Environmental Research 169 (2019) 139–146

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Impacts of cold weather on emergency hospital admission in Texas, 2004–2013

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ARTICLE INFO

Keywords:
Cold wave
Cold weather
Emergency hospital admission
Heart disease
Temperature

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 °C (°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.

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

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https://doi.org/10.1016/j.envres.2018.10.031

Received 22 February 2018; Received in revised form 25 October 2018; Accepted 27 October 2018

Available online 30 October 2018

0013-9351/

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 °C (^{0}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 adaptions 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 (Fig. 1).

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, 2004–2013). 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; Turner et al., 2012).

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 Fig. 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:

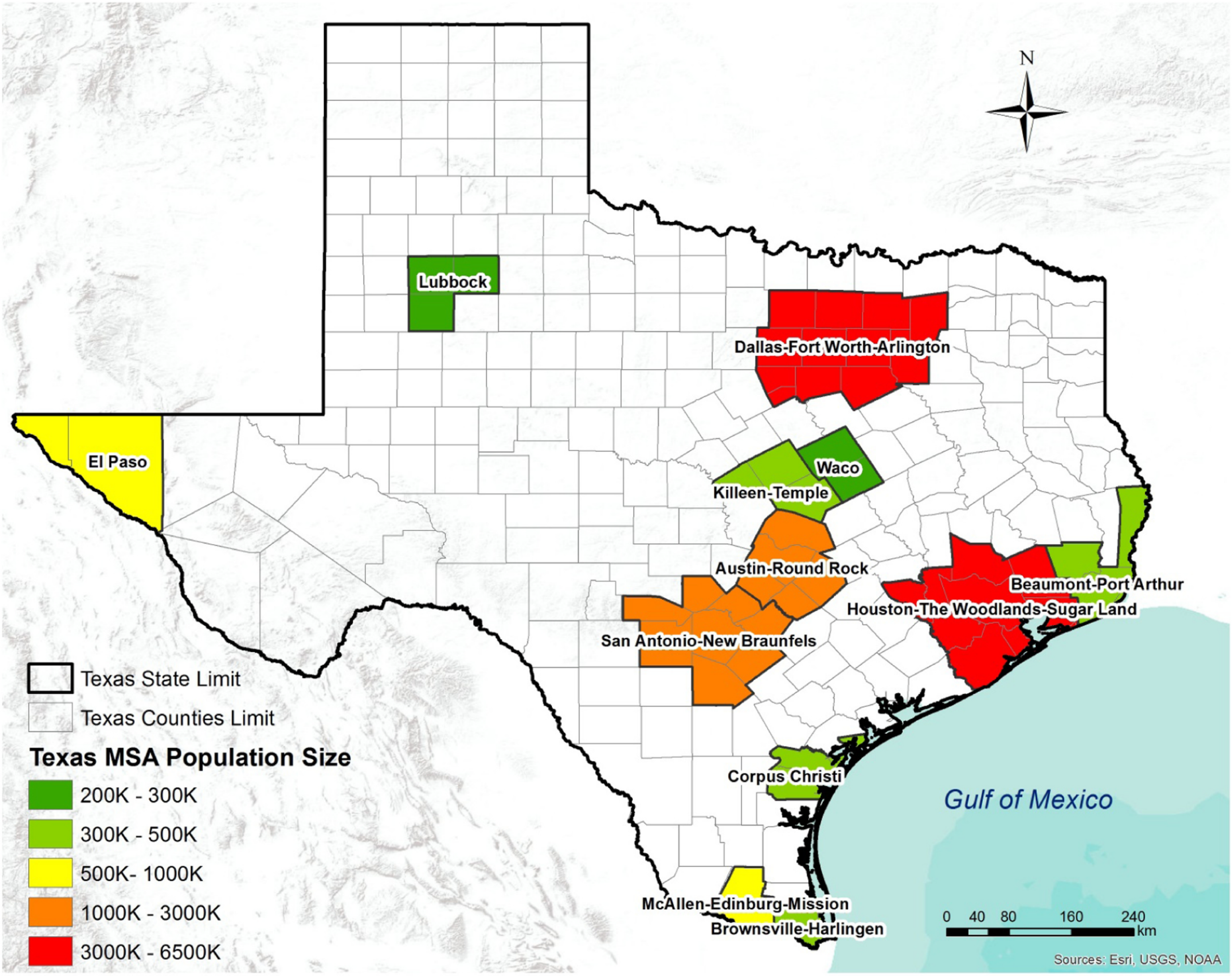

Fig. 1. Twelve Texas Metropolitan Statistical Areas (MSAs) in the study. MSAs were selected based on the size of population and availability of weather and air pollution data during the 10-year study period.

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

Where Y_t is the counts of EHA on day t; α is the intercept; $cb(meTMP_{t,l})$ 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 modeled 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 Eq. (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 and 25 ^{0}C (visually observed from the preliminary DLNM results, Supplemental Fig. A1.) and repeated the model presented in Eq. (1) with potential cold thresholds from 10 to 25 by 0.1 ^{0}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 ^{0}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)× 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. (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.

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 temperature (°C)[a]	Average daily all-cause EHA[b]	Average daily all-cause EHA by age group Mean (Min, Max)			Average daily EHA by disease Mean (Min, Max)		Total counts EHA[c]	Cold wave days	Population size[d]	Cold thresholds (°C)
	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	1716,289	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)	1058 (38, 1478)	721.3 (29, 983)	132.8 (5, 240)	203.7 (4, 376)	117.4 (6, 190)	113.1 (8, 310)	3864,102	310	6426,214	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)	3628,070	251	5920,416	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)	1118,559	269	2142,508	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

[a] Average daily mean temperature throughout the study period.
[b] Emergency hospital admissions.
[c] Total counts of EHA throughout the study period.
[d] Based on 2010 U.S. Census data.
[e] Cardiovascular disease.
[f] Respiratory diseases.

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. (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, 20–25 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 Bureau, 2014). 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 1058 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).

Fig. 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%]) (Fig. 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%

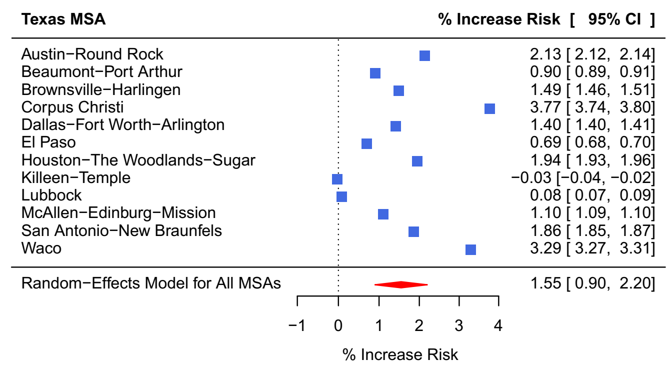

Fig. 2. Meta-analysis for cold effects on all-cause emergency hospital admissions at lag 0–25 in 12 major Texas MSAs during 2004–2013.

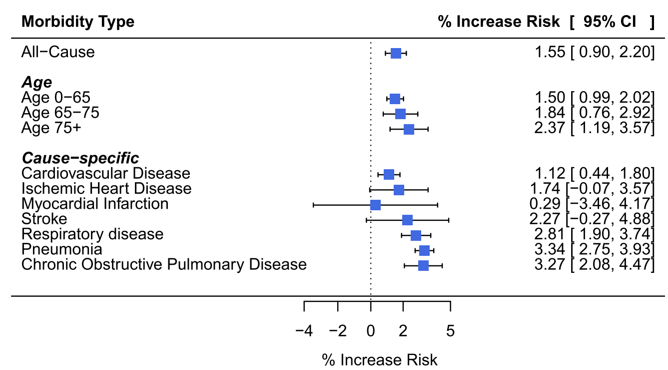

Fig. 3. Pooled estimations of cold effect to age-stratified and cause-specific emergency hospital admissions at State-level in Texas.

[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).

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

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 1st percentile Cold wave	Below 3rd percentile Cold wave	Temperature	Below 1st percentile Cold wave	Temperature	Below 3rd 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)

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

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 11.1 ^{0}C 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 1 ^{0}C 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 Fig. 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 sees that the overall cold wave effects in Texas MSAs were observed more during less intensive cold waves (daily mean temperature below 3st percentile of the annual mean temperature for two or more consecutive days with an extended 7 days period) compared to intense cold waves (below 1rd 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, 2009). 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 accounted 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 (The 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.

Acknowledgments

The research described in this paper was supported through the start-up funds provided by The University of Texas Health Science Center at Houston (UTHealth) School of Public Health. This paper does not necessarily reflect the views of the UTHealth School of Public Health.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envres.2018.10.031.

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