM 410), and categorized RESPs into chronic obstructive pulmonary disease (COPD, ICD-9-CM 490-496 except 493) and pneumonia (PNEU, ICD-9-CM 480-486). Cause-specific outcomes were selected based on previous studies showing increased risk of cold-related morbidity (Bunker et al. 2016; Phung et al. 2016).

2.2.2. Weather data

Hourly weather data at weather stations in Texas were obtained from the National Climate Data Center (NCDC) through the Integrated Surface Database (ISD) (NCDC 2014). For each MSA, one weather station that could best represent its population exposure was selected (e.g., airport weather station which is closest to the most populous city in the MSA). Daily mean, minimum, and maximum temperature and dew point temperature were then calculated. We primarily used mean temperature as it represents the temperature exposure for both day and night (Guo et al. 2014). A rigorous quality control procedure, developed by the NCDC, to check for internal consistency and extreme values were applied to the ISD weather data (Lott 2004).

2.3. *Statistical analysis*

We performed a two-stage approach in the analysis. In the first stage, counts of daily EHA were modeled as a function of temperature separately for each MSA using Poisson

regression. In the second stage, the estimated associations from each MSA were combined at state level through a meta-analysis. This two-stage approach has been widely used in multi-city studies of daily deaths and HAs (Guo et al. 2014; Gasparrini et al. 2012; Schwartz et al. 2004).

2.3.1. MSA-specific models

There are two steps in building up the MSA-specific models. The associations between temperature and daily count EHA were first explored using distributed lag non-linear models (DLNMs). In order to account for the delayed effect of cold temperature, a “cross-basis” function embedded in generalized linear models (GLM) was constructed to express exposure-response dependencies and delayed effects simultaneously. In brief, we applied a natural cubic spline with 5 degrees of freedom (df) for the lag dimensions and 4 df for the temperature change dimension. To capture the overall cold temperature effect, we used lags up to 25 days. Confounding variables such as day of the week, day of the year and mean dew point temperature were also included in the models.

Unlike previous studies conducted in the Northern US or European counties that the relationship between temperature and morbidity is usually V-, U- or J-shaped with the optimum temperature corresponding to the lowest point or range in the curve (Ye et al. 2012), our initial analysis indicated that although the amplitude of the fluctuations showed some variations across MSAs, the association between temperature and EHA were generally linear with increased risk of EHA only at lower temperatures (Supplemental Figure A1).

Secondly, to quantify the excess risks of EHA attributable to cold weather, we applied single threshold DLNMs assuming the effect of cold temperature was linear below cold

thresholds. A number of covariates were also incorporated through Poisson regression model as follow:

$$\text{Log}[E(Y_t)] = \alpha + \mathbf{cb}(meTMP_{t,l}) + \boldsymbol{\beta}CW_t + \boldsymbol{\gamma}DOW_t + s(DOY_t, 7/year) + s(meDWP_t, 3) [1]$$

Where Y_t is the counts of EHA on day t ; α is the intercept; $\mathbf{cb}(meTMP_{t,l})$ is a cross-basis with threshold-type function in predictor dimension, which describes the log-linear increase in EHA for a unit decrease in lag 0-25 mean temperature below the threshold; CW_t is a binary variable for cold waves (1 if day t was classified as part of a cold wave, 0 otherwise); DOW_t represents day of the week which modelled with six indicator variables through a dummy parameterization; $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the vectors of regression coefficients; $s()$ is a smooth function; DOY_t represents day of year specified through a natural cubic spline with 7 df per year to account for seasonality and long-term trends; $meDWP_t$ represents the mean dew point temperature with 3 degrees of freedom to account for the amount of moisture in the air.

The Akaike information criterion (AIC) was commonly utilized in model selection. In general, a lower AIC value reflects a better fit of the model. Cold thresholds used in equation [1] were determined by minimizing quasi-Akaike information criterion (Q-AIC) for regression models using quasi-Poisson distribution. Specifically, we decided potential cold thresholds can be identified between 10 to 25 °C (visually observed from the preliminary DLNM results, Supplemental Figure A1.) and repeated the model presented in equation [1] with potential cold thresholds from 10 to 25 by 0.1 °C for each MSA. The temperature corresponding to the model with the minimum Q-AIC was chosen as the threshold temperature for each MSA. We reported the estimated EHA relative risk as with a 1 °C decrease in temperature below the cold threshold. The results are presented as the percentage increase in Relative Risks (RR), which

is derived as $(RR-1) \times 100$. Stratified analyses were performed by causes of EHA and age groups. For age stratification, we used age 65 as the cutoff point (0-64) and further divided the older population into two subgroups: the elderly (65-74), and the very elderly (above 75 years old).

We also examined the effects of cold waves on EHA. Currently, there is no universal operational definition of cold waves. For the purpose of this study, we defined cold waves as two or more consecutive days with daily mean temperatures below the 1st or 3rd percentiles of the local mean temperature of the study period. Furthermore, previous studies reported that the impact of cold temperature on mortality had a longer lagged effect (Anderson and Bell 2009). In order to capture the potential lagged effects, we then extended each cold wave event with 7 days beyond its last day as described by Barnett et al. in 2012.

2.3.2. Meta-analysis

In the second stage, MSA-specific effect estimates obtained from the first-stage were then combined through a multivariate meta-analysis. The multivariate meta-analysis was fitted using a random-effect model by maximum likelihood and was applied at the state level. Variables at MSA level, such as latitude, population size, percentage of population below poverty, percentage of elderly population, percentage of Hispanic population, and percentage of black population were further included as a single meta-predictor. Potential effect modification was examined by predicting the cold temperature-EHA association at two levels of the meta-variables (25th and 75th percentile) and assessed through a Wald test. This method has been described previously by Gasparrini et al. in 2012. The Cochran Q-test and heterogeneity statistic I^2 were used to evaluate the extent of heterogeneity between MSAs. All

statistical analyses were performed in the R statistical software (version 3.3.3; R Development Core Team; <http://R-project.org>). DLNMs were fitted using ‘dlnm’ package (version 2.0.6) (Gasparrini et al. 2010); and meta-analysis was performed using ‘mvmeta’ package (version 0.4.11) (Gasparrini et al. 2012) and ‘metafor’ package (version 1.9-7) (Viechtbauer 2010).

2.3.3. Sensitivity-analysis

Sensitivity analyses were carried out to evaluate how the choice of lag days affected cold effects estimates. The choice of lag days varies with studies. In general, heat-related mortality/morbidity was most associated with shorter lags (0-1 to 0-3 days) while cold-related mortality/morbidity was most associated with longer lags (up to 30 days) (Bunker et al. 2016; Anderson and Bell 2009). We used maximum lags for 5, 10, 15, 20 to 25 days for the DLNMs among all-cause, cause-specific and age stratified EHAs.

3. Results

Table 1 summarizes the meteorology and population characteristics in the 12 MSAs, which consist of 62 counties in Texas. The population sizes of Texas MSAs varied. As of 2010, Dallas-Fort Worth-Arlington was the most populous MSA with nearly 6.5 million residences followed by Houston-The Woodlands-Sugar Land MSA with nearly 6 million population; and Waco was the least populous MSA with approximately 250,000 population (U.S. Census 2010). Overall, approximately 90% of the Texas MSAs population (80% of the Texas state population) were included in the study. During 2004-2013, there were nearly 12 million emergency hospital admissions. The average daily mean temperatures in Texas MSAs ranged from 16.4°C to 24.6°C during the study period. The lowest annual mean temperature was

observed in Lubbock MSA and the highest in McAllen-Edinburg-Mission, and these two MSAs are the northernmost and the southernmost MSA respectively included in this study. The average daily counts of all-cause EHA ranged from 42 to 1,058 with the highest daily counts observed in Dallas-Fort Worth-Arlington and the lowest in Waco MSA. Additionally, MSA-specific cold thresholds for all-cause EHA were identified between 10.0 °C and 25.0 °C (Table 1).

Table 1. Summary of mean temperatures, daily counts of all-cause, cause-specific and age-stratified emergency hospital admissions, population sizes, cold wave days and selected cold thresholds in 12 major Texas Metropolitan Areas, 2004-2013.

MSA	Average daily mean temp (°C) ^a	Average daily all-cause EHA ^b	Average daily all-cause EHA by age group			Average daily EHA by disease		Total counts EHA ^c	Cold wave days	Population size ^d	Cold thresholds (°C)
	Mean (Min, Max)	Mean (Min, Max)	Mean (Min, Max)	0-64	65-74	75+	CVD ^e	RESP ^f			
Austin-Round Rock	20.3 (-5.0, 34.2)	211 (5, 439)	142.4 (4, 338)	24.9 (0, 62)	43.4 (1, 87)	23.2 (0, 49)	22.4 (2, 69)	769,664	256	1,716,289	10.0
Beaumont-Port Arthur	20.9 (-2.2, 32.5)	63 (0, 100)	35.5 (0, 65)	9.8 (0, 24)	17.4 (0, 36)	9.5 (0, 25)	9.0 (0, 27)	228,880	298	403,190	25.0
Brownsville-Harlingen	24.0 (0.0, 33.6)	71 (0, 167)	44.3 (0, 85)	9.8 (0, 29)	16.7 (0, 53)	8.2 (0, 22)	9.0 (0, 35)	258,964	303	406,220	15.6
Corpus Christi	22.8 (-1.9, 35.0)	93 (2, 156)	60.2 (1, 106)	12.3 (0, 34)	20.7 (1, 44)	10.8 (0, 27)	11.1 (0, 32)	340,606	293	428,185	11.9
Dallas-Fort Worth-Arlington	19.9 (-8.6, 36.7)	1,058 (38, 1478)	721.3 (29, 983)	132.8 (5, 240)	203.7 (4, 376)	117.4 (6, 190)	113.1 (8, 310)	3,864,102	310	6,426,214	10.0
El Paso	18.8 (-12.5, 34.2)	159 (6, 256)	105.6 (4, 200)	20.0 (1, 42)	33.6 (1, 63)	13.9 (0, 32)	16.2 (0, 60)	581,584	268	804,123	25.0
Houston-The Woodlands-Sugar Land	21.4 (-2.5, 34.7)	993 (19, 1401)	697.7 (11, 988)	120.1 (6, 204)	175.4 (2, 303)	111.0 (1, 173)	97.9 (3, 222)	3,628,070	251	5,920,416	11.2
Killeen-Temple	20.4 (-6.1, 35.0)	54 (2, 106)	34.0 (2, 73)	7.7 (0, 28)	12.4 (0, 32)	7.2 (0, 19)	7.1 (0, 30)	197,727	262	405,300	21.1
Lubbock	16.4 (-13.6, 34.7)	72 (2, 123)	47.3 (2, 84)	9.5 (0, 28)	15.2 (0, 38)	9.0 (0, 27)	7.8 (0, 28)	263,212	273	290,805	25.0
McAllen-Edinburg-Mission	24.6 (-7.5, 35.0)	128 (5, 243)	85.7 (3, 158)	15.6 (0, 37)	27.1 (1, 62)	14.0 (0, 38)	13.8 (0, 52)	469,050	258	774,769	24.6
San Antonio-New Braunfels	21.4 (-4.4, 35.6)	306 (3, 451)	202.9 (3, 332)	37.9 (0, 72)	65.4 (0, 116)	34.2 (0, 61)	31.7 (0, 86)	1,118,559	269	2,142,508	12.5
Waco	19.9 (-6.9, 35.8)	42 (2, 74)	27.2 (2, 58)	5.2 (0, 14)	9.8 (0, 23)	5.1 (0, 15)	5.1 (0, 19)	154,046	274	252,772	10.5

^aAverage daily mean temperature throughout the study period. ^bEmergency hospital admissions. ^cTotal counts of EHA throughout the study period. ^dBased on 2010 U.S. Census data. ^eCardiovascular disease. ^fRespiratory diseases.

Figure 2 shows all MSAs had a statistically significant increase in all-cause EHA risk ranging from 0.1% to 3.8% with a 1°C decrease in temperature below the cold threshold, except for Killeen-Temple MSA (-0.03%). The estimated increase in EHA associated with cold temperature was highest in Corpus Christi MSA (3.8%), followed by Waco MSA (3.3%) and Austin-Round Rock MSA (2.1%). The effect estimates for overall Texas showed a 1 °C decrease in temperature below the threshold was associated with 1.6% [95%CI: 0.9%, 2.2%] increase in all-cause EHA. The pooled age-stratified analysis showed an increased all-cause EHA risk among all age groups with the highest risk for people over 75 years old (2.4% [95%CI: 1.2%, 3.6%]) (Figure 3). The pooled estimates of cause-specific EHA risk were generally higher in respiratory diseases than in cardiovascular diseases. The pooled cause-specific EHA association was highest in pneumonia (3.3% [95%CI: 2.8%, 4.0%]), followed by chronic obstructive pulmonary disease (3.3% [95%CI: 2.1%, 4.5%]) and respiratory diseases (2.8% [95%CI: 1.9%, 3.7%]). Increased EHA risks were also observed in CVDs (1.1% [95%CI: 0.4%, 1.8%]), stroke (2.3% [95%CI: -0.3%, 4.9%]), CVD subgroups (IHD 1.7% [95%CI: -0.1%, 3.6%], and MI 0.3% [95%CI: -3.5%, 4.2%]), although the increased risk of stroke, IHD and MI were not statistically significant.

The significant heterogeneity between MSAs was found in all-cause, elderly, and very elderly EHAs with percentage of total variation across MSA were high (89.8%, 87.5% and 89.5%, respectively; See Supplemental Table A1a). We further extended meta-regression models with MSA-level meta-predictors (See Supplemental Table A1b) to characterize differences of temperature-EHA associations between MSAs, and the heterogeneity statistic values remained high. The percent of variability due to heterogeneity between MSAs was low and not statistically significant for CVD, IHD, Stroke and COPD. Moderate heterogeneity

across MSAs was found for age group 0-64, MI, RESP and PNEU. This I^2 statistic values were generally higher for the all-cause analysis compared to cause-specific analysis, and this was partially due to the fact that I^2 values tend to increase as the number of sample size increases (Rücker et al. 2008). Latitude seems to explain part of heterogeneity in age group 0-64 and MI but the test for residual heterogeneity still significant. On the other hand, latitude explained a substantial part of heterogeneity between-MSA for RESP and PNEU with I^2 of 2.9% and 10.3% compared to 65.3% and 40.1% without predictor in models (Supplemental Table A1a).

Figure 2. Meta-analysis for cold effects on all-cause emergency hospital admissions at lag 0-25 in 12 major Texas MSAs during 2004-2013.

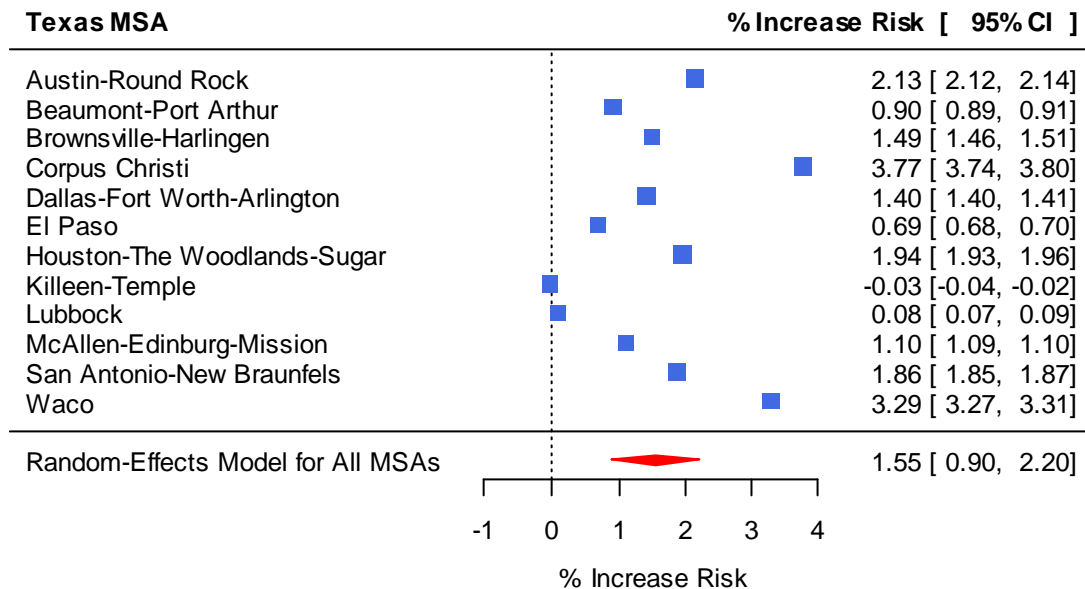


Figure 3. Pooled estimations of cold effect to age-stratified and cause-specific emergency hospital admissions at State-level in Texas.

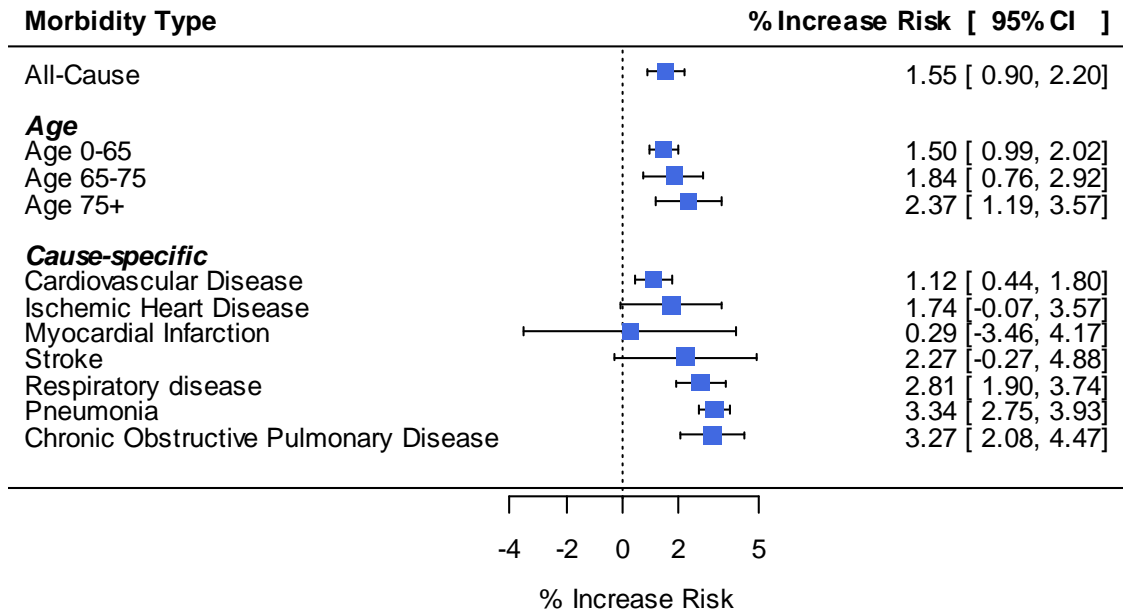


Table 2. Estimates of cold wave effects on emergency hospital admissions using two different models in 12 Major Texas Metropolitan Areas, 2004-2013.

Texas MSA	Cold wave model ^a		Temperature and Cold wave model ^b			
	Below 1 st percentile Cold wave	Below 3 rd percentile Cold wave	Temperature	Below 1 st percentile Cold wave	Temperature	Below 3 rd percentile Cold wave
Austin-Round Rock	2.57 (0.74, 4.43)*	3.73 (2.31, 5.17)*	2.13 (2.12, 2.15)*	-0.01 (-2.28, 2.31)	1.65 (1.63, 1.66)*	2.37 (0.47, 4.29)*
Beaumont-Port Arthur	3.30 (-0.34, 7.06)	3.54 (1.07, 6.08)*	0.86 (0.85, 0.87)*	-1.18 (-2.57, 5.08)	0.75 (0.74, 0.76)*	2.56 (-0.17, 5.36)
Brownsville-Harlingen	4.00 (0.33, 7.80)*	2.78 (0.69, 4.92)*	1.37 (1.35, 1.40)*	0.89 (-3.61, 5.60)	1.43 (1.40, 1.46)*	0.21 (-2.75, 3.26)
Corpus Christi	4.39 (1.23, 7.64)*	2.70 (0.79, 4.64)*	3.69 (3.66, 3.73)*	0.41 (-3.58, 4.55)	3.74 (3.71, 3.77)*	0.12 (-2.48, 2.78)
Dallas-Fort Worth-Arlington	1.25 (-0.17, 2.69)	1.99 (1.00, 2.99)*	1.59 (1.59, 1.60)*	-1.91 (-3.50, -0.30)	1.46 (1.45, 1.47)*	-0.36 (-1.67, 0.98)
El Paso	-0.88 (-3.24, 1.53)	0.76 (-0.90, 2.45)	0.77 (0.76, 0.78)*	-1.77 (-4.28, 0.82)	0.65 (0.64, 0.66)*	0.56 (-1.35, 2.50)
Houston-The Woodlands-Sugar Land	1.86 (0.23, 3.52)*	1.64 (0.50, 2.80)*	2.08 (2.06, 2.09)*	-1.02 (-2.90, 0.90)	2.23 (2.21, 2.24)*	-1.34 (-2.81, 0.14)
Killeen-Temple	2.65 (-0.98, 6.40)	1.26 (-1.01, 3.57)	-0.15 (-0.16, -0.14)	2.49 (-1.55, 6.70)	-0.18 (-0.19, -0.17)	2.00 (-0.78, 4.86)
Lubbock	-0.77 (-4.15, 2.72)	-0.06 (-2.09, 2.00)	0.08 (0.07, 0.09)*	-0.04 (-3.57, 3.62)	0.07 (0.06, 0.07)*	0.27 (-2.04, 2.64)
McAllen-Edinburg-Mission	2.36 (-0.09, 4.88)	1.76 (0.11, 3.43)*	1.03 (1.02, 1.04)*	1.39 (-1.44, 4.30)	1.14 (1.13, 1.15)*	-0.35 (-2.40, 1.75)
San Antonio-New Braunfels	0.94 (-0.93, 2.84)	1.23 (0.04, 2.43)*	1.84 (1.83, 1.85)*	0.31 (-1.84, 2.50)	1.98 (1.96, 1.99)*	-0.59 (-2.17, 1.02)
Waco	2.71 (-1.26, 6.84)	6.44 (3.81, 9.13)*	3.57 (3.55, 3.59)*	-3.64 (-7.94, 0.87)	2.92 (2.90, 2.94)*	2.27 (-1.21, 5.87)

^aModels included a cold wave indicator and did not include daily mean temperature term. ^bModels included a cross-basis function of daily mean temperature and a cold wave indicator. *Statistically significant at p value less than 0.05.

Potential cold wave effects were examined using two different models: modeling for cold wave only (overall cold wave effects) and modeling for daily mean temperature and cold waves simultaneously (additional cold wave effects). The selected effect estimates of cold wave on EHA were shown in Table 2. Overall cold wave effects were observed in most coastal MSAs when using daily mean temperature below 1st percentile of the annual mean temperature for two or more consecutive days with an extended 7 days period as the definition of cold wave. With a less intense cold wave definition (below 3rd percentile), overall cold wave effects were found in more MSAs except three: the far west MSA- El Paso, the northernmost MSA- Lubbock and the Killeen-Temple MSA. Additional cold wave effect was only observed in the Austin-Round Rock MSA when using a less intense cold wave definition with a prolonged 7-day period.

The sensitivity analysis shows that our results were robust with lag selection (See Supplemental Tables A2, A3, and A4). Similar cold thresholds and cold effect estimates were identified for each MSA when using similar lag ranges. For example, cold thresholds for all-cause EHAs in Houston-The Woodlands-Sugar land with lag days 0-15, 0-20 and 0-25, were identified at 11.1, 11.2, and 11.1⁰C with estimated excess risk of 1.83%, 2.03%, and 1.95%, respectively (See Supplemental Table A2). Our sensitivity analysis also demonstrates that cold effects were more prominent with longer lag days (0-15, 0-20, and 0-25 days) among all-cause, CVD, RESP, PNEU, COPD, STROKE, and all age groups EHAs with similar estimates. The cold effects for IHD and MI were associate with relatively shorter lag days. Overall, the strongest cold effects were mostly found with 0-25 lag days although the lag effects vary by MSAs and by cause-specific diseases.

4. Discussion

In this study, we depicted the impacts of cold weather (both cold temperature and cold wave effects) on all-cause and cause-specific EHA using distributed lag non-linear models for 12 major MSAs in Texas. Our findings showed that cold temperature generally had significant effects on emergency HA at the state and MSA levels, and the risks were generally higher in respiratory diseases than in cardiovascular diseases. To the best of our knowledge, this appears to be the first study that examined the associations between cold weather and cause-specific emergency hospital admissions among the general population in Texas.

In general, cold temperature showed statistically significant impacts on all-cause EHA in Texas. However, there was no clear spatial pattern of the association between cold and EHA that is associated with latitude as we have seen in mortality (coefficient= -0.15, 95% CI[-0.47, 0.17]). Previous cold-mortality study conducted in Texas have found that with a 1⁰C decrease in temperature below the cold threshold, the scale of the increased risk of all-cause mortality was positively associated with MSAs' year-round average mean temperature (coefficient= 0.53, 95% CI[0.28, 0.78]) and negatively associated with the MSAs' latitudes (coefficient= -0.49, 95% CI[-0.70, -0.28]) (Chen et al. 2017). However, in the present study, the strongest cold effect estimate among all-cause EHA was found in the Corpus Christi MSA (3.8%) and the weakest in the Killeen-Temple MSA (-0.03%) where both MSAs are neither the northernmost or southernmost MSA. Although multi-city studies conducted in other parts of the world observed the trend that the effect of cold temperature on all-cause morbidity was greater in southern areas (Zhao et al. 2017), geographic location is unlikely to be the primary cause of heterogeneity in Texas. Our results also showed with latitude and other MSA-

indicators included in the models as a single meta-predictor, the heterogeneity across MSAs' cold - all-cause EHA associations remained high. However, these geographic characteristics or sociodemographic factors may have modified cold and cause-specific EHA associations. For example, higher cold effects among RESP and PNEU occurred in northern MSAs, although no significant effect modification were observed (See Supplemental Figure A2). Future studies are needed to further explore potential modifying predictors.

Our findings showed that cold temperature generally had greater impact on EHA related to respiratory diseases than cardiovascular diseases (2.8 % vs. 1.1%), with the strongest impact on pneumonia (3.3%) and COPD (3.3%). Studies conducted in European countries also showed the hospital admissions of respiratory diseases were particularly elevated by cold temperature with the greatest impact on COPD (8.53%, 95% CI: 7.71%, 9.36%) (Hajat et al. 2016). This greater impact on respiratory diseases than cardiovascular diseases phenomenon was found even more exaggerated in outpatient study. Study conducted in other subtropical area, Taiwan, reported the risk of outpatient in respiratory diseases increased ranging from 18% to 31%, but no effects on outpatient of cardiovascular diseases were observed by comparing with the Z score (a standardized values) of the lowest risk (Lin et al. 2013). Furthermore, our finding of elevated CVD emergency hospital admissions is similar with a study conducted in Hong Kong, which reported 2.1% increased risk of CVD hospital admission for every 1°C decreased in temperature within the 8.2–26.9°C range (Chan et al. 2013).

Compared with the cold-mortality associations in Texas in our previous study (Chen et al. 2017), similar trends were observed that in general, cold temperature has significant impact on overall respiratory diseases and to a lesser extent on overall cardiovascular diseases (3.17% vs. 1.85%). The highest increased mortality risk was also observed in pneumonia although the

effect was not statistically significant (7.0%, 95%CI: -0.9%, 15.46%). However, in the cause-specific disease subtypes analysis, even though the impact of cold temperature on mortality was more pronounced in MI (4.30% [95%CI: 1.18%, 7.51%]) and IHD (2.54% [95%CI: 1.08%, 4.02%]) compared with diseases in the respiratory category (Chen et al. 2017), the impact on emergency HA of diseases subtypes was observed with an opposite trend. In the present study, the increased risks of EHA were found in overall CVDs (1.12%, 95% CI: 0.44%; 1.80%) and CVD subtypes, however, the associations were not statistically significant (IHD, 1.74% [95%CI: -0.07%; 3.57%]; MI, 0.29% [95% CI: -3.46%; 4.17%]).

A plausible explanation for this difference between cause-specific mortality and EHA may be due to a potential harvesting effect. For example, MI, commonly known as a heart attack, is a life-threatening condition with blocked blood flow to the heart and is often fatal within a short time. It is possible that the cold-induced MI led to a patient's death immediately and left no time for the patient to be admitted to hospitals, which is reflected in a higher impact of cold on MI mortality and a relatively lower or no impact of cold on MI EHA. However, this explanation is speculative, since we were limited in our outcome measures to either deaths or hospital admissions rather than the occurrence (both fatal and non-fatal including outpatients, emergency room visits etc.). On the other hand, Madrigano et al. (2013) examined the association of temperature with occurrence of acute MI as well as post-discharge mortality in Boston and found that exposure to cold increase the risk for the occurrence of MI on the same day but not for mortality. Their findings seem to contradict our results, however, this disagreement may have caused by the different lag day used in the analysis (lagged 6 days vs. up to 25 days in our study). Moreover, Wolf et al. (2009) reported an inverse association between cold temperature and MI occurrence in Germany where a 10°C decrease in 5-day

average temperature was associated with a 10% risk increase (95% CI: 4%–15%). Bhaskaran et al. (2010) reported a statistically significant short-term increased risk of MI hospital admissions in England and Wales at lower temperatures. These findings implied that instead of long-term lagged cold effects, the impact of cold temperature on MI may be more pronounced for short-term effects. Our sensitivity analysis results confirm that when modeled the association between cold temperature and MI with cumulative RR up to 5 days, the short-term association was captured with an increased risk ranging from 0.17% to 4.6% varied by MSAs (pooled estimates: 1.0% [95% CI: 0.2%, 1.8%]). Therefore, future studies on disease occurrence (both fatal and non-fatal event) with different length of lagged effects are needed to provide more comprehensive understanding of the association between cold temperature and adverse health impacts.

Increased risks of cold temperature on all-cause EHA were observed in our study in all age groups, and the risk was greatest for the very elderly (aged over 75 years, 2.4% [95% CI: 1.2%, 3.6%]). This finding is consistent with previous study conducted in England that the very elderly is the most vulnerable to cold temperature (Hajat et al. 2016). However, there have been debates regarding the associations between cardiovascular morbidity and cold exposure in the general population and in the elderly population (Song et al. 2017). A review on cold-related cardiovascular showed an elevated morbidity risk in general population (2.8%, 95% CI: 2.1%, 3.5%) (Phung et al. 2016), interestingly, increased morbidity risk was not observed in the elderly population (0%, 95% CI: -0.67%, -0.66%) (Bunker et al. 2016). Specifically, Bunker et al. (2016) showed the direction and magnitude of cold-related morbidity in CVDs widely varied by disease causes in the elderly population despite that the associations were not statistically significant. The wide variation and inconsistency of the associations between cold

temperature and CVD causes suggest assessing the cold effects on cause-specific morbidities and in different age groups is necessary for future studies in order to have a more effective prevention strategy could be provided for the vulnerable population. Furthermore, previous studies have detected a stronger association between cold temperature or cold wave and sudden cardiac death in patients without history of coronary heart disease (CHD) than those with a prior CHD (Gerber et al. 2006; Ryti et al. 2017). This finding implied healthy individuals might expose themselves more to cold weather whereas coronary patients might have been advised to avoid outdoor cold stress. This may also partially explain the weaker or absence of cold-HA risk of CVDs in the elderly population that they may stay indoors and not engaging in activities that may lead to adverse health events (Bobb et al. 2017).

Cold wave effects on all-cause EHAs were observed in most eastern and southern Texas MSAs as overall effects. Although it seems that the overall cold wave effects in Texas MSAs were observed more during less intensive cold waves (daily mean temperature below 3rd percentile of the annual mean temperature for two or more consecutive days with an extended 7 days period) compared to intense cold waves (below 1st percentile), the magnitude of the effects were similar, only a wider confidence interval reported for the later ones (Table 2). This finding may be a reflection of the difference in sample size that low number of intensive cold wave events limited the power to detect cold wave effects. Furthermore, these effects were largely diminished when including the daily mean temperature term, suggesting in little or no evidence of additional cold wave effects.

There are several limitations to this study. One limitation is the lack of control for air pollution. Airborne particles have been reported to be the most influenced pollutant on CVD hospital admissions (Schwartz et al. 2004) and were suggested in some but not all studies (Basu

et al. 2008). However, the air born particles data, such as PM_{2.5}, were measured in every 6 days, and not available for all our studied MSAs (data not available in the Killeen-Temple MSA). Thus, air pollutions were not included in this study. Also, we analyzed the cold temperature -EHA associations using data from fixed meteorological stations rather than the individual-level exposure which introduced measurement bias. Furthermore, there are some debates over the relative importance of indoor cold stress versus outdoor cold stress with regard to winter mortality. The uncertainty of individual behavior was not taken into account in this study. For example, some people may tend to stay indoors during cold days, this will then introduce more error into our exposure measure when temperature drops. While the present study emphasized the ambient temperature, there is evidence that the indoor cold temperature could also play a contributory role on the impact of health events (Eurowinter Group, 1997). Connecting our understanding with this potential behavioral change may improve our ability to accurately estimate the impacts of cold weather and inform decisions about mitigating future adverse health events.

5. Conclusions

In general, cold temperature showed statistically significant impacts on all-cause emergency hospital admissions in Texas. However, unlike mortality which depends on latitude, there was no clear spatial pattern of the association between cold and EHA. The pooled estimates of cause-specific EHA risk were generally higher for respiratory diseases than in cardiovascular diseases. Future research should address cause-specific morbidity outcomes such as hospital admissions in respiratory and cardiovascular subtypes for different

age group populations to make predictions more optimally for the corresponding vulnerable populations.

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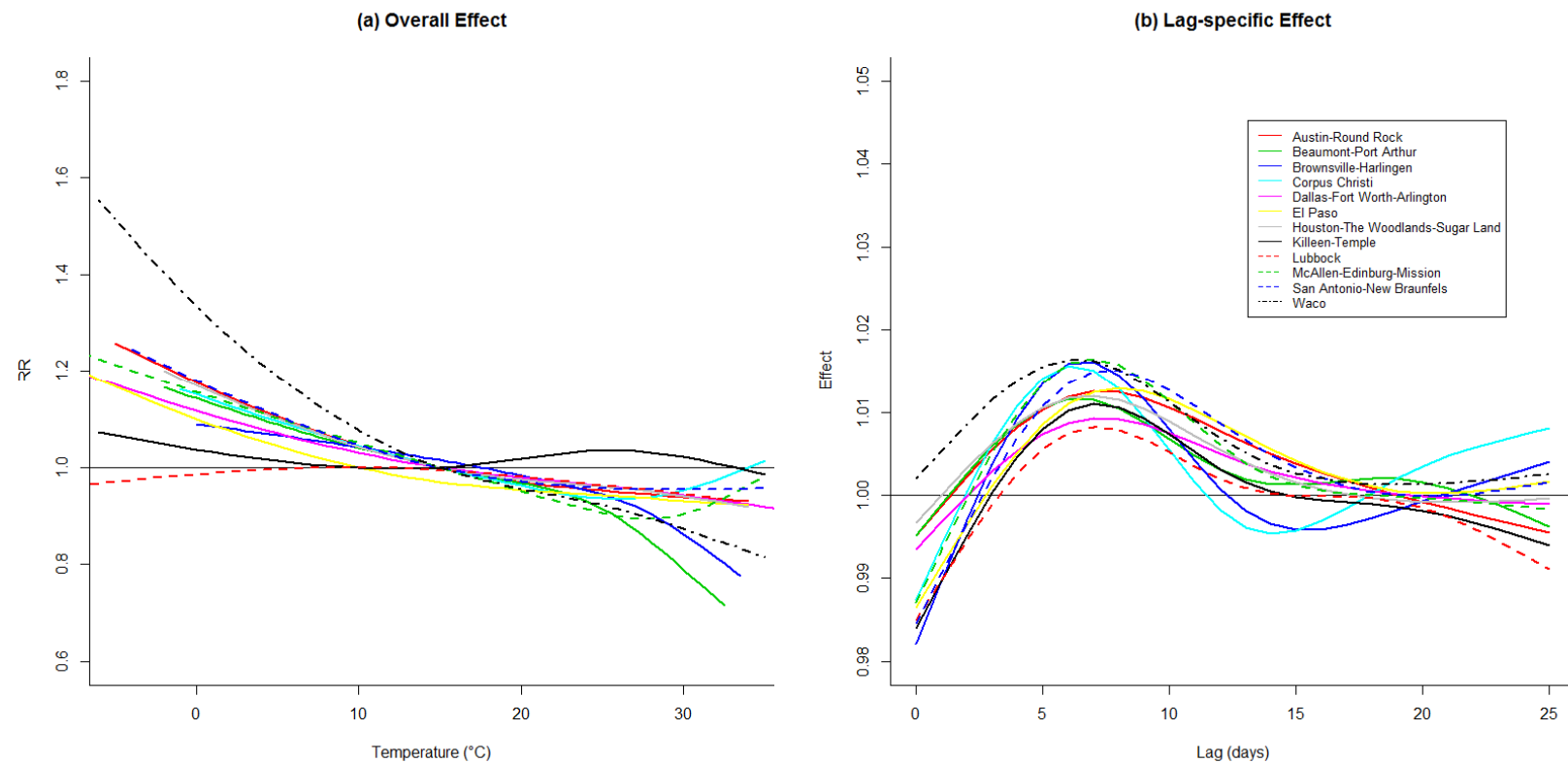
Ye X, Wolff R, Yu W, Vaneckova P, Pan X, Tong S. 2012. Ambient temperature and morbidity: a review of epidemiological evidence. Environ Health Perspect 120(1):19-28.

Zhao Q, Zhang Y, Zhang W, Li S, Chen G, Wu Y et al. 2017. Ambient temperature and emergency department visits: Time-series analysis in 12 Chinese cities. Environ Pollut. 224:310-316. doi: 10.1016/j.envpol.2017.02.010. Epub 2017 Feb 17.

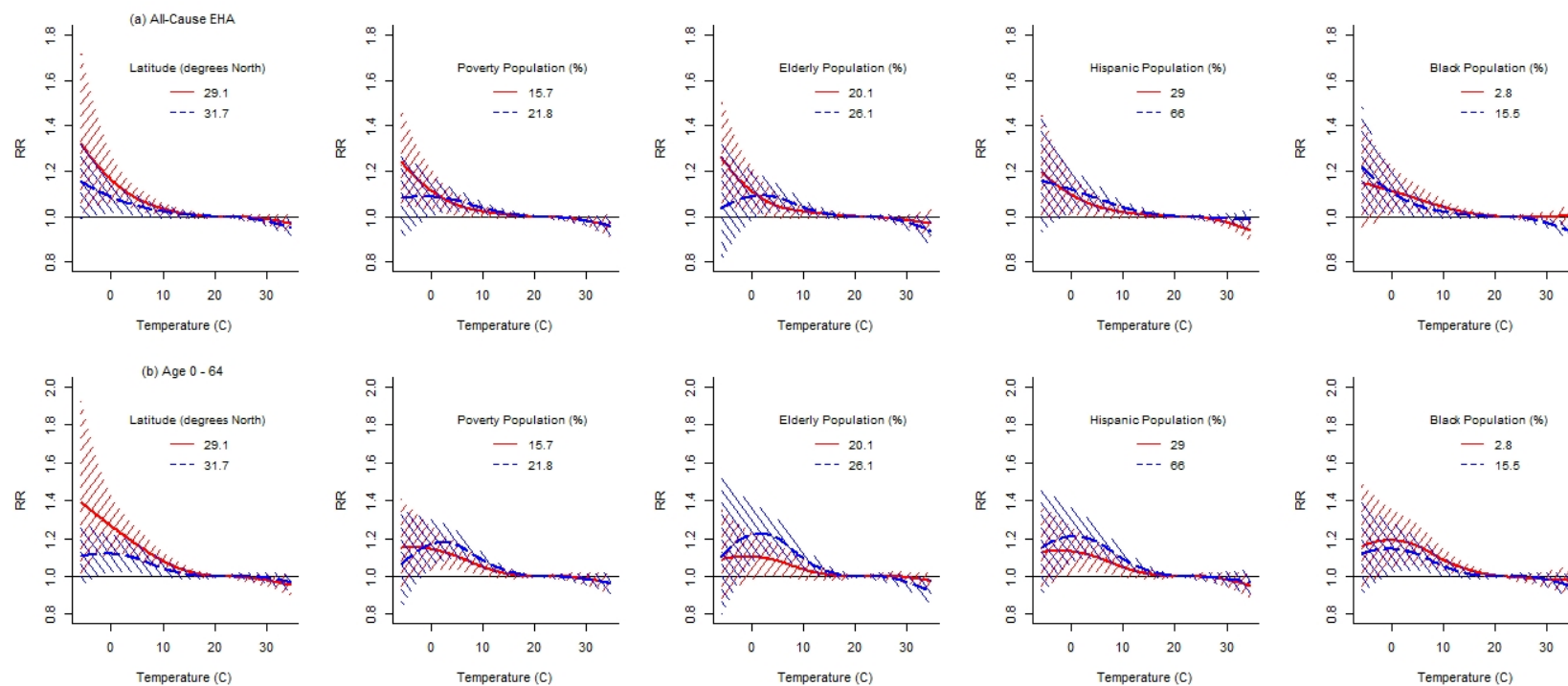
Appendices

Appendix B: Journal Article II Supplemental Materials

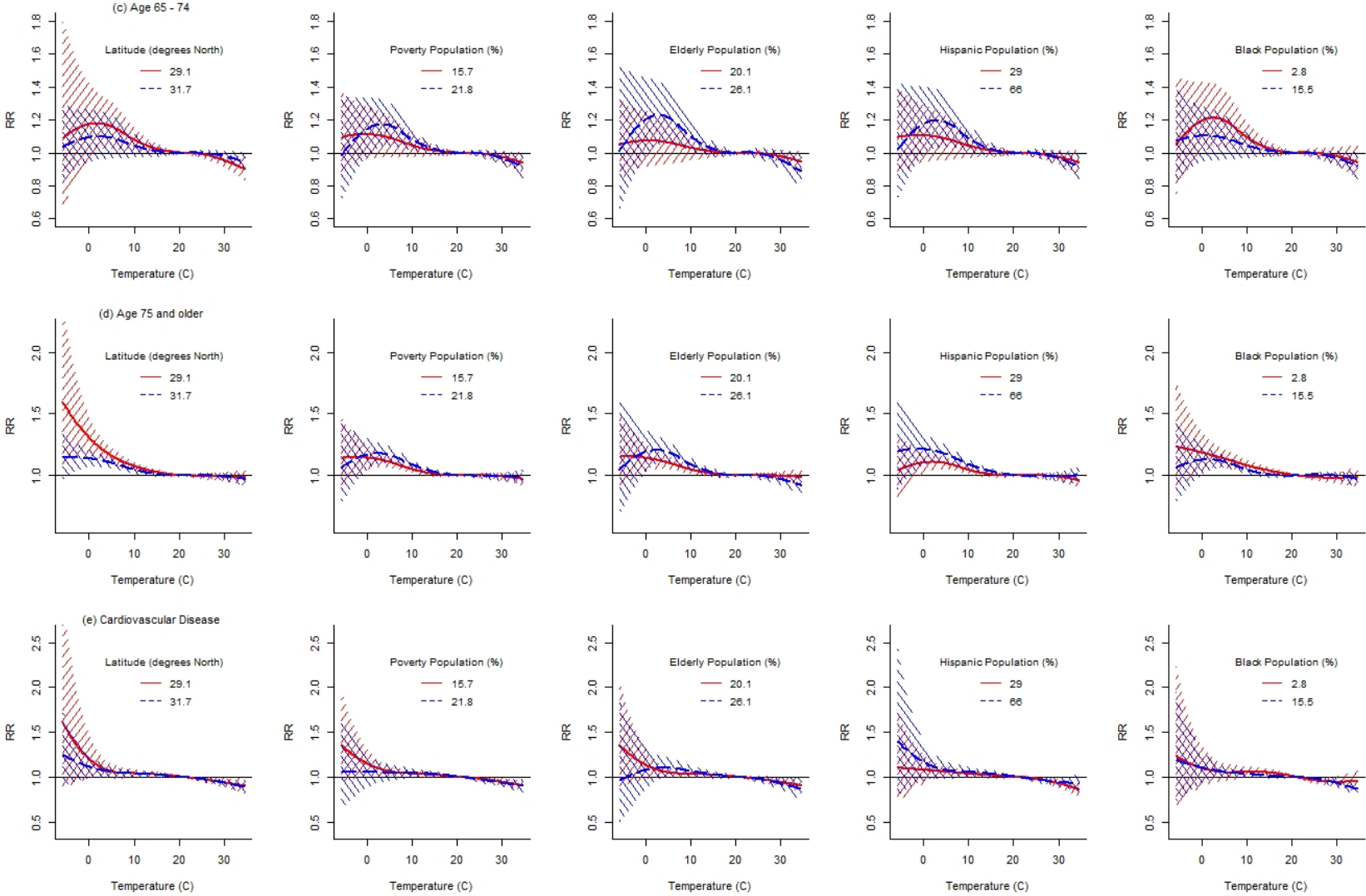
Supplemental Figure A1. The association between temperature and the risk of emergency hospital admission in 12 major Texas MSAs (2004-2013) using distributed lag non-linear models: (a) Overall RR; (b) Lag-specific RR with reference at 10 to 18 degree Celsius, varied by MSAs.



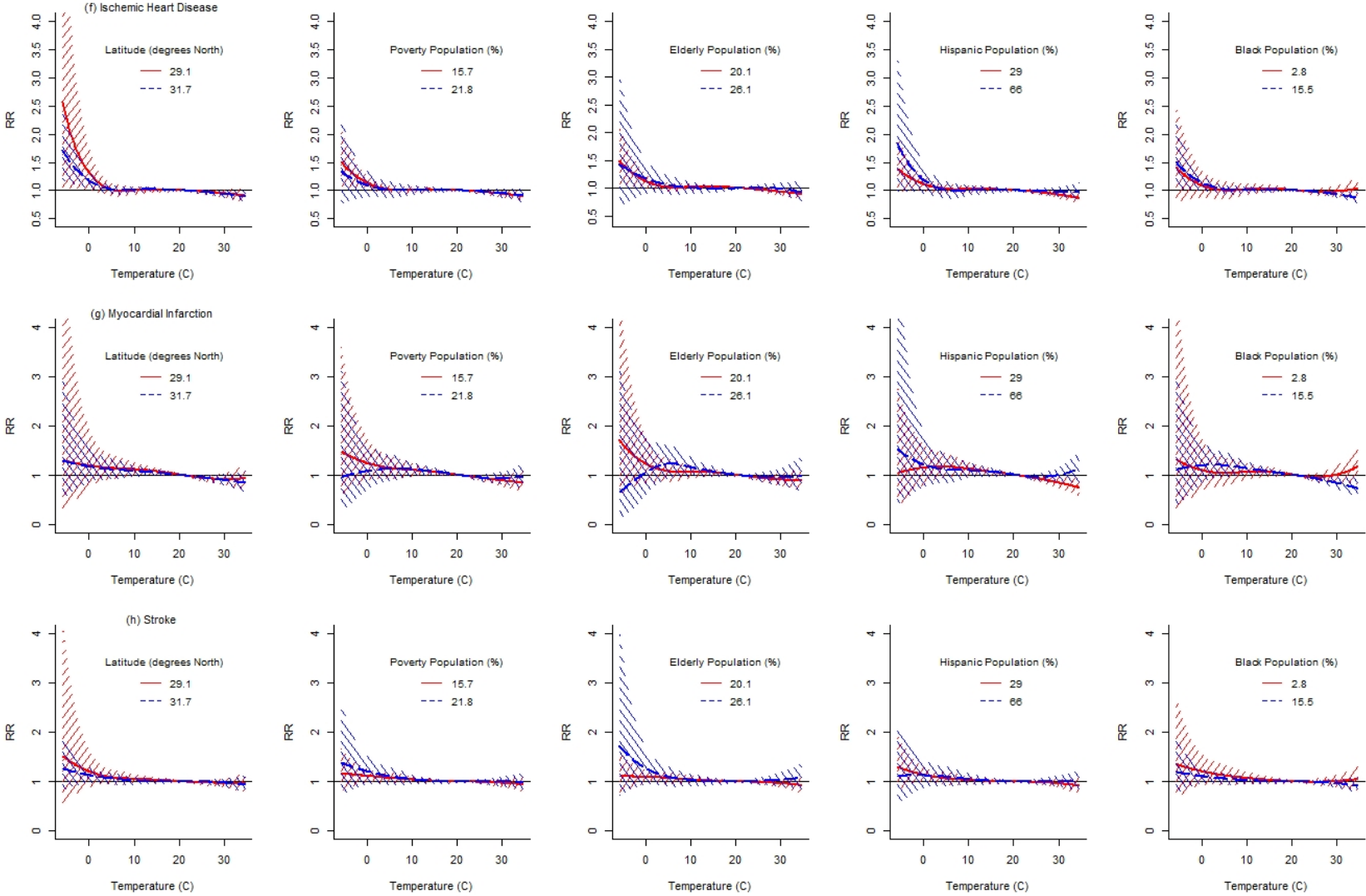
Supplemental Figure A2. Pooled temperature - emergency hospital admission association by causes or age and by MSA-specific variables in 12 major Texas MSAs (2004-2013). Two levels of the meta-variables: 25th and 75th percentiles were predicted and showed in solid red line and dashed blue line, respectively. Selected meta-variables were latitude, percent of population below poverty, percent of elderly population, percent of Hispanic population and percent of black population. Wald test results suggest no effect modification were significant.



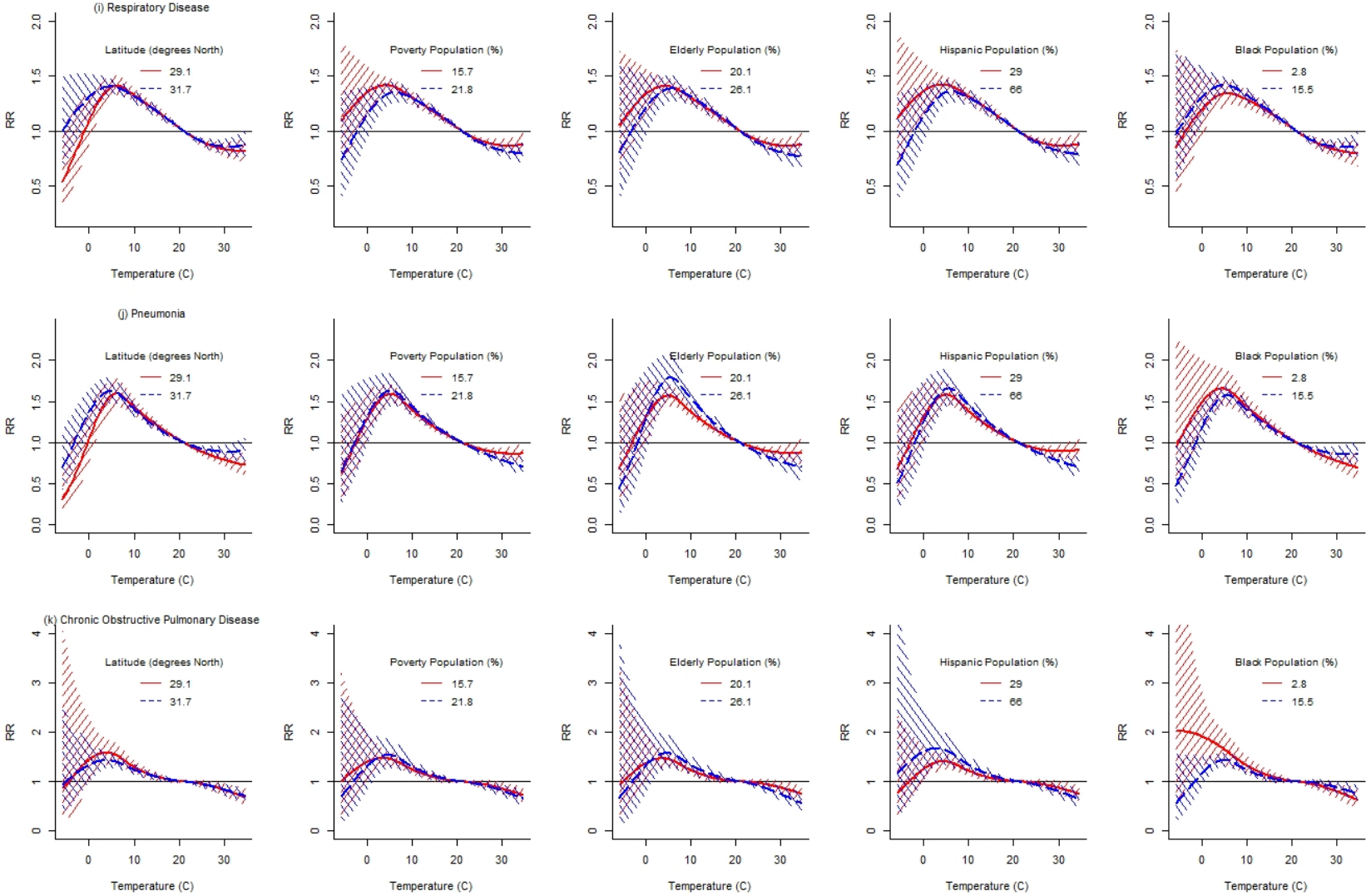
Supplemental Figure A2. (continued)



Supplemental Figure A2. (continued)



Supplemental Figure A2. (continued)



Supplemental Table A1a. Cochran Q-test, I^2 of multivariate meta-analysis models for age stratified, cause-specific emergency hospital admissions by specific covariates.

	Overall			Latitude			% Below Poverty			% Elderly (aged 65+)			% Hispanic			% Black			Population		
	Q ^a	P-val ^b	I ^{2c}	Q	P-val	I ²	Q	P-val	I ²	Q	P-val	I ²	Q	P-val	I ²	Q	P-val	I ²	Q	P-val	I ²
All-Cause	79.9	<0.00	89.8	71.3	<0.00	89.3	79.5	<0.00	90.5	79.8	<0.00	90.7	79.6	<0.00	90.5	79.9	<0.00	90.6	63.9	<0.00	89.7
Age 0-64	29.1	0.002	65.0	22.1	0.015	57.2	25.5	0.005	66.3	26.6	0.003	66.6	28.3	0.002	66.8	27.6	0.002	67.8	25.5	0.005	65.5
Age 65-74	43.3	<0.00	87.5	37.0	<0.00	85.6	42.5	<0.00	88.5	41.5	<0.00	87.3	40.1	<0.00	87.9	42.5	<0.00	88.2	43.3	<0.00	87.3
Age 75+	56.7	<0.00	89.5	39.8	<0.00	83.7	55.1	<0.00	89.6	53.6	<0.00	89.3	54.5	<0.00	89.0	56.1	<0.00	89.3	56.2	<0.00	87.1
CVD ^d	10.0	0.531	16.5	8.7	0.561	8.8	9.9	0.452	22.8	9.9	0.453	0.0	8.6	0.568	13.0	10.0	0.445	0.3	9.5	0.488	20.1
IHD ^e	15.7	0.151	0.0	15.4	0.117	2.0	15.4	0.118	1.6	15.7	0.110	1.7	15.5	0.114	0.1	15.0	0.131	0.1	15.7	0.109	1.0
MI ^f	23.5	0.015	57.7	21.5	0.018	48.5	22.2	0.014	60.2	20.6	0.024	45.4	23.4	0.010	67.1	23.2	0.010	67.9	22.6	0.012	65.8
Stroke	17.6	0.091	23.9	17.4	0.066	30.0	16.3	0.092	19.4	15.7	0.108	16.7	15.9	0.103	15.9	17.2	0.069	28.2	14.1	0.170	2.4
RESP ^g	27.9	0.003	65.3	13.8	0.184	2.9	26.4	0.003	67.7	26.9	0.003	69.7	26.6	0.003	68.4	27.9	0.002	69.3	27.7	0.002	68.6
PNEU ^h	18.3	0.074	40.1	10.8	0.372	10.3	14.7	0.145	32.4	10.5	0.397	14.3	14.4	0.156	29.4	15.7	0.108	34.5	12.2	0.271	14.4
COPD ⁱ	11.3	0.418	12.2	5.3	0.870	0.0	9.8	0.455	8.3	10.0	0.44	7.5	7.2	0.711	0.0	9.1	0.523	1.5	9.7	0.467	0.0

^a Cochran Q-test for heterogeneity; ^b Q-test P-value; ^c I^2 heterogeneity index (%); ^d Cardiovascular diseases; ^e Ischemic heart disease; ^f Myocardial fraction; ^g Respiratory disease; ^h Pneumonia; ⁱ Chronic obstructive pulmonary disease.

Supplemental Table A1b. MSA-level variables used in meta-regression models.

MSA	Black	Hispanic	Poverty	Elderly	Total Population	Latitude
Austin-Round Rock	7%	33%	14%	17%	1,990,437	30.18
Beaumont-Port Arthur	24%	15%	18%	27%	417,449	29.95
Brownsville-Harlingen	0%	89%	34%	29%	449,166	25.91
Corpus Christi	3%	60%	18%	27%	449,323	27.77
Dallas-Fort Worth-Arlington	15%	30%	15%	20%	7,117,896	32.90
El Paso	2%	84%	23%	25%	877,248	31.81
Houston-The Woodlands-Sugar	17%	38%	16%	20%	6,622,047	29.98
Killeen-Temple	18%	22%	15%	20%	454,994	31.07
Lubbock	7%	35%	19%	23%	307,992	33.67
McAllen-Edinburg-Mission	0%	91%	34%	25%	883,903	26.18
San Antonio-New Braunfels	6%	56%	16%	24%	2,380,005	29.54
Waco	15%	26%	22%	26%	263,208	31.62

*U.S. Census Bureau 2010.

Supplemental Table A2. Sensitivity analysis of estimating association between cold temperatures and all-cause, cause-specific emergency hospital admissions by changing maximum lag for mean temperature.

Lag Days	MSA Name	All-Cause EHA			CVD EHA			IHD EHA			MI EHA		
		Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC
5	Austin-Round Rock	23.4	-0.16 (-0.17, -0.16)	32130.6	25	0.02 (0.01, 0.03)	22046.0	23.6	-0.33 (-0.34, -0.32)	17646.2	17.8	0.46 (0.44, 0.48)	15437.3
	Beaumont-Port Arthur	10.3	0.65 (0.64, 0.67)	27585.7	17.5	0.3 (0.28, 0.32)	18832.3	10.3	1.77 (1.71, 1.83)	14467.6	10.3	4.6 (4.52, 4.68)	11796.4
	Brownsville-Harlingen	25	-0.47 (-0.48, -0.47)	27983.8	25	-0.82 (-0.83, -0.8)	18329.0	22.5	-1.48 (-1.51, -1.46)	13603.1	25	0.17 (0.14, 0.2)	11581.8
	Corpus Christi	25	-0.26 (-0.26, -0.25)	28486.8	25	-0.14 (-0.15, -0.13)	19247.4	12.5	1.35 (1.29, 1.4)	14877.9	24.2	0.81 (0.78, 0.83)	12314.4
	Dallas-Fort Worth-Arlington	25	-0.16 (-0.16, -0.16)	49466.3	12.2	0.04 (0.04, 0.05)	29727.1	25	-0.18 (-0.19, -0.17)	24394.6	25	0.19 (0.18, 0.19)	21762.0
	El Paso	25	-0.26 (-0.26, -0.26)	32278.5	25	-0.33 (-0.34, -0.32)	20316.4	25	-0.29 (-0.3, -0.27)	15580.1	25	0.25 (0.23, 0.27)	12332.1
	Houston-The Woodlands-Sugar	25	-0.1 (-0.1, -0.1)	51344.0	25	-0.12 (-0.12, -0.11)	29677.3	25	0.19 (0.19, 0.2)	24180.5	25	0.51 (0.51, 0.52)	21132.4
	Killeen-Temple	25	-0.38 (-0.39, -0.38)	25904.5	25	-0.16 (-0.17, -0.15)	17588.4	25	0.29 (0.27, 0.3)	13124.8	16.2	1.72 (1.69, 1.75)	11299.1
	Lubbock	25	-0.3 (-0.3, -0.29)	27446.8	24.6	-0.06 (-0.07, -0.05)	18687.8	23.9	0.03 (0.02, 0.05)	14936.3	25	-0.68 (-0.7, -0.66)	10615.1
	McAllen-Edinburg-Mission	25	0 (-0.01, 0)	30083.0	25	-0.22 (-0.23, -0.21)	20160.0	20.2	0.51 (0.49, 0.53)	15969.2	25	0.86 (0.83, 0.88)	13170.2
	San Antonio-New Braunfels	23.9	-0.33 (-0.33, -0.32)	34588.2	25	-0.37 (-0.37, -0.36)	23759.9	25	-0.44 (-0.45, -0.43)	19251.7	21.7	0.34 (0.32, 0.35)	17023.5
	Waco	25	0.19 (0.19, 0.2)	24856.7	10.5	0.23 (0.21, 0.26)	16294.0	10	2.56 (2.51, 2.61)	12126.0	15.6	3 (2.96, 3.04)	9813.4
10	Austin-Round Rock	21.8	0.29 (0.29, 0.3)	32044.9	23.6	0.41 (0.4, 0.42)	22005.7	22.3	-0.44 (-0.46, -0.43)	17613.9	23.1	-0.1 (-0.12, -0.09)	15418.4
	Beaumont-Port Arthur	25	0.25 (0.24, 0.26)	27539.0	17.5	0.71 (0.69, 0.73)	18809.8	10.3	1.93 (1.86, 2)	14456.0	19.5	2.51 (2.47, 2.55)	11778.2
	Brownsville-Harlingen	25	0.19 (0.19, 0.2)	27937.8	22.5	-0.3 (-0.32, -0.28)	18303.3	21.4	-1.16 (-1.19, -1.13)	13586.4	13.6	3.35 (3.25, 3.46)	11566.9
	Corpus Christi	25	0.27 (0.26, 0.27)	28446.0	12.6	2.33 (2.29, 2.37)	19218.4	12.5	1.79 (1.73, 1.86)	14860.6	16.1	3.65 (3.6, 3.71)	12301.0
	Dallas-Fort Worth-Arlington	25	0.21 (0.2, 0.21)	49286.2	10.8	0.77 (0.77, 0.78)	29630.2	10	0.73 (0.71, 0.74)	24350.1	10	1.5 (1.49, 1.52)	21734.3
	El Paso	25	0.1 (0.1, 0.1)	32231.7	21.7	0.13 (0.12, 0.14)	20285.7	25	-0.59 (-0.61, -0.58)	15563.2	25	0.31 (0.28, 0.34)	12312.0
	Houston-The Woodlands-Sugar	14.5	0.86 (0.86, 0.87)	51108.8	25	0.39 (0.38, 0.39)	29583.6	25	0.68 (0.67, 0.68)	24138.2	25	1.07 (1.06, 1.08)	21103.4
	Killeen-Temple	25	-0.1 (-0.11, -0.1)	25829.4	25	0.26 (0.25, 0.27)	17531.4	25	0.64 (0.62, 0.66)	13093.0	10.5	3.29 (3.23, 3.35)	11268.4
	Lubbock	25	-0.11 (-0.12, -0.11)	27421.3	24.5	0.1 (0.09, 0.12)	18660.3	25	0.37 (0.36, 0.39)	14919.8	25	-0.75 (-0.77, -0.72)	10606.5
	McAllen-Edinburg-Mission	24.7	0.51 (0.51, 0.52)	29892.0	25	0.44 (0.43, 0.45)	20036.9	10	0.35 (0.23, 0.47)	15868.4	25	1.23 (1.2, 1.25)	13087.4
	San Antonio-New Braunfels	20.6	0.14 (0.14, 0.14)	34488.8	25	0 (-0.01, 0.01)	23729.3	25	-0.33 (-0.34, -0.32)	19229.9	21.9	0.44 (0.42, 0.45)	17002.8
	Waco	12.8	1.59 (1.58, 1.6)	24813.7	24.2	0.74 (0.72, 0.75)	16263.3	12	4.7 (4.65, 4.76)	12105.5	12.5	6.36 (6.3, 6.42)	9794.3
15	Austin-Round Rock	12	1.54 (1.55, 2.24)	31968.8	23.4	0.74 (0.73, 0.75)	21974.3	23.1	0.13 (0.12, 0.15)	17595.4	22.5	0.38 (0.36, 0.4)	15400.1
	Beaumont-Port Arthur	25	0.74 (0.76, 0.94)	27510.4	18.3	1.16 (1.14, 1.18)	18781.2	18.1	0.37 (0.33, 0.4)	14432.2	23.6	3.26 (3.22, 3.3)	11759.9
	Brownsville-Harlingen	15.8	1.19 (1.23, 1.84)	27934.7	20.7	-0.15 (-0.18, -0.13)	18281.3	19.8	-0.5 (-0.54, -0.45)	13569.8	18.9	1.12 (1.06, 1.18)	11554.0
	Corpus Christi	11.9	2.31 (2.35, 2.81)	28411.3	12.3	2.55 (2.5, 2.6)	19182.6	12.5	1.5 (1.42, 1.59)	14838.8	19.3	1.74 (1.7, 1.79)	12282.6
	Dallas-Fort Worth-Arlington	10.2	1.16 (1.17, 1.42)	49186.0	11.2	0.93 (0.92, 0.94)	29590.8	10	1.02 (1, 1.03)	24319.3	18	0.66 (0.65, 0.67)	21706.9
	El Paso	25	0.45 (0.46, 0.65)	32200.9	22	0.33 (0.32, 0.35)	20264.0	25	0.21 (0.19, 0.24)	15541.4	10	1.43 (1.36, 1.49)	12294.3
	Houston-The Woodlands-Sugar	11.1	1.83 (1.85, 2.03)	51005.3	10.6	3.01 (2.99, 3.02)	29534.1	25	0.88 (0.87, 0.89)	24104.2	25	1.31 (1.3, 1.33)	21074.8
	Killeen-Temple	25	0.11 (0.12, 0.11)	25788.4	25	0.39 (0.38, 0.4)	17487.6	15	1.49 (1.46, 1.53)	13062.5	10	4.84 (4.76, 4.92)	11242.5
	Lubbock	25	0.08 (0.09, 0.24)	27382.5	24.6	0.53 (0.51, 0.54)	18625.1	25	0.49 (0.47, 0.51)	14895.9	25	-1.09 (-1.12, -1.05)	10593.0
	McAllen-Edinburg-Mission	15	1.93 (1.96, 1.05)	29756.8	25	0.95 (0.93, 0.96)	19913.7	10	2.2 (2.04, 2.36)	15775.3	25	1.07 (1.04, 1.11)	13008.4
	San Antonio-New Braunfels	18.8	0.62 (0.63, 1.14)	34455.2	25	0.65 (0.64, 0.66)	23667.6	25	0.28 (0.26, 0.29)	19198.9	22.2	0.33 (0.31, 0.35)	16980.9
	Waco	12.5	2.24 (2.26, 2.72)	24772.0	25	0.87 (0.85, 0.88)	16228.8	10.5	4.72 (4.65, 4.79)	12066.1	13.6	5.77 (5.7, 5.84)	9767.1
20	Austin-Round Rock	10.7	2.24 (2.23, 2.25)	31963.7	23.3	0.56 (0.55, 0.57)	21954.5	25	0.83 (0.81, 0.85)	17592.0	18	0.81 (0.78, 0.84)	15395.4
	Beaumont-Port Arthur	25	0.94 (0.93, 0.95)	27478.3	22.5	0.82 (0.8, 0.84)	18767.2	18.3	0.09 (0.05, 0.13)	14412.3	24.1	2.93 (2.89, 2.98)	11740.6
	Brownsville-Harlingen	15.8	1.84 (1.82, 1.86)	27912.0	20.8	0.59 (0.56, 0.62)	18254.7	20.6	-0.3 (-0.35, -0.26)	13544.7	10	-2.11 (-2.41, -1.8)	11525.4
	Corpus Christi	11.9	2.81 (2.78, 2.83)	28380.7	11.7	2.65 (2.58, 2.72)	19157.2	15	2.13 (2.06, 2.19)	14818.5	25	1.04 (1, 1.08)	12262.9
	Dallas-Fort Worth-Arlington	10	1.42 (1.41, 1.42)	49264.0	25	0.65 (0.65, 0.66)	29589.4	25	0.64 (0.63, 0.65)	24300.3	25	0.9 (0.89, 0.91)	21686.8
	El Paso	25	0.65 (0.64, 0.65)	32171.1	22.7	0.27 (0.25, 0.29)	20234.8	25	-0.33 (-0.36, -0.3)	15519.8	10	1.66 (1.59, 1.74)	12281.1
	Houston-The Woodlands-Sugar	11.2	2.03 (2.02, 2.04)	51051.9	14.5	1.95 (1.94, 1.96)	29514.1	25	1.24 (1.23, 1.25)	24069.1	25	1.84 (1.82, 1.85)	21037.5
	Killeen-Temple	25	0.11 (0.1, 0.12)	25736.0	25	0.38 (0.36, 0.4)	17438.5	25	0.73 (0.71, 0.76)	13027.8	10	4.86 (4.76, 4.95)	11217.2
	Lubbock	25	0.24 (0.24, 0.25)	27383.4	24.5	0.86 (0.85, 0.88)	18608.7	25	0.67 (0.64, 0.69)	14880.9	10	-0.25 (-0.31, -0.19)	10572.1
	McAllen-Edinburg-Mission	24.5	1.05 (1.04, 1.06)	29603.8	23.6	1.17 (1.15, 1.19)	19795.0	10	5 (4.79, 5.2)	15690.2	25	1.63 (1.59, 1.66)	12941.3
	San Antonio-New Braunfels	15.3	1.14 (1.14, 1.15)	34481.1	25	0.92 (0.91, 0.93)	23656.4	25	0.85 (0.83, 0.86)	19183.2	21.7	1.15 (1.12, 1.17)	16971.9
	Waco	10.5	2.72 (2.7, 2.74)	24744.1	25	1.52 (1.5, 1.54)	16207.3	10.5	4.51 (4.43, 4.59)	12056.3	13.7	6.61 (6.53, 6.69)	9760.9
25	Austin-Round Rock	10	2.13 (2.12, 2.14)	31925.0	23.2	0.44 (0.43, 0.45)	21929.6	10.6	-0.54 (-0.6, -0.49)	17569.4	13.3	-0.63 (-0.68, -0.58)	15374.8
	Beaumont-Port Arthur	25	0.9 (0.89, 0.91)	27445.9	25	0.23 (0.2, 0.25)	18740.4	24.5	-0.56 (-0.6, -0.52)	14393.4	23.8	2.32 (2.27, 2.38)	11730.4
	Brownsville-Harlingen	15.6	1.49 (1.46, 1.51)	27880.4	19.7	0.5 (0.46, 0.53)	18231.2	17	-3.07 (-3.15, -2.99)	13525.4	10	-17.84 (-18.15, -17.52)	11503.4
	Corpus Christi	11.9	3.77 (3.74, 3.81)	28345.4	11.6	4.75 (4.67, 4.84)	19132.2	11.1	8.81 (8.65, 8.98)	14799.5	25	3.51 (3.45, 3.56)	12245.7
	Dallas-Fort Worth-Arlington	10	1.41 (1.4, 1.41)	49247.1	25	0.83 (0.82, 0.84)	29558.4	25	0.71 (0.7, 0.72)	24274.2	25	0.98 (0.97, 1)	21664.3
	El Paso	25	0.69 (0.68, 0.7)	32136.8	22.8	0.91 (0.89, 0.93)	20208.1	14.5	1.42 (1.37, 1.47)	15502.4	22.5	1.92 (1.87, 1.97)	12267.3
	Houston-The Woodlands-Sugar	11.2	1.95 (1.93, 1.96)	51011.5	14.4	1.58 (1.57, 1.6)	29475.2	25	0.46 (0.45, 0.47)	24020.4	24.7	1.4 (1.38, 1.41)	21013.4
	Killeen-Temple	21.1	-0.03 (-0.04, -0.02)	25670.4	20	0.56 (0.54, 0.59)	17385.7	21.7	1 (0.96, 1.03)	12995.5	10	6.85 (6.73, 6.96)	11181.0
	Lubbock	25	0.08 (0.07, 0.09)	27352.1	24.4	0.26 (0.24, 0.28)	18581.4	25	0.38 (0.35, 0.41)	14861.7	25	-1.87 (-1.92, -1.83)	10558.4
	McAllen-Edinburg-Mission	24.6	1.1 (1.09, 1.1)	29461.7	23.6	1.32 (1.29, 1.34)	19691.7	10	1.89 (1.65, 2.12)	15593.9	25	2.24 (2.2, 2.29)	12870.2
	San Antonio-New Braunfels	12.5	1.86 (1.85, 1.87)	34442.3	25	1.18 (1.17, 1.19)	23632.0	10	5.23 (5.16, 5.29)	19173.1	20.3	0.73 (0.7, 0.76)	16959.2
	Waco	10.5	3.29 (3.27, 3.31)	24710.3	20.6	0.98 (0.95, 1)	16189.7	10.6	5.67 (5.58, 5.77)	12046.16	25	6.17 (6.11, 6.23)	9749.5

Supplemental Table A3. Sensitivity analysis of estimating association between cold temperatures and cause-specific emergency hospital admissions by changing maximum lag for mean temperature.

Lag Days	MSA Name	RESP EHA			PNEU EHA			COPD EHA			STROKE EHA		
		Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC
5	Austin-Round Rock	20	-0.38 (-0.39, -0.37)	22198.0	24.8	-0.84 (-0.85, -0.83)	17475.7	23.1	0.12 (0.1, 0.13)	15105.7	10	-1.41 (-1.45, -1.38)	16846.6
	Beaumont-Port Arthur	24.7	-0.39 (-0.4, -0.38)	18568.4	25	0.05 (0.03, 0.07)	14564.9	13.6	-1.76 (-1.8, -1.71)	12256.0	18.9	-0.79 (-0.82, -0.76)	13577.5
	Brownsville-Harlingen	25	-0.66 (-0.67, -0.64)	18496.9	15.8	2.64 (2.6, 2.68)	13993.3	22.3	-0.81 (-0.85, -0.77)	9940.4	25	1.53 (1.49, 1.56)	12503.8
	Corpus Christi	25	-0.54 (-0.55, -0.53)	19284.6	25	-0.23 (-0.25, -0.22)	15287.7	24.5	-0.33 (-0.35, -0.3)	12454.8	10	0.29 (0.2, 0.37)	13901.1
	Dallas-Fort Worth-Arlington	25	-0.1 (-0.11, -0.1)	30524.1	25	-0.34 (-0.34, -0.33)	24601.5	20.3	-0.26 (-0.27, -0.25)	22117.7	10	0.47 (0.46, 0.48)	23201.6
	El Paso	25	-0.29 (-0.3, -0.29)	21072.8	25	0.08 (0.06, 0.09)	16009.2	25	-0.12 (-0.14, -0.1)	12194.6	10	0.44 (0.41, 0.47)	15006.5
	Houston-The Woodlands-Sugar	25	0.24 (0.24, 0.25)	29383.0	25	-0.3 (-0.3, -0.29)	23913.1	10.3	2.62 (2.59, 2.64)	21659.3	25	-0.46 (-0.47, -0.46)	22936.6
	Killeen-Temple	14.1	-0.83 (-0.85, -0.82)	17472.3	11.6	-1.92 (-1.95, -1.9)	13272.5	10	-1.49 (-1.54, -1.44)	9929.8	24.4	-0.91 (-0.93, -0.89)	11542.5
	Lubbock	15.3	-0.98 (-0.99, -0.97)	17797.5	10	-1.73 (-1.75, -1.71)	13838.9	22.2	-1.56 (-1.58, -1.54)	9839.7	23	0.96 (0.94, 0.98)	11948.4
	McAllen-Edinburg-Mission	20.9	0.81 (0.8, 0.82)	20328.2	15	-0.48 (-0.52, -0.45)	15298.7	22.7	-0.35 (-0.37, -0.33)	12499.4	25	0.2 (0.18, 0.22)	14333.7
	San Antonio-New Braunfels	24.5	-0.13 (-0.14, -0.13)	23790.0	25	-0.28 (-0.29, -0.27)	19428.3	10	0.1 (0.06, 0.14)	16142.0	11.7	0.9 (0.88, 0.93)	18324.9
	Waco	25	0.18 (0.17, 0.19)	16218.3	25	0.79 (0.77, 0.81)	11888.0	25	0.79 (0.76, 0.83)	7920.3	18.1	2.14 (2.11, 2.17)	11026.0
10	Austin-Round Rock	19.2	0.88 (0.88, 0.89)	22134.4	13.9	1.36 (1.34, 1.38)	17429.9	25	1.28 (1.27, 1.3)	15075.3	10	-1.2 (-1.24, -1.17)	16828.5
	Beaumont-Port Arthur	25	0.56 (0.54, 0.57)	18518.0	25	0.76 (0.74, 0.78)	14532.8	21.2	-0.11 (-0.14, -0.08)	12240.8	18.1	-0.45 (-0.48, -0.42)	13558.4
	Brownsville-Harlingen	25	0.19 (0.18, 0.21)	18463.4	14.7	4.74 (4.68, 4.8)	13978.9	20.3	0.01 (-0.04, 0.06)	9916.6	25	0.82 (0.79, 0.86)	12484.0
	Corpus Christi	25	0.71 (0.69, 0.72)	19254.6	25	1.55 (1.53, 1.57)	15261.3	24.5	0.48 (0.45, 0.5)	12438.3	19	2.36 (2.33, 2.4)	13882.1
	Dallas-Fort Worth-Arlington	25	0.75 (0.74, 0.75)	30295.3	25	0.55 (0.54, 0.56)	24479.8	25	0.67 (0.66, 0.68)	22039.1	13.1	0.71 (0.7, 0.72)	23172.3
	El Paso	25	0.52 (0.51, 0.53)	21028.3	25	0.88 (0.86, 0.89)	15981.4	10.6	2.91 (2.86, 2.95)	12173.0	12.2	1.26 (1.23, 1.29)	14991.2
	Houston-The Woodlands-Sugar	25	1.1 (1.1, 1.1)	29223.1	25	0.59 (0.59, 0.6)	23842.3	14.8	2.27 (2.25, 2.29)	21617.5	25	0.1 (0.09, 0.11)	22900.3
	Killeen-Temple	20	0.33 (0.32, 0.34)	17425.6	25	0.1 (0.08, 0.12)	13222.3	16.1	1.65 (1.61, 1.69)	9903.4	24.4	-0.51 (-0.54, -0.49)	11508.3
	Lubbock	14.7	-0.9 (-0.91, -0.89)	17783.7	10	-0.99 (-1.01, -0.96)	13817.8	20.9	-1.33 (-1.36, -1.3)	9831.4	20.3	1.15 (1.13, 1.18)	11926.7
	McAllen-Edinburg-Mission	25	2.18 (2.17, 2.2)	20164.3	25	2.37 (2.35, 2.39)	15197.5	22.5	1.33 (1.3, 1.36)	12416.3	11.4	6.72 (6.6, 6.83)	14251.1
	San Antonio-New Braunfels	25	1.02 (1.01, 1.02)	23676.4	21.3	1.06 (1.04, 1.07)	19382.4	25	0.92 (0.91, 0.94)	16095.4	16.7	0.56 (0.54, 0.58)	18300.3
	Waco	25	0.67 (0.66, 0.69)	16188.5	25	0.89 (0.86, 0.91)	11854.8	23.4	0.87 (0.83, 0.91)	7905.1	18	2.9 (2.86, 2.94)	11018.1
15	Austin-Round Rock	25	1.73 (1.72, 1.74)	22095.0	25	1.89 (1.87, 1.91)	17409.7	21.9	2.54 (2.52, 2.56)	15047.2	10	0.51 (0.46, 0.55)	16808.7
	Beaumont-Port Arthur	24.7	2.13 (2.12, 2.15)	18484.1	25	2.45 (2.43, 2.48)	14500.3	21.4	1.3 (1.26, 1.33)	12217.1	20	1.01 (0.97, 1.04)	13541.9
	Brownsville-Harlingen	25	1 (0.98, 1.02)	18447.3	25	1.69 (1.66, 1.72)	13952.3	22.3	0.48 (0.43, 0.53)	9906.3	25	0.73 (0.69, 0.77)	12470.4
	Corpus Christi	10.5	5.14 (5.08, 5.2)	19232.3	25	2.24 (2.22, 2.26)	15225.8	13	4.06 (3.97, 4.15)	12419.8	16.7	1.92 (1.87, 1.97)	13861.2
	Dallas-Fort Worth-Arlington	25	1.44 (1.44, 1.44)	30155.9	25	1.41 (1.41, 1.42)	24401.4	21.3	1.35 (1.34, 1.36)	22001.5	10	1.74 (1.73, 1.76)	23147.1
	El Paso	25	1.21 (1.2, 1.23)	20995.5	25	1.86 (1.84, 1.88)	15954.7	25	1.9 (1.87, 1.93)	12157.0	20.9	-0.21 (-0.23, -0.18)	14970.7
	Houston-The Woodlands-Sugar	24.1	1.76 (1.75, 1.77)	29163.7	25	1.4 (1.39, 1.41)	23800.1	14.7	2.89 (2.87, 2.91)	21583.9	25	0.64 (0.63, 0.64)	22878.3
	Killeen-Temple	19.8	1.08 (1.06, 1.09)	17372.6	25	0.62 (0.59, 0.64)	13196.6	18.8	1.96 (1.93, 2)	9876.1	23.3	-0.24 (-0.27, -0.21)	11478.0
	Lubbock	25	0.04 (0.03, 0.05)	17760.4	10	0.07 (0.04, 0.1)	13800.6	15	-1.92 (-1.96, -1.88)	9816.9	21.6	1.1 (1.07, 1.13)	11916.1
	McAllen-Edinburg-Mission	25	2.96 (2.95, 2.98)	20057.3	25	3.49 (3.46, 3.51)	15116.1	15	5.56 (5.48, 5.65)	12348.1	11.4	15.29 (15.13, 15.44)	14170.5
	San Antonio-New Braunfels	25	1.89 (1.88, 1.9)	23652.1	21.9	1.97 (1.96, 1.99)	19356.3	25	2.56 (2.54, 2.58)	16071.5	10.3	2.24 (2.19, 2.29)	18273.0
	Waco	25	1.05 (1.03, 1.07)	16165.9	25	2.17 (2.14, 2.2)	11832.4	18.9	1.36 (1.3, 1.41)	7887.9	17.3	3.6 (3.56, 3.64)	10999.9
20	Austin-Round Rock	25	2.57 (2.56, 2.58)	22053.0	19.7	3.45 (3.43, 3.48)	17377.6	21.9	3.72 (3.69, 3.75)	15016.7	10.3	3.18 (3.13, 3.24)	16789.1
	Beaumont-Port Arthur	24.7	3.07 (3.05, 3.09)	18452.0	25	4.57 (4.54, 4.6)	14466.1	23.6	1.79 (1.75, 1.83)	12203.3	20.6	0.51 (0.47, 0.55)	13526.2
	Brownsville-Harlingen	25	2.3 (2.28, 2.32)	18417.8	19.3	5.29 (5.25, 5.34)	13933.9	21.8	1.3 (1.24, 1.36)	9889.7	25	0.96 (0.92, 1.01)	12458.1
	Corpus Christi	10.6	7.62 (7.54, 7.7)	19199.7	25	2.62 (2.59, 2.65)	15203.1	13	5.79 (5.68, 5.91)	12399.7	18.9	1.01 (0.96, 1.06)	13846.4
	Dallas-Fort Worth-Arlington	25	1.8 (1.8, 1.81)	30083.1	25	1.93 (1.92, 1.94)	24344.1	25	1.95 (1.94, 1.96)	21968.7	10	2.04 (2.03, 2.06)	23117.3
	El Paso	25	1.59 (1.58, 1.61)	20961.8	25	2.4 (2.37, 2.42)	15934.5	25	3.42 (3.38, 3.46)	12140.2	19.4	-0.1 (-0.13, -0.06)	14954.9
	Houston-The Woodlands-Sugar	25	2.22 (2.21, 2.23)	29119.6	25	2.09 (2.08, 2.1)	23763.4	17.1	2.99 (2.97, 3.01)	21550.6	25	0.73 (0.72, 0.74)	22842.0
	Killeen-Temple	20	1.49 (1.47, 1.5)	17332.8	25	0.65 (0.63, 0.68)	13168.4	13	1.85 (1.79, 1.92)	9855.0	18.3	0.12 (0.08, 0.17)	11446.4
	Lubbock	25	0.14 (0.12, 0.15)	17743.2	10	0.79 (0.76, 0.83)	13782.8	14.2	-1.6 (-1.65, -1.55)	9809.0	20.3	1.01 (0.97, 1.05)	11903.2
	McAllen-Edinburg-Mission	25	3.36 (3.34, 3.37)	19945.9	25	3.95 (3.92, 3.97)	15031.2	17.5	6.49 (6.42, 6.56)	12276.6	11.4	15.19 (15, 15.39)	14087.5
	San Antonio-New Braunfels	25	2.3 (2.29, 2.31)	23620.0	25	2.9 (2.88, 2.91)	19320.1	25	3.35 (3.33, 3.37)	16051.0	10	1.93 (1.87, 1.99)	18252.7
	Waco	25	1.69 (1.67, 1.71)	16137.6	24.7	2.77 (2.74, 2.8)	11813.0	18.6	0.95 (0.89, 1.01)	7874.8	17.2	2.35 (2.3, 2.4)	10984.8
25	Austin-Round Rock	25	2.81 (2.8, 2.82)	22019.9	25	3.46 (3.44, 3.48)	17349.8	21.9	3.28 (3.25, 3.31)	14999.4	10	2.33 (2.26, 2.4)	16769.5
	Beaumont-Port Arthur	24.7	3.62 (3.6, 3.64)	18426.3	25	5.19 (5.16, 5.23)	14444.1	21.9	3.36 (3.31, 3.41)	12177.8	23.6	0.19 (0.15, 0.23)	13510.3
	Brownsville-Harlingen	25	2.56 (2.54, 2.59)	18395.6	25	3.98 (3.94, 4.02)	13914.9	22.5	4.22 (4.15, 4.29)	9873.0	25	0.35 (0.3, 0.4)	12444.8
	Corpus Christi	10.6	7.36 (7.26, 7.45)	19172.2	24.5	3.4 (3.36, 3.43)	15180.1	19.5	2.4 (2.34, 2.46)	12390.4	21	1.13 (1.08, 1.18)	13827.2
	Dallas-Fort Worth-Arlington	25	2.12 (2.11, 2.12)	30022.2	25	2.34 (2.34, 2.35)	24313.9	25	2.3 (2.29, 2.32)	21939.7	11.6	1.83 (1.81, 1.84)	23092.6
	El Paso	25	1.78 (1.76, 1.8)	20918.8	25	3.71 (3.68, 3.74)	15906.0	25	3.27 (3.22, 3.31)	12116.7	22.5	-1.8 (-1.84, -1.76)	14933.6
	Houston-The Woodlands-Sugar	25	2.71 (2.7, 2.72)	29059.2	25	3.01 (3, 3.02)	23710.4	17.2	2.94 (2.92, 2.96)	21525.1	10	1.36 (1.32, 1.4)	22808.6
	Killeen-Temple	20	1.4 (1.38, 1.42)	17282.3	25	1.09 (1.06, 1.13)	13132.6	13	2.5 (2.42, 2.58)	9831.5	23.1	-0.72 (-0.76, -0.67)	11409.5
	Lubbock	25	0.74 (0.72, 0.76)	17707.7	11.7	2.4 (2.36, 2.44)	13754.2	20.6	0.89 (0.84, 0.95)	9791.6	20.3	1.27 (1.23, 1.32)	11887.9
	McAllen-Edinburg-Mission	25	3.54 (3.52, 3.56)	19830.8	25	3.66 (3.63, 3.69)	14939.7	15.2	9.08 (8.96, 9.21)	12200.8	11.4	16.97 (16.74, 17.21)	14006.7
	San Antonio-New Braunfels	25	2.65 (2.63, 2.66)	23583.9	25	3.85 (3.83, 3.87)	19286.8	25	4.47 (4.44, 4.5)	16028.1	10.2	3.54 (3.47, 3.62)	18225.1
	Waco	25	2.63 (2.61, 2.65)	16110.3	25	4.03 (3.99, 4.07)	11794.2	18.6	0.72 (0.65, 0.79)	7850.5	18	2 (1.95, 2.06)	10976.5

Supplemental Table A4. Sensitivity analysis of estimating association between cold temperatures and age-stratified emergency hospital admissions by changing maximum lag for mean temperature.

Lag Days	MSA Name	0-64 All-Cause EHA			65-74 All-Cause EHA			75+ All-Cause EHA		
		Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC	Threshold	% increased RR	minQAIC
5	Austin-Round Rock	25	-0.21 (-0.21, -0.21)	30053.0	10	0.63 (0.61, 0.64)	22285.2	22.6	-0.18 (-0.18, -0.17)	24508.5
	Beaumont-Port Arthur	24.6	-0.31 (-0.32, -0.3)	24746.0	10	-0.61 (-0.65, -0.58)	18827.4	10.9	1.14 (1.11, 1.16)	21293.9
	Brownsville-Harlingen	25	-0.47 (-0.48, -0.47)	25615.0	10	2.72 (2.64, 2.79)	19033.3	25	-0.81 (-0.82, -0.8)	21144.0
	Corpus Christi	25	-0.34 (-0.35, -0.34)	26468.9	25	-0.5 (-0.51, -0.49)	19681.2	12.3	1.19 (1.17, 1.21)	21760.0
	Dallas-Fort Worth-Arlington	12	-0.05 (-0.05, -0.05)	44282.3	25	-0.16 (-0.17, -0.16)	29964.9	25	-0.09 (-0.1, -0.09)	32282.6
	El Paso	25	-0.34 (-0.34, -0.34)	30010.5	24.3	-0.17 (-0.18, -0.17)	21682.2	24.7	-0.05 (-0.06, -0.05)	23920.9
	Houston-The Woodlands-Sugar	25	-0.11 (-0.11, -0.11)	46530.2	25	-0.07 (-0.07, -0.06)	29615.0	25	-0.08 (-0.08, -0.07)	31488.0
	Killeen-Temple	25	-0.44 (-0.44, -0.43)	24031.8	25	-0.3 (-0.31, -0.29)	17927.6	24.4	-0.3 (-0.31, -0.29)	19599.4
	Lubbock	25	-0.31 (-0.32, -0.31)	25463.7	24.8	-0.43 (-0.44, -0.42)	18809.6	15.3	-0.22 (-0.22, -0.21)	20620.0
	McAllen-Edinburg-Mission	15	0.06 (0.05, 0.07)	28247.7	22.8	0.09 (0.08, 0.1)	20501.3	25	0.15 (0.15, 0.16)	22646.0
	San Antonio-New Braunfels	25	-0.42 (-0.42, -0.42)	32531.0	20.6	-0.06 (-0.06, -0.05)	24010.4	22.5	-0.22 (-0.22, -0.22)	26283.9
	Waco	13.6	0.74 (0.73, 0.75)	23050.2	15.2	-0.2 (-0.21, -0.18)	16282.1	22	0.44 (0.43, 0.45)	18669.9
10	Austin-Round Rock	11.1	0.89 (0.88, 0.89)	29996.3	10.9	1.72 (1.7, 1.74)	22242.2	22.3	0.54 (0.53, 0.55)	24462.2
	Beaumont-Port Arthur	25	0.1 (0.09, 0.11)	24707.3	10	-0.07 (-0.11, -0.03)	18802.1	11.6	2.06 (2.04, 2.09)	21251.0
	Brownsville-Harlingen	25	0.14 (0.14, 0.15)	25579.3	10	4.32 (4.23, 4.42)	19005.5	25	0.1 (0.08, 0.11)	21109.0
	Corpus Christi	25	0.14 (0.13, 0.15)	26441.0	24.7	0.52 (0.51, 0.53)	19646.8	10	1.99 (1.95, 2.03)	21726.3
	Dallas-Fort Worth-Arlington	10.3	0.58 (0.58, 0.59)	44153.1	25	0.27 (0.26, 0.27)	29911.8	25	0.39 (0.38, 0.39)	32184.3
	El Paso	25	0.02 (0.02, 0.03)	29962.8	25	0.22 (0.21, 0.23)	21657.8	25	0.27 (0.27, 0.28)	23887.9
	Houston-The Woodlands-Sugar	14.4	0.76 (0.75, 0.76)	46333.3	25	0.39 (0.39, 0.4)	29534.4	25	0.42 (0.41, 0.42)	31433.1
	Killeen-Temple	25	-0.12 (-0.12, -0.11)	23972.5	21.9	-0.37 (-0.38, -0.35)	17885.6	22.8	0.07 (0.06, 0.08)	19537.2
	Lubbock	25	-0.08 (-0.08, -0.07)	25431.7	25	-0.55 (-0.56, -0.54)	18777.7	15	0.01 (0, 0.02)	20594.8
	McAllen-Edinburg-Mission	24.8	0.27 (0.27, 0.28)	28089.5	23.8	1.15 (1.14, 1.16)	20368.3	24.9	0.84 (0.83, 0.84)	22523.0
	San Antonio-New Braunfels	25	-0.08 (-0.08, -0.08)	32445.5	20.5	0.54 (0.53, 0.55)	23977.7	22.2	0.36 (0.36, 0.37)	26257.0
	Waco	10	2.32 (2.31, 2.34)	23012.9	13.6	1.59 (1.56, 1.61)	16258.2	21.6	0.89 (0.87, 0.9)	18641.2
15	Austin-Round Rock	11.1	1.38 (1.37, 1.39)	29932.4	10.8	2.46 (2.44, 2.48)	22214.0	25	1.07 (1.06, 1.08)	24445.8
	Beaumont-Port Arthur	25	0.76 (0.75, 0.77)	24688.6	10	2.65 (2.6, 2.7)	18771.0	11.1	2.01 (1.98, 2.04)	21223.3
	Brownsville-Harlingen	15.8	1.13 (1.11, 1.15)	25567.1	10	4.94 (4.83, 5.06)	18979.7	23	0.16 (0.15, 0.17)	21086.6
	Corpus Christi	11.7	1.85 (1.82, 1.87)	26419.0	25	0.83 (0.82, 0.85)	19621.0	12	2.77 (2.74, 2.81)	21695.3
	Dallas-Fort Worth-Arlington	10	1.05 (1.05, 1.06)	44033.4	25	0.54 (0.53, 0.54)	29892.8	25	0.7 (0.7, 0.7)	32183.1
	El Paso	25	0.43 (0.42, 0.44)	29911.4	10	1.3 (1.28, 1.32)	21637.6	25	0.55 (0.54, 0.55)	23857.3
	Houston-The Woodlands-Sugar	11	1.61 (1.6, 1.61)	46228.7	11.1	2.65 (2.63, 2.66)	29517.4	11.2	2.22 (2.21, 2.23)	31403.6
	Killeen-Temple	10	1.38 (1.37, 1.4)	23923.5	19.7	-0.72 (-0.74, -0.7)	17833.2	21.4	0.58 (0.57, 0.59)	19491.0
	Lubbock	25	0.1 (0.09, 0.1)	25393.4	24.7	-0.2 (-0.21, -0.18)	18752.9	18.9	0.37 (0.35, 0.38)	20580.4
	McAllen-Edinburg-Mission	14.1	1.24 (1.22, 1.26)	27942.4	23.6	1.8 (1.78, 1.81)	20258.4	14.7	4.02 (3.99, 4.05)	22385.8
	San Antonio-New Braunfels	19.9	0.38 (0.38, 0.39)	32400.5	18.9	1.22 (1.21, 1.23)	23954.3	12.4	1.86 (1.85, 1.87)	26230.7
	Waco	10.3	2.45 (2.43, 2.46)	22980.2	12.5	3.37 (3.34, 3.4)	16231.4	20.8	1.51 (1.49, 1.52)	18609.0
20	Austin-Round Rock	10	2.31 (2.3, 2.32)	29906.6	10.8	3.11 (3.09, 3.14)	22187.9	15.9	1.4 (1.38, 1.41)	24423.0
	Beaumont-Port Arthur	25	0.76 (0.75, 0.77)	24658.5	10	4.77 (4.71, 4.84)	18745.8	10.8	3 (2.96, 3.04)	21197.5
	Brownsville-Harlingen	15.8	1.69 (1.67, 1.72)	25539.4	10	4.33 (4.19, 4.47)	18960.0	23.1	0.55 (0.54, 0.57)	21067.5
	Corpus Christi	11.6	2.11 (2.08, 2.14)	26385.0	25	1.08 (1.07, 1.1)	19598.9	12	3.71 (3.66, 3.76)	21670.0
	Dallas-Fort Worth-Arlington	10	1.22 (1.22, 1.23)	44047.7	25	0.74 (0.74, 0.75)	29904.2	25	0.88 (0.88, 0.89)	32184.1
	El Paso	25	0.47 (0.46, 0.47)	29885.3	10	2.48 (2.45, 2.5)	21602.0	25	0.97 (0.96, 0.98)	23828.5
	Houston-The Woodlands-Sugar	11.9	1.52 (1.51, 1.53)	46238.1	16.4	1.6 (1.59, 1.61)	29498.6	11.2	2.58 (2.56, 2.59)	31380.0
	Killeen-Temple	10	1.21 (1.19, 1.24)	23866.9	19.7	-0.83 (-0.85, -0.81)	17789.4	21.1	0.55 (0.53, 0.56)	19447.1
	Lubbock	25	0.34 (0.33, 0.35)	25377.0	25	-0.48 (-0.49, -0.46)	18729.6	10	0.36 (0.34, 0.38)	20568.7
	McAllen-Edinburg-Mission	12	2.59 (2.55, 2.63)	27805.7	23.6	2.15 (2.13, 2.17)	20140.1	15	5.08 (5.05, 5.11)	22268.9
	San Antonio-New Braunfels	12.5	1.24 (1.23, 1.25)	32401.8	16.7	1.65 (1.64, 1.67)	23934.9	10	4.15 (4.13, 4.17)	26202.5
	Waco	10	2.59 (2.57, 2.61)	22954.3	10	5.31 (5.27, 5.36)	16213.5	17.2	1.59 (1.57, 1.61)	18580.9
25	Austin-Round Rock	10	1.91 (1.89, 1.92)	29870.8	10.8	3.05 (3.02, 3.08)	22158.5	14.6	1.27 (1.25, 1.28)	24392.0
	Beaumont-Port Arthur	25	0.67 (0.66, 0.69)	24627.4	10.5	4.26 (4.2, 4.33)	18731.2	10.9	3.29 (3.25, 3.34)	21173.7
	Brownsville-Harlingen	15.6	0.84 (0.81, 0.87)	25513.1	10	4 (3.83, 4.16)	18940.8	23	1.17 (1.15, 1.19)	21032.0
	Corpus Christi	11.7	3 (2.96, 3.04)	26349.4	25	1.4 (1.38, 1.43)	19574.6	10	6.63 (6.54, 6.71)	21641.5
	Dallas-Fort Worth-Arlington	10	1.17 (1.17, 1.18)	44013.4	25	0.88 (0.87, 0.88)	29871.6	25	0.93 (0.93, 0.94)	32164.4
	El Paso	25	0.58 (0.58, 0.59)	29841.6	10	1.9 (1.87, 1.93)	21571.1	25	0.81 (0.8, 0.82)	23803.1
	Houston-The Woodlands-Sugar	11.9	1.39 (1.37, 1.4)	46195.8	16.4	1.5 (1.49, 1.51)	29463.8	11.2	2.86 (2.84, 2.88)	31346.8
	Killeen-Temple	10	1.6 (1.57, 1.62)	23807.2	17.7	-1.75 (-1.78, -1.73)	17732.9	19.5	0.32 (0.31, 0.34)	19397.8
	Lubbock	25	0.23 (0.22, 0.23)	25349.9	25	-0.43 (-0.45, -0.42)	18712.9	10	-0.35 (-0.37, -0.33)	20542.5
	McAllen-Edinburg-Mission	12	2.13 (2.08, 2.17)	27657.0	23.6	1.31 (1.29, 1.33)	20020.1	14.9	4.73 (4.69, 4.77)	22159.1
	San Antonio-New Braunfels	12.5	1.43 (1.42, 1.44)	32360.7	16.7	1.45 (1.43, 1.46)	23905.0	10	4.78 (4.76, 4.81)	26168.4
	Waco	10	3.14 (3.12, 3.17)	22924.1	13.3	4.66 (4.62, 4.7)	16190.0	13.9	2.24 (2.21, 2.26)	18560.3

CHAPTER IV

JOURNAL ARTICLE III: PROJECTIONS OF COLD-RELATED MORTALITY UNDER CLIMATE CHANGE SCENARIOS FOR TEXAS IN THE 2050s AND 2080s

Title of Journal Article

Projections of Cold-related Mortality under Climate Change Scenarios for Texas in the 2050s
and 2080s

Name of Journal Proposed for Submission

Science of the Total Environment

**Projections of cold – related mortality under climate change scenarios for Texas in the
2050s and 2080s**

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Abstract

While future warming may be expected as the consequence of global climate change, however, cold-related health impacts may not correspondently decrease. Previous studies have examined the impact of shifted temperature distribution at regional or global trends. However, an effective adaptation plan should be provided at a finer scale. Our studies have shown that cold weather is related to significant levels of mortality in Texas. In order to provide actionable evidence to inform local adaptation plan, we estimated cold temperature-related deaths using 9 climate models with a total of 53 runs under 3 different emission scenarios to address climate uncertainties through the end of the century in 12 Texas Metropolitan Areas (MSAs). Population projection was also considered in the projection of public health burdens attributable to cold temperatures in the 2050s and 2080s. Our results showed that the projected future temperatures were associated with lower cold-mortality rate. However, with population projection, the annual deaths attributable to cold increased largely in several major MSAs. The Houston-Woodlands-Sugar Land areas were projected to experience 1690 deaths a year in 2050s and 1275 deaths a year in 2080s under climate change. Although not all of the MSAs were projected with an increase in annual cold-related death counts by the end of the century, the total number of cold-related deaths during the baseline (1990-2011), 2050s (2046-2065) and 2080s (2081-2099) was estimated to be over 300,000 deaths. Cold-related deaths remain as an important public health burden through the end of the century in Texas. Hence, by looking at MSA level estimates, the state government or community leaders would be able to locate areas with excessive cold burdens and help local governments allocate resources to the areas in greatest need.

Keywords

Cold weather; Climate change; Temperature; Attributable mortality; Cold-related mortality

1. Introduction

Global average temperatures will continue to rise over the next few decades. Researchs of the health impacts of climate change worldwide have often concluded that mitigated winter due to global warming would substantially reduce winter mortality, which may offset the increased heat-related mortality partially or entirely. However, the magnitude and degree of uncertainty of the net change in the temperature-related deaths is expected to vary by location, depending on the shape of the temperature-mortality association curves (Gasparrini et al. 2017; Weinberger et al. 2017). Furthermore, fewer studies have accounted for population growth scenarios when estimating future temperature-related health burden. Therefore, whether the changing climate will be harmful or beneficial to temperature-related health burden in the future remains debatable.

Previous studies have shown that the association between ambient temperature and the risk of death is usually V-, U- or J-shaped with risks increasing progressively once the temperatures drop or above specific thresholds (Guo et al. 2014; Medina-Ramon M, Schwartz J. 2007; Ye et al. 2012). These thresholds were often referred to the lowest point or range in the exposure-response curve as an optimal temperature or minimum mortality temperature (MMT) and also vary considerably by locations (Ye et al. 2012). Several studies projected a substantial increase of heat-related mortality and a lower rate of cold-related mortality under the impact of climate change through the end of the century (Gasparrini et al. 2017; Hajat et al. 2013). However, the accuracy of these predictions depends on how much of these mortalities are directly dependent on temperatures alone. With increasing awareness of the risk of non-optimal temperature, increased prevalence of HVACs, improved housing and health

care, the link between temperature and mortality may not remain the same as before. Potential adaptation was not being considered, despite previous evidence has suggested that an increase in mean summer temperature was associated with a decrease in heat-related mortality, implying potential adaptation (Nordio et al. 2015). Although cold adaptation modified by mean winter temperature remains unsure, evidence has shown a stronger cold-related mortality observed in mild winter climate regions or in regions with decreasing latitude, suggesting that acclimatization exists (Curriero et al. 2002; Medina-Ramon and Schwartz 2007). Therefore, while climate change is considered as the biggest threat of the globe in the 21st century, providing comprehensive information at local level is crucial to reduce potential temperature-related mortality burden requires action by local policymakers and government officials.

With an area of 267,339 square miles, Texas covers a variety of demographical and geographical feature with a general mild winter climate as located in the southern USA. Although evidence has shown that cold weather is related to significant levels of mortality in Texas (Chen et al. 2017), a complete description of future mortality attributable to cold weather is still lacking. In addition, as one of the most populous and diverse states in the U.S., Texas encompasses three of the top five largest population gains city and 7 of the 15 with fastest-growing rate city in the U.S. (US Census 2018). This rapid growing in population should be considered and incorporated into the projections of cold-related mortality when interpreting the future public health burden of cold-related deaths. Therefore, with the aim of providing credible and actionable evidence for local policymakers to design strategies in reducing future public health burden of temperature-related deaths, we projected cold-mortality using 9 bias-corrected downscaled global climate models under three difference greenhouse gas scenarios

(with a total of 53 runs) and estimated cold-related health burdens by incorporating projected populations in 2050s and 2080s for 12 major Texas Metropolitan Areas (MSAs).

2. Material and methods

We estimated future cold-related mortality associated with climate change in two steps. First we performed epidemiological modeling using observed weather and mortality data to estimate MSA-specific association. Second, we conducted risk assessment using cold effect estimates from epidemiological modeling and temperature projections from climate models. Population projections were also considered.

2.1. Data sources and study domain

2.1.1. Historical data

Twelve Texas MSAs delineated by the U.S. Office of Management and Budget (OMB) in 2013 (U.S. Census 2013) were included in the study based on the weather data availability and the population sizes. Daily mortality data during the period of 1990-2011 were obtained from the Texas Department of State Health Services (DSHS) and were aggregated at the MSA level. All causes of deaths, including external causes, were included and identified by the International Classification of Disease (ICD) Ninth Revision (ICD-9) codes 001-897 and Tenth Revision (ICD-10) codes A00-R99, V01 and W00 (World Health Organization 1975, 1993).

Observed weather data were downloaded from the National Climate Data Center (NCDC) through the Integrated Surface Database (ISD) (NCDC 2014). Each MSA had a corresponding weather station, which is the closest to the most populous city in the MSA, to

represent its population exposure. Daily mean temperature and dew point temperature were calculated totaling 8035 observations for the period 1990-2011 in each of 12 MSAs in Texas.

2.1.2. Climate Model Projections

Future temperature projections were obtained for three Special Report on Emissions Scenarios (SRES) greenhouse gas emissions (GHG) scenarios (A1B, A2 and B1) based on global climate projections from the World Climate Research Programme's (WCRP's) Coupled Model Inter-comparison Project phase 3 (CMIP3) multi-model dataset referenced in the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report. (IPCC 2007).

SRES represent different assumptions of future demographic, socioeconomic, energy technological patterns and land-use. The SRES A2 represents relatively high GHG, describes a very heterogeneous world. The assumption is that population growth will be high but the sharing of technology and economic growth will be limited, which resulted in more disparate between countries and regions and the energy use will be high. The SRES B1 represents relatively low GHG, describes a convergent world. The assumption is that the global population growth remained but assumes a high level of environmental and social consciousness, which leads to sustainable development, high technological advancement, and low energy use. The A1B scenario describes a future world of rapid economic growth with global population peaks in mid-century and declines thereafter, but more emphasized on new and efficient technologies (IPCC 2000).

Specifically, future time series temperature for each SRES were generated from daily bias-correction and constructed analogs (BCCA) climate projections, which has also been downscaled to reflect local climatological features (spatial resolutions at 1/8 degree ($^{\circ}$)). We

included projections from 9 global scale general circulation models climate models (GCMs) with a total of 17 to 18 runs in each GHG scenarios (table 1) which were developed and made available by the “Downscaled CMIP3 and CMIP5 Climate and Hydrology projections”, archived at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ (DCHP).

Finally, the daily BCCA CMIP3 provided daily maximum temperature and daily minimum temperature in three time slices: 1961-2000, 2046-2065, and 2081-2099. We extracted the projected temperatures for each MSA using the coordinates of MSA corresponding weather station where we obtained the historical weather data and calculated daily mean temperature by averaging the maximum and minimum temperature to represent climates in 2050s (2046-2065) and 2080s (2081-2099).

2.1.3. Population Projections

Texas population projections were obtained from the “Texas Population Estimates and Projections program” (TPEPP) website (<http://osd.texas.gov/Data/TPEPP/>) prepared by Office of State Demographer, Texas State Data Center. Briefly, the projections were completed using a cohort-component projection technique, meaning the projections were made from separate cohorts (single years of age by gender by racial groups) and then sum up these cohorts as projected total population. Special populations, fertility rates, mortality rates, and residual migration rates were incorporated into the population projection model. The projections were based on the 2010 census population and projected for each year from 2010 through 2050. Three projection scenarios were available assuming different degree of net migration, derived from 2000-2010 patterns, which were one of the expansive growth in the Texas economy and population. The scenarios are referred as the zero migration (0.0) scenario, the one-half 2000-

2010 (0.5) scenario, and the 2000-2010 (1.0) scenario. We chose the (0.5) scenario which assumes a continued growth but at reduced levels, and is also suggested for long-term projection by the TPEPP. For the population beyond 2050, we assume the population will be held constant after 2050s.

2.2. *Epidemiology modeling*

MSA-specific association between cold temperature and daily counts of death was developed using single threshold distributed lag non-linear models (DLNMs) with an quasi-Poisson family, as previously described (Chen et al. 2017). This method was constructed to express exposure-response dependencies and delayed effects simultaneously, which was developed by Gasparrini et al. (2012). In brief, we modeled historical daily mean temperature using the bi-dimensional spline function with a natural cubic spline with 5 degrees of freedom (df) for the lag dimensions and 4 df for the temperature change dimension. Lags were used up to 25 days to capture the long lagged effects of cold temperature. A number of confounding variables including day of the week, day of the year (natural cubic spline with 7 df per year) and mean dew point temperature (natural cubic spline with 3 df) were incorporated in the models.

As stated above, the temperature-mortality association curves in Texas were generally linear with increased risk of mortality only evident in lower temperatures (see Supplemental Figure 1), unlike studies conducted in a colder winter region where curves are usually V-, U- or J-shaped (Ye et al. 2012). Instead of using minimum mortality temperature (MMT) or the optimum temperature corresponding to the lowest point or range in the curve, we used the temperature values corresponding to the model with the minimum Q-AIC as the cold threshold

temperature for each MSA. We reported the estimated mortality relative risk (RR) as with a 1 °C decrease in temperature below the cold threshold. The MSA-specific effect estimates were then pooled through meta-analysis using a random-effect model to obtain an overall effect estimate at the state level.

2.3. Risk assessment

We estimated future health impacts based on the historical data (1990-2011, hereafter referred to as “baseline”). From there, we calculated the annual temperature-related mortality rate (deaths per 100,000 people) in 2050s (2046-2065) and 2080s (2081-2099) for each SRES in each MSA. Projected mortality impacts were estimated using modeled daily mean temperatures incorporated with MSA specific models. For any day in each MSA with mean temperature lower than the MSA’s cold threshold, the additional deaths due to cold temperature were calculated relative to the cold threshold. Daily additional deaths were estimated as

$$\Delta Mortality = POP \times Y_0 \times AF \quad (1)$$

Where $\Delta Mortality$ represents daily temperature-related additional deaths; POP is the MSA population; Y_0 is the baseline averaged daily mortality rate; AF is the attributable risk fraction, which was proposed by Steenland and Armstrong in 2006 and defined as “the fraction of cases or deaths from a specific disease that would not have occurred in the absence of exposure to a specific risk factor either in the exposed population or the population as a whole.” (Steenland and Armstrong 2006). A general definition of the AF can be provided using relative risks (RR) as

$$AF = (RR - 1)/RR \quad (2)$$

In order to incorporate our results from linear exposure-response association, the RR was calculated as

$$RR = \exp(\beta \times \Delta T) \quad (3)$$

Where β is the cold temperature-mortality coefficient, quantified from the first stage of epidemiology modeling; ΔT is the temperature difference between the day and MSA specific threshold. We calculated the mortality rate attributable to cold temperature (per 100,000) and summed up the contributions from the days with temperatures lower than the cold threshold as the total excess deaths attributed to cold temperature for each year in the baseline (1990s) and future time periods (2050s and 2080s).

All statistical analyses were performed using SAS (version 9.4, SAS Institute, Cary NC, USA) and the RStudio Desktop (version 1.1.456 RStudio, Inc. Boston, MA; <http://www.rstudio.com>) (RStudio Team 2016). DLNMs were fitted using “dlnm” package (version 2.3.6) (Gasparrini et al. 2010); meta-analysis was performed using ‘mvmeta’ package (version 0.4.11) (Gasparrini et al. 2012) and figures were rendered using ‘plotly’ package (version 2.0) (Plotly Technologies Inc 2015).

3. Results

Table 1 shows the population and meteorology characteristics in the 12 TX MSAs for each study time period. At baseline, the estimated cold effects on mortality were generally significant (RR ranged from 1.01 to 1.05 with 1°C below the cold threshold), with the highest in McAllen-Edinburg-Mission, followed by Brownsville-Harlingen, two of the southernmost MSAs in Texas. The pooled effect estimate between daily mean temperature and all-cause

mortality showed that a 1 °C decrease in temperature below threshold was associated with overall increase in all-cause mortality of 1.58% [95% CI: 0.81%, 2.37%] (data now showed). Cold thresholds were found ranging from 12 to 20 °C. The average daily mortality rates ranged from 1.2 to 2.7 per 100,000 people with the highest in Beaumont-Port Arthur and lowest in Dallas-Fort Worth-Arlington. As of 2010, Dallas-Fort Worth-Arlington was the most populous MSA in the Texas and was projected continuing to be by the end of the century. The population increase rates were highest in McAllen-Edinburg-Mission, followed by Austin-Round Rock and Brownsville-Harlingen with lowest in Beaumont-Port Arthur. The average daily mean temperatures in Texas MSAs during baseline period ranged from 16.2°C to 24.3°C. It was projected that the temperature will increase on average 1°C (ranged from 0.2 to 1.8°C) for the best case scenario (SRES B1) and 1.6°C (0.8 to 2.4°C) for the worst case scenario (SRES A2) in 2050s; and 1.7°C (0.9 to 2.6°C) and 3.4°C (2.6 to 4.3°C) increase in 2080s for the best and worst scenarios, respectively. By the end of the century, the largest projected temperature increase was found in Austin-Round Rock with the smallest temperature increase in Killeen-Temple (under SRES B1) and McAllen-Edinburg-Mission (under SRES A2). A graphical representation of the overall temperature trends in Texas is also provided in Figure 1. In the middle of the century, the projected temperature increase was the highest under SRES A1B, but a steep increase is consistently projected throughout the study period under SRES A2.

Table 2 summarized annual excessive cold days and excessive mortality attributable to cold temperature over time in each MSA. The average cold days was 123 (range: 17-216 days) a year during baseline and inclined to 101 (range: 12-188 days) a year under SRES B1 and 85 (range: 8-167 days) a year under SRES A2 in 2080s. The average annual attributable cold

mortality rate was 13.1 per 100,000 (range: -0.5-44.9 per 100,000) at baseline and reduced to 9.4 per 100,000 (range: -0.4-35.0 per 100,000) under SRES B1 and 7.2 per 100,000 (range: -0.3-28.3 per 100,000) under SRES A2 in 2080s. The average annual excessive deaths attributable to cold temperature were 205.9 deaths at baseline and increased to 347.5 deaths under SRES B1 and 317.8 deaths under SRES A2 in 2050s, and slightly decreased to 306.7 and 241.3 deaths under SRES B1 and A2 in 2080s, respectively. A pooled estimated cold temperature impact at the state level is shown as a bar-line chart in Figure 2. Average annual cold-related mortality rates were estimated to be 22.7, 18.3 and 15.3 per 100,000 at baseline, 2050s and 2080s, respectively. Estimated excess cold-related death counts were shown as bars with an average of 3742, 6105 and 5119 deaths annually during baseline, 2050s and 2080s respectively. A set of detailed projection is provided in Supplemental Figure 1 with graphical representation depicting the excess cold-related mortality and death counts overtime under different greenhouse gases scenarios in each MSA (Supplemental Figure 2).

4. Discussion

In this study, we depicted future cold-related health burden using a total of 53 projections under three different emission scenarios incorporating with projected population throughout the 21 century for 12 major MSAs in Texas. Our results showed that although the pooled and MSA-specific estimated cold-mortality rate decreased largely by the end of the century, the estimated number of deaths attributable to cold temperature increased sustainably as compared to the baseline in Texas. This study may be particularly useful to inform local adaptation plans in areas with mild winter climate.

Several general trends emerged from the pooled and 12 MSA-specific projection patterns. The attributable mortality rate decreased gradually overtime, with a flatter slope observed under SRES B1 and steeper slope observed under SRES A2. The difference of attributable mortality rates was not distinct between SRES A1B and A2 in the 2050s and became more separately in the 2080s. This may be due to the storyline of SRES A1 and A2 that the underlying assumption of global population were both continuously increasing in 2050s, and the population growth under SRES A1B then declines thereafter. This pattern was observed across all MSAs except McAllen-Edinburg-Mission. The cold-mortality rates were quite similar and no particular emission scenario stands consistently out throughout the projected period. Although it seems that the cold-mortality rate was not impacted by different GHG, McAllen-Edinburg-Mission also reported with the least number of annual cold days (8-17 days). This finding may be a reflection of the smaller sample size limiting the interpretation difference under different scenarios. Also, due to the fact that we were unable to identify the lowest point as our optimal temperature for our threshold definition, we choose the best fit of model with minimum AIC and used the corresponding temperature as our cold threshold. Hence, the results should be interpreted with caution.

Furthermore, although the cold-mortality rates were generally higher at baseline, they fluctuated widely with peaks around 1997, 2002 and 2010. During these years, two of them were corresponding to cold waves in the US: the 1997 Northern plains cold air outbreak and the 2010 Deep South cold wave. Our previous study has shown the overall cold wave effects were only observed in some coastal MSAs in Texas (Chen et al. 2017). However, studies projecting the effect of cold waves on mortality were scarce. Wang et al. (2016) projected a slightly increase of attributable mortality in the Southwest US. Although cold waves are

projected with a decrease in the frequency, duration and intensity, additional studies are needed to provide more evidence to draw the conclusion.

In addition to the cold-mortality rate, we reported the annual cold-related death counts at the state and MSA levels to illustrate the health burden for public health planning efforts. Houston-The Woodlands-Sugar Land areas were estimated with the highest number of deaths attributable to cold, with annual estimate of 1105 deaths, followed by Dallas-Fort Worth-Arlington areas with annual estimate of 529 death at baseline. With population projection, annual cold-related deaths counts were almost doubled for both MSA with 1848 and 1030 deaths in Houston and Dallas under SRESB1 and with 1690 and 956 deaths under SRESA2 in 2050s. The annual cold-related death counts were then slightly decreased to 1631 and 930 deaths in Houston and Dallas under SRESB1 and with 1275 and 763 deaths in Dallas under SRESA2 in 2080s. This large increase in deaths in 2050s and slight decrease in 2080s were partially driven by the population projection which assumed a growing population until 2050s the hold constant thereafter. Our results were similar to the study for the estimated number of deaths attributable to cold in 2050 and 2090 under two representation concentration pathways (RCP4.5 and RCP8.5) defined in the updated IPCC report for 10 large US MSAs (Weingerger et al. 2017). Weingerger et al. (2017) reported the projected number of cold-related deaths accounting for projected population growth were 1713 and 965 deaths in Houston and Dallas under RCP4.5 and 1623 and 910 deaths in Houston and Dallas under RCP8.5.

However, not all the MSAs were projected with an increase in annual cold-related death counts by the end of the century. Beaumont-Port Arthur, Brownsville-Harlingen, Corpus Christi and El Paso will experience a decrease of total number of cold-mortality under climate change. With that being said, there are still over 300,000 deaths attributable to cold

temperatures for the study time slice. Even if the decreasing cold-related mortality rate can offset partially the increased heat-related mortality, it does not necessarily mean the overall temperature-related mortality can benefit from the climate change, especially these 300,000 deaths could be preventable with well-planned public health strategies, such as wearing adequate clothing and gears or stay indoors.

There are some strengths and limitations in this study. First, our estimates are affected by considerable uncertainties and need to be interpreted with caution. Due to the complexity of modeling and different assumptions used to derive the location-specific temperature-mortality association, it is difficult to compare results between studies quantitatively. However, our findings were consistent with previous studies in overlapping cities in terms of the direction and magnitudes. Second, we did not include the impact of hot temperatures in our study. We did not observe increased risk in hot temperatures as reported in other studies. This might be resulted from the different modelling approaches used between studies. However, as our goal was aiming to provide evidence for the development of adaptation plan, it would be appropriate to separate hot and cold temperature burdens in the discussion. Combining heat- and cold-mortality and reported in net change may be misleading if not interpreted carefully. Moreover, assuming the same mortality curve and extrapolate the log-linear beyond the observed temperature range will introduce uncertainties and would underestimate the heat-related impacts for the future. Third, we assessed future cold-related mortality in the absence of adaptation. Evidence has suggested that an increase in mean summer temperature was associated with a decrease in heat-related mortality (Nordio et al. 2015). Moreover, study examining long-term temperature-mortality association reported an attenuation in heat-related health impacts (Gasparrini et al. 2015), possibly reflecting adaptation. However, the adaptation

in cold temperatures remain unsure. Future studies are needed to explore potential effect modifier in cold-mortality association. Lastly, we incorporated population projections accounting for demographic changes in future projections which contribute greatly to future cold-mortality burdens. However, due to the data availability limitation, we only have the projected population through 2050 and assumed the population will be constant thereafter. Therefore, our estimates may be relatively conservative for future mortality effects after 2050s.

5. Conclusions

In general, Texas experiences a substantial mortality burden attributable to cold temperature annually with current weather patterns. With MSA-specific temperature-mortality associations and 9 climate models temperature projections under three emission scenarios, we found that, although the annual cold- mortality rates reduced with projected temperature under climate change, the number of deaths attributable to cold temperature increased largely with projected population through the end of the century. This study provides evidence in the development of adaptation plan for local policy.

Founding Sources

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Figure 1. Distribution of baseline and projected temperatures in Texas in the 2000s, 2050s and 2080s from 9 climate models under three greenhouse gas scenarios (A1B, A2 and B1).

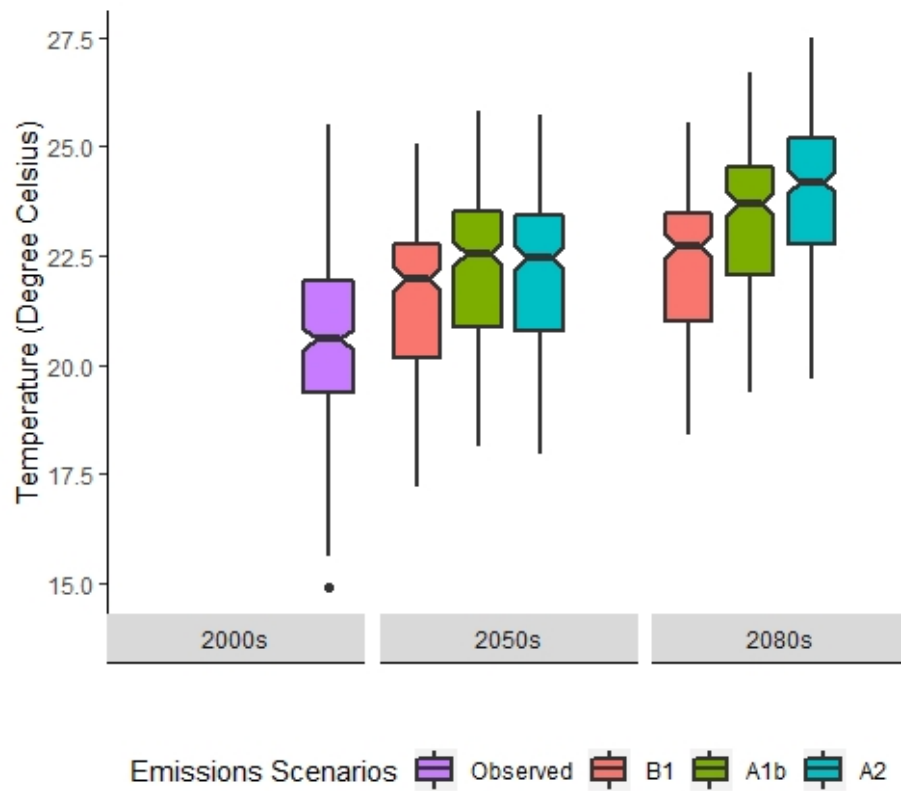


Figure 2 Estimated deaths attributable to cold temperatures in baseline (1990-2011), 2050s (2046-2065) and 2080s (2081-2099) under three emissions scenarios (SRESB1, SRESA1B and SRESA2), incorporating population projection in Texas. Death counts in each timeslice is differentiated by bar chart colors .

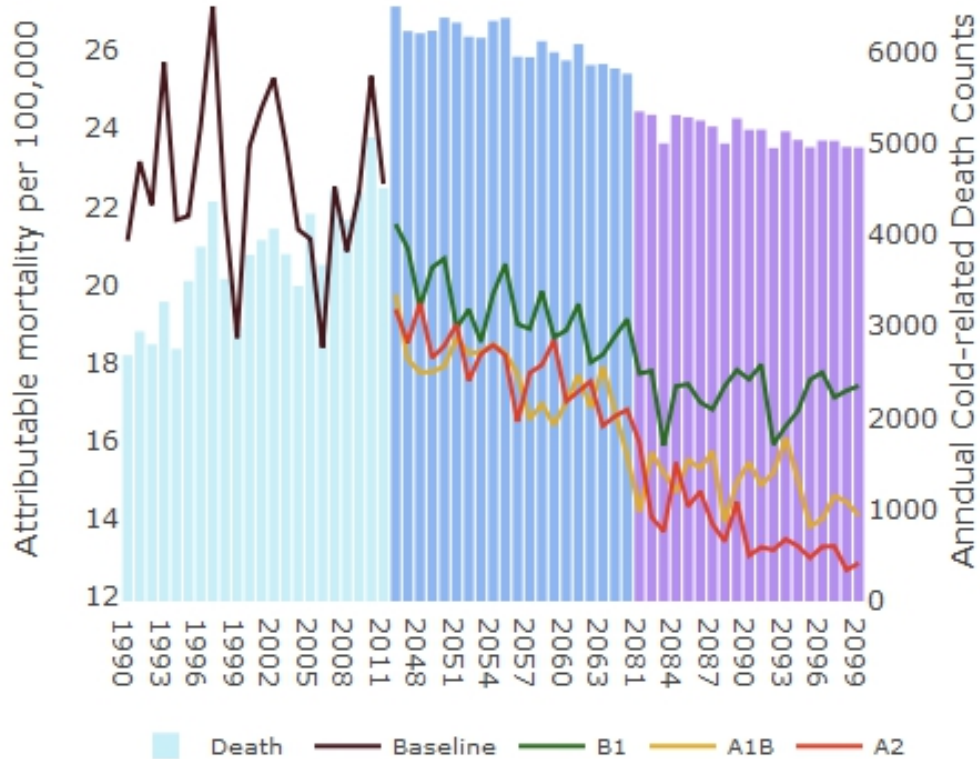


Table 1. Descriptive statistics of climate and population for 12 major Texas Metropolitan Areas in 2000s (baseline), 2050s and 2080s.

MSA	Cold hreshold	Daily mortality	RR ^a	Baseline ^b population	Projected Population		Baseline meTmp ^d	Projected Temperature Increase vs. Baseline					
					2050s	2080s		2050s			2080s		
								B1 ^c	A1B	A2	B1	A1B	A2
Austin ^f	18.4	1.4	1.013	1,716,289	2,475,934	3,255,574	20.4	1.8	2.5	2.4	2.6	3.6	4.3
Beaumont ^g	14.5	2.7	1.017	403,190	452,983	498,736	20.8	1.2	1.9	1.8	1.9	2.9	3.6
Brownsville ^h	17	1.6	1.033	406,220	566,018	728,518	23.7	0.9	1.5	1.4	1.5	2.4	3.0
Corpus Christi	16.7	2.1	1.019	428,185	496,051	545,602	22.5	1.2	1.7	1.7	1.8	2.8	3.4
Dallas ⁱ	20	1.2	1.006	6,426,214	8,590,287	10,838,399	19.4	0.6	1.3	1.2	1.4	2.5	3.2
El Paso	10.6	1.5	1.013	804,123	1,053,491	1,277,950	18.6	0.5	1.2	1.1	1.2	2.3	2.9
Houston ^j	20	1.6	1.016	5,920,416	7,986,256	10,004,950	21.0	1.2	1.8	1.7	1.9	2.9	3.6
Killeen-Temple	19.4	1.7	1.001	405,300	552,879	696,115	20.2	0.2	0.9	0.8	0.9	2.0	2.7
Lubbock	20	2.1	0.999	290,805	352,125	410,896	16.2	1.6	2.3	2.2	2.4	3.5	4.2
McAllen ^k	12	1.3	1.050	774,769	1,159,407	1,553,142	24.3	0.4	1.0	0.9	1.1	2.0	2.6
San Antonio ^l	20	1.9	1.010	2,142,508	2,801,937	3,387,802	21.0	1.1	1.8	1.7	1.8	2.8	3.5
Waco	20	2.6	1.014	252,772	291,035	325,432	19.7	1.2	1.9	1.8	2.0	3.0	3.7

^a Relative risk; ^b 2010 US Census data; ^c Daily mean temperature; ^d Emission Scenario (IPCC 2000); ^f Austin-Round Rock; ^g Beaumont-Port Arthur; ^h Brownsville-Harlingen; ⁱ Dallas-Fort Worth-Arlington; ^j Houston-The Woodlands-Sugar Land; ^k McAllen-Edinburg-Mission; ^l San Antonio-New Braunfels.

Table 2. Summary of projected cold-related mortality estimates in 12 major Texas Metropolitan Areas under different emission scenarios in 2000s (baseline), 2050s and 2080s.

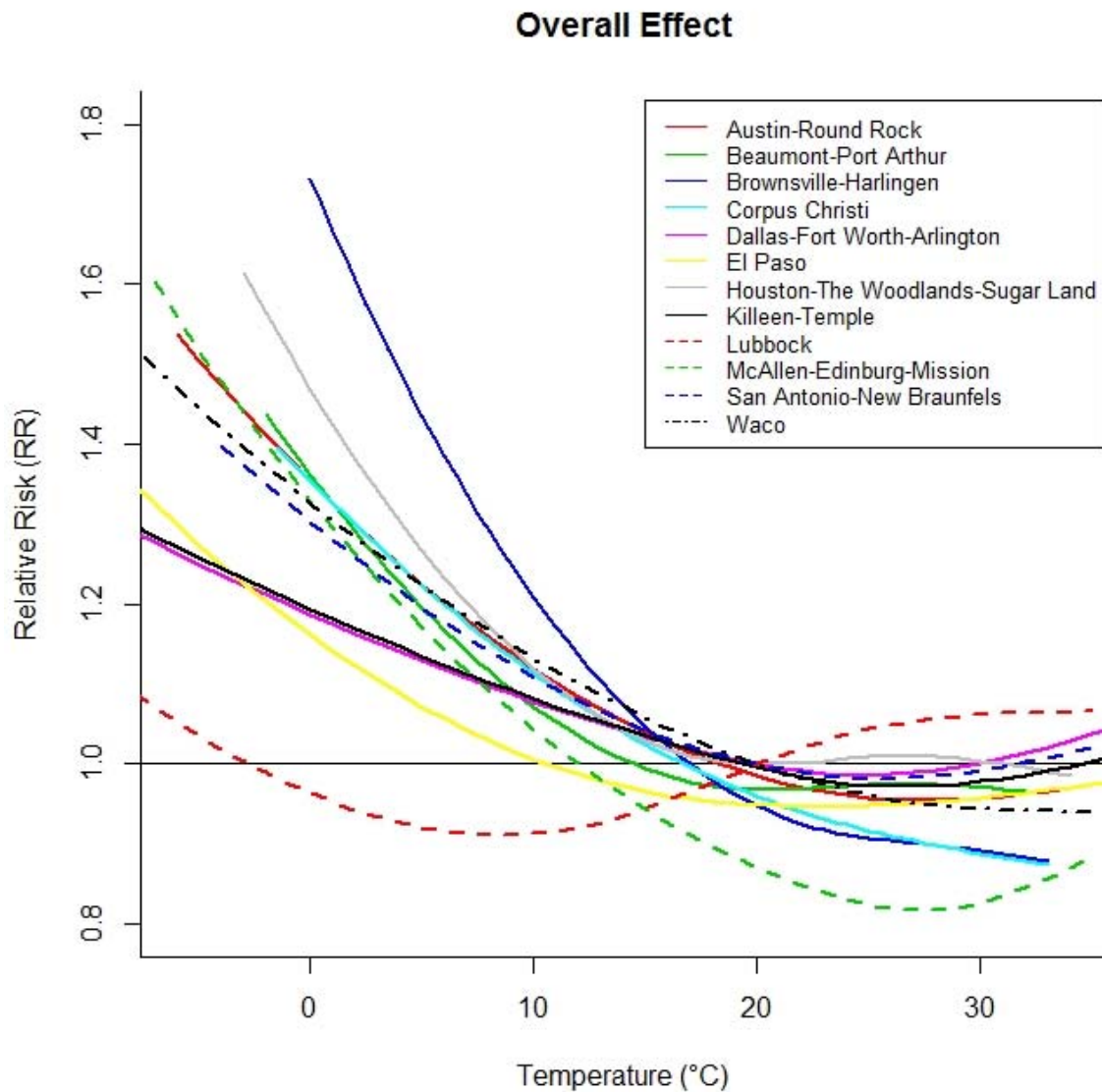
	Annual Cold days					Annual Excessive Cold Deaths (counts)					Annual Attributable Mortality Rate ^c				
	Baseline	2050s		2080s		Baseline	2050s		2080s		Baseline	2050s		2080s	
		B1	A2	B1	A2		B1	A2	B1	A2		B1	A2	B1	A2
Austin ^d	142.2	113.8	106.2	103.3	85.0	205.1	366.5	330.4	316.4	241.5	15.5	11.3	10.2	9.7	7.4
Beaumont ^e	80.8	64.2	58.2	55.7	42.7	58.1	56.8	50.4	47.5	34.0	14.7	11.4	10.1	9.5	6.8
Brownsville ^f	55.2	42.6	38.1	36.7	27.1	32.7	50.5	43.8	41.5	29.2	9.6	7.0	6.1	5.7	4.0
Corpus Christi	75.3	61.0	55.4	53.0	41.0	51.2	52.5	46.0	43.8	31.5	12.7	9.6	8.5	8.0	5.8
Dallas ^g	178.3	169.9	162.5	160.0	139.0	528.8	1029.5	955.9	929.6	763.7	10.0	9.6	8.9	8.6	7.0
El Paso	82.1	75.1	68.7	65.0	47.4	41.6	67.9	59.2	55.4	36.4	5.9	5.3	4.7	4.3	2.8
Houston ^h	148.2	130.3	122.8	120.1	100.2	1105.2	1848.4	1690.1	1630.8	1275.1	22.8	18.6	17.0	16.3	12.7
Killeen-Temple	155.2	153.8	146.3	143.6	123.3	3.7	7.5	6.8	6.6	5.3	1.1	1.1	1.0	1.0	0.8
Lubbock	215.9	196.1	189.7	187.7	167.2	-1.3	-1.8	-1.7	-1.6	-1.4	-0.5	-0.4	-0.4	-0.4	-0.3
McAllen ⁱ	17.4	14.2	12.0	11.5	7.9	16.5	35.5	30.0	28.1	18.3	2.7	2.3	1.9	1.8	1.2
San Antonio ^j	151.0	135.1	128.3	125.7	106.4	324.6	529.6	485.5	468.0	369.3	18.3	15.7	14.4	13.8	10.9
Waco	173.5	158.6	151.5	148.8	128.6	104.5	127.1	117.6	113.8	92.2	44.9	39.2	36.2	35.0	28.3
Overall average	122.9	109.5	103.3	100.9	84.6	205.9	347.5	317.8	306.7	241.3	13.1	10.9	9.9	9.4	7.3

^aBaseline referred to 1990-2000; ^bEmission Scenario (IPCC 2000); ^cAnnual attributable mortality rate number per 100,000; ^dAustin-Round Rock; ^eBeaumont-Port Arthur; ^fBrownsville-Harlingen; ^gDallas-Fort Worth-Arlington; ^hHouston-The Woodlands-Sugar Land; ⁱMcAllen-Edinburg-Mission; ^jSan Antonio-New Braunfels.

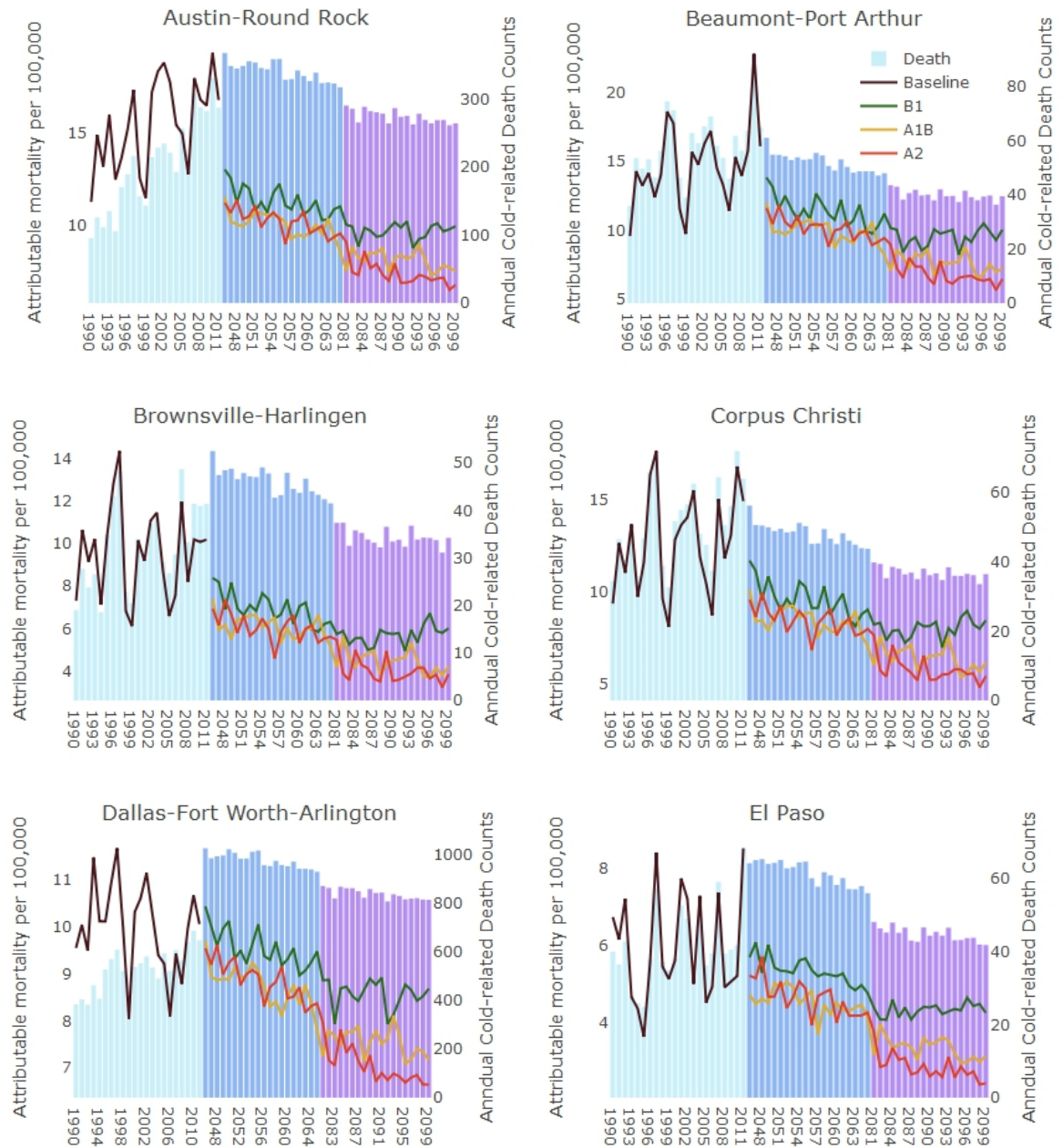
Appendices

Appendix C: Journal Article III Supplemental Materials

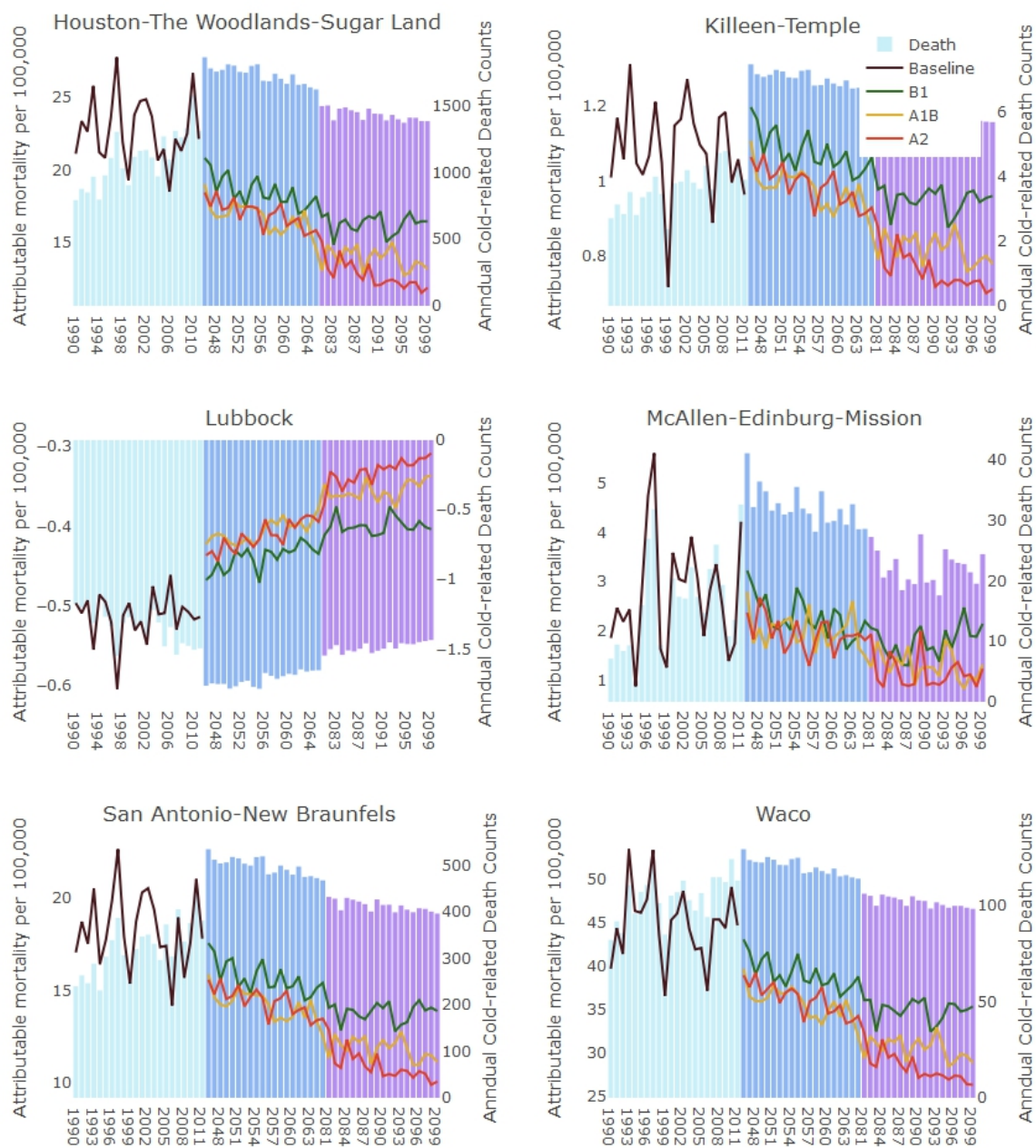
Supplemental Figure 1. The MSA-specific linear-threshold exposure-response relationships. Relative risk (RR) of all-cause mortality was examined with daily mean temperature using single threshold distributed lag non-linear with lag up to 25 days. RR with reference at 12 to 20 degree Celsius, varied by MSAs.



Supplemental Figure 2 Estimated mortality impacts attributable to cold temperatures in baseline (1990-2011), 2050s (2046-2065) and 2080s (2081-2099) under three emissions scenarios (SRESB1, SRESA1B and SRESA2), in corperating population projection in 12 Texas metropolitan areas.



Supplemental Figure 2 (continued)



Supplemental Table 1. List of BCCA CMIP3 projection ensembles used in the study with number of runs under each emission scenario defined in IPCC 2000.

WCRP CMIP3 Climate Modeling Group	WCRP CMIP3 Climate Model ID	SRESA2	SRESA1B	SRES B1
Canadian Centre for Climate Modeling and Analysis, Canada	CGCM3.1 (T47)	<i>1-3</i>	<i>1-3</i>	<i>1-3</i>
Meteo-France/Centre National de Recherches Meteorologiques, France	CNRM-CM3	<i>1</i>	<i>1</i>	<i>1</i>
U.S. Dept. of Commerce/NOAA/ Geophysical Fluid Dynamics Laboratory, USA	GFDL CM2.0	<i>1</i>	<i>1</i>	<i>1</i>
U.S. Dept. of Commerce/NOAA/ Geophysical Fluid Dynamics Laboratory, USA	GFDL CM2.1	<i>1</i>	<i>1</i>	<i>1</i>
Institut Pierre Simon Laplace, France	IPSL-CM4	<i>1</i>	<i>1</i>	<i>1</i>
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change, Japan	MIROC3.2 (medres)	<i>1-2</i>	<i>1-2</i>	<i>1-2</i>
Meteorological Institute of the University of Bonn, Meteorological Research Institute of the Korean Meteorological Association, Germany/Korea	ECHO-G	<i>1-3</i>	<i>1-3</i>	<i>1-3</i>
Max Planck Institute for Meteorology, Germany	ECHAM5/ MPI-OM		<i>1</i>	<i>1</i>
Meteorological Research Institute, Japan	MRI CGCM2.3.2	<i>1-5</i>	<i>1-5</i>	<i>1-5</i>
Number of BCCA Climate Projections = 53		<i>17</i>	<i>18</i>	<i>18</i>

CHAPTER V

SYNTHESIS

Summary of Conclusions from Previous Chapters

This dissertation shows that cold weather generally increases health risks significantly in Texas and the cold effects varied with MSAs, age groups and cause-specific diseases. As we hypothesized, we found the risk of cold-mortality increased as the latitude decrease. However, there was no clear spatial pattern of the association between cold and EHA that is associated with latitude as we have seen in mortality. With that being said, latitude explained a substantial part of heterogeneity between-MSA for respiratory diseases and pneumonia, although no significant effect modification were observed. The very elderly population (aged 75 and older) was the most vulnerable population in both cold-mortality and EHA associations. The strongest cold effect was found in the mortality risk for heart diseases and EHA risk for respiratory diseases. Cold effects were generally more prominent with longer lag days (up to 25 days) among all-cause and cause-specific mortality/EHAs except EHAs for IHD and MI, which were associate with relatively shorter lag days. We found although the annual cold-mortality rates reduced with projected temperature under climate change, the number of deaths attributable to cold temperature increased largely with projected population through the end of the century. In general, Texas experiences a substantial mortality burden attributable to cold temperature annually with current weather patterns. Public health planning to reduce cold impacts will remain important in Texas. This is the first multi-city study of the association between cold weather (cold temperature and cold wave) and health outcomes (mortality and morbidity) with over 20 years of study period in the southern U.S.

Strengths and Limitations

There are some limitations must be acknowledged. The primary limitation of this dissertation research is potential exposure misclassification. We used the temperature exposure from a single weather station per MSA rather than using personal exposures. It is usually impractical for population-based epidemiological studies using personal exposure due to cost and logistic reasons. We used spatial-temporal kriging interpolation for exposure at a finer scale, however, this may introduce more uncertainties due to the relatively small sample size of weather stations in Texas.

Another major limitation is ecologic fallacy (or aggregation bias), that we did not use individual-level characteristics, instead we included MSA-level predictors (e.g., percentage of population living in poverty, percentage of black population, percentage of Hispanic population, etc.) in the meta-analysis to explore the potential effect modifications. However, we did considered age in this study as it is a crucial indicator of vulnerable population.

Furthermore, we assume the temperature-mortality curve will remain the same through then end of the century and did not include future adaptation in our projected estimates. The prevalence of HVACs, severe weather alert system, as well as gradual physiological adaptation could ameliorate the exposure to temperature stress. However, the distribution of HVACs may reflect socioeconomic status and increase reliance of HVACs may imply an exacerbated energy consumption. The direction of effect modification on cold-related mortality from these adaptations remained unsure. Future studies are needed to be done with the consideration with adaptation.

The last limitation is the population projection for Texas beyond 2050s is assumed to be constant throughout 2080s. Texas was reported to be the largest numeric increase in population states according to the latest U.S. Census Bureau estimates, however the nation's overall growth rate is now at its lowest point since the 1940s.^{37,38} Although the bias direction of future population projection remains unsure, we believe this study can still provide a comprehensive picture of future cold weather related health impacts under climate change.

Some strengths of this study include the use of a population-based data that covered all-age cases throughout the state of Texas for over a decade study period. Previous studies conducted in the U.S. mostly focus at elderly or using data before the early 2000s. Our study includes more recent cold events and perform future projection under climate change. Furthermore, the climate change projection of temperature-related health outcomes were more focused on regional or global trends using cluster analysis, however, with the aim of providing actionable evidence to local policymakers, we provided detail assessment in each studied MSAs, as the public health burdens varied widely across MSA. Also, to address uncertainty related to climate, we included all 9 climate models with a total of 53 runs under three greenhouse gas scenarios to account for the variability in projected temperatures. This is the most comprehensive cold-related mortality and morbidity study with future public health burden projected in Texas.

Recommendations for Future Studies

There are many possible extensions to this dissertation. First, projections of cause-specific and age-stratified mortality, morbidity should be performed. Cold effects were varied by cause-specific and age groups, thus projections on cause-specific health outcomes such as hospital admissions in respiratory and cardiovascular subtypes for different age group populations to make predictions more optimally for the corresponding vulnerable populations.

Second, projections of the cold wave effect should be measured for mortality and morbidity. Cold waves were defined using percentile based definitions instead of using absolute cut off thresholds, moreover, with a lingering period of cold waves (extended seven days from the last cold wave day), projected cold wave days may not necessarily decreased over the century. Nevertheless, the cold wave effects under future climate scenarios remain poorly understand.

Third, future studies may consider using different forms of temperature data to better characterize the exposures. As mentioned above, one of the major limitations in investigating the association between temperature and health outcomes were exposure misclassification. A considerable increase in the availability of remote sensing data in the past decade has gaining popularity in the fields of meteorology and climatology as a tool to calculate land surface temperature (LST), which can provide increased spatial coverage compare to paucity of in-situ weather stations.³⁹

Last but not least, potential cold effect modifying predictors should be further explored and adaptation should be included for projections of future cold-related health impacts.

Currently, considerations for how populations will adapt to the climate change in the near or far future are often not included in the studies.⁴⁰ The prevalence of HVAC, health care, urban infrastructure etc., may play an important role in future adaptation to climate change. In addition, a range of new “pathways”, shared socioeconomic pathways (SSPs), examine how societal choices will affect greenhouse gas emission are feeding into the latest climate models for the IPCC sixth assessment report. These SSPs include socioeconomic and environmental conditions as affected by both climate change and climate policy and could be used for adjustments to human adaptation for public health burden projections.

HUMAN SUBJECTS CONSIDERATIONS

This research is a secondary data analysis using existing, de-identified data from Texas Department of State Health Service. No individuals were contacted nor there any primary data collection. This dissertation is part of two parent studies previously approved by the Committee for the Protection of Human Subjects (CPHS) of The University of Texas Health Science Center at Houston (HSC#: HSC-SPH-14-0240 and HSC-SPH-14-0783).

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