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The influence of extreme cold events on mortality in the United States

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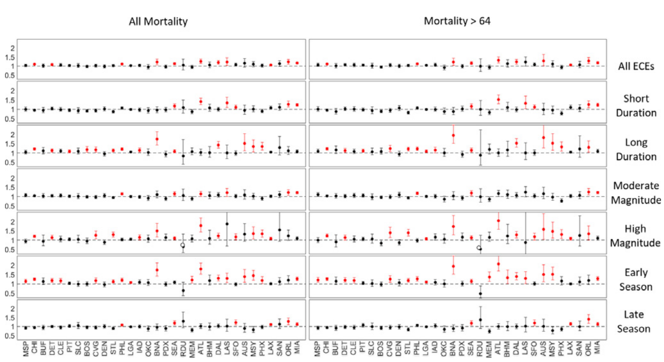
HIGHLIGHTS

- Increased mortality during ECEs is most likely during early winter.
- Warmer cities generally have a larger increased RR during ECEs.
- Magnitude and duration of ECEs significantly increase RR of mortality.
- Atlanta, Austin, and Nashville had largest increased RRs of mortality during ECEs.

GRAPHICAL ABSTRACT



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ABSTRACT

Many studies have analyzed the effects of extreme heat on human mortality, however fewer studies have focused on the effects of cold related mortality due to the complicated nature of the lagged response. This study utilized a Distributed Lag Non-Linear Model with a 30-day lag to determine the cumulative effects of extreme cold events (ECEs) on mortality across 32 cities in the United States for the period of 1975–2010. ECEs were divided into specific categories based on duration, magnitude, and timing of occurrence. Mortality was divided into all-age mortality as well as mortality of individuals >64 years old. The findings suggest a strong relationship between a city's latitude as well as the timing of an ECE with mortality. Early season ECEs result in a much higher relative risk of increased mortality, particularly in cities with higher mean winter temperatures, while the RR of mortality of individuals >64 was consistently higher for each city. This study suggests early season ECEs should receive enhanced preparedness efforts as individuals may be particularly vulnerable when not acclimatized to extreme cold.

1. Introduction

There is a well-documented connection between increases in human mortality and extreme temperature events (e.g., Gasparrini et al., 2015; Anderson and Bell, 2009; McMichael et al., 2008). Temperature extremes, especially those lasting multiple days, put a strain on cardiovascular, cerebrovascular, and respiratory systems (Gasparrini et al., 2015). However, these impacts may be reduced with increased preparedness and by limiting exposure (Barnett et al., 2012). This said, understanding the spatial and temporal variability in extreme-temperature vulnerability is key to any mitigation efforts. Research has generally shown that locations ill-prepared for extreme temperature are more substantially impacted; for instance, cities in warmer climates tend to exhibit greater sensitivity to cold extremes, and vice versa (e.g. Anderson and Bell, 2009, Analitis et al., 2008, Curriero et al., 2002, Ng et al., 2014), although the magnitude varies from study to study. In differentiating between the impacts of heat and cold, far more studies

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have discussed the effects of extreme heat on mortality (Allen and Lee, 2014), since the impacts are relatively easy to model. The effects of extreme cold on health have been studied less frequently, as the relationship has been more difficult to model due to a greater lagged influence (Allen and Sheridan, 2018), a result of there being a greater proportion of winter-related mortality being indirectly associated with extreme temperature (Kinney et al., 2015). Further, while the heat-mortality literature includes studies that look at heat waves as well as the overall temperature-mortality relationship (Allen and Sheridan, 2018), the majority studies that have examined extreme cold and mortality tend to analyze the overall temperature-mortality relationship (Ng et al., 2014; Ma et al., 2014), with few analyzing cold waves explicitly. Those that have defined cold waves (e.g. Barnett et al., 2012, Rocklöv et al., 2014) have utilized absolute percentiles of temperature as criteria for their definition.

There is no formally accepted definition of an extreme temperature event, which has thus led to myriad different definitions. The classification a discrete cold event requires both a duration and magnitude criteria. The magnitude is often determined via anomalies, percentiles, or standard deviations. Wheeler et al. (2011) used standardized anomalies to develop a climatology of cold air outbreaks (CAOs) across North America. Cellitti et al. (2006) used the top 30 coldest 5-day anomalies from 17 stations in the eastern U.S. to classify CAOs. Vavrus et al. (2006) defined the magnitude and duration of CAOs by using general circulation models to look at surface temperatures two standard deviations below the December through February mean for 2 consecutive days. Barnett et al. (2012) used the 95th–99th percentiles as thresholds for cold waves which lasted a minimum of two consecutive days.

As mentioned, the increased mortality associated with extreme cold can persist for several or more weeks (Anderson and Bell, 2009). Because of this lagged response of mortality with extreme cold, cumulative measures are needed to fully encapsulate the impacts, however few studies agree on the ideal lag to incorporate, and the seasonal cycle of mortality can be a substantial confounder in terms of using any lag (Kinney et al., 2015). Lee (2015) showed that dry cool weather patterns resulted in a significant increase of cardiovascular related mortality during the 2 weeks following the event. Analitis et al. (2008) found that the effects of cold could last up to 23 days and affected warmer cities more than colder cities. Anderson and Bell (2009) found that cold waves resulted in increased mortality for up to 25 days. The relative risk has been shown to be particularly useful for determining the cumulative risk of increased mortality during extreme cold. Recent studies (Ng et al., 2014; Ma et al., 2014; Barnett et al., 2012) have utilized the Distributed Lag Non-Linear Model (DLNM), first developed by Gasparrini (2011), to examine cumulative impacts of extreme temperatures on mortality percentiles.

It is important to fully understand the impacts of winter weather on human health, as with demographic changes, the percentage of the population most vulnerable to extreme temperature events will increase more rapidly. Moreover, climate change may result in more extreme cold events even with an overall warming, and the overall notion that a warmer world would lead to a decrease in winter mortality has been questioned (Staddon et al., 2014). To contribute to this understanding, in this study we assess the association between discrete ECEs in 32 cities across the United States for the period 1975–2010, sub-setting the impacts of ECEs by duration, magnitude, location, age, and time of year. ECEs are defined in relative, not absolute terms, based on a city's climate and seasonality.

2. Data and methods

2.1. Extreme cold events

Quality controlled daily maximum and minimum temperature were obtained from NOAA for the surface weather stations located at the primary airports of the 32 metropolitan areas used in this study (Table 1).

Table 1
Surface weather stations.

Weather station	FAA location ID
Atlanta, Georgia	ATL
Austin, Texas	AUS
Birmingham, Alabama	BHM
Boston, Massachusetts	BOS
Buffalo, New York	BUF
Chicago, Illinois	Chicago Area
Cincinnati, Ohio	CVG
Cleveland, Ohio	CLE
Dallas, Texas	DAL
Denver, Colorado	DEN
Detroit, Michigan	DET
Los Angeles, California	LAX
Las Vegas, California	LAS
Memphis, Tennessee	MEM
Miami, Florida	MIA
Minneapolis-Saint Paul, MN	MSP
Nashville, Tennessee	BNA
New Orleans, Louisiana	MSY
New York, New York	LGA
Oklahoma City, Oklahoma	OKC
Orlando, Florida	Orlando Area
Phoenix, Arizona	PHX
Philadelphia, Pennsylvania	PHL
Pittsburgh, Pennsylvania	PIT
Portland, Oregon	PDX
Raleigh, North Carolina	RDU
San Diego, California	SAN
Seattle, Washington	SEA
San Francisco, California	SFO
Salt-Lake City, Utah	SLC
St. Louis, Missouri	STL
Washington D.C.	IAD

Threaded Station Extremes (ThreadEX stations), listed as Area Stations in Table 1, were used for Chicago, IL and Orlando, FL due to significant amounts of missing data. The temperature data were gathered for the months of November through March, from 1975 to 2010, and were used to calculate the magnitude and duration of the ECEs. The criteria used to define an ECE comes from Smith and Sheridan (2018) in which the mean daily maximum and minimum temperature is required to be at least 1.25 σ below the 35-year climatological mean for a minimum of 5 consecutive days.

For each city, the mean and standard deviation of temperature for each day from 1 November to 31 March over the 1975–2010 period was calculated. To smooth day-to-day fluctuations, a 2nd order polynomial was fit to the mean and standard deviation values; it is these fitted values that are used as the reference climatological mean and standard deviation for each day. This definition thus identifies ECE that represent extremely cold conditions relative to a given time of year in a given city. Thus, it may account for seasonal acclimatization and the seasonal variability of mortality associated with early season ECEs (Barnett et al., 2012). Individuals ill-acclimatized to extreme cold may be more heavily impacted by an early season ECE that features a dramatic change in temperature following a period of higher temperatures.

2.2. Mortality data

According to Analitis et al. (2008) and Anderson and Bell (2009), cold waves may result in increased mortality for up to 25 days after the onset. However, multiple cities experienced an increased RR of mortality beyond 25 days, thus a 30-day lag was used to explore the RR of increased mortality after the onset of an ECE. Of all mortality datasets, all-cause total mortality is the least influenced by limitations (Dixon et al., 2005), therefore, all-cause mortality is used instead of specific cause mortality to eliminate the subjectivity of the medical examiner while also providing a larger sample size. All-cause mortality data were obtained from the National Center for Health Statistics (NCHS)

Table 2
Number of ECEs per category.

City	ECEs	ECE days	Short duration	Long duration	Mod. magnitude	High magnitude	Early season	Late season
Atlanta	14	89	11	3	11	3	6	8
Austin	16	102	14	2	13	3	7	9
Birmingham	11	70	9	2	8	3	4	7
Boston	20	126	18	2	18	2	8	12
Buffalo	19	133	15	4	18	1	7	12
Chicago	32	234	22	10	24	8	14	18
Cincinnati	29	190	24	5	26	3	8	21
Cleveland	27	189	19	8	23	4	12	15
Dallas	19	127	15	4	14	5	5	14
Denver	33	224	25	8	23	10	13	20
Detroit	25	171	19	6	22	3	8	17
Los Angeles	12	75	10	2	11	1	8	4
Las Vegas	22	165	13	9	16	6	10	12
Memphis	20	134	15	5	15	5	6	14
Miami	33	215	25	8	27	6	16	17
Minneapolis	33	238	21	12	25	8	16	17
Nashville	14	96	11	3	12	2	3	11
New Orleans	13	81	11	2	10	3	5	8
New York	31	195	26	5	25	6	14	17
Oklahoma City	21	148	16	5	17	4	8	13
Orlando	22	138	19	3	19	3	11	11
Philadelphia	27	190	21	6	22	5	10	17
Phoenix	27	169	21	6	18	9	19	8
Pittsburgh	19	131	16	3	16	3	4	15
Portland	31	240	18	13	22	9	19	12
Raleigh	9	54	8	1	9	0	3	6
San Diego	9	54	8	1	8	1	6	3
Seattle	32	242	20	12	16	16	17	15
San Francisco	22	138	18	4	18	4	13	9
Salt-Lake City	32	243	20	12	25	7	15	17
St. Louis	28	206	22	6	23	5	12	16
Washington D.C.	22	153	18	4	19	3	9	13

for the years of 1975 through 2010 for 32 Metropolitan Statistical Areas (MSA) across the eastern U.S. The data were divided into two age categories, 1.) all-age mortality and 2.) mortality of individuals >64 years old to further delineate the impacts of ECEs of different age groups. Though mortality data was not available for November–December 1974 and January–March 2011, the winter seasons of 1974–1975 and 2010–2011 are included in the study to maximize the number of seasons in the sample. The 1974–1975 and 2010–2011 winter seasons are not included in the discussion of ECE seasonal trends for this reason.

2.3. Distributed Lag Non-Linear Model

The day-to-day risk of increased mortality during extreme cold is generally small compared to heat. This may in part be the reason for numerous studies that show insignificant impacts from extreme cold events on mortality (Dixon et al., 2005). However, the cumulative RR of increased mortality over an extended period following an ECE can be measured through use of the distributed lag nonlinear model (DLNM; Gasparrini, 2011). The DLNM accounts for the non-linearity of the data and the delayed effects of ECEs on mortality by determining the change in mortality during a specified period after the ECE. Since mortality resembles a seasonal cycle in that the annual peak occurs during the winter (Sheridan and Dixon, 2016), the DLNM normalizes the data by creating a crossbasis, or a baseline of expected mortality on any given day based on prior observations (Gasparrini, 2011). The daily mortality was assumed to follow a quasi-Poisson distribution and the data was fit with a non-natural penalized spline (B-spline) with 7 degrees of freedom (df) for each of the 36 years of data to account for seasonality and trends. Ng et al. (2014) found that using >3 df for the lag introduced an artificial increase in RR, thus 3 df were applied to the 30-day lag used for mortality analysis.

In addition to the overall impacts of ECEs, to examine the impacts of duration, magnitude, and timing of occurrence, ECEs were divided into subset categories:

1.) -1.25 ≥ $\sigma > -1.75$ (‘moderate’), $\sigma \le -1.75$ (‘extreme’)
2.) Duration ≤8 days (‘short’), Duration >8 days (‘long’), and
3.) November–December (‘early season’), January–March (‘late season’)

for both mortality groups (all age mortality and mortality >64). All mortality analyses were performed with the R Project for Statistical Computing (3.4.3) and utilized the DLNM, DataCombine, and Splines packages. The two functions regarding the DLNM parameters are as follows:

$$basis.off<-crossbasis(mortse, lag = 30, argvar = list\left(fun = ''integer''\right), arglag = list\left(fun = ''poly'', degree = 3\right));$$

$$model<-glm\ (mortOldMort \sim basis.off + ps\left(mortTime, 7 * 36\right), family = quasipoisson(), mort);$$

Table 3
Number of ECEs, mean duration of ECEs in days, and the mean z-score of ECEs by month.

Month	# ECEs	Mean duration	Mean Z-score
November	112	7	−1.65
December	204	8	−1.66
January	212	7	−1.60
February	108	7	−1.60
March	88	6	−1.57

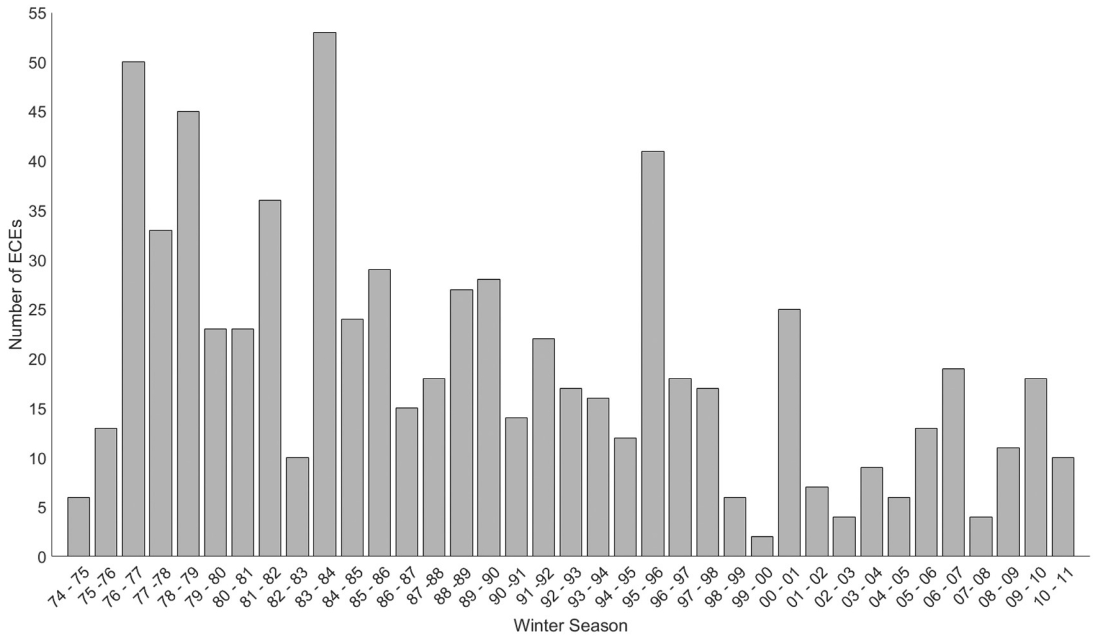

Fig. 1. Number of ECEs per year for all cities.

3. Results and discussion

The total number of ECEs and ECE days, along with the number of ECEs per ECE category are shown for each city in Table 2. As intended, very few ECEs fall into the high magnitude (Z-score ≤ −1.75 σ) or long duration (≥8 days) category, thus helping to delineate between ECEs and the most extreme ECEs. The number of ECEs per month along with the average duration and magnitude by month are shown in Table 3. January and December experience the most ECEs, with nearly 60% of the total number of ECEs occurring during this 2-month period. December features the longest average duration ECEs of 8 days while March ECEs average 6 days in duration. The magnitude of ECEs tends to be higher toward the front end of the winter season, though the difference between November and March is only 0.08 σ. The total number of ECEs per year for all cities decreased throughout the study period (Fig. 1). The winters from 1976 through 1986 accounted for 326 ECEs, or 45% of the total number of ECEs during the 37 winter seasons in the study. The most recent decade of the study, 2000–2010, accounted for only 116 ECEs or 16% of the total number of events.

The numbers of ECEs was not evenly distributed among the cities. Cities with smaller temperature variations, such as Miami or Seattle, typically experienced more ECEs during the study period while inland southern cities experienced fewer ECEs (Fig. 2). Overall, results revealed ECEs generally increased the RR of all age mortality with 11 cities

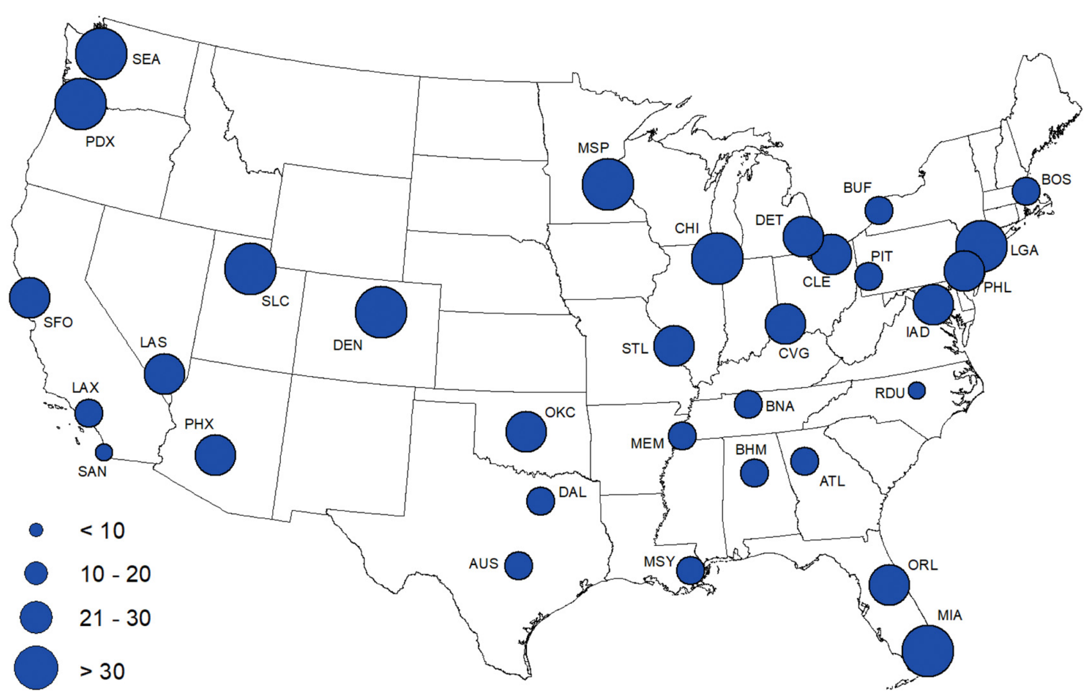

Fig. 2. Extreme Cold Events (ECEs) by city.

having a significant increase (Table 4). An additional slight increase in RR was observed when only examining mortality >64 with 10 cities having a significant RR (Table 5). Western U.S. cities experienced a much less variable RR for both age groups and all ECE categories as compared to cities in the eastern U.S. This may partially be attributed to the lower variation in temperatures for cities on the west coast and the complex topographic influenced, climates of Denver and Salt Lake City. It may also be a result of a higher frequency of synoptic-scale winter precipitation events across the eastern U.S. resulting in extreme cold in the wake of the event. Further subdividing the ECEs into duration, magnitude, and time of season categories resulted in several distinct patterns.

Table 4
Relative Risk and confidence intervals for all-age, all-cause mortality for each category organized by mean winter temperature (MWT). The RR categories from left to right are: All ECEs, moderate magnitude (z-score > -1.75), high magnitude (z-score ≤ -1.75), short duration (duration < 8 days), long duration (duration ≥ 8 days), early season ECEs (November–December), and late season ECEs (January–March). Statistically significant RR values are denoted in bold italic.

City	MWT (°C)	All ECEs All age	Short duration	Long duration	Mod. magnitude	High magnitude	Early season	Late season
Minneapolis	−8	1.03 [0.96–1.10]	1.00 [0.90–1.11]	1.04 [0.96–1.13]	1.07 [0.99–1.16]	0.94 [0.84–1.05]	***1.14 [1.04–1.25]***	0.92 [0.84–1.00]
Chicago	−3	***1.10 [1.06–1.14]***	0.95 [0.90–1.00]	***1.21 [1.16–1.27]***	1.04 [0.99–1.09]	***1.20 [1.13–1.27]***	***1.25 [1.19–1.31]***	0.94 [0.90–0.99]
Buffalo	−3	1.02 [0.92–1.12]	0.94 [0.82–1.09]	1.11 [0.95–1.29]	1.03 [0.93–1.15]	0.94 [0.70–1.27]	1.13 [0.97–1.31]	0.94 [0.82–1.07]
Detroit	−2	***1.08 [1.02–1.14]***	1.03 [0.96–1.12]	***1.13 [1.04–1.23]***	1.04 [0.97–1.11]	***1.14 [1.03–1.26]***	***1.18 [1.08–1.28]***	1.00 [0.93–1.07]
Cleveland	−2	1.05 [0.98–1.13]	0.98 [0.89–1.09]	1.10 [1.00–1.20]	1.05 [0.97–1.14]	1.05 [0.91–1.20]	***1.16 [1.05–1.29]***	0.95 [0.86–1.04]
Pittsburgh	−1	1.03 [0.97–1.08]	0.95 [0.88–1.03]	***1.08 [1.01–1.15]***	1.02 [0.95–1.09]	1.04 [0.97–1.12]	1.03 [0.96–1.10]	1.02 [0.94–1.11]
Salt-Lake City	0	1.02 [0.92–1.14]	0.92 [0.79–1.08]	1.09 [0.95–1.25]	1.01 [0.89–1.15]	1.04 [0.86–1.25]	0.99 [0.86–1.15]	1.05 [0.90–1.22]
Boston	0	0.98 [0.91–1.04]	0.91 [0.84–0.98]	***1.18 [1.03–1.34]***	0.98 [0.91–1.05]	0.95 [0.81–1.11]	1.00 [0.90–1.11]	0.96 [0.88–1.04]
Cincinnati	0	1.02 [0.95–1.10]	0.93 [0.84–1.02]	***1.17 [1.04–1.32]***	0.97 [0.89–1.06]	***1.26 [1.07–1.50]***	***1.17 [1.03–1.32]***	0.94 [0.86–1.04]
Denver	1	0.98 [0.90–1.07]	1.02 [0.92–1.13]	0.95 [0.84–1.07]	1.05 [0.95–1.16]	0.88 [0.76–1.01]	0.96 [0.84–1.10]	1.00 [0.91–1.11]
St. Louis	1	1.02 [0.97–1.08]	0.87 [0.80–0.95]	***1.13 [1.05–1.22]***	0.95 [0.89–1.01]	***1.29 [1.16–1.43]***	***1.12 [1.05–1.21]***	0.89 [0.82–0.97]
Philadelphia	2	***1.11 [1.07–1.16]***	***1.06 [1.00–1.13]***	***1.20 [1.13–1.28]***	***1.14 [1.09–1.20]***	1.03 [0.95–1.11]	***1.20 [1.11–1.30]***	***1.08 [1.02–1.13]***
New York	2	1.02 [0.99–1.06]	0.99 [0.95–1.04]	1.05 [1.00–1.10]	1.00 [0.96–1.05]	1.05 [0.99–1.10]	***1.07 [1.02–1.13]***	0.98 [0.93–1.02]
Washington D.C.	3	1.04 [0.97–1.11]	0.97 [0.88–1.06]	***1.14 [1.03–1.26]***	0.98 [0.90–1.06]	***1.15 [1.02–1.29]***	1.09 [0.99–1.21]	0.99 [0.91–1.08]
Oklahoma City	4	0.95 [0.84–1.08]	0.93 [0.80–1.08]	1.02 [0.86–1.22]	0.91 [0.79–1.06]	1.07 [0.89–1.28]	1.06 [0.91–1.23]	0.87 [0.73–1.04]
Nashville	4	***1.22 [1.07–1.39]***	0.95 [0.81–1.13]	***1.74 [1.42–2.13]***	1.10 [0.94–1.29]	***1.49 [1.17–1.90]***	***1.74 [1.42–2.13]***	0.95 [0.81–1.13]
Portland	6	0.96 [0.88–1.05]	0.97 [0.86–1.09]	0.92 [0.79–1.08]	0.89 [0.79–0.99]	1.14 [0.98–1.33]	0.98 [0.88–1.09]	0.89 [0.75–1.05]
Seattle	6	***1.13 [1.06–1.19]***	***1.17 [1.06–1.28]***	***1.08 [1.01–1.17]***	***1.15 [1.05–1.26]***	***1.10 [1.02–1.19]***	1.08 [1.00–1.16]	***1.19 [1.09–1.31]***
Raleigh	6	1.05 [0.79–1.39]	1.09 [0.80–1.49]	0.83 [0.40–1.72]	1.05 [0.79–1.39]	0.65 [0.32–1.32]	0.64 [0.38–1.08]	1.29 [0.92–1.81]
Memphis	6	0.94 [0.85–1.03]	0.87 [0.77–0.98]	1.07 [0.90–1.28]	0.89 [0.79–1.00]	1.07 [0.90–1.27]	***1.21 [1.04–1.40]***	0.80 [0.70–0.90]
Atlanta	7	***1.26 [1.14–1.39]***	***1.41 [1.25–1.59]***	1.02 [0.87–1.20]	***1.14 [1.01–1.27]***	***1.78 [1.45–2.19]***	***1.79 [1.52–2.11]***	1.02 [0.90–1.15]
Birmingham	7	1.06 [0.91–1.23]	1.07 [0.90–1.27]	1.01 [0.77–1.34]	1.05 [0.89–1.24]	1.09 [0.78–1.52]	1.17 [0.94–1.46]	0.98 [0.80–1.19]
Dallas	9	***1.20 [1.10–1.31]***	1.00 [0.90–1.10]	***1.42 [1.26–1.61]***	1.08 [0.97–1.20]	***1.23 [1.11–1.38]***	***1.30 [1.16–1.46]***	1.03 [0.93–1.14]
Las Vegas	9	***1.22 [1.03–1.45]***	***1.34 [1.09–1.64]***	1.00 [0.70–1.42]	***1.20 [1.01–1.43]***	1.87 [0.68–5.10]	***1.29 [1.06–1.57]***	1.02 [0.74–1.40]
San Francisco	11	1.07 [0.99–1.15]	***1.11 [1.01–1.21]***	0.98 [0.87–1.12]	1.02 [0.94–1.11]	***1.17 [1.02–1.34]***	0.98 [0.90–1.07]	***1.22 [1.08–1.37]***
Austin	11	1.16 [0.95–1.42]	0.94 [0.73–1.21]	***1.51 [1.12–2.04]***	1.08 [0.86–1.35]	1.32 [0.93–1.88]	***1.38 [1.08–1.77]***	0.89 [0.68–1.18]
New Orleans	12	1.10 [0.97–1.25]	1.01 [0.86–1.19]	***1.34 [1.06–1.69]***	1.02 [0.87–1.18]	***1.35 [1.06–1.71]***	***1.44 [1.20–1.72]***	0.82 [0.67–0.99]
Phoenix	14	1.03 [0.94–1.12]	0.90 [0.81–1.00]	***1.34 [1.15–1.56]***	0.90 [0.80–1.00]	***1.34 [1.15–1.55]***	***1.18 [1.01–1.39]***	0.97 [0.87–1.07]
Los Angeles	14	***1.06 [1.01–1.10]***	1.07 [0.99–1.17]	1.04 [1.00–1.09]	1.02 [0.96–1.08]	***1.08 [1.02–1.15]***	1.01 [0.95–1.06]	***1.11 [1.05–1.18]***
San Diego	14	1.13 [0.98–1.30]	1.11 [0.95–1.28]	1.29 [0.88–1.89]	1.10 [0.95–1.27]	1.55 [0.94–2.55]	1.12 [0.95–1.33]	1.13 [0.90–1.42]
Orlando	17	***1.23 [1.10–1.37]***	***1.26 [1.11–1.43]***	1.11 [0.92–1.34]	***1.21 [1.07–1.36]***	1.23 [0.98–1.54]	***1.20 [1.00–1.43]***	***1.28 [1.11–1.48]***
Miami	21	***1.17 [1.12–1.23]***	***1.23 [1.16–1.30]***	1.07 [0.99–1.15]	***1.20 [1.14–1.27]***	1.09 [1.00–1.19]	***1.27 [1.18–1.36]***	***1.12 [1.05–1.20]***

3.1. RR and ECE duration

For both age categories, the RR was generally higher in cities with warmer MWTs for short duration ECEs. A much higher increased RR was evident in long duration ECEs, especially in cities with warmer MWT. The smaller increase in RR for cities with colder MWTs during long duration ECEs may suggest these cities are better prepared to deal with long periods of extreme cold as opposed to cities with warmer MWTs. It may also be a result of these cities having experienced cold prior to the beginning of the study period (November), as they are more likely to be impacted by a southward propagating polar jet prior to November, thus resulting in a more acclimatized population by

Table 5
Relative Risk and confidence intervals for all-cause mortality >64 years old for each category organized by mean winter temperature (MWT). The RR categories from left to right are: All ECEs, moderate magnitude (z-score > −1.75), high magnitude (z-score ≤ −1.75), short duration (duration <8 days), long duration (duration ≥ 8 days), early season ECEs (November–December), and late season ECEs (January–March). Statistically significant RR values are denoted in bold italic.

City	MWT (°C)	All ECEs Age > 64	Short duration	Long duration	Mod. magnitude	High magnitude	Early season	Late season
Minneapolis	−8	1.06 [0.98–1.15]	1.01 [0.90–1.14]	1.09 [1.00–1.20]	***1.10 [1.00–1.21]***	0.99 [0.86–1.13]	***1.21 [1.09–1.35]***	0.92 [0.83–1.02]
Chicago	−3	***1.11 [1.06–1.16]***	0.95 [0.89–1.01]	***1.22 [1.16–1.29]***	1.03 [0.98–1.09]	***1.23 [1.15–1.32]***	***1.27 [1.19–1.34]***	0.94 [0.89–1.00]
Buffalo	−3	1.01 [0.90–1.13]	0.88 [0.74–1.04]	1.16 [0.97–1.38]	1.03 [0.91–1.16]	0.90 [0.63–1.29]	1.14 [0.96–1.36]	0.91 [0.78–1.06]
Detroit	−2	1.07 [1.00–1.14]	1.02 [0.93–1.12]	***1.12 [1.02–1.24]***	1.02 [0.94–1.11]	***1.14 [1.01–1.28]***	***1.20 [1.09–1.33]***	0.97 [0.89–1.06]
Cleveland	−2	1.06 [0.97–1.15]	1.01 [0.90–1.14]	1.08 [0.97–1.21]	1.06 [0.96–1.17]	1.05 [0.90–1.23]	***1.18 [1.05–1.33]***	0.94 [0.84–1.06]
Pittsburgh	−1	1.05 [0.99–1.12]	0.97 [0.89–1.06]	***1.11 [1.03–1.20]***	1.05 [0.97–1.13]	1.06 [0.97–1.15]	1.04 [0.97–1.13]	1.07 [0.97–1.17]
Salt-Lake City	0	1.01 [0.88–1.15]	0.93 [0.77–1.13]	1.06 [0.90–1.25]	0.97 [0.83–1.14]	1.06 [0.84–1.33]	1.02 [0.86–1.22]	0.99 [0.82–1.19]
Boston	0	0.94 [0.88–1.02]	0.89 [0.82–0.97]	1.08 [0.93–1.26]	0.96 [0.88–1.04]	0.84 [0.70–1.01]	0.97 [0.86–1.10]	0.91 [0.83–1.01]
Cincinnati	0	1.05 [0.96–1.14]	0.94 [0.83–1.05]	***1.23 [1.07–1.41]***	0.98 [0.88–1.08]	***1.39 [1.14–1.69]***	***1.25 [1.08–1.44]***	0.94 [0.84–1.06]
Denver	1	1.00 [0.91–1.11]	1.06 [0.93–1.20]	0.93 [0.81–1.08]	1.09 [0.96–1.23]	0.86 [0.73–1.02]	1.06 [0.90–1.24]	0.97 [0.86–1.10]
St. Louis	1	1.03 [0.97–1.10]	0.82 [0.74–0.90]	***1.21 [1.11–1.31]***	0.93 [0.87–1.00]	***1.39 [1.23–1.57]***	***1.18 [1.09–1.29]***	0.83 [0.75–0.92]
Philadelphia	2	***1.12 [1.07–1.18]***	1.06 [0.99–1.14]	***1.22 [1.13–1.32]***	***1.17 [1.11–1.24]***	0.98 [0.89–1.08]	***1.26 [1.15–1.38]***	1.06 [1.00–1.12]
New York	2	1.04 [1.00–1.08]	0.99 [0.94–1.05]	***1.08 [1.02–1.15]***	1.01 [0.96–1.06]	***1.07 [1.01–1.14]***	***1.10 [1.04–1.17]***	0.98 [0.93–1.04]
Washington D.C.	3	1.06 [0.98–1.15]	0.99 [0.89–1.11]	***1.15 [1.01–1.31]***	1.01 [0.91–1.11]	***1.16 [1.00–1.34]***	1.08 [0.95–1.23]	1.04 [0.93–1.15]
Oklahoma City	4	0.91 [0.78–1.05]	0.88 [0.74–1.06]	1.00 [0.81–1.24]	0.86 [0.72–1.02]	1.05 [0.84–1.32]	1.00 [0.83–1.21]	0.84 [0.68–1.03]
Nashville	4	***1.22 [1.04–1.44]***	0.88 [0.72–1.09]	***1.94 [1.51–2.49]***	1.03 [0.84–1.26]	***1.73 [1.29–2.32]***	***1.94 [1.51–2.49]***	0.88 [0.72–1.09]
Portland	6	0.99 [0.89–1.09]	1.02 [0.89–1.17]	0.91 [0.76–1.09]	0.92 [0.81–1.04]	1.16 [0.97–1.39]	1.01 [0.89–1.15]	0.91 [0.75–1.11]
Seattle	6	***1.16 [1.08–1.24]***	***1.15 [1.03–1.28]***	***1.14 [1.04–1.25]***	***1.18 [1.05–1.31]***	***1.13 [1.03–1.24]***	***1.14 [1.04–1.25]***	***1.18 [1.06–1.31]***
Raleigh	6	0.99 [0.69–1.41]	1.00 [0.68–1.47]	0.88 [0.35–2.24]	0.99 [0.69–1.41]	0.52 [0.22–1.25]	0.48 [0.25–0.90]	1.37 [0.89–2.11]
Memphis	6	0.93 [0.83–1.05]	0.83 [0.71–0.96]	1.19 [0.95–1.48]	0.86 [0.74–0.99]	1.15 [0.93–1.42]	***1.36 [1.13–1.63]***	0.73 [0.62–0.85]
Atlanta	7	***1.32 [1.17–1.50]***	***1.52 [1.30–1.77]***	1.00 [0.82–1.23]	***1.16 [1.00–1.33]***	***2.04 [1.57–2.65]***	***2.06 [1.68–2.52]***	1.00 [0.86–1.16]
Birmingham	7	1.13 [0.94–1.35]	1.10 [0.89–1.36]	1.16 [0.82–1.63]	1.10 [0.90–1.34]	1.22 [0.81–1.85]	***1.33 [1.01–1.74]***	0.99 [0.77–1.27]
Dallas	9	***1.23 [1.11–1.36]***	0.98 [0.87–1.11]	***1.52 [1.31–1.76]***	1.06 [0.93–1.21]	***1.28 [1.12–1.46]***	***1.39 [1.21–1.60]***	1.00 [0.88–1.13]
Las Vegas	9	1.22 [0.99–1.51]	***1.32 [1.03–1.71]***	1.00 [0.64–1.55]	1.23 [0.99–1.52]	0.87 [0.22–3.50]	***1.29 [1.01–1.65]***	1.02 [0.69–1.51]
San Francisco	11	1.08 [0.99–1.18]	***1.12 [1.01–1.24]***	1.00 [0.86–1.16]	1.03 [0.93–1.14]	***1.18 [1.01–1.38]***	1.01 [0.91–1.12]	***1.19 [1.04–1.37]***
Austin	11	***1.29 [1.02–1.64]***	0.98 [0.72–1.32]	***1.82 [1.27–2.60]***	1.15 [0.88–1.50]	***1.58 [1.04–2.42]***	***1.50 [1.12–2.02]***	1.01 [0.73–1.41]
New Orleans	12	1.11 [0.94–1.30]	0.95 [0.77–1.16]	***1.52 [1.14–2.03]***	0.97 [0.80–1.18]	***1.47 [1.10–1.97]***	***1.51 [1.21–1.89]***	0.77 [0.60–0.98]
Phoenix	14	0.93 [0.84–1.04]	0.78 [0.69–0.89]	***1.32 [1.09–1.59]***	0.77 [0.68–0.88]	***1.30 [1.09–1.56]***	1.15 [0.95–1.39]	0.85 [0.75–0.96]
Los Angeles	14	***1.06 [1.01–1.12]***	1.10 [1.00–1.22]	1.04 [0.99–1.10]	1.03 [0.96–1.11]	***1.09 [1.01–1.16]***	1.00 [0.94–1.07]	***1.14 [1.06–1.22]***
San Diego	14	1.07 [0.91–1.26]	1.05 [0.88–1.25]	1.21 [0.77–1.92]	1.06 [0.89–1.25]	1.25 [0.68–2.31]	1.11 [0.91–1.36]	0.99 [0.76–1.30]
Orlando	17	***1.29 [1.13–1.47]***	***1.25 [1.08–1.45]***	***1.30 [1.04–1.64]***	***1.24 [1.08–1.43]***	***1.34 [1.02–1.76]***	1.18 [0.96–1.47]	***1.40 [1.18–1.66]***
Miami	21	***1.18 [1.12–1.25]***	***1.23 [1.15–1.32]***	***1.09 [1.00–1.19]***	***1.21 [1.13–1.28]***	1.10 [1.00–1.21]	***1.28 [1.18–1.39]***	***1.13 [1.05–1.22]***

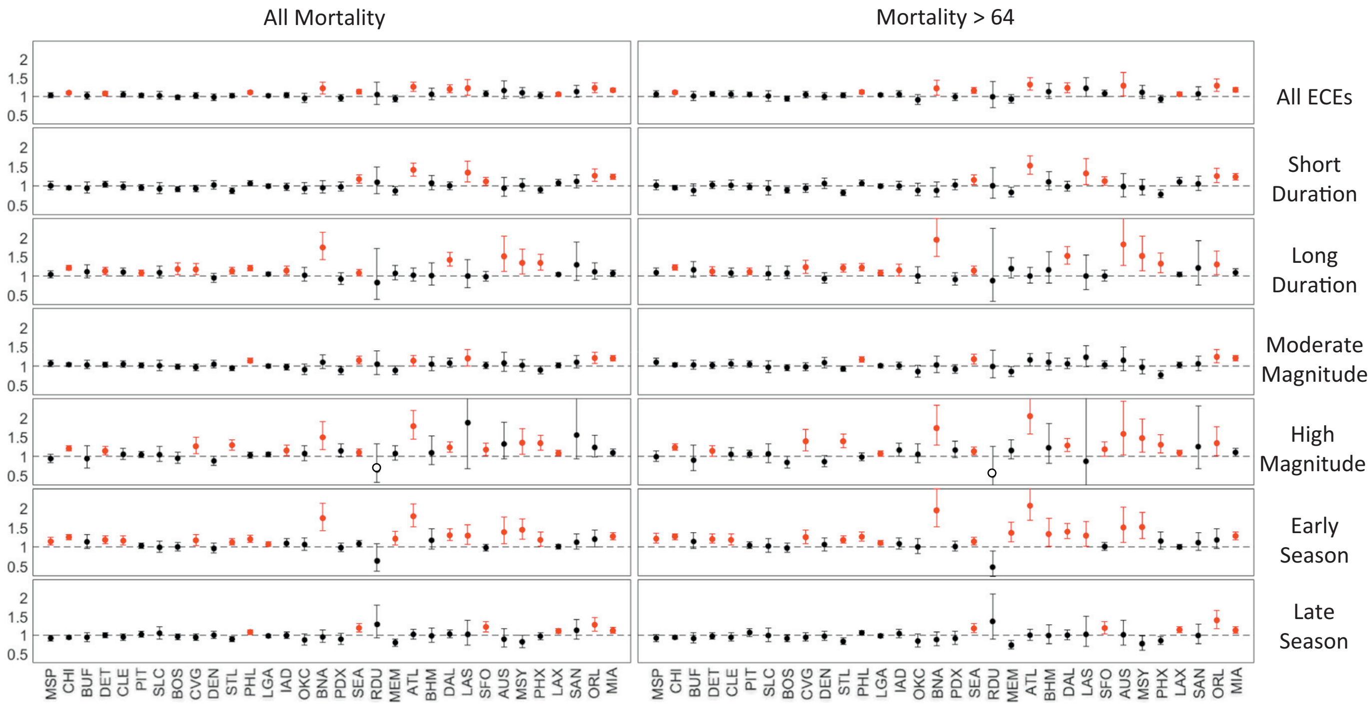

Fig. 3. Relative Risk (RR) by city with mean winter temperature (MWT) increasing from left to right. Red bars are statistically significant RRs. Hollow markers for RDU represent 0 ECEs for the category. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

November. Nashville and Austin experienced the largest increased RR for long duration ECEs, with Nashville having an increased RR of 1.74 [1.42–2.13] for all-age mortality and 1.94 [1.51–2.49] for mortality >64 and Austin having an increased RR of 1.51 [1.12–2.04] for all-age mortality and 1.82 [1.27–2.60] for mortality >64. It should be noted that the RR for Atlanta, Las Vegas, Orlando, and Miami decreases from short duration to long duration ECEs. Atlanta and Orlando have relatively small sample sizes (3 long duration ECEs), thus may partially explain the decrease in RR for long duration events. Miami and Las Vegas have relatively large sample sizes (8 and 9 long duration ECEs), therefore the decrease in RR may be a result of changing demographics or relatively low magnitude ECEs. Moreover, the occurrence of long duration ECEs may have played a part in the decreased RR for these cities. Long duration ECEs that occur late in the winter, or following an early season ECE, may ultimately lower the susceptible population and result in a reduced RR. This concept is further explored in Section 3.3.

3.2. RR and ECE magnitude

The importance of categorizing ECEs is further supported by the difference in the RR between moderate and high magnitude ECEs. Though moderate ECEs resulted in a significantly increased RR for six cities (four cities for mortality >64), high magnitude ECEs generally had much larger RRs with 13 cities being significant for all-age mortality and 16 significant for mortality >64. Furthermore, there is a clear relationship between the cities MWT and the RR as cities with warmer MWTs tend to have higher RRs during high magnitude ECEs (Fig. 3). Particularly

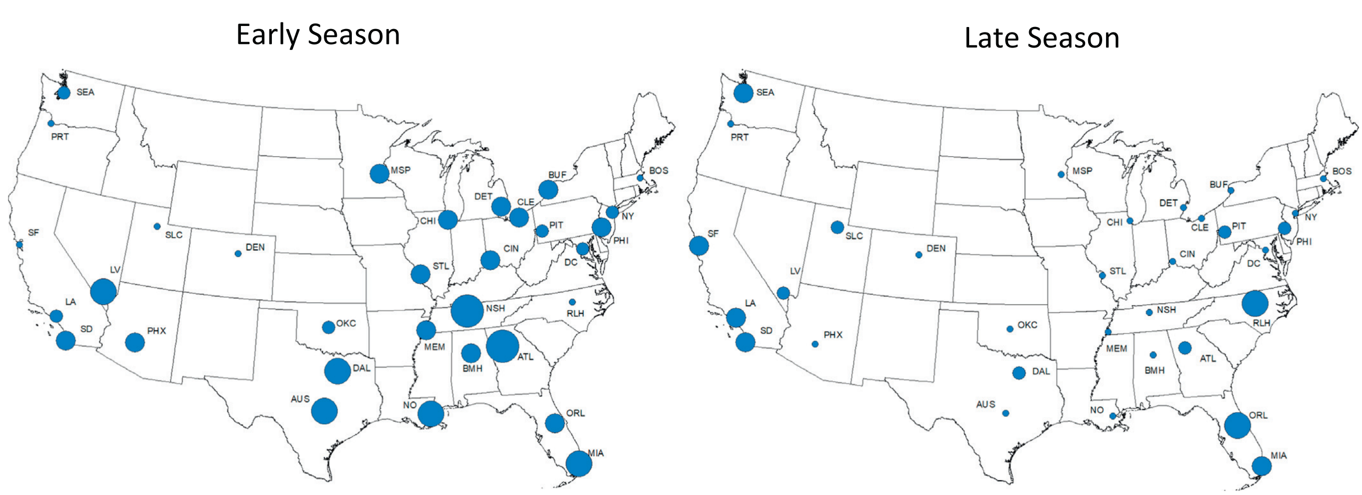

Fig. 4. RR for all-age mortality associated with early season and late season ECEs by city.

elevated RRs occurred during high magnitude ECEs in Nashville (1.49 [1.17–1.90]) and Atlanta (1.78 [1.45–2.19]) for all-age mortality with much higher RRs evident when only considering the mortality of individuals >64 in Nashville (1.73 [1.29–2.32]) and Atlanta (2.04 [1.57–2.65]). Of the colder MWT cities, Chicago, Cincinnati, and St. Louis had the highest increased RR with values near 1.30. High magnitude ECEs resulted in the largest increased RR for several cold MWT cities, however, more cities experienced a significant increase in RR during early season ECEs.

3.3. RR and early vs. late season ETEs

Dividing ECEs into early and late season events reveals the strongest relationship to mortality (Fig. 3 & Fig. 4) with 18 cities having significantly increased RRs during early season ECEs for both age categories (Tables 4 and 5). Late season ECEs result in much fewer significant increases in RR for all-age mortality (6 cities significant) and mortality >64 (5 cities significant). Furthermore, early season ECEs generally have a much longer period of increased mortality following the ECE

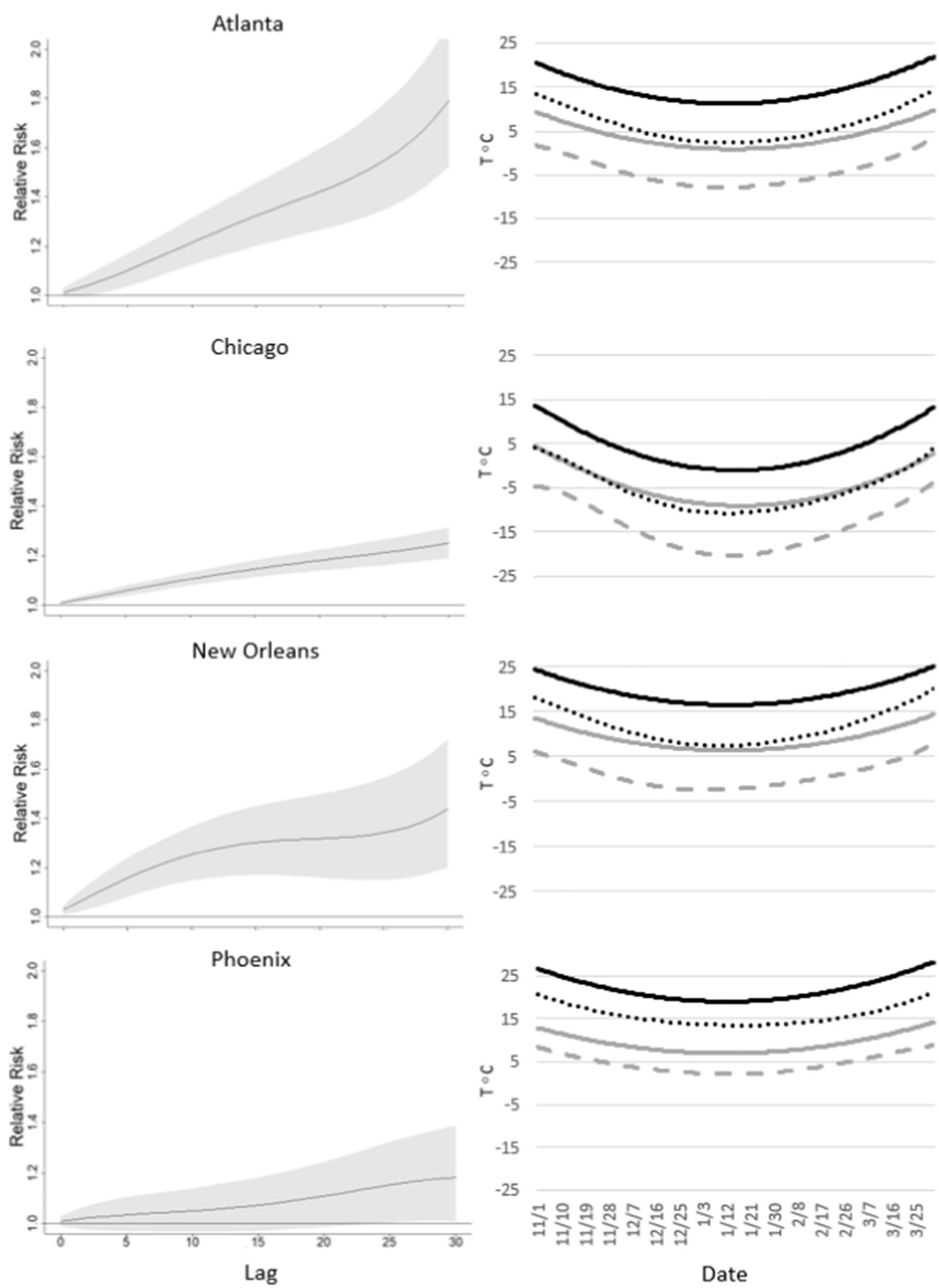

Fig. 5. On the left: Relative risk of all-cause mortality during early season ECEs for Atlanta, Chicago, New Orleans, and Phoenix. On the right: Mean daily maximum (black line) and minimum (gray line) temperatures and the respective temperature 1.5σ below the mean daily maximum temperature (black dotted line) and minimum temperature (gray dashed line).

onset, as opposed to late season ECEs. The highest RRs occur in cities with warmer MWTs, further suggesting that cities with warmer MWTs are particularly vulnerable to ECEs. While colder MWT cities generally have a lower RR than warmer MWT cities during early season ECEs, the number of significant increased RRs is larger than from high magnitude ECEs. The lower RRs in cities with colder MWTs may be a result of an earlier onset of cold weather, acclimatizing the population before the study period begins in November. It may also be attributed to better preparedness in these cities as they typically experience a larger number of ECEs. Nonetheless, the large number of significantly increased RRs for most cities suggests that early season ECEs may be particularly impactful on populations not yet acclimatized to extreme cold. Cities such as Orlando, Miami, Los Angeles, San Francisco, and Seattle still had significant increased RRs during late season ECEs, with the RR increasing from early season to late season for all cities but Miami. These cities have warmer climates, with little variation in temperature due to maritime influences, thus it requires an idealized circulation pattern to result in an ECE in these locations. Cold fronts that propagate southeastward toward Orlando and Miami are typically moderated by the warm waters of the Gulf of Mexico. Furthermore, the southward extent of these two cities requires a potent cold front with a circulation pattern capable of sustaining anomalous cold in a heavily maritime influenced region. These conditions are much more likely during the middle of winter when the polar vortex is more capable of displacing large, cold air masses across the eastern U.S. Los Angeles, San Francisco, and Seattle are impacted by ECEs differently as cold air masses are often a result of unusually strong surface high pressure in and south of the Gulf of Alaska (Grotjahn and Zhang, 2017). An air mass capable of sustaining the southward cold air advection must be in place in these regions to prevent moderation, thus late season ECEs may favor mid-winter on the western coast of the U.S.

3.4. Discussion

The results show that extreme low temperatures should be considered relative to the climate as opposed to using a single temperature threshold for all cities. This is represented in Fig. 5 which shows how the cumulative increased RR differs for all-age mortality during early season ECEs for four cities with vastly different climates. The increased RR for Atlanta during early season ECEs (November–December) is 1.79, yet the daily maximum temperature of an ECE 1.5σ below the climatological average would be between 5 °C and 15 °C. Conversely, Chicago would expect a daily maximum temperature between −10 °C and 5 °C for a similar magnitude ECE, yet the increased RR for early season ECEs is 1.25. This further suggests that human mortality may be more dependent on a city's climate than absolute temperature thresholds.

Similar to (Sheridan and Dixon, 2016), this study finds that the elderly population (mortality >64) are more prone to the impacts of extreme temperatures as the RR for mortality >64 was consistently higher than that of all-age mortality. The RR of increased all-age mortality during early season ECEs was 1.74 for Nashville and 1.79 for Atlanta (Table 4), however the RR increased to 1.94 for Nashville and 2.06 for Atlanta when only including mortality >64 (Table 5). Much like Ng et al., 2014 and Curriero et al. (2002), a clear relationship exists between ECEs and the increased RR of cities with a warmer MWT as these cities generally experienced a much higher increased RR as opposed to cities with colder MWTs. Atlanta and Nashville had a particularly high increased RR during long duration, high magnitude, and early season ECEs. Though colder MWT cities generally had lower RRs, many of them still experienced significant increases in RR during long duration, high magnitude, and early season ECEs. These findings are consistent with Kinney et al. (2015) and Staddon et al. (2014) in which it was shown that warmer temperatures do not necessarily equate to lower mortality. Furthermore, a warming climate may not result in reduced winter mortality as the highest RRs of increased mortality are evident in cities with warmer MWTs. These findings should be considered by health professionals as they prepare policies regarding climate change mitigation.

4. Conclusions

While the effect of extreme cold is less apparent than extreme heat, this study suggests that ECEs certainly have a large impact on human mortality. The findings of this study were similar to (Ng et al. (2014); Ma et al. (2014); Curriero et al. (2002); Whitman et al. (1997)) in which the RR of increased mortality increased with ECEs, particularly in cities with a warmer MWT. The division of ECEs by categories provided further insight on how mortality is affected by ECEs of various magnitudes and duration by showing high magnitude and long duration ECEs generally result in a much larger and more significant increased RR for cities. Furthermore, early season ECEs result in a much longer period of increased risk as opposed to late season ECEs, while also having the most cities with statistically significant RRs. This can likely be attributed to individuals not being acclimatized to the extreme cold early in the winter season. The large disparity in RRs may also suggest that individuals who are more likely to succumb to the effects of ECEs do so earlier in the winter, leaving a less vulnerable population during late season ECEs. Individuals older than 64 were most prone to increased mortality as the RR was generally higher when compared to all-age mortality. The differences of the two mortality age groups may have been even more significant if a third group of mortality, mortality <64 years old, had been included for comparison. Out of all 32 cities in this study, Atlanta, Nashville, and Austin had the highest RRs, especially during long duration, high magnitude, and early season ECEs. Moreover, all three of these cities had relatively warm MWTs. A more in-depth study of why these three cities had such a large increased RR during ECEs may be beneficial.

Further research comparing the trends in cold related mortality would reveal if mortality maintains the same clear decrease as shown in the study on heat related trends by Sheridan and Dixon (2016). It may also help delineate the impacts of population growth and demographic change on mortality, particularly in cities with large retirement communities or high poverty. Expanding the mortality dataset and the number of cities in the study would provide an even stronger relationship between ECEs and mortality. Nonetheless, a significant relationship between ECEs and mortality has been presented. A continued push to understand how extreme cold impacts mortality is vital toward implementing policies and enhancing the technology that protects individuals.

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