Int J Biometeorol
DOI 10.1007/s00484-013-0640-4

ICB 2011 - STUDENTS / NEW PROFESSIONALS

High-mortality days during the winter season: comparing meteorological conditions across 5 US cities

Michael J. Allen · Scott C. Sheridan

Received: 23 March 2012 / Revised: 27 January 2013 / Accepted: 31 January 2013

Abstract While the relationship between weather and human health has been studied from various perspectives, this study examines an alternative method of analysis by examining weather conditions on specific high-mortality days during the winter season. These high-mortality days, by definition, represent days with dramatic increases in mortality and the days with the highest mortality. By focusing solely on high-mortality days, this research examines the relationship between weather variables and mortality through a synoptic climatology, environment-to circulation approach. The atmospheric conditions during high-mortality days were compared to the days prior and the days not classified as high-mortality days. Similar patterns emerged across all five locations despite the spatial and temporal variability. Southern locations had a stronger relationship with temperature changes while northern locations showed a greater relationship to atmospheric pressure. Overall, all high-mortality days were associated with warmer temperatures, decreased pressure, and a greater likelihood of precipitation when compared to the previous subset of days. While the atmospheric conditions were consistent across all locations, the importance of the lag effect should not be overlooked as a contributing factor to mortality during the winter season. Through a variety of diverse, methodological approaches, future studies may build upon these results and explore in more detail the complex relationship between weather situations and the impact of short-term changes in weather and health outcomes.

Keywords Synoptic climatology · Winter · Weather · Mortality · Short-term variability

M. J. Allen (✉) · S. C. Sheridan
Department of Geography, Kent State University,
Kent, OH 44242, USA
e-mail: mallen34@kent.edu

Introduction

Weather plays an important role in our everyday lives, and the relationship the environment has with human health has been studied extensively from various perspectives. Many atmospheric variables, including temperature and snowfall, have been found to have relationship to winter mortality (e.g., Gorjanc et al. 1999; McGregor 1999; Hajat et al. 2007) . In addition, several weather indices have been created in an attempt to understand the role weather conditions have on human health (e.g., Jendritzky et al. 2001; Sheridan 2002; Anderson and Bell 2009). In this study, we investigate weather conditions on high-mortality days using a mortality *spike/non-spike* classification, a different methodological approach that classifies high-mortality days a priori to analyzing the atmospheric characteristics.

While much research focusing on the impact of heat on human health exists, more deaths occur during the winter season (Curriero et al. 2002). However, part of the difficulty in studying winter-related mortality is that besides weather, there are many confounding factors such as disease prevalence and enhanced lag effects that make the relationship difficult to discern (Keatinge 2002; Diaz et al. 2005; Anderson and Bell 2009). With an increased prevalence of pathogen-based diseases, illnesses are more common throughout the winter (Dushoff et al. 2005). Respiratory diseases such as asthma and influenza have been observed to increase in occurrence during the winter season (Curriero et al. 2002; Dushoff et al. 2005; Raatikka et al. 2007). Cardiovascular-related illnesses also increase as low temperatures cause additional strain on the cardiovascular system (McKee 1990; Basu and Samet 2002). The Eurowinter Group (1997) concluded that low temperatures were related to the observed increase in heart disease mortality during the winter season.

Published online: 19 February 2013

The lag effect is also an important consideration associated with weather-related mortality. In winter, there is often a delayed physiological response of human health to environmental conditions, which is different than heat-related mortality, in which the human response is more acute (Kunst et al. 1993; Anderson and Bell 2009). Since weather conditions vary significantly more during winter than any other season, from day to day and from one winter to the next, the lag effect is difficult to examine. Research indicates that the majority of deaths related to cardiovascular diseases occur within 3 days, whereas respiratory-related deaths may occur upwards of 14 days after an environmental stimulus (Gorjanc et al. 1999; Patz et al. 2000; Keatinge 2002). With this in mind, it is important to note that the cold effect may be delayed by several weeks (Kunst et al. 1993; Braga et al. 2001). Several studies have used distributed-lag models to analyze the temporal structure of the weather-mortality relationship (e.g., Gasparrini and Armstrong 2010; Barnett et al. 2010; Gasparrini 2011). Gasparrini (2011) provides details regarding this flexible modeling technique, which was used to examine temperature thresholds as well as various lagged periods. Other statistical techniques, such as time series modeling, have been used to examine weather-health relationships in greater detail (Dominici et al. 2003; Schwartz 2005).

Fewer studies have examined the relationship between sudden changes in temperature and pressure and their relationship to mortality (e.g., Plavcová and Kyselý 2010). Similarly, given the large day-to-day variability in mortality in winter, one question relatively unexplored is whether specific weather conditions can be associated with mortality 'spikes'—large increases in mortality over the preceding days. As a way to examine the short-term impact of winter weather on human health, this research compared winter (defined herein as October–March) weather conditions across 5 US cities on days when mortality was high—a *spike day*—to weather conditions on *non-spike days*. High-mortality or spike days were days on which mortality was significantly greater (at least 1.5 or 2 standard deviations) than previous days, therefore, representing days during the winter season with the highest mortality (Table 1). By comparing the weather conditions on such high-mortality days to non-spike days, this study represents an environment-to-circulation study, in which the environmental response of mortality is used as a basis for assessing surface weather conditions (Yarnal 1993).

Materials and methods

Mortality and weather data

Mortality data (1975–2004) were obtained from the National Center for Health Statistics (NCHS), and were compiled into daily totals, from which subsets segregated by race (white, black, other), sex (male, female), and age (< 65, 65–74, 75 +) were calculated. Using the International Classification of Death (ICD-10) codes, primary cause of death was also divided into three categories: cardiovascular (I00–I99), respiratory (J00–J99), and other. While time of death may be important to consider, this variable was not available for analysis. The five Metropolitan Statistical Areas (MSA) of Minneapolis-St. Paul, Pittsburgh, St. Louis, San Antonio, and Miami were chosen based upon climatic variability and their representation of the variability in US demographics (Table 2; Fig. 1). Mortality from all counties within the MSA was aggregated to increase sample size. For each MSA, the weather station at the primary airport was chosen to represent weather conditions. Daily mean temperature, mean sea-level pressure, and precipitation data were obtained for these stations from the National Climatic Data Center. Other temperature and pressure metrics were created to account for the changes in weather conditions during the winter season (Table 3). In addition, daily precipitation was classified as binary (yes/no). The "winter season" in this research was defined broadly, October–March, to account for both early and late winter seasonal mortality which has been noted by previous studies (e.g., Medina-Ramón and Schwartz 2007).

Spike day methodology

A mortality spike was defined as an increase in mortality greater than a specific wintertime standard deviation threshold when compared to a previous number of days. Standard deviations were based on location and were computed for each winter season. Therefore, spike days represent both dramatic increases in mortality as well as the days during the winter season with the highest mortality. On high-mortality days, daily mortality was at least 1.5 standard deviations (1.5 SD, hereafter) greater than the mean of the previous 14 days. Various definitions of a spike were considered based upon 3-, 7-, and 14-day periods to account for weather patterns and lagging effect of weather; different thresholds of mortality increase (1.0, 1.5, 2.0, and 2.5 standard deviations) were also assessed. Since all definitions and thresholds provided similar results, only the high-mortality days associated with the 14-day 1.5 SD and a higher threshold of 14-day 2.0 standard deviation (2.0 SD, herein) results will be discussed.

Using both historical mortality and climatic data (1975–2004), the weather conditions on high-mortality (spike) days were compared with non-high-mortality days. The differences in temperature and sea-level pressure values between spike days and non-spike days were compared using a two sample *t*-test. Similarly, a two-sample difference of proportions test was used to compare the likelihood of precipitation

Table 1 Number of wintertime mortality spike days (1975–2004) based on the results from 1.5 SD and 2.0 SD

	October	November	December	January	February	March	Season
1.5 SD							
Minneapolis-St. Paul	79	62	84	67	52	58	402
Pittsburgh	42	48	78	50	37	46	301
St. Louis	54	47	98	66	45	45	355
San Antonio	51	55	78	61	46	63	354
Miami	30	40	55	48	28	25	226
2.0 SD							
Minneapolis-St. Paul	23	20	29	25	22	19	138
Pittsburgh	13	15	25	22	14	24	113
St. Louis	13	17	25	18	16	15	104
San Antonio	17	22	35	20	18	29	141
Miami	7	7	20	8	10	9	61

variables between spike and non-spike mortality days. This statistic takes into account the percentage of days in which a particular outcome occurred (e.g., precipitation on high-mortality days) and compares it with the opposite outcome (e.g., precipitation on non-spike days). For both tests, significant results are those with a $P<.0.05$; for further comparison, we also indicated those tests that were near significant defined as $P<0.10$.

Results

Although Minneapolis-St. Paul reported the most spike days, the number of mortality spikes varied spatially and temporally (Table 1). Miami had the fewest spike days during the winter season (226). In all cities, the month of December had the greatest number of mortality spike days. In addition, all locations had more mortality-spike days during the early winter season (October–December) as opposed to the latter half, to be expected given the general upward trend in mean mortality over this period of the year. With a higher threshold definition, the 2.0 SD results were similar but with fewer mortality-spike days across the locations; this contributed to the increased variability in the 2.0 SD results.

In all locations, all-cause mortality increased by at least 25 % on mortality-spike days. However, not all causes of death changed by the same magnitude across the cities (Table 4). In the northern locations, cardiovascular deaths increased more on mortality-spike days while the southern locations of San Antonio and Miami resulted in greater increases in respiratory deaths. Despite these variations, cardiovascular and respiratory deaths increased more than all other causes in all locations except Miami. While other analyses were conducted regarding the population demographics, the 1.5 SD and 2.0 SD results associated with sex, race, and age were both inconsistent and inconclusive and therefore are not shown.

Table 2 A comparison of demographic characteristics (age, race, sex) for each of the Metropolitan Statistical Areas (MSA) used in this research. The respective counties are listed as footnotes

	Age			Race			Sex		Total
	<65	65–74	75+	White	Black	Other	Male	Female	
Minneapolis[a]	90.4 %	4.9 %	4.7 %	86.1 %	5.3 %	8.6 %	49.4 %	50.6 %	2,968,806
St. Louis[b]	87.1 %	6.7 %	6.1 %	78.3 %	18.3 %	3.4 %	48.0 %	52.0 %	2,406,139
Pittsburgh[c]	82.3 %	8.8 %	8.9 %	89.5 %	8.1 %	2.4 %	47.7 %	52.3 %	2,431,087
San Antonio[d]	89.3 %	5.8 %	4.9 %	70.6 %	6.6 %	22.8 %	48.7 %	51.3 %	1,711,694
Miami[e]	85.5 %	7.2 %	7.3 %	70.1 %	20.4 %	9.5 %	48.3 %	51.7 %	5,007,564

[a] Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Ramsey, Scott, Sherburne, Washington, Wright (MN), Pierce, St. Croix (WI)

[b] Franklin, Jefferson, Lincoln, St. Charles, St. Francois, St. Louis, Warren, Washington (MO), Bond, Calhoun, Clinton, Jersey, Macoupin, Madison, Monroe, St. Clair (IL)

[c] Allegheny, Armstrong, Beaver, Butler, Fayette, Washington, Westmoreland (PA)

[d] Atascosa, Bandera, Bexar, Comal, Guadalupe, Kendall, Medina, Wilson (TX)

[e] Miami-Dade, Broward, Palm Beach (FL)

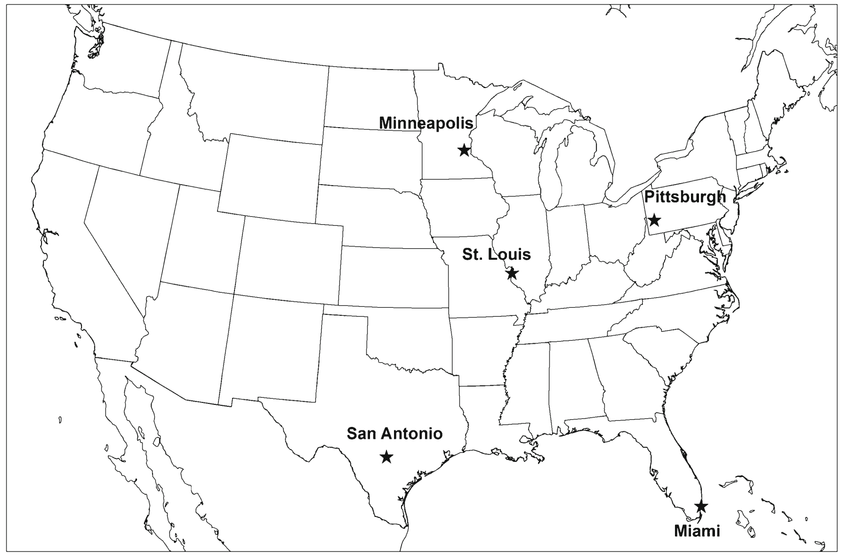

Fig. 1 The five US cities used in this research

Temperature

Throughout the locations, most of the 1.5 SD ΔT and ΔT_{1day} values that were at or near statistical significance were positive, suggesting that temperatures on mortality spike days were warmer than both all non-high mortality days and the preceding day (Table 5). While the ΔT results were more variable, six of seven significant monthly values were positive. The largest temperature differences were observed in St. Louis, with three monthly ΔT values exceeding 1.5 °C. The only other value to exceed this threshold occurred in Minneapolis during the month of January (2.29 °C ΔT).

The most consistent relationships were associated with the more southern locations and ΔT_{1day} results. For example, on the monthly level, the three significant values of St. Louis were more than Minneapolis-St. Paul, which had only one. Additionally, every value for Miami ΔT_{1day} was significant except for November—the most of any location. With two of these temperature differences being at least 1.0 °C, the most consistent relationship throughout the winter season between temperature and high-mortality days was observed in Miami.

When comparing seasonal values, the largest temperature differences were in the southern locations of St. Louis (0.83 °C ΔT_{1day}) and Miami (0.72 °C ΔT). More variability was found with the ΔT results likely due to the large

Table 3 The metrics of atmospheric variables used to account for the weather leading up to a mortality spike day

Atmospheric variable	Definition
ΔT (average temperature)	Difference between average temperature on a high-mortality day and non-spike day
	Positive value signifies temperature is warmer on high-mortality days than non-spike days
ΔT_{1day} (1 day temperature)	Difference in temperature between day 0 (high-mortality day) and the previous day
	Positive value signifies temperature is warmer on high-mortality days than the days preceding them
ΔP (average pressure)	Difference between average pressure on a high-mortality day and non-spike day
	Negative values signify pressure is lower on high-morality days than non-spike days
ΔP_{1day} (1 day pressure)	Difference in pressure between day 0 (high-mortality day) and the previous day
	Negative values signify pressure is lower on high-mortality days than the days preceding them
Precipitation	Binary comparison as to whether any precipitation occurred ($x > 0$)
	Values greater than 1.00 represent an increase in likelihood

Table 4 Mean percent increase in mortality on high mortality days compared to non high mortality days. Mortality is separated based upon cause of death

	Minneapolis	Pittsburgh	St. Louis	San Antonio	Miami
Cause of death					
1.5 SD					
Cardiovascular	33 %	28 %	32 %	41 %	22 %
Respiratory	32 %	28 %	31 %	45 %	29 %
Other	28 %	24 %	29 %	40 %	27 %
All	30 %	26 %	31 %	41 %	25 %
2.0 SD					
Cardiovascular	38 %	35 %	38 %	45 %	27 %
Respiratory	34 %	39 %	39 %	51 %	44 %
Other	36 %	27 %	31 %	48 %	31 %
All	37 %	31 %	35 %	47 %	30 %

Table 5 Differences in weather conditions between high-mortality and non-high mortality days using the 1.5 SD threshold. Temperature values are in °C, pressure values are in millibars; positive numbers represent higher values on spike days. For precipitation, a value of 1.00 represents a relative frequency increase of 0 %. Therefore, values greater than 1.00 signify days in which precipitation was more likely to occur on high-mortality days

	October	November	December	January	February	March	Season
ΔT							
Minneapolis	0.65	0.18	−0.55	2.29**	−0.40	−0.24	0.52
Pittsburgh	0.62	0.12	−0.07	1.27*	1.00	0.82	0.12**
St. Louis	1.53**	3.01**	−0.29	−0.75	−0.99	1.64*	−0.29**
San Antonio	0.21	0.48	−0.89*	0.23	−1.11	−0.11	−0.48**
Miami	1.00**	0.20	0.38	0.09	0.45	0.61	0.10**
ΔT1day							
Minneapolis	0.31	0.36	−0.21	0.50	0.44	0.72*	0.32**
Pittsburgh	0.25	0.30	0.87**	0.39	1.00*	0.91*	0.64**
St. Louis	0.70**	1.46**	0.35	0.37	0.86	2.00**	0.83**
San Antonio	−0.21	0.90**	0.79**	0.22	0.69	0.63*	0.52**
Miami	0.22*	0.22	1.18**	0.68*	1.38**	0.46**	0.72**
ΔP							
Minneapolis	−1.80**	−2.90**	−1.10	−3.50**	−2.10*	−1.80*	−1.40**
Pittsburgh	0.50	−1.10	−1.30*	0.00	−2.20*	−1.70*	−0.20
St. Louis	−0.80	−2.00**	0.10	−0.40	0.80	0.00	0.40*
San Antonio	−1.00*	−0.40	0.50	0.30	0.30	−0.90	0.30
Miami	0.00	0.90**	0.20	0.10	−1.30*	1.50**	0.40**
ΔP1day							
Minneapolis	−2.20**	−2.60**	−0.40	−1.90**	−2.00**	−2.00**	−1.30**
Pittsburgh	−0.70	−1.60**	−1.20*	−0.90	−2.90**	−1.20	−1.30**
St. Louis	−1.70**	−2.70**	−0.60	−1.70**	−1.50	−2.20**	−1.10**
San Antonio	0.00	−1.00*	−0.80	−0.20	−1.10*	−0.50	−0.40**
Miami	0.10	0.30	−0.70**	−0.40	−1.00**	0.10	−0.20**
Precipitation							
Minneapolis	1.11	1.52**	1.10	1.29*	1.46**	1.61**	1.31**
Pittsburgh	0.74	1.07	1.15	1.17	0.91	1.15	1.09**
St. Louis	0.76	1.21	1.14	1.13	1.43*	0.86	1.06
San Antonio	0.96	0.80	0.88	1.43*	1.00	1.19	1.00
Miami	0.79	0.65**	0.96	0.57**	0.91	0.57*	0.73**

**Statistically significant values, * near significant values

number of non-spike days as compared to the ΔT_{1day}, which compares only the day immediately before a high-mortality event. When aggregated across the entire winter season, for all MSAs all ΔT_{1day} were statistically significantly positive. The same relationship was observed in the results associated with the transitional month of March, with the smallest temperature difference in San Antonio (0.63 °C ΔT_{1day}). In all cases, these values were positive, indicating the warmest temperatures occurring on high-mortality days when compared to the previous day (Fig. 2).

Both ΔT and ΔT_{1day} showed January and February as having the fewest number of statistically significant values. For all other months, results varied across the locations, suggesting a seasonal pattern associated with temperature and high-mortality days. While the 2.0 SD results were consistent with 1.5 SD results, more variation was evident due to the smaller sample size.

Pressure

The monthly ΔP results showed a total of 13 at or near significant values across the locations (Table 5). Similar to ΔT, the ΔP results showed more variability than ΔP_{1day}. Minneapolis-St. Paul had five significant monthly values with the largest differences occurring in January (−3.50 mb ΔP). Except for Miami's November value, all of the significant ΔP results were negative, indicating lower pressure on high-mortality days when compared to non-high mortality days. Aggregated seasonally, a less consistent relationship was observed with only Minneapolis-St. Paul displaying a negatively significant value; some of this may be attributed to the seasonal variability in the response, which is cancelled out when aggregated. Unlike temperature, the northern location of Minneapolis-St. Paul had larger seasonal pressure changes (−1.40 mb ΔP and −1.30 mb ΔP_{1day}) when compared to the southern location

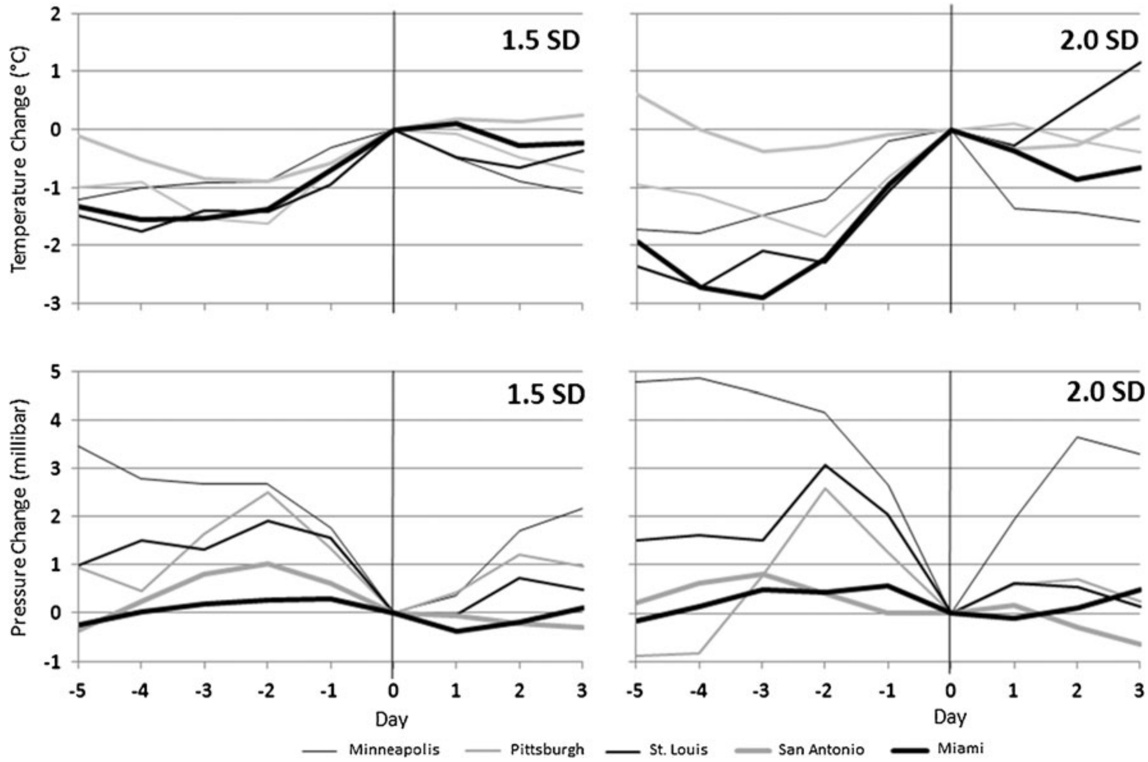

Fig. 2 Mean temperature (*top*) and pressure (*bottom*) changes on the 5 days prior and 3 days after a high-mortality day (Day 0). Despite increased variability associated with 2.0 SD results, the results showed similar V-shaped trends

of Miami (0.40 mb ΔP and −0.20 mb ΔP_{1day}). Additionally, Minneapolis-St. Paul showed the strongest month-to-month relationship with ten statistically significant values showing pressure decreases ranging between 1.8 mb and 3.5 mb. With all of these values suggesting lower pressure on high-mortality days, Minneapolis-St. Paul was the most consistent location. While five statistical significant values were observed in Miami, there was greater variability of the pressure differences. The relationship in San Antonio was the least consistent of the results with only three near statistically significant values, though these values all represented cases where the pressure was at least 1.0 mb lower on high-mortality days.

All 16 significant results associated with ΔP_{1day} were statistically significant and negative. This would indicate lower pressure on high-mortality days when compared to the preceding day (Fig. 2). Minneapolis-St. Paul had the strongest monthly relationships with only one value not significant (December −0.40 mb ΔP_{1day}). In addition to spatial variability between the northern and southern locations, temporal trends were also observed. The transition months of November, February, and March showed more significant values than the mid-winter months of December and January. All seasonal values were negative and significant with the strongest relationships in the northern locations of Minneapolis-St. Paul and Pittsburgh (−1.30 mb ΔP_{1day}). As with the temperature results, more seasonal variation was observed for ΔP than ΔP_{1day}. Additionally, the 2.0 SD pressure results were consistent but showed more variability due to the small sample size.

Precipitation

In all locations except Miami, an increased likelihood of precipitation was observed during mortality spike days (Table 5). Across all months, a total of nine values were at or near statistical significance, but only three of these values were less than 1.0. Values less than 1.0 signify that high-mortality days are less likely to experience precipitation. In addition, the only seasonal value less than 1.0 occurred in Miami (0.73). Minneapolis-St. Paul had the largest likelihood of precipitation on high-mortality days with four of the six winter months showing significant values. Most of the larger significant increases occurred during the latter portion of winter (January–March). Results associated with heavy precipitation (>25 mm), snowfall, and heavy snowfall (>25 cm) were also tested for significance. Increased variability was observed with these variables due to the small sample size, and thus are not shown.

Trends in temperature and pressure

Beyond the significance testing above, temporal trends in variables leading up to a mortality spike day were also examined to help assess synoptic meteorological conditions. The trend of temperature leading up to and following a high-mortality day showed consistent V-shape patterns across the study region (Fig. 2). The largest temperature changes occurred in the southern locations which is consistent with the results presented. Temperature increases generally linearly for the 3 days leading up to a mortality spike day, across all cities using both the 1.5 and 2.0 SD thresholds. The largest temperature increases occurred in St. Louis with 1.5 SD results showing an increase of 1.76 °C (from Day −4). The warmest temperatures thus occur on the high-mortality day when compared to the previous 5 days. The response of temperature following a high-mortality day is variable.

Alternatively, atmospheric pressure showed an inverse relationship with pressure decreasing on days leading up to a mortality spike day. Pressure values fell to a minimum value on high-mortality days when compared to the previous 5 days. Danet et al. (1999) has previously noted a similar V-shaped relationship with winter mortality and pressure. The largest pressure decreases occurred in the northern locations. Pressure in Minneapolis-St. Paul was at least 1.8 mb higher on the 5 days prior to a high-mortality day, whereas, the pressure falls in San Antonio and Miami were minimal (0.6 mb and 0.3 mb, respectively). Despite the regional variations, these patterns were consistent throughout the season for all locations. In addition, these patterns were also evident in the 2.0 SD results, but the smaller sample size increased the variability of temperature and pressure across all of the locations.

Discussion

In an attempt to better understand the physiological response to the environment, this research examines the specific weather conditions leading to high-mortality days during the winter season. Additionally, it examines the weather on high mortality days compared to non-high mortality days. While only five cities were used in the analysis, consistent relationships across the cities emerged with regard to temperature, pressure, and precipitation. Variable through both time and space, the main conclusion from this research is that there are significant differences between weather conditions during mortality spike days than non-spike days. Increasing temperatures, falling atmospheric pressure, and an increased likelihood of precipitation were all more common on high-mortality days when compared both to days leading up to a mortality-spike day as well as to non-spike days in general. The seasonal values of ΔT and ΔP were less consistent, likely due to overall atmospheric variability over the course of the winter season.

The relationship between temperature and mortality is not entirely consistent with previous research that suggests mortality increases the most during low temperatures (Huynen et al. 2001; Analitis et al. 2008). Despite an increase in blood viscosity during low temperatures, this research showed that days with warmer temperatures were associated with higher mortality. However, the importance of the lag effect and a delayed physiological response to the environment should not be overlooked as a probable, contributing factor (Armstrong 2006; Basu and Samet 2002; Gasparrini et al. 2010). This research is consistent with that of Plavcová and Kyselý (2010), which showed significant increases in mortality following a warming trend. O'Neill et al. (2003) suggested that the variance in temperature may be a large contributing factor in increased respiratory deaths. Additionally, Morabito et al. (2008) showed an increase in blood pressure following a sudden change in weather patterns—an important risk factor associated with cardiovascular mortality events.

The effect of atmospheric pressure on winter mortality has been studied less frequently than other variables (e.g., Plavcová and Kyselý 2010). A V-shape pressure pattern, similar to that shown by Plavcová and Kyselý (2010), was evident in all locations but varied considerably in magnitude. The relationship with pressure was strongest in the northern locations with largest changes occurring during the transitional months. Although this variability verifies the regional differences associated with winter mortality discussed by Keatinge (2002), it also incorporates the synoptic climatology of the circulation patterns of the atmosphere. As temperatures change throughout the year, the jet stream, which controls the movement of weather systems, migrates accordingly. This weather-system progression through the atmosphere changes spatially and temporally throughout the winter season and may account for some of the north–south relationships shown in the presented results.

While it may be difficult to distinguish the impact of the results on mortality, research indicates that unsettled atmospheric conditions may contribute to higher winter mortality (Kassomenos et al. 2007; McGregor 1999). With warming temperatures and decreasing pressure, and an increased likelihood for precipitation, a transitional or changing synoptic weather pattern, with an approaching mid-latitude cyclone, may be likely. However, further analysis was done with a synoptic-weather typing scheme, the Spatial Synoptic Classification (Sheridan 2002), and no favorable weather type was consistently identified. Recurring weather patterns were found, however, through a manual classification of a random sample of synoptic weather maps, although no statistical comparison was conducted.

Much research has uncovered a lag effect associated with winter (cold) mortality (Barnett et al. 2010; Gasparrini et al. 2010). This delayed response may not be accounted for within this research since this study examined only the short term changes in weather on high-mortality days without direct inclusion of such a lag effect. Thus, while warmer temperatures were found to be associated with high-mortality events, the extent to which the weather on high-mortality days could be attributed directly to these deaths remains unresolved. Increasing temperatures and decreasing pressure may be associated directly with a strong cold frontal passage, which would typically precede the observed spike-day conditions by several days.

While the weather relationships were similar throughout all of the cities, San Antonio showed the weakest correlations. However, despite this, a north–south relationship existed between the cities, with Miami exhibiting some of the largest temperature increases and Minneapolis-St. Paul showed the most significant pressure decreases.

Conclusion

While previous studies have examined the numerous factors contributing to high winter mortality (Kassomenos et al. 2007; McGregor 1999; Barnett et al. 2010), this research examined an alternative method of analysis, by defining the environmental condition of high-mortality days and considering solely the weather conditions associated with these days and those immediately preceding. In addition, by incorporating trends in variables, the weather was also examined on the days prior to a mortality spike (e.g., T_{1day}). High-mortality days represented dramatic increases in mortality and the days with the highest winter (October–March) mortality. While the presented analysis showed differences between the atmospheric conditions on high-mortality spike days and non-spike days (Table 5), further statistical techniques may be used to examine the relationships in greater detail.

Although temporally variable, the atmospheric shifts associated with high-mortality days were generally consistent across all cities. Temperatures were generally warmer on high-mortality days than non-high mortality days or the 5 days prior to a spike in mortality. A V-shaped pattern associated with pressure was evident in all locations—signifying a decrease in pressure leading up to a high-mortality day. The results of a pressure fall and a temperature rise on a spike day, along with greater likelihood of precipitation, suggest an approaching mid-latitude cyclone. However, the Spatial Synoptic Classification did not suggest any consistent weather pattern. The results of this study are consistent with those of others that have examined the importance of short term changes in weather on mortality (e.g., O'Neill 2003; Plavcová and Kyselý 2010). Examining the weather on high-mortality days coupled with advanced modeling techniques both provide a holistic perspective of the impact of weather on mortality.

Within wintertime climate-health research, few studies have examined the relationship between atmospheric conditions and mortality through an environment-to-circulation approach in which the environmental response of mortality is used as a basis for assessing weather conditions (Yarnal 1993). While the presented results show consistency regarding the weather leading up to a high-mortality day, they also raise important questions regarding the issue of lag during the winter season. Other techniques, including time series and distributed-lag modeling, may enhance the results of this research (Armstrong 2006; Gasparrini et al. 2010; Schwartz 2005; Dominici et al. 2003). By evaluating more locations and improving the spatial resolution, the impact of short-term weather variability may be further examined. Further examination of the specific synoptic weather patterns associated with high-mortality events may improve our understanding regarding the role winter weather has on human health, the physiological response to the environment, and how it may change in the future.

Acknowledgments We would like to thank Tom Schmidlin and Debarchana Ghosh for their insight and assistance with this research, and the helpful comments of the anonymous reviewers in improving our manuscript.

References

Analitis A, Katsouyanni K, Biggeri A, Baccini M, Forsberg B, Bisanti L, Kirchmayer U, Ballester F, Cadum E, Goodman PG, Hojs A, Sunyer J, Tiittanen P, Michelozzi P (2008) Effects of cold weather on mortality: results from 15 European cities within the PHEWE project. Am J Epidemiol 168:1397–1408

Anderson BG, Bell ML (2009) Weather-related mortality how heat, cold, and heat waves affect mortality in the United States. Epidemiology 20:205–213

Armstrong B (2006) Models for the relationship between ambient temperature and daily mortality. Epidemiology 17:624–631

Barnett AG, Tong S, Clements ACA (2010) What measure of temperature is the best predictor of mortality? Environ Res 110:604–611

Basu R, Samet JM (2002) Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol Rev 24:190–202

Braga AL, Zanobetti A, Schwartz J (2001) The time course of weather-related deaths. Epidemiology 12:662–667

Curriero FC, Heiner KS, Samet JM, Zeger SL, Strug L, Patz JA (2002) Temperature and mortality in 11 cities of the Eastern United States. Am J Epidemiol 155:80–87

Danet S, Richard F, Montaye M, Beauchant S, Lemaire B, Graux C, Cottel D, Marècaux N, Amouyel P (1999) Unhealthy effects of atmospheric temperature and pressure on the occurrence of myocardial infarction and coronary deaths: a 10 year survey: the Lille-world health organization MONICA project (Monitoring Trends and Determinants in Cardiovascular Disease). Circulation 100:e1–e7

Diaz J, Garcia R, Lopez C, Linares C, Tobias A, Prieto L (2005) Mortality impact of extreme winter temperatures. Int J Biometeorol 49:179–183

Dominici F, McDermott A, Zeger SL, Samet JM (2003) Airborne particulate matter and mortality: timescale effects in four US cities. Am J Epidemiol 157:1055–1065

Dushoff J, Plotkin JB, Viboud C, Earn D, Simonsen L (2005) Mortality due to influenza in the United States—an annualized regression approach using multiple-cause mortality data. Am J Epidemiol 163:181–187

Eurowinter Group, Keatinge WR, Donaldson GC (1997) Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe. Lancet 349:1341–1346

Gasparrini A (2011) Distribute lag linear and non-linear models in R: the package dlnm. J Stat Softw 43:1–20

Gasparrini A, Armstrong B, Kenward MG (2010) Distributed Lag non-linear models. Stat Med 29:2224–2234

Gorjanc ML, Flanders WD, VanDerslice J, Hersh J, Malilay J (1999) Effects of temperature and snowfall on mortality in Pennsylvania. Am J Epidemiol 149:1152–1160

Hajat S, Kovats RS, Lachowycz K (2007) Heat-related and cold-related deaths in England and Wales: who is at risk? Occup Environ Med 64:93–100

Huynen MM, Martens P, Schram D, Weijenberg MP, Kunst AE (2001) The impact of heat waves and cold spells on mortality rates in the Dutch population. Environ Health Perspect 109:463–470

Jendritzky G, Maarouf A, Staiger H (2001) Looking for a Universal Thermal Climate Index UTCI for Outdoor Applications. Windsor-Conference on Thermal Standards, April 5–8, 2001

Kassomenos PA, Gryparis A, Katsouyanni K (2007) On the association between daily mortality and air mass types in Athens, Greece during winter and summer. Int J Biometeorol 51:315–322

Keatinge WR (2002) Winter mortality and its causes. Int J Circumpolar Health 61:292–299

Kunst AE, Looman CWN, Mackenbach JP (1993) Outdoor air temperature and mortality in the Netherlands: a time-series analysis. Am J Epidemiol 137:331–341

McGregor GR (1999) Winter ischaemic heart disease deaths in Birmingham, United Kingdom: a synoptic climatological analysis. Climate Res 13:17–31

McKee CM (1990) Deaths in winter in Northern Ireland: the role of low temperature. Ulster Med J 59:17–22

Medina-Ramón M, Schwartz J (2007) Temperature, temperature extremes, and mortality: a study of acclimatization and effect modification in 50 United States cities. Occup Environ Med 64:827–833

Morabito M, Crisci A, Orlandini S, Maracchi G, Gensini GF, Modesti PA (2008) A synoptic approach to weather conditions discloses a relationship with ambulator blood pressure in hypertensives. Am J Hypertens 21:748–752

O'Neill MS, Zanobetti A, Schwartz J (2003) Modifiers of the temperature and mortality association in seven US cities. Am J Epidemiol 157:1074–1082

Patz JA, Engelberg D, Last J (2000) The effects of changing weather on public health. Annu Rev Public Health 21:271–307

Plavcová E, Kyselý J (2010) Relationships between sudden weather changes in summer and mortality in the Czech Republic, 1986–2005. Int J Biometeorol 54:539–551

Raatikka V, Rytkönen M, Hassi J (2007) Prevalence of cold-related complaints, symptoms and injuries in the general population: the FINRISK 2002 cold substudy. Int J Biometeorol 51:441–448

Schwartz J (2005) Who is sensitive to extremes of temperature? A case-only approach. Epidemiology 16:67–72

Sheridan SC (2002) The redevelopment of a weather-type classification scheme for North America. Int J Climatol 22:51–68

Yarnal B (1993) Synoptic climatology in environmental analysis: a primer. Belhaven/CRC, London/Boca Raton