

# Mortality risks during extreme temperature events (ETEs) using a distributed lag non-linear model

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**Abstract** This study investigates the relationship between all-cause mortality and extreme temperature events (ETEs) from 1975 to 2004. For 50 U.S. locations, these heat and cold events were defined based on location-specific thresholds of daily mean apparent temperature. Heat days were defined by a 3-day mean apparent temperature greater than the 95th percentile while extreme heat days were greater than the 97.5th percentile. Similarly, calculations for cold and extreme cold days relied upon the 5th and 2.5th percentiles. A distributed lag non-linear model assessed the relationship between mortality and ETEs for a cumulative 14-day period following exposure. Subsets for season and duration effect denote the differences between early- and late-season as well as short and long ETEs. While longer-lasting heat days resulted in elevated mortality, early season events also impacted mortality outcomes. Over the course of the summer season, heat-related risk decreased, though prolonged heat days still had a greater influence on mortality. Unlike heat, cold-related risk was greatest in more southerly locations. Risk was highest for early season cold events and decreased over the course of the winter season. Statistically, short episodes of cold showed the highest relative risk, suggesting unsettled weather conditions may have some relationship to cold-related mortality. For both heat and cold, results indicate higher risk to the more

extreme thresholds. Risk values provide further insight into the role of adaptation, geographical variability, and acclimatization with respect to ETEs.

**Keywords** Mortality · Distributed lag non-linear model · Heat wave · Cold spell · Extreme temperature events

## Introduction

Studies have shown changes in the frequency, duration, and seasonal timing of heat waves and cold spells (Kuglitsch et al. 2010; Gosling et al. 2009; Ding et al. 2010). These changes are important as extreme temperature events (ETEs) have been shown to impact physiological processes and human health outcomes. In heat events, increases in cardiovascular and respiratory deaths have been observed (e.g., Ma et al. 2014). Cold-related mortality increases are also linked to cardiovascular and respiratory causes (e.g., Zeka et al. 2014; Braga et al. 2002).

Despite higher mortality rates in winter, fewer studies explicitly investigate cold-related health issues (Allen and Sheridan 2014; Morabito et al. 2014; Ma et al. 2013; Dushoff et al. 2006). There are many reasons for this including health care accessibility, pre-existing conditions, and air quality which play a role and add complexity to cold-related health outcomes (Analitis et al. 2008; Basu and Samet 2002). Additionally, a more delayed exposure-response lag effect has been cited by previous research (Curriero et al. 2002; Anderson and Bell 2009; Anderson and Bell 2011). This lagging refers to the delay time between exposure to environmental conditions (i.e., extreme temperature) and the body's physiological response to it (i.e., sickness or death). Overall, excessive deaths associated with heat are often acute while cold-related relationships are generally delayed, appearing more

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broadly over longer periods of time. As a result, the weather-health relationships are often difficult to discern and vary through both time and space (Wu et al. 2013; Morabito et al. 2012; Anderson and Bell 2009).

One difficulty in assessing the impact of ETEs is the various ways in which these events are defined. Using synoptic climatological approaches, offensive weather types have been linked to elevated mortality during the warm season (Sheridan 2002; Greene et al. 2011). Models focused on behavior as well as thermo-physiological and heat exchanges have also been used in temperature-related studies (Blazejczyk et al. 2012; Jendritzky et al. 2012). Thresholds of ambient air and apparent temperature have been used (Curriero et al. 2002; Son et al. 2012; Barnett et al. 2010), although variability in such thresholds exists. Similar to differences in ETEs definitions, seasonal definition also varies. Aggregated to the monthly scale, seasons often reflect some variation of meteorological or astronomical winter as defined by the declination of the sun, although variation exists, spatio-temporally as well as within season. While many studies fail to consider the spatial or temporal variability of seasons, the implications of seasonal changes are important and play a role in various bioclimatological processes (Allen and Sheridan 2015).

While research shows vulnerability associated with ETEs (Bobb et al. 2014; Morabito et al. 2012; Hondula et al. 2012; Koppe et al. 2004), the relationship between human health and environmental conditions depends on both climate and non-climate factors (e.g., Barnett 2007; Anderson and Bell 2009). Temperate regions often feel the impact of cold-related issues more than cooler regions that are acclimated to such temperatures. Infrastructure, adequate clothing, and familiarity of environmental conditions serve as protective factors to cold-related mortality in cold regions (Keatinge 2002; Eurowinter Group 1997). Conversely, colder regions have been found to be more vulnerable to extreme heat episodes for the same reasons (Keatinge et al. 2000; Curriero et al. 2002; Anderson and Bell 2009).

## Material and methods

### a. Mortality data

County-level, daily all-cause mortality data (1975–2004) were obtained through the National Center for Health Statistics. Mortality data were aggregated to the U.S. metropolitan statistical areas (MSA). All U.S. metropolitan areas (MSAs) with a population greater than 1 million were used in this research. In total, 51 locations met these criteria, but San Jose was disregarded due to data quality issues (Table 1).

Across the time period, there were 46 instances in which events (e.g., plane crash) impacted mortality. By examining 5-year centered rolling averages, daily z-scores were calculated

**Table 1** Mortality data were obtained for each of the 50 largest U.S. metropolitan statistical areas

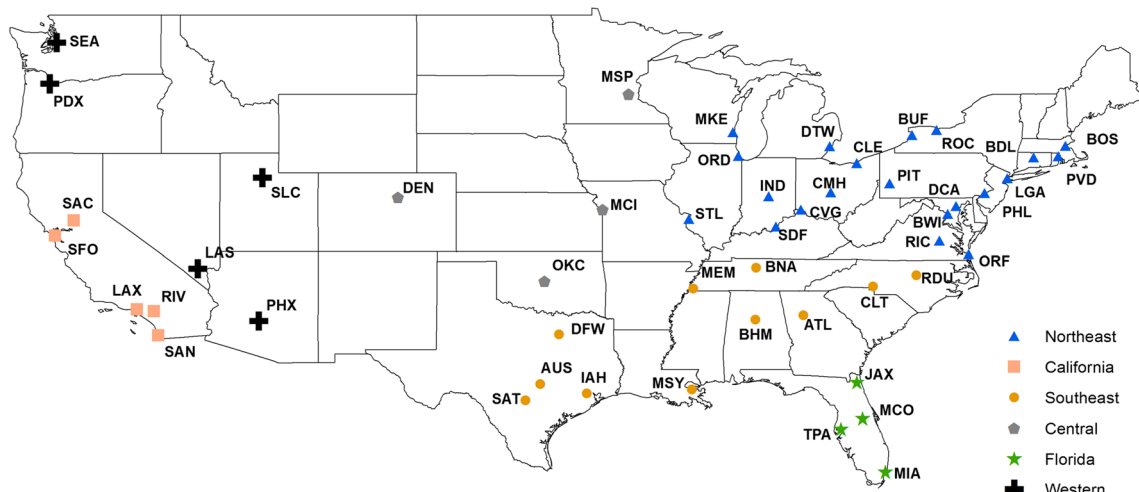
MSA	2010 Population	MSA	2010 Population
New York	19,567,410	San Antonio	2,142,508
Los Angeles	12,828,837	Orlando	2,134,411
Chicago	9,461,105	Cincinnati	2,114,580
Dallas	6,426,214	Cleveland	2,077,240
Philadelphia	5,965,343	Kansas City	2,009,342
Houston	5,920,416	Las Vegas	1,951,269
Washington	5,636,232	Columbus	1,901,974
Miami	5,564,635	Indianapolis	1,887,877
Atlanta	5,286,728	Austin	1,716,289
Boston	4,552,402	Virginia Beach	1,676,822
San Francisco	4,335,391	Nashville	1,670,890
Detroit	4,296,250	Providence	1,600,852
Riverside	4,224,851	Milwaukee	1,555,908
Phoenix	4,192,887	Jacksonville	1,345,596
Seattle	3,439,809	Memphis	1,324,829
Minneapolis	3,348,859	Oklahoma City	1,252,987
San Diego	3,095,313	Louisville	1,235,708
St. Louis	2,787,701	Hartford	1,212,381
Tampa	2,783,243	Richmond	1,208,101
Baltimore	2,710,489	New Orleans	1,189,866
Denver	2,543,482	Buffalo	1,135,509
Pittsburgh	2,356,285	Raleigh	1,130,490
Portland	2,226,009	Birmingham	1,128,047
Charlotte	2,217,012	Salt Lake City	1,087,873
Sacramento	2,149,127	Rochester	1,079,671

and compared to expected mortality values for that day of the year. Days which exceeded a z-score of 5 and were not directly related to heat were removed from the analysis. Further investigation showed that most of these events were associated with airplane crashes, tornadoes, or holidays (Online Resource 1).

### b. Atmospheric data

For each MSA, a single weather station was chosen to represent weather conditions (Fig. 1). Though atmospheric conditions may vary across the MSA (e.g., urban heat island), single observations are often used in climate-health research. Using four time daily observations (4, 10, 16, 22 LST), daily mean apparent temperature values were calculated (Eq. 1). Apparent temperature was chosen as it represents a wide range of physiological conditions the human body may experience by incorporating air temperature ( $T_a$ , °C), vapor pressure ( $P_v$ , Kpa), and wind speed ( $v_{10}$ , m/s) into a single variable (Steadman 1994).

$$AT = T_a + 3.30P_v - 0.7v_{10} - 4 \quad (1)$$



**Fig. 1** Represented by a single airport, locations were geographically clustered for comparison purposes

Using daily mean apparent temperature, thresholds were independently calculated for each of the locations based upon the full period of record (1975–2004). Therefore, the definition of ETEs varied spatially but not temporally. Additionally, rather than defining a ETE by a single day, 3-day means were calculated whereby day 0 was averaged with the previous 2 days. When the 3-day mean was greater than the 95th percentile, the day was classified as a heat day. Cold days were days in which the 3-day mean apparent temperature was less than the 5th percent. Extreme cold (2.5th) and heat (97.5th) thresholds were also used to account for the variability in an event’s strength (Table 2). A similar methodology has been used in prior studies (Saha et al. 2014; Zacharias et al. 2014) to determine anomalous temperature events.

To account for duration, ETEs were subdivided into short and long periods. Short events were defined as events lasting no more than 2 days. Long events include the third day onwards of events that were at least 3 days. Therefore, by definition, all long events started as short events and included the full length of the ETE. This study defined summer as June–August and winter as December–February. In order to assess the seasonal influence, subdivided periods classified early and late season. January 15 and July 17 divided early and late winter and summer seasons, respectively.

**c. Distributed lag non-linear model**

In order to depict the non-linear, delayed effects and the relationship to health outcomes in a time series, a distributed lag non-linear model (DLNM) was developed (Gasparrini et al. 2010; Armstrong 2006; Gasparrini and Armstrong 2011). Developed as a time series analysis, the statistical model considers the health effects of exposures to environmental factors such as air pollution and/or temperature. A DLNM

simultaneously evaluates both the non-linear exposure-response relationships and delayed effects with time.

Unlike some other studies using DLNM (e.g., Gou et al. 2011; Morabito et al. 2012; Barnett et al. 2012), this research evaluated the mortality responses associated with specific ETEs which were determined a priori to analysis. For each ETE, binary classifications were determined based upon event duration (short or long) and seasonal timing (early or late). As a result of both duration and seasonal considerations, four binaries were independently analyzed: short-early, long-early, short-late, long-late for heat, cold, extreme heat, and extreme cold. Each binary represented a set of extreme temperature days ( $ETE_{subset}$ ) based on a specific criterion; these days were used as predictors of daily mortality. For example, all short-early heat days were compared against all non-heat days. Relative risk values were computed based upon DLNM iterations for each of the classifications.

The model used a quasi-Poisson regression to model the daily counts of deaths as a function of ETEs:

$$\begin{aligned}
 ETE_{subset} &= \begin{cases} 1 & \text{if ETE exists} \\ 0 & \text{else} \end{cases} \\
 Y_{subset} &\sim \text{quasipoisson}(ETE_{subset}) \\
 \text{Log}(ETE_{subset}) &= \alpha + S(\text{time}_{year}, \text{var.df} = 4) \\
 &+ S(\text{time}_{JulianDay}, 7*30) + \text{DOW}
 \end{aligned}
 \tag{2}$$

where  $ETE_{subset}$  is a binary representative of heat or cold day;  $Y_{subset}$  is the observed daily mortality on day  $_{subset}$ ;  $\alpha$  is the intercept;  $\text{time}_{year}$  represents long-term trends;  $\text{time}_{JulianDay}$  represented seasonal trends; and DOW was a dummy variable representing day of week (Eq. 2).  $S$  is the natural cubic spline function whereby var.df is the degree of freedom (df) for each variable. Confounders were accounted for as daily mortality varies by season, year, and day of week. Four

**Table 2** Apparent temperature 3-day thresholds for heat, extreme heat, cold, and extreme cold

Region	Station	Heat	XHeat	Cold	XCold
Northeast	Baltimore	28.4	29.8	-8.6	-11.4
	Boston	24.5	26.2	-12.6	-15.5
	Buffalo	23.3	24.8	-15.5	-18.2
	Chicago	26.1	27.9	-15.7	-19.6
	Cincinnati	27.3	28.8	-11.2	-14.5
	Cleveland	25.2	26.7	-13.9	-16.9
	Columbus	26.9	28.5	-12.1	-15.3
	Detroit	25.3	26.9	-14.6	-17.5
	Hartford	25.6	27.2	-12.7	-15.5
	Indianapolis	27.3	28.9	-12.9	-16.4
	Louisville	29.3	30.8	-8.8	-12
	Milwaukee	24.4	26.2	-16.8	-20.7
	New York	27	28.5	-10.7	-13.5
	Philadelphia	28	29.5	-9.6	-12.3
	Pittsburgh	25.1	26.6	-13	-16
	Providence	24.9	26.5	-11.7	-14.6
	Richmond	29.4	30.7	-5.9	-8.5
	Rochester	24.2	25.9	-15.1	-17.9
	St. Louis	30	31.5	-11.1	-14.8
	Virginia Beach	29.4	30.6	-5.2	-7.8
Washington	29.4	30.7	-7.4	-10.2	
	<i>Northeast <math>\alpha</math></i>	26.7	28.2	-11.7	-14.7
	<i>Northeast <math>\sigma</math></i>	2.0	1.9	3.1	3.3
California	Los Angeles	21.6	22.8	7.5	6.1
	Riverside	26.1	27.3	4	2.5
	Sacramento	24.2	25.8	1.6	0.1
	San Diego	23	24.3	8.7	7.5
	San Francisco	16	17.4	3.4	2.2
		<i>California <math>\alpha</math></i>	22.2	23.5	5.0
	<i>California <math>\sigma</math></i>	3.4	3.4	2.6	2.7
Southeast	Atlanta	29.3	30.4	-4	-6.7
	Austin	31.8	32.5	0.5	-2.5
	Birmingham	30.6	31.5	-2.7	-5.4
	Charlotte	29.3	30.4	-3.6	-5.9
	Dallas	31.9	32.8	-2.9	-5.7
	Houston	32.9	33.6	2.4	-0.2
	Memphis	31.9	33.1	-4.7	-7.6
	Nashville	30	31.2	-6.2	-9.4
	New Orleans	32.5	33.3	2.6	-0.1
	Raleigh	29.3	30.4	-4.5	-7
	San Antonio	31.2	31.9	1.7	-1.1
	<i>Southeast <math>\alpha</math></i>	31.0	31.9	-1.9	-4.7
	<i>Southeast <math>\sigma</math></i>	1.3	1.2	3.0	3.0
Central	Denver	21.4	22.5	-12.2	-15.6
	Kansas City	28.7	30.3	-13	-17.3
	Minneapolis	24.9	26.9	-21.5	-25
	Oklahoma City	29.3	30.4	-8.2	-11.5
		<i>Central <math>\alpha</math></i>	26.1	27.5	-13.7

**Table 2** (continued)

Region	Station	Heat	XHeat	Cold	XCold	
Florida	<i>Central <math>\sigma</math></i>	3.2	3.2	4.8	4.9	
	Jacksonville	31.4	32.1	3.3	0.7	
	Miami	32.4	32.9	13.8	10.8	
	Orlando	31.5	32.2	7.7	4.9	
	Tampa	32.1	32.8	7.8	5.1	
		<i>Florida <math>\alpha</math></i>	31.9	32.5	8.2	5.4
		<i>Florida <math>\sigma</math></i>	0.4	0.4	3.7	3.6
Western	Las Vegas	31.3	32.6	-0.4	-2.3	
	Phoenix	34.8	35.8	5.6	3.8	
	Portland	20.4	22.2	-2.9	-5	
	Salt Lake City	23.8	24.9	-10	-12.4	
	Seattle	18.3	20	-3	-4.8	
		<i>Western <math>\alpha</math></i>	25.7	27.1	-2.1	-4.1
	<i>Western <math>\sigma</math></i>	6.3	6.1	5.0	5.2	

Regional means ( $\alpha$ ) and standard deviations ( $\sigma$ ) are also shown

degrees of freedom were assigned to the long-term trend line while 7 df/year were used to identify the seasonality curve. As noted by Gou et al. (2011), the options for DLNM such as degrees of freedom, maximum lag day, and cross-basis type are vast, and therefore, the decisions for DLNM may be chosen according to the best model fit. Although there is no consensus on the most appropriate lag structure, a 14-day lag model has been used often when accounting for cold-related mortality (Armstrong 2006; Gasparrini et al. 2010). Consequently, in this study, relative risk was computed based upon a 14-day lag to consider both the acute response of heat and the delayed response of cold. Various lags were considered (3-, 5-, 7-, 10-, 14-day), yet the differences in results were generally minimal.

For each subset of ETEs, a distributed lag non-linear model (dlnm package in R) assessed the cumulative impact of weather on mortality. Cumulative relative risks were assessed with the mean relative risk as well as the 95 % confidence intervals. Statistical significance was based upon the 95 % confidence intervals whereby if the minimum relative risk value was greater than 1.0, significance was assigned to the value. In addition to calculating risk for each of the 50 locations, six geographic regions were compared (Fig. 1).

## Results

### d. Heat and extreme heat events

Across the domain, California experienced the fewest heat and extreme heat days (Table 3). The southeast and central portions of the country recorded the most heat days while

**Table 3** Total number of cold, extreme cold, heat, and extreme heat days for each location. Regional means ( $\alpha$ ) and standard deviations ( $\sigma$ ) are also shown

Region	Station	Heat	XHeat	Cold	XCold	
Northeast	Baltimore	409	186	429	183	
	Boston	378	172	390	176	
	Buffalo	392	192	423	171	
	Chicago	431	191	491	192	
	Cincinnati	427	204	474	204	
	Cleveland	409	197	455	185	
	Columbus	407	191	476	186	
	Detroit	411	197	470	191	
	Hartford	407	204	431	176	
	Indianapolis	430	199	479	208	
	Louisville	418	217	462	210	
	Milwaukee	389	173	468	197	
	New York	378	189	418	171	
	Philadelphia	400	202	420	183	
	Pittsburgh	416	211	431	172	
	Providence	413	182	407	176	
	Richmond	429	191	434	181	
	Rochester	403	168	411	165	
	St. Louis	426	204	474	214	
	Virginia Beach	419	187	413	151	
Washington	409	197	442	176		
	Northeast $\alpha$	409.6	193.0	442.8	184.2	
	Northeast $\sigma$	15.3	12.2	28.1	15.5	
California	Los Angeles	302	125	338	164	
	Riverside	314	135	385	196	
	Sacramento	150	56	302	145	
	San Diego	370	180	369	190	
	San Francisco	358	164	433	207	
		California $\alpha$	298.8	132.0	365.4	180.4
	California $\sigma$	78.7	42.8	44.1	22.7	
Southeast	Atlanta	428	208	423	183	
	Austin	443	185	394	161	
	Birmingham	431	202	419	186	
	Charlotte	446	194	442	176	
	Dallas	436	197	397	181	
	Houston	427	181	373	158	
	Memphis	442	206	433	192	
	Nashville	443	200	446	186	
	New Orleans	415	174	370	156	
	Raleigh	453	187	433	175	
	San Antonio	387	184	379	164	
		Southeast $\alpha$	431.9	192.5	409.9	174.4
		Southeast $\sigma$	17.5	10.6	26.9	12.0
Central	Denver	454	174	368	169	
	Kansas City	445	176	467	196	
	Minneapolis	432	176	451	191	
	Oklahoma City	444	205	417	185	

**Table 3** (continued)

Region	Station	Heat	XHeat	Cold	XCold	
Florida	Central $\alpha$	443.8	182.8	425.8	185.3	
	Central $\sigma$	7.8	12.9	37.9	10.2	
	Jacksonville	404	155	348	136	
	Miami	324	131	365	160	
	Orlando	338	134	362	142	
	Tampa	360	166	365	139	
		Florida $\alpha$	356.5	146.5	360.0	144.3
		Florida $\sigma$	30.3	14.6	7.0	9.3
Western	Las Vegas	464	230	432	214	
	Phoenix	447	186	429	191	
	Portland	410	181	426	212	
	Salt Lake City	453	219	446	221	
	Seattle	414	181	407	196	
		Western $\alpha$	437.6	199.4	428.0	206.8
		Western $\sigma$	21.6	20.9	12.5	11.4

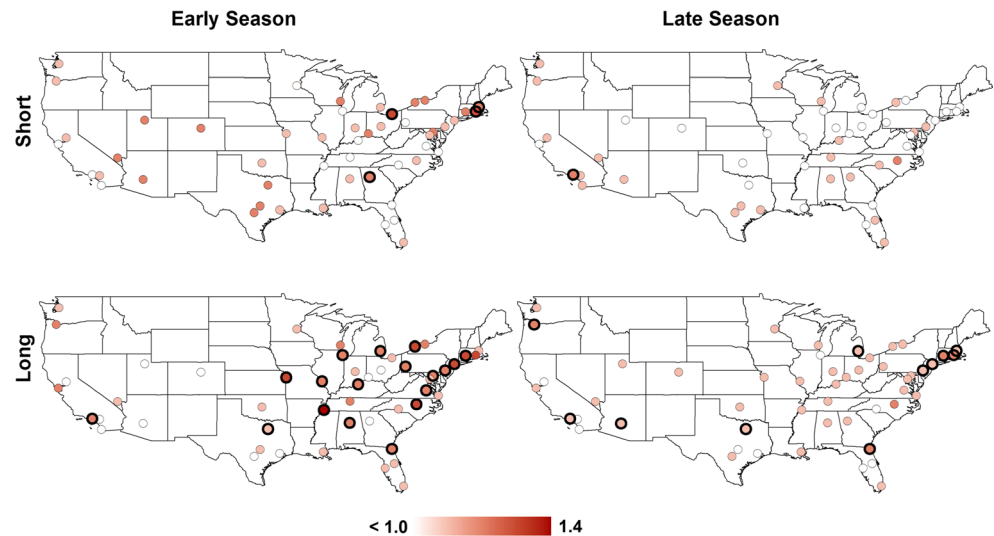
extreme heat was more variable. Las Vegas experienced the most heat and extreme heat days. Because of the location-specific thresholds, fewer warm ETEs were found in Florida.

Heat and extreme heat events showed elevated risk for early season events (Figs. 2 and 3). Despite this finding, only four locations for short-early heat and eight locations for short-early extreme heat events were found to be significant. Of the 50 locations, 40 showed relative risk values in excess of 1.0 for long-early heat days. Longer events during the first half of summer showed the most significant values for heat (18) and extreme heat (14) events compared to the other subsets. On average, relative risk values were also the highest for these events with 1.09 and 1.13 for heat and extreme heat, respectively (Table 4). This result supports the finding that more sustained events in the early part of the summer have a greater impact on human mortality. Comparing different thresholds of heat, more extreme days generally resulted in higher risk of mortality outcomes.

With respect to late season warm events, variability was found in terms of duration. Shorter events showed the lowest impact on mortality of all subsets. These short-late events also resulted in the fewest significant values across all permutations of heat (1) and extreme heat (4). However, comparing duration, the longer events still showed a higher risk compared to shorter events where significant values found for 11 locations. Across the 50 cities, an average (minimum, maximum) risk for long-late heat (1.04 [0.62, 1.59]) and extreme heat (1.06 [0.077; 1.61]) was shown (Table 4). Similar to the earlier ETEs, more extreme events showed higher risk, suggesting more deadly heat waves are those with higher apparent temperature thresholds.

Generally, Florida experienced lower risk for warm ETEs compared to other, more northern locations. Providence,

**Fig. 2** Mean cumulative relative risk values for heat days. Results are shown for short-early, long-early, short-late, and long-late heat criteria. *Darker color* represents higher relative risk and significant values are denoted with a *black circle*



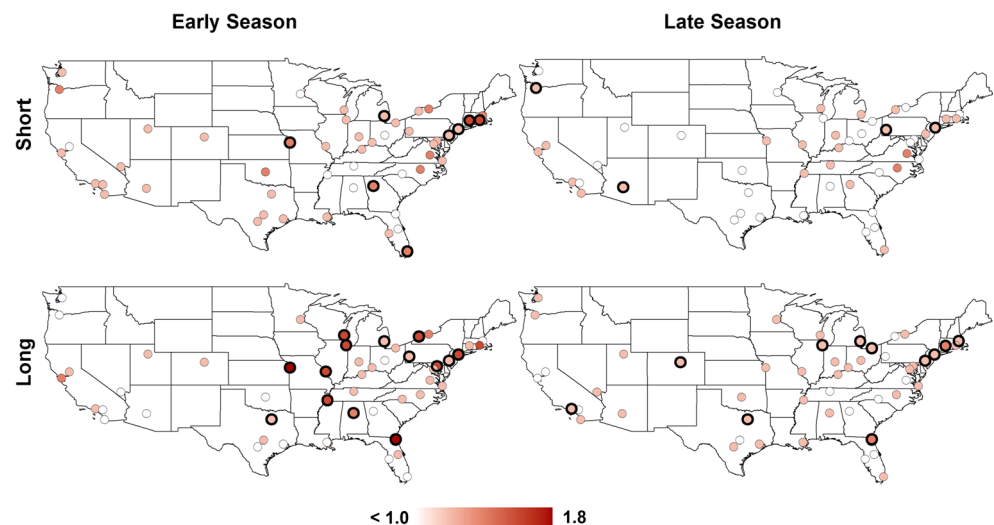
Hartford, and New York consistently showed the highest risk associated with heat and extreme heat events, with New York being the only location where all types of extreme heat events significantly impacted mortality. Given California's unique climate, it is not surprising that California showed variable results, with some locations showing elevated risk while others did not.

#### e. Cold events and extreme cold events

As with heat, locations in Florida had few cold ETEs. More variability was found in California where Los Angeles and San Francisco both showed few cold ETEs while the other locations experienced a higher number. While northeast locations recorded the greatest number of cold days, western locations consistently observed more extreme cold. With 491 cold days, Chicago experienced the most cold days while Salt Lake City experienced the most extreme cold days with 221.

Results from cold events indicate a strong relationship between early season events and increased risk for mortality (Figs. 4 and 5). Across the domain, average risk values were higher than heat counterparts. An average relative risk of 1.19 was found for short cold and 1.26 for extreme cold events. These short-lasting, early occurring events had the highest relative risk for any other subset of ETEs analyzed. In both instances, significant values were found for at least 30 locations. However, unlike heat, many of these values were not only found in the northeast. Similar significant results were found for long-early events, but with an average risk value of 1.10, the values were slightly lower than the shorter episodes of cold. With 33 significant values for cold and 15 for extreme cold, a majority of locations still showed a significant relationship between longer cold events and mortality. As with shorter events, geographic variability was found with the highest risks found in more southern locations.

**Fig. 3** Mean cumulative relative risk values for extreme heat days. Results are shown for short-early, long-early, short-late, and long-late extreme heat criteria. *Darker color* represents higher relative risk and significant values are denoted with a *black circle*



**Table 4** Regional comparison of mean cumulative relative risk values (minimum, maximum) for heat, extreme heat, cold, and extreme cold

Regions	Heat			
	Short-early	Long-early	Short-late	Long-late
Northeast	1.07 (0.73, 1.59)	1.13 (0.80, 1.61)	0.97 (0.77, 1.22)	1.05 (0.92, 1.27)
Southeast	1.04 (0.62, 1.56)	1.09 (0.78, 1.56)	1.03 (0.82, 1.45)	1.02 (0.88, 1.26)
Central average	1.00 (0.75, 1.30)	1.09 (0.87, 1.43)	0.97 (0.82, 1.15)	1.04 (0.96, 1.13)
Florida	1.00 (0.80, 1.23)	1.08 (0.95, 1.35)	0.98 (0.77, 1.17)	1.02 (0.86, 1.29)
Western	1.09 (0.85, 1.49)	1.02 (0.77, 1.45)	1.00 (0.68, 1.27)	1.06 (0.95, 1.21)
California	0.96 (0.75, 1.24)	1.05 (0.77, 1.51)	1.03 (0.80, 1.21)	1.00 (0.87, 1.21)
U.S. average	1.04	1.09	0.99	1.04
Total significant values	4	18	1	11
	XHeat			
Northeast	1.17 (0.79, 2.09)	1.20 (0.61, 2.46)	1.01 (0.62, 1.47)	1.07 (0.78, 1.45)
Southeast	1.09 (0.63, 1.99)	1.09 (0.55, 2.19)	1.03 (0.73, 1.78)	1.03 (0.77, 1.45)
Central average	1.12 (0.79, 1.67)	1.18 (0.81, 2.01)	0.99 (0.77, 1.30)	1.10 (0.912, 1.38)
Florida	1.04 (0.64, 1.40)	1.22 (0.78, 2.53)	0.96 (0.71, 1.21)	1.04 (0.78, 1.44)
Western	1.18 (0.78, 1.86)	0.91 (0.52, 1.55)	1.05 (0.72, 1.36)	1.08 (0.94, 1.31)
California	1.05 (0.68, 1.45)	1.03 (0.44, 1.74)	1.06 (0.84, 1.37)	1.00 (0.71, 1.29)
U.S. average	1.13	1.13	1.02	1.06
Total significant values	8	14	4	11
	Cold			
Northeast	1.25 (0.83, 1.70)	1.07 (0.92, 1.32)	1.03 (0.72, 1.40)	1.01 (0.87, 1.19)
Southeast	1.08(0.73, 1.62)	1.20 (0.97, 1.55)	1.04 (0.81, 1.51)	1.08 (0.88, 1.47)
Central average	1.05 (0.77, 1.40)	1.06 (0.92,1.22)	1.07 (0.89, 1.34)	1.02 (0.91, 1.13)
Florida	1.29 (1.05,1.67)	1.20 (1.03, 1.46)	1.19 (0.96, 1.39)	1.06 (0.88, 1.29)
Western	1.18 (0.67, 1.55)	1.05 (0.89, 1.16)	0.91 (0.57, 1.18)	1.00 (0.76, 1.23)
California	1.24 (0.88, 1.66)	1.03 (0.91, 1.16)	0.92 (0.68, 1.14)	1.07 (0.91, 1.27)
U.S. average	1.19	1.10	1.02	1.04
Total significant values	33	33	8	13
	XCold			
Northeast	1.30 (0.80, 1.95)	1.08 (0.41, 2.17)	1.00 (0.63, 1.40)	1.03 (0.79, 1.36)
Southeast	1.24 (0.74, 2.06)	1.24 (0.72, 1.80)	1.11 (0.74, 1.68)	1.09 (0.67, 2.07)
Central average	1.14 (0.83, 1.54)	1.06 (0.91, 1.25)	1.12 (0.77, 1.58)	0.98 (0.70, 1.27)
Florida	1.46 (1.18, 1.98)	1.28 (0.96, 1.84)	1.19 (0.79, 1.49)	1.04 (0.63, 1.84)
Western	1.14 (0.63, 1.71)	1.08 (0.86, 1.33)	0.91 (0.56, 1.34)	1.04 (0.68, 1.34)
California	1.26 (0.90, 1.74)	1.01 (0.80, 1.23)	0.93 (0.66, 1.37)	1.19 (0.92, 1.87)
U.S. average	1.26	1.12	1.03	1.06
Total significant values	31	15	6	10

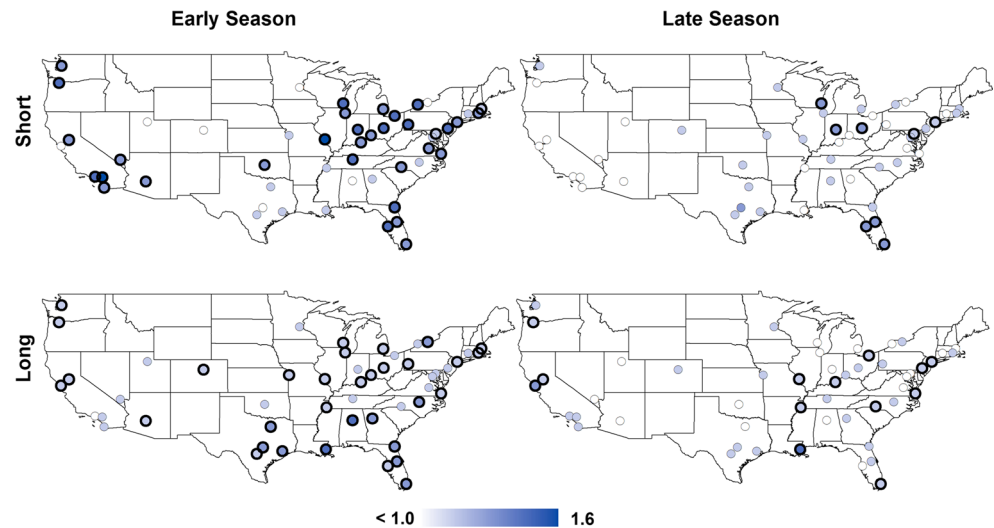
While the domain observed elevated relative risks associated with late occurring cold and extreme cold events, the risks were not as high throughout much of the country when compared with other iterations of cold events. As the winter season progresses, relative risks associated with cold events was found to be reduced slightly. On average, the highest risk values were found in Florida, yet other locations such as Milwaukee (1.21) and Columbus (1.18) were still elevated. Results indicate that other southern locations such as Nashville, Atlanta, and New Orleans also showed significant relationships between late season cold and mortality. While

elevated risk was found, on average, these later occurring events did not negatively impact health as much as earlier events. With higher values for extreme cold ETEs compared to cold ETEs, the strength of a cold event seems to have a role in human response to long lasting, late occurring cold events.

### Discussion

While higher risk values were found for more extreme heat events, duration and seasonal timing emerged as critical

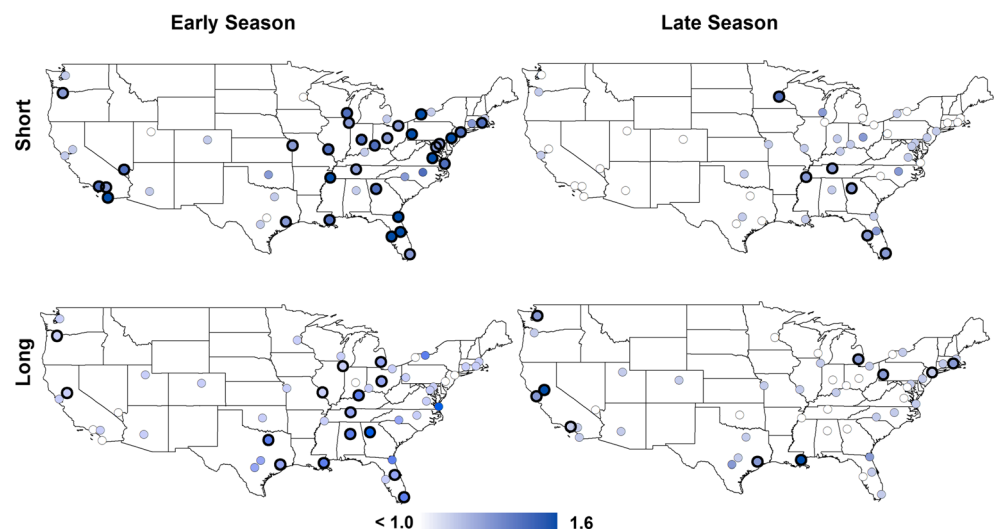
**Fig. 4** Mean cumulative relative risk values for cold days. Results are shown for short-early, long-early, short-late, and long-late cold criteria. *Darker color* represents higher relative risk and significant values are denoted with a *black circle*



factors associated with mortality (Table 4). Similar to other studies (Baccini et al. 2008; Basu and Samet 2002), elevated risk was found for early heat and extreme heat events when compared to later occurring events. Risk also increased with longer-lasting events. While cold is assessed in fewer studies, short, early cold, and extreme cold events consistently showed the highest vulnerability, with greater vulnerability than longer early cold events. Higher relative risk values were also found for early season cold events compared to later season events. By the second half of the winter season, risk decreased suggesting possible acclimatization or adaptation to cold environments. As with heat, higher risks were generally found for more extreme events. In terms of geographic variability, Florida consistently showed the most elevated risk associated with cold ETEs, while more northern locations with higher risk for warm ETEs. These results support the findings that seasonal timing, duration, and relative strength of an event plays a role in temperature-related vulnerability.

Periods of elevated temperature have been linked to excess mortality (e.g., Anderson and Bell 2011; Curriero et al. 2002). In this study, significant relationships between longer heat episodes and elevated mortality, regardless of seasonal timing, was evident. Sustained periods of heat have been shown to negatively influence health outcomes (e.g., Hajat et al. 2002; Sheridan and Lin 2014; Xu et al. 2014). Studies have also linked comorbidities associated with prolonged elevated temperature including cardiovascular-, respiratory-, and diabetes-related conditions (Medina-Ramon and Schwartz 2007). In addition to duration, seasonal timing of heat events has also been shown to influence human health responses. Baccini et al. 2008 showed greater heat-related mortality during the early summer than later on, a finding supported by others suggesting that populations may acclimatize to elevated temperatures over time (e.g., Páldy et al. 2005; Sheridan and Kalkstein 2010; Hajat et al. 2005; Gosling et al. 2009). While this study cannot determine the degree to which acclimatization takes place or if

**Fig. 5** Mean cumulative relative risk values for extreme cold days. Results are shown for short-early, long-early, short-late, and long-late extreme cold criteria. *Darker color* represents higher relative risk and significant values are denoted with a *black circle*





certain thresholds exist in which this adaptation to environmental conditions does not occur, higher risk associated with early season heat events was shown. Consequently, this study showed the importance of seasonality on heat-health related outcomes. Similarly, the intensity of heat events have been shown to influence mortality (Anderson and Bell 2009; Hajat et al. 2006; Gasparrini and Armstrong 2011; Zacharias et al. 2014). For instance, Aström et al. (2013) found a 4.6 % increase in mortality on extreme heat days compared to normal summer days. Together, duration, seasonal timing, and relative event strength were all found to have an impact on the risk associated with warm ETEs.

While increased risk to heat events have been previously shown (e.g., Sheridan and Kalkstein 2010; Hajat et al. 2005), fewer studies have considered the influence of cold waves on human health (e.g., Analitis et al. 2008; Barnett et al. 2012; Eurowinter Group 1997; Rocklöv et al. 2014). This study showed the highest risk associated with short, early cold, and extreme cold events. These early events also showed higher vulnerability when compared to later events. Unsettled weather conditions have been shown to have some relationship to cold-related mortality (Allen and Lee 2014; Kassomenos et al. 2007; McGregor 1999; O'Neill 2003). Following the passage of frontal boundaries, Curson (1996) showed an increase in blood viscosity—an important risk factor associated with cardiovascular mortality events. Allen and Sheridan (2014) found a similar conclusion as Plavcová and Kyselý (2014), with rising temperatures and decreasing pressure preceding high mortality days. Gerber et al. (2006) suggested the observed increases in wintertime cardiac arrests may be attributed to the relative—and not absolute—changes in temperature based upon season or geographic region. During the winter, Rocklöv et al. (2014) found a relationship between mortality and decreases in temperature. As cold air exposure has been attributed to increases in cardiovascular strain (e.g., Kyselý et al. 2009; Gorjanc et al. 1999; Keatinge 2002), the Eurowinter Group (1997) concluded that low temperatures were related to the observed increase in heart disease mortality during the winter season. However, as noted in other studies, cold-related health outcomes have also been linked to other, more local factors such as air pollution, socioeconomic resources, and education (e.g., Frost and Auliciems 1993; Eurowinter Group 1997; Madrigano et al. 2013) and are not necessarily indicative of temperature alone (Kyselý et al. 2009; Ebi and Mills 2013). The results of this research are supported by Barnett et al. (2012) which found heat and cold events earlier in the season to be more dangerous than later season events. However, the reason for this seems unclear as there has been minimal research into acclimatization related to cold events. Early season, short-lasting cold events may be more dangerous due to an increased susceptible population and inadequate resources, education, or preparations to cope with the cold (Frost and Auliciems 1993; Eurowinter Group 1997; Conlon et al. 2011).

This research showed higher vulnerability associated with heat in more northern locations such as New York while increased risk related to cold was found in the south. The spatial heterogeneity of heat and cold effects is consistent with other studies which suggest variability associated with vulnerability to anomalous temperature events (Chestnut et al. 1998; Braga et al. 2002; Barnett 2007; Anderson and Bell 2009). For instance, studies have shown a greater risk of heat-related mortality in high latitude locations where populations may not be accustomed to elevated temperatures (Hattis et al. 2012; McGeehin and Mirabelli 2001; Hajat and Kosatky 2010). However, others (Baccini et al. 2008; D'Ippoliti et al. 2010) have showed greater effects of heat in more southern locations. The Eurowinter Group (1997) suggested a greater vulnerability to cold in milder regions. Keatinge et al. (2000) suggested behavior as a possible explanation to adaptation to environmental conditions. Despite these findings, Barnett et al. (2012) suggests people are less able to cope with extreme heat than extreme cold. In cold, people can wear more clothes or stay indoors while heat relief requires additional interventions such as air conditioning. In addition to large-scale spatial variability associated with heat and cold, intra-urban variability and individual heterogeneity has also been shown especially related to heat effect (Kuras et al. 2015; Hondula et al. 2012; Vaneckova et al. 2010).

Most studies which have utilized a distributed lag non-linear model have originated within the epidemiological research community (Wu et al. 2013; Morabito et al. 2012). The results of this research draw attention to vulnerability associated with ETEs through a DLNM approach in applied climatological research. By incorporating a distributed lag non-linear model, risk to heat and cold events was determined across the USA. While not analyzed, it is important to note that in addition to elevated ambient air temperature, other confounding factors such as air pollution may also be associated with increased mortality during ETEs (Analitis et al. 2014; Vanos et al. 2014). While the issue of mortality displacement or harvesting (e.g., Hajat et al. 2006) was considered in the 14-day lag, the study did not directly attribute an amount of displacement as a result of ETEs. Future research may evaluate differential responses associated with other demographics such as age, sex, or cause of death to further understand temperature-mortality risk. With more insight into the risks associated with ETEs, focused resources may be provided to better prepare regions or subpopulations in coping with heat and cold. Through education or warning systems, vulnerable populations may cope with increased temperature variability in a changing climate.

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