Theoretical and Applied Climatology
https://doi.org/10.1007/s00704-019-02977-8

ORIGINAL PAPER

Thermal comfort and mortality in a dry region of Iran, Kerman; a 12-year time series analysis

Omid Aboubakri[1] · Narges Khanjani[2,3] · Younes Jahani[4] · Bahram Bakhtiari[5]

Received: 4 October 2018 / Accepted: 12 August 2019

Abstract

This study was conducted in order to explore the effect of thermal comfort on all-cause mortality using three indices in different lag times, in a semi-arid to dry region of Iran. Three thermal comfort indices based on the energy balance of the human body including physiologically equivalent temperature (PET), predicted mean vote (PMV), and standard effective temperature (SET) were used to assess the effects of thermal comfort on mortality. Distributed lag non-linear models were used to assess the relation. The natural cubic spline was chosen as the basis function for the space of predictors and lags, with 4 degrees of freedom. All three indices showed the same pattern in general, but the relative risk for PMV values were more than the other indices in different lags. For all three indices, lag 0 had the highest relative risk of mortality in warm and hot indices. The relative risk for warm and hot values was more than cool and cold values in lag 0, and for the PMV index, it was larger than the two other indices. These results were different in lags 5 to 8, and the relative risks for cool and cold values were more than warm and hot values. This study showed that heat stress has a stronger and more immediate adverse effect on mortality than cold stress. Also, the elderly and females are more vulnerable than others. The most apparent effect was seen in lags 0–12.

1 Introduction

The effects of weather parameters on mortality or morbidity have been under investigation in many studies recently. Most of these studies have applied atmospheric parameters (air temperature, humidity, wind speed, or rain) as exposure variables (Aboubakri et al. 2018; Dadbakhsh et al. 2018; Dadbakhsh et al. 2017; Dastoorpoor et al. 2016; Hajat et al. 2014; Kalankesh et al. 2015). However, these parameters do not consider human physiology and behavior factors. Human thermal comfort models consider not only the atmospheric parameters, but also complex metabolic processes, including physical activity level and clothing (Urban and Kyselý 2014). Human thermal comfort (HTC) is defined as "a condition of mind that expresses satisfaction with the thermal environment" (Humphreys et al. 2015). HTC is an outcome of the energy balance between the human body surface and the environment and is influenced by the above mentioned factors.

Several indices have been developed in order to measure thermal comfort. Coccolo et al. (2016) have explained three categories of outdoor human comfort indices including thermal indices, empirical indices, and indices based on linear equations. Cheng et al. (2012a) have illustrated human thermal models in two categories including human thermal physiological models and human thermal psychological models. The categories of thermal indices are based on human's energy balance and show the relation between metabolic activities, clothing and environmental parameters, and the pedestrian's thermal perception (Coccolo et al. 2016). Several indices based on the energy balance of the human body have been used to assess outdoor thermal comfort, e.g., predicted mean vote (PMV), effective temperature (ET), and standard effective temperature (SET) (Lin 2009).

Although many studies have been done about sustainable urban development or in other fields such as tourism, a few

✉ Narges Khanjani
n_khanjani@kmu.ac.ir

1 Neurology Research Center, Kerman University of Medical Sciences, Kerman, Iran

2 Environmental Health Engineering Research Center, Kerman University of Medical Sciences, Kerman, Iran

3 Monash Centre for Occupational & Environmental Health, School of Public Health and Preventive Medicine, Monash University, Melbourne, Australia

4 Modeling in Health Research Center, Institute for Futures Studies in Health, Kerman University of Medical Sciences, Kerman, Iran

5 Water Engineering Department, College of Agriculture, Shahid Bahonar University, Kerman, Iran

Published online: 29 August 2019

studies have assessed the effects of thermal comfort indices on human health. Nastos and Matzarakis (2012) investigated the effect of human thermal indices on mortality and found a relation between thermal indices (physiologically equivalent temperature (PET) and Universal Thermal Climate Index (UTCI)) and mortality. Also, a study conducted in a cold mountainous region of Iran found that the number of hospital admissions for cardiovascular diseases was higher in cool and cold conditions than warm conditions, based on PMV and PET (Mohammadi and Karimi 2017).

The SET, PMV, and physiologically equivalent temperature (PET) indices require the same climate data for their calculations. They are used as both indoor and outdoor comfort indices (Honjo 2009; Matzarakis et al. 2007). This study was conducted in order to explore the effect of thermal comfort on all-cause mortality in different lag times, in a semi-arid to dry region of Iran.

2 Methods

2.1 Data and area under study

Kerman City has a population of about 740,000 people and is located in Kerman Province in southeastern Iran. It is located at 56° 52′ 30″–57° 07′ 30″ E and 30° 07′ 30″–30° 22′ 30″ N and in a flat plain with an altitude of 1754 m. Its climate is semi-arid to dry with hot summers and cold winters (Atapour 2015; Hamzeh et al. 2011). In this study, daily meteorological data such as mean air temperature, relative humidity, nebulosity, and wind speed were obtained from the Iran Meteorological Organization. Daily mortality and ambient air pollutants data (PM_{10}, SO_2, O_3, NO_2, NOx, CO, NO, and $PM_{2.5}$) were obtained from the Health Deputy of Kerman University of Medical Sciences and the Kerman Department of Environment, respectively. The data were obtained from January 2005 to March 2017.

2.2 Thermal comfort indices

Three thermal comfort indices based on the energy balance of the human body including PET, PMV, and SET were used to assess the effects of thermal comfort on mortality in this study. PET is defined as the air temperature at which the heat balance of the human body is maintained with core and skin temperature equal to those under the conditions being assessed (Höppe 1999; Lin 2009). PMV is defined as the average thermal sensation vote of a group of people (Coccolo et al. 2016). SET is defined as the air temperature at which an individual in a reference environment wearing 0.6 clo with a metabolic rate of 1.2 mets has the same mean skin temperature and skin wittedness as the individual in the complex environment (Lin 2009). The cutoff points for grading thermal perception and physiological stress in each index are shown in Table 1. The indices were calculated using 4 data sets. They were as follows: (a) meteorological data including mean air temperature (°C), wind speed (m/s), nebulosity (octas), and relative humidity (%); (b) thermophysiological data including activity and clothing; (c) personal data including age, sex, weight, and height; (d) geographical data including longitude, latitude, and altitude.

The RayMan model (Matzarakis et al. 2006) was used for doing the calculations and standard values (height = 1.75 m, weight = 75 kg, age = 35 year, sex = male, clothing = 0.9 clo and activity = 80 w) were used for the personal and thermophysiological data in the model (Nastos and Matzarakis 2012). The wind speed used in this study was recorded at an elevation of ten meters from ground level. Therefore, we estimated wind speed at 2-m elevation by using Eq. 1 (Yarahmadi 2003).

$$U2 = \left(\frac{4.868}{\mathrm{Ln}(67.75Z - 5.42)}\right)Uz \tag{1}$$

where $U2$ is wind speed at 2-m elevation, Uz is wind speed at Z-m elevation, and Z is the altitude of the measured wind speed.

2.3 Statistical analysis

Distributed lag non-linear models (DLNM) were used to assess the relations in a bi-dimensional perspective which can vary non-linearly along the space of the predictors and lags (Gasparrini 2013). The natural cubic spline was chosen as the basis function for the space of the predictors and lags, with 4 degrees of freedom. Spline knots were placed at equally spaced quantiles in the space of the predictors and they were placed at equally spaced values in the log scale of lags, for lags in the spline. The average of comfortable range values (Table 1) were chosen as reference values. The reference values were 20.5 °C, 0, and 20 °C for PET, PMV, and SET, respectively. Four different high and low values were used in order to assess cold and heat stress on mortality. We selected the average of cool and cold range, and warm and hot range values. We also assessed extreme high (very hot) and low (very cold) values' effect on total mortality by different lags. According to previous studies, the maximum lag of 24 was used in order to capture all potential effects (Huang et al. 2015; Tian et al. 2012).

Initially generalized linear models and Poisson models were applied. Three models that were different only in the main exposure (thermal comfort index) were fitted in order to compare the results in different lags. The model is shown in Eq. 2. In this equation, Y_t is the number of deaths on day t. Index is the main exposure variable (thermal comfort index) at time t, α is the intercept, Cb is the cross-basis function in

Table 1 The ranges of PET, PMV, and SET for different grades of thermal perception and physiological stress (Daneshvar et al. 2013; Farajzadeh and Matzarakis 2009; Matzarakis et al. 2007; Matzarakis 2007)

Grades of physiological stress	Thermal perception	PET (°C)	PMV (−)	SET (°C)
Extremely cold	Very cold	≤ 4	≤ −3.5	≤ −10
Very cold	Cold	4.1 − 8	−3.4 − −2.5	−9.9 − 1.67
Moderately cold	Cool	8.1 − 13	−2.4 − −1.5	1.68 − 15.5
Slightly cold	Slightly cool	13.1 − 18	−1.4 − −0.5	15.6 − 17.8
No thermal stress	Comfortable	18.1 − 23	−0.4 − 0.5	17.9 − 22.2
Slight heat	Slightly warm	23.1 − 29	0.6 − 1.5	22.3 − 25.6
Moderate heat	Warm	29.1 − 35	1.6 − 2.5	25.7 − 27.5
Strong heat	Hot	35.1 − 41	2.6 − 3.5	27.6 − 30
Extreme heat	Very hot	> 41	> 3.5	> 30

DLNM that shows the index value at day t and lag time l, and is a matrix (there were 24 lags in this study). NS and ε_t are the natural spline function and the residual at time t, respectively. According to the lowest Akaike information criterion (AIC), the degree of freedom equal to 3 was also selected for the natural spline. The time variable with a degree of freedom equal to 5 per year was entered into the model in order to control the trend and seasonal effects. The degree of freedom of 5 was also selected based on the lowest AIC. In these models, DOW and Holiday are the days of the week and the public holidays, respectively. Holiday was introduced as a binary variable into the model. The DOW variable is a qualitative variable with 7 categories and Friday (the weekend in Muslim countries) was considered as the reference.

$$\begin{aligned}\log(Y_t) = {} & \alpha + \mathrm{CbIndex}_{tl} + \mathrm{NS}\,(\mathrm{SO_2}, 3) \\ & + \mathrm{NS}\,(\mathrm{PM_{10}}, 3) + \mathrm{NS}\,(\mathrm{O_3}, 3) \\ & + \mathrm{NS}\,(\mathrm{Time}, 5 \times \mathrm{year}) + \mathrm{DOW} + \ \mathrm{Holiday} \\ & + \varepsilon_t \qquad (2)\end{aligned}$$

Y_t Poisson (μ_t)

The Akaike information criterion (AIC) was used for comparing the models (Akaike 1998, 2011). A lower AIC value indicates a better fit. In order to select which air pollutants as confounders should be in the model, the models with and without confounders were also compared by change in estimations. There was more than 10% difference between estimates in some cases, suggesting the confounding air pollution variables (SO_2, PM_{10}, and O_3) should be in the model. In other confounders (NO_2, NO, CO, NO_x, and $PM_{2.5}$), a lower change in estimations was seen. Air pollutants have been reported to be significantly associated with mortality in previous Iranian studies (Dadbakhsh et al. 2015, 2016; Dastoorpoor et al. 2018a, b; Dehghan et al. 2018; Khanjani et al. 2012) and need to be adjusted. The analysis was performed using Excel 2013, SPSS 21, and R software version 3.3.2.

3 Results

The average daily mortality count was 10.54 and men had higher average daily mortality than women (6.20 versus 4.30). The average daily mortality count for the < 65- and ≥ 65-year age groups were 5.43 and 5.13, respectively (Table 2). The average values for PET, PMV, and SET were 20.81 °C, − 0.34, and 18.22 °C, respectively. Based on the cutoff point defined in Table 1, these values are within the no thermal stress (comfortable perception) range. Other information about mortality and the thermal indices is shown in Table 2.

We evaluated the models' fit using Akaike's information criterion (AIC) for Poisson. Our initial results (AIC was 13898 for PMV; and these were 13901 and 13900 for PET and SET, respectively) showed that PMV was a better predictor than PET and SET. The 3-dimensional relation between each thermal comfort index and mortality in different lags (up to lag 24) has been shown in Fig. 1. The relation between these indices and mortality appears non-linear. For all three indices, high values (warmer sense of air temperature) in lag 0 had the highest relative risk of mortality. But after lag 0, the relative risk rapidly decreased, and then an increase in relative risk was seen in the middle lags (from 5 to 8). Although, all three indices had the same pattern in general, but the relative risk for PMV values were more than the other indices in different lags.

The relations between each index and total mortality in high (hot and warm), low (cool and cold), and very hot and cold values in different lags (up to lag 24) are shown in Fig. 2. The relative risks for mortality in warm and hot values are more than other values in lag 0, and for the PMV index, the difference was larger than other indices. These results were different in lags 5 to 8, and the relative risks for cool and cold values tended to be more than warm and hot values. The same pattern was also seen for extreme high and low values (Fig. 2b). Figure 3 shows the maximum relative risks, which according to Fig. 2 happened in lag 0 and lag 6, for all three indices. In all three indices, high values had a significant effect (relative risk) on mortality in lag 0. This effect was seen from around the value of 32 °C in PET, 1.5 in PMV, and 27 °C in

Table 2 Summary statistics for all and subgroup mortality and thermal comfort indices in Kerman, Iran, during 2005 to 2017

Variable		Mean (SD)	Minimum	Maximum	Percentile		
					25	50	75
Mortality	Male	6.20 (3.05)	0	21	4.00	6.00	8.00
	Female	4.30 (2.42)	0	15	3	4	6
	≥ 65	5.13 (2.67)	0	15	3	5	7
	< 65	5.43 (2.92)	0	20	3	5	7
	Total	10.54 (4.31)	0	32	8	10	13
PET (°C)		20.81 (10.29)	− 9.20	41.70	11.80	20.90	29.70
PMV		− 0.34 (2)	− 6.70	3.50	− 2.10	− 0.20	1.40
SET (°C)		18.22 (7.93)	− 11.10	33	12.10	19.40	24.80

SET onwards. Also, in lag 6, low values (around − 4 to 20 °C in PET, − 5 to 0 in PMV, and − 4 to 20 °C in SET) had a significant effect on death.

Table 3 shows the cumulative relative risk of mortality in age and sex groups and for high values (warm and hot) of the three indices in different lags. The italicized values are significant at the 95% confidence level. The cumulative relative risk for total mortality was significant in some cases only until the 0–12th and 0–16th lags and in hot values; but in age and sex subgroups, the results were different and there was a significant effect on women's mortality in some cases in lags 0–4, 0–16, and 0–20 days. Also, there was a significant effect on ≥ 65 mortality in some cases in lags 0–8, 0–12, 0–16, and 0–20 days. The cumulative relative risk of women's mortality in some warm and hot values of the SET index and also the hot value of PET index was significant. But, there was no significant effect on men's mortality in any of the lags and indices. Significant relative risks were greater for hot values than warm and were larger in the PMV index than the two other indices, in all age and sex subgroups.

Table 4 shows the cumulative relative risk of total and subgroup mortality for the low (cool and cold) values of the indices in different lags (the italicized values are significant at the 95% confidence level). Significant effects were observed only in some cases in lags 0–12. Significant cumulative relative risk for total mortality was seen for both cool and cold values in the PET index. But, in two other indices, it was seen in less extreme values (cool). Unlike warm and hot values, the cumulative effect of low values was not significant for any of the age groups in all three indices, and for women, a significant relation was seen only for the PET index and in lags 0–12 in low (cool) values.

4 Discussion

The results of this study showed a similar pattern for the three indices in different lag times. The relative risks were higher for higher (hot and warm) values in lag 0. The low (cold and cool) value effects become stronger in lags 5–8. In general, the cumulative effects of high air temperature indices were more apparent than low values. The effects of both high and low values were more prominent in lags 0–12. The results also showed that women and ≥ 65-year-olds had a higher risks of

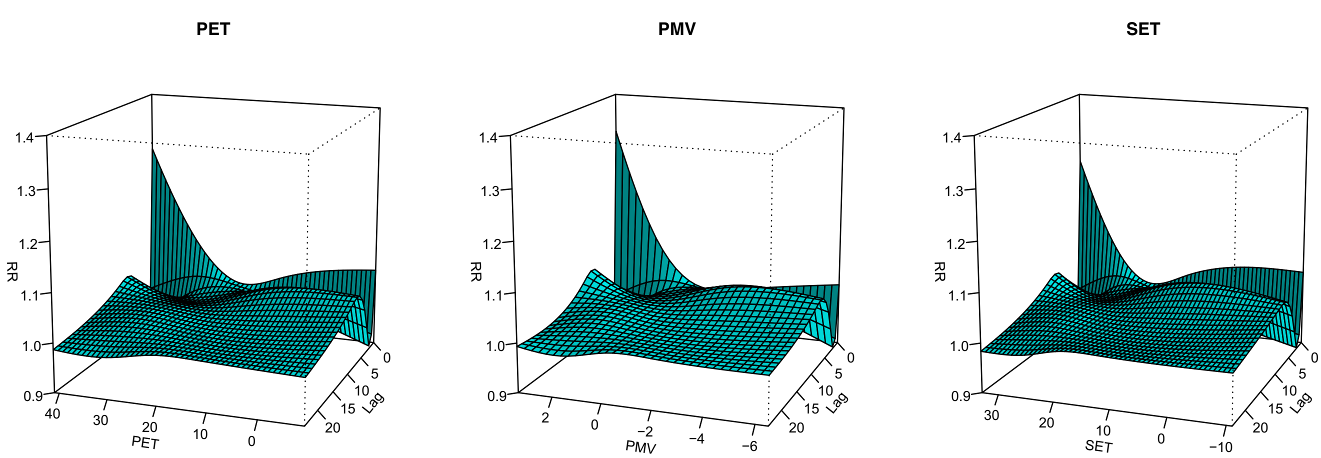

Fig. 1 Relative risks of mortality by PET, PMV, and SET and days of lag. The reference values were comfort values (20.5 °C, 0, and 20 °C for PET, PMV, and SET, respectively)

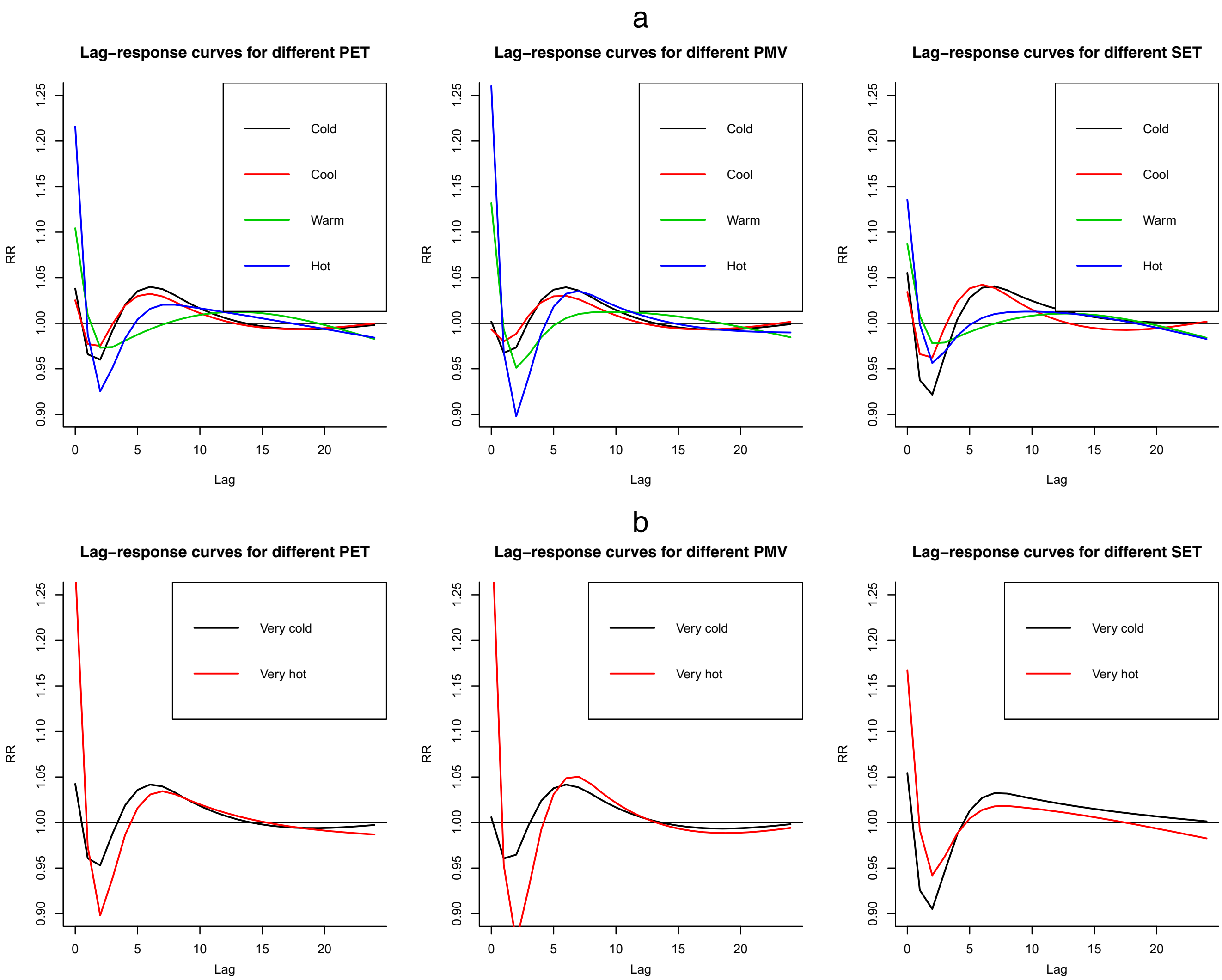

Fig. 2 The non-linear effects (relative risk) of thermal comfort indices on mortality at lags 0–24 by different thermal perceptions. **a** Low and high values. **b** Extreme low and high values

mortality than others. But there was no significant effect on men's mortality.

There are a few studies which have used important thermal comfort indices as predictors of mortality, and most studies have used atmospheric parameters such as daily air temperature. Kim et al. (2006) conducted a time series analysis in order to estimate the effect of high air temperature on mortality in 6 cities of Korea. They found that using average daily air temperature was better than the average heat index and resulted in a smaller AIC. Also, a study conducted in two cities, located in different areas of Central Italy, about the most effective thermal predictors of heat-related mortality, found that the urban daily average and minimum apparent temperature assessed outdoors (AT) showed the lowest AIC values and were the best predictors of heat-related all-cause mortality (Morabito et al. 2014).

In our study, the three indices had a similar pattern of effect. Although the equations for calculating the indices were different, the same pattern was expected, because they were calculated using the same atmospheric parameters. In this study, PMV was a better predictor of mortality than PET and SET, and had a smaller AIC. However, we cannot be confident that PMV is better than other indices in all health studies. Apparently, there is no consensus about which index should be selected as the standard approach. Some researchers think PET is the index which has the ability to represent bioclimatic conditions that are applicable to the human species under a wide range of climatic conditions. Nonetheless, authors should consider different situations in applying these indices (Thach et al. 2015).

Outdoor and indoor comfort zones may differ and climatic variables may have more psychological effects when we stay outdoors in comparison with indoors (Honjo 2009). PET is a widely used index to assess thermal comfort in the outdoor environment (Gulyás and Matzarakis 2009; Lin et al. 2012;

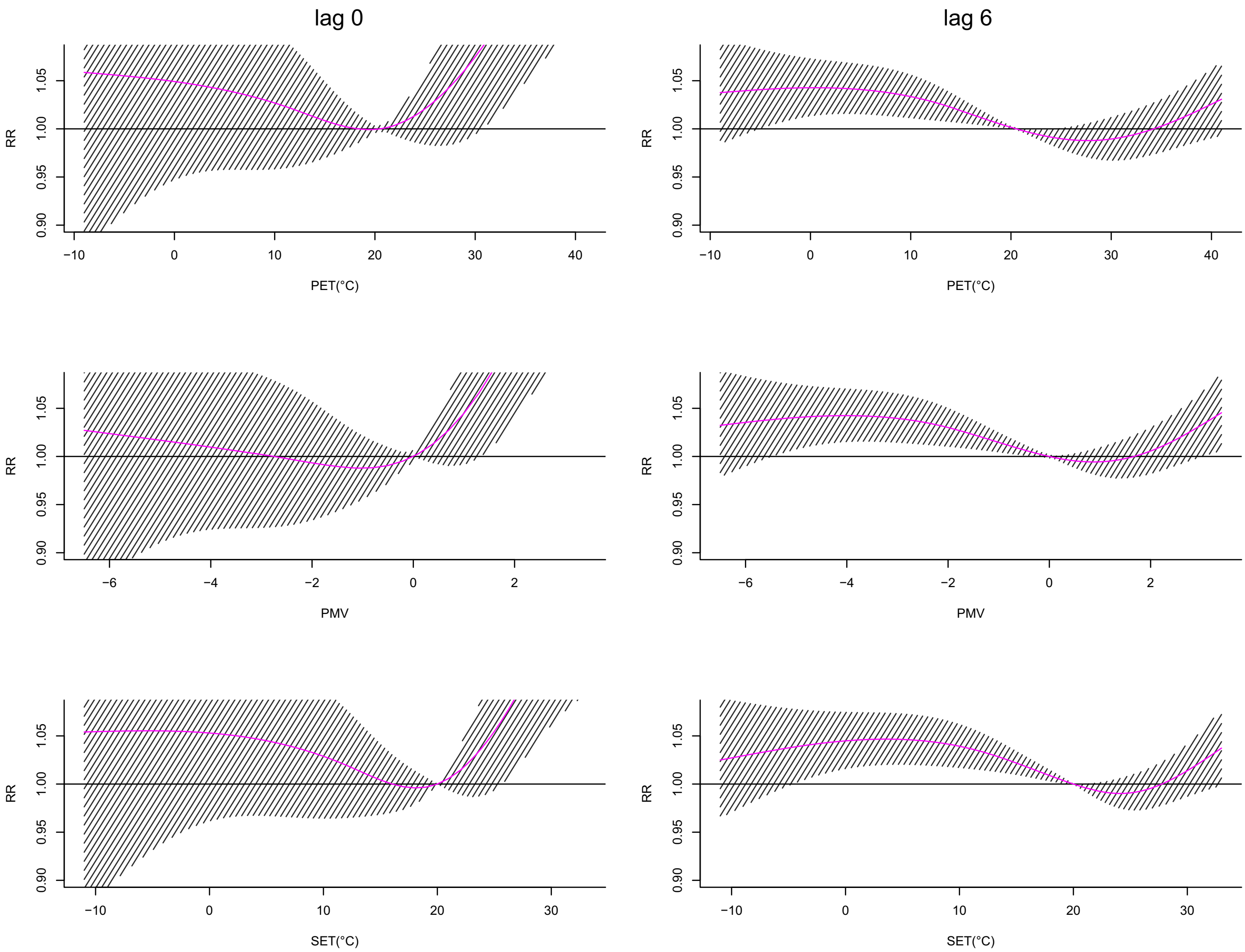

Fig. 3 The estimated effects of PET (°C), PMV, and SET (°C) on mortality at different lags 0 and 6. The pink lines are the relative risks, the black lines are reference lines (RR = 1), and the gray regions are the 95% confidence intervals

Oliveira and Andrade 2007) and has been validated in some studies (Cheng et al. 2012b; Katzschner et al. 2007) by building correlations between the actual thermal sensation vote and PET. PMV and SET were initially designed for indoor and then adapted to outdoor environments. Some studies think that the three indices can be used as an index for both indoor and outdoor environments (Spagnolo and De Dear 2003; Xi et al. 2012). We recommend that the researchers select the best index according to their research objective and the geographical characteristics of their region.

Most previous studies have used a simple parameter such as minimum, mean, or maximum air temperature as an environmental factor to understand the effect of heat or cold on mortality, but few studies have assessed thermal comfort indices' effect on mortality in different climate conditions. Our results on heat stress are consistent with previous studies. Urban and Kyselý (2014) studied the effect of the UTCI index and other thermal comfort indices such as PET and AT on cardiovascular mortality (during 1994–2009) in the city of Prague and Southern Bohemian Region. They found that there was a higher excess mortality on hot days for any index, but they did not observe higher mortality in any index on cold days. The study conducted by Nastos and Matzarakis (2012) in Athens, Greece, during the period 1992–2001 showed a significant relation between PET and all-cause mortality. They observed that strong heat stress conditions (PET > 35 °C) had two times the odds (2.054; significant level = 0.009) of daily mortality when comparing the upper 90th percentile (i.e., > 99 deaths) with the lower 10th percentile (< 64 deaths). Sharafkhani et al. (2018) recently assessed the relation between heat and cold stress and mortality in a cold and mountainous zone of Iran. Their results were similar to our study and there was a clear effect of high values of the PET index on mortality. But, in contrast to our study, some studies have found a stronger effect for cold. For example, Thach et al. (2015), which assessed the spatial association between thermal stress and mortality in Hong Kong, showed an excess risk (%) of mortality associated with a 1 °C decrease in physiologically equivalent temperature (PET) in the cold period. Other studies that have

Table 3 Cumulative relative risk of mortality in different lag times up to lag 24 (high values risk relative to comfortable values of thermal comfort indices). The italicized values are significant at the 95% confidence level

Index	Value			Lag time					
				0–4	0–8	0–12	0–16	0–20	0–24
PET	32 (°C)*	Sex	Male	0.94 (0.82, 1.08)	0.94 (0.8, 1.1)	0.98 (0.83, 1.15)	1.01 (0.84, 1.21)	1.01 (0.83, 1.24)	0.97 (0.78, 1.21)
			Female	1.18 (1.0, 1.4)	1.14 (0.94, 1.38)	1.17 (0.96, 1.44)	1.24 (0.99, 1.54)	1.26 (0.99, 1.61)	1.22 (0.93, 1.59)
		Age	≥ 65	1.09 (0.94, 1.27)	1.18 (0.99, 1.40)	*1.23 (1.03, 1.48)*	*1.24 (1.01, 1.51)*	1.2 (0.96, 1.50)	1.13 (0.89, 1.44)
			< 65	0.99 (0.85, 1.15)	0.89 (0.75, 1.05)	0.92 (0.77, 1.10)	1 (0.82, 1.21)	1.05 (0.85, 1.30)	1 (0.79, 1.27)
		Total	–	1.04 (0.93, 1.15)	1.02 (0.90, 1.15)	1.06 (0.93, 1.20)	1.11 (0.96, 1.27)	1.12 (0.96, 1.31)	1.07 (0.90, 1.27)
	38 (°C)**	Sex	Male	0.92 (0.78, 1.09)	1.04 (0.86, 1.26)	1.12 (0.91, 1.37)	1.11 (0.89, 1.39)	1.08 (0.83, 1.39)	1.04 (0.78, 1.38)
			Female	*1.25 (1.01, 1.54)*	1.2 (0.95, 1.51)	1.25 (0.97, 1.60)	*1.33 (1.01, 1.75)*	*1.37 (1.00, 1.87)*	1.29 (0.91, 1.83)
		Age	≥ 65	1.16 (0.96, 1.39)	*1.38 (1.12, 1.70)*	*1.47 (1.17, 1.83)*	*1.42 (1.11, 1.83)*	*1.34 (1.01, 1.78)*	1.28 (0.93, 1.76)
			< 65	0.95 (0.79, 1.15)	0.9 (0.74, 1.10)	0.96 (0.77, 1.19)	1.04 (0.82, 1.32)	1.07 (0.82, 1.41)	1.01 (0.74, 1.37)
		Total	–	1.04 (0.91, 1.19)	1.1 (0.96, 1.28)	*1.17 (1.00, 1.37)*	*1.21 (1.01, 1.43)*	1.19 (0.98, 1.45)	1.13 (0.91, 1.42)
PMV	2*	Sex	Male	0.93 (0.81, 1.06)	0.98 (0.84, 1.13)	1.03 (0.88, 1.20)	1.04 (0.88, 1.23)	1.02 (0.85, 1.24)	0.99 (0.80, 1.22)
			Female	1.15 (0.98, 1.36)	1.13 (0.95, 1.36)	1.18 (0.98, 1.43)	*1.25 (1.02, 1.53)*	*1.27 (1.01, 1.60)*	1.22 (0.94, 1.57)
		Age	≥ 65	1.08 (0.93, 1.25)	*1.22 (1.04, 1.44)*	*1.3 (1.09, 1.54)*	*1.29 (1.07, 1.56)*	*1.24 (1.01, 1.53)*	1.17 (0.93, 1.48)
			< 65	0.96 (0.84, 1.11)	0.9 (0.77, 1.05)	0.93 (0.79, 1.10)	1 (0.83, 1.20)	1.03 (0.84, 1.26)	0.99 (0.79, 1.24)
		Total	–	1.02 (0.92, 1.12)	1.04 (0.93, 1.17)	1.09 (0.97, 1.23)	1.13 (0.99, 1.29)	1.13 (0.97, 1.31)	1.08 (0.92, 1.27)
	3**	Sex	Male	0.9 (0.76, 1.08)	1.11 (0.92, 1.34)	1.19 (0.98, 1.46)	1.15 (0.92, 1.44)	1.08 (0.84, 1.40)	1.06 (0.80, 1.41)
			Female	1.22 (0.98, 1.51)	1.19 (0.95, 1.50)	1.25 (0.98, 1.60)	*1.33 (1.01, 1.74)*	1.35 (0.99, 1.84)	1.27 (0.90, 1.81)
		Age	≥ 65	1.14 (0.94, 1.39)	*1.44 (1.17, 1.77)*	*1.54 (1.23, 1.93)*	*1.47 (1.14, 1.88)*	*1.37 (1.03, 1.81)*	1.32 (0.96, 1.82)
			< 65	0.93 (0.77, 1.12)	0.93 (0.76, 1.13)	0.99 (0.79, 1.22)	1.04 (0.82, 1.32)	1.05 (0.80, 1.38)	0.99 (0.73, 1.34)
		Total	–	1.02 (0.89, 1.17)	1.14 (0.99, 1.32)	*1.22 (1.04, 1.43)*	*1.22 (1.03, 1.45)*	1.19 (0.98, 1.45)	1.14 (0.92, 1.43)
SET	26.7 (°C)*	Sex	Male	0.95 (0.85, 1.07)	0.96 (0.84, 1.10)	0.99 (0.86, 1.15)	1.02 (0.87, 1.19)	1.02 (0.85, 1.22)	0.98 (0.81, 1.19)
			Female	*1.16 (1.01, 1.34)*	1.12 (0.95, 1.32)	1.15 (0.96, 1.37)	1.21 (0.99, 1.46)	1.23 (0.99, 1.53)	1.18 (0.93, 1.49)
		Age	≥ 65	1.09 (0.96, 1.24)	*1.18 (1.02, 1.38)*	*1.24 (1.06, 1.46)*	*1.24 (1.04, 1.48)*	1.2 (0.98, 1.46)	1.12 (0.90, 1.39)
			< 65	0.98 (0.87, 1.12)	0.89 (0.77, 1.03)	0.91 (0.78, 1.07)	0.98 (0.83, 1.16)	1.03 (0.85, 1.24)	0.99 (0.81, 1.23)
		Total	–	1.03 (0.94, 1.13)	1.02 (0.92, 1.13)	1.06 (0.95, 1.18)	1.1 (0.97, 1.24)	1.11 (0.96, 1.27)	1.06 (0.91, 1.23)
	28.8 (°C)**	Sex	Male	0.94 (0.82, 1.07)	1.01 (0.86, 1.17)	1.06 (0.90, 1.25)	1.08 (0.90, 1.29)	1.06 (0.86, 1.30)	1.02 (0.81, 1.28)
			Female	*1.2 (1.02, 1.41)*	1.15 (0.96, 1.39)	1.19 (0.98, 1.46)	*1.26 (1.01, 1.58)*	*1.29 (1.00, 1.66)*	1.22 (0.92, 1.62)
		Age	≥ 65	1.12 (0.96, 1.30)	*1.28 (1.08, 1.52)*	*1.36 (1.13, 1.63)*	*1.34 (1.09, 1.64)*	*1.28 (1.01, 1.61)*	1.2 (0.92, 1.56)
			< 65	0.97 (0.84, 1.12)	0.9 (0.76, 1.06)	0.94 (0.78, 1.12)	1.01 (0.83, 1.23)	1.05 (0.84, 1.31)	1 (0.78, 1.28)
		Total	–	1.04 (0.93, 1.15)	1.06 (0.95, 1.20)	1.12 (0.98, 1.27)	*1.16 (1.00, 1.33)*	1.15 (0.98, 1.35)	1.1 (0.92, 1.31)

*Warm

**Hot

assessed the effect of crude air temperature on mortality have found a relation between cold and mortality as well. For example, Yi and Chan (2015) found that the mortality risk in the 1st percentile of air temperature relative to 25th percentile of air temperature was 1.17 (95% CI 1.04, 1.29) for lags 0–13; a study conducted in China found that the relative risk was 1.61 (95% CI 1.48–1.74) for extremely cold air temperature (1st percentile of air temperature relative to 75th percentile), and another study conducted in China found that cold air temperature that persisted for approximately 12 days increased the risk of mortality to 20.39% (95% CI 11.78 to 29.01%) (Ma et al. 2015; Yang et al. 2012; Yi and Chan 2015). Explaining the reason for the weaker effect of cold on mortality in this study is difficult, but it may be because of the fact that this city has shorter and less severe winters (Khanjani and Bahrampour 2013). Other previous studies done in Kerman, Iran, have also shown the relation between heatwaves, increased mortality and years of life loss (YYL) (Aboubakri et al. 2019a, b).

In this study, elderly people and women were more at risk of death from extreme air temperature than young and male people. Basu (2009) in a review reported that elderly over 65 years of age and women were more vulnerable to high air temperatures. Song et al. (2017) also conducted an overview of systematic reviews in 2016, to summarize evidence from systematic reviews assessing the impact of ambient

Table 4 Cumulative relative risk of mortality by different lag times up to lag 24 (low values risk relative to comfortable value of thermal comfort indices). The italicized values are significant at the 95% confidence level

Index	Value			Lag time					
				0–4	0–8	0–12	0–16	0–20	0–24
PET	10.5 (°C)*	Sex	Male	0.98 (0.86, 1.11)	1.07 (0.92, 1.25)	1.1 (0.93, 1.30)	1.09 (0.91, 1.31)	1.07 (0.87, 1.31)	1.05 (0.85, 1.31)
			Female	1.02 (0.88, 1.18)	1.18 (0.98, 1.41)	*1.23 (1.01, 1.51)*	1.22 (0.97, 1.52)	1.18 (0.92, 1.51)	1.17 (0.90, 1.53)
		Age	≥ 65	1 (0.87, 1.15)	1.11 (0.94, 1.31)	1.18 (0.98, 1.41)	1.21 (0.99, 1.48)	1.24 (0.99, 1.55)	1.27 (1.00, 1.61)
			< 65	0.99 (0.87, 1.13)	1.12 (0.95, 1.32)	1.14 (0.95, 1.36)	1.08 (0.88, 1.31)	1 (0.80, 1.25)	0.96 (0.75, 1.21)
		Total	–	1 (0.91, 1.09)	1.12 (0.99, 1.25)	*1.16 (1.02, 1.31)*	1.14 (0.99, 1.31)	1.11 (0.95, 1.30)	1.1 (0.93, 1.30)
	6 (°C)**	Sex	Male	0.96 (0.83, 1.12)	1.1 (0.92, 1.32)	1.15 (0.94, 1.42)	1.14 (0.90, 1.44)	1.11 (0.85, 1.43)	1.09 (0.82, 1.44)
			Female	0.99 (0.83, 1.18)	1.15 (0.92, 1.44)	1.23 (0.96, 1.59)	1.24 (0.93, 1.64)	1.22 (0.89, 1.67)	1.2 (0.85, 1.70)
		Age	≥ 65	0.9 6(0.81, 1.12)	1.1 (0.90, 1.35)	1.2 (0.96, 1.50)	1.24 (0.96, 1.60)	1.27 (0.96, 1.69)	1.3 (0.96, 1.78)
			< 65	1 (0.85, 1.16)	1.14 (0.93, 1.39)	1.17 (0.94, 1.47)	1.12 (0.87, 1.44)	1.04 (0.78, 1.38)	0.98 (0.72, 1.33)
		Total	–	0.97 (0.87, 1.09)	1.12 (0.97, 1.29)	*1.19 (1.01, 1.39)*	1.18 (0.98, 1.41)	1.15 (0.94, 1.40)	1.13 (0.91, 1.41)
PMV	− 2*	Sex	Male	0.98 (0.88, 1.10)	1.07 (0.93, 1.23)	1.09 (0.93, 1.27)	1.07 (0.90, 1.27)	1.05 (0.87, 1.27)	1.06 (0.86, 1.30)
			Female	1 (0.87, 1.15)	1.15 (0.97, 1.36)	1.2 (0.99, 1.45)	1.18 (0.95, 1.45)	1.14 (0.90, 1.44)	1.11 (0.86, 1.43)
		Age	≥ 65	1 (0.88, 1.14)	1.09 (0.93, 1.26)	1.14 (0.96, 1.36)	1.18 (0.98, 1.43)	1.22 (0.99, 1.50)	1.24 (0.99, 1.56)
			< 65	0.98 (0.87, 1.11)	1.12 (0.96, 1.30)	1.12 (0.95, 1.33)	1.04 (0.86, 1.26)	0.97 (0.79, 1.19)	0.94 (0.75, 1.17)
		Total	–	0.99 (0.91, 1.08)	1.1 (0.99, 1.23)	*1.13 (1.00, 1.28)*	1.11 (0.97, 1.27)	1.08 (0.94, 1.26)	1.08 (0.92, 1.27)
	− 3**	Sex	Male	0.96 (0.83, 1.11)	1.08 (0.9, 1.3)	1.12 (0.91, 1.38)	1.1 (0.87, 1.40)	1.08 (0.83, 1.40)	1.08 (0.81, 1.44)
			Female	0.98 (0.82, 1.17)	1.15 (0.92, 1.43)	1.23 (0.95, 1.58)	1.23 (0.92, 1.64)	1.19 (0.87, 1.64)	1.15 (0.81, 1.63)
		Age	≥ 65	0.96 (0.82, 1.13)	1.09 (0.89, 1.33)	1.19 (0.95, 1.49)	1.25 (0.97, 1.61)	1.29 (0.97, 1.72)	1.32 (0.96, 1.81)
			< 65	0.98 (0.84, 1.15)	1.13 (0.93, 1.38)	1.15 (0.92, 1.44)	1.06 (0.82, 1.37)	0.98 (0.73, 1.30)	0.93 (0.68, 1.27)
		Total	–	0.97 (0.87, 1.09)	1.11 (0.97, 1.28)	1.17 (1.00, 1.37)	1.15 (0.96, 1.38)	1.12 (0.92, 1.38)	1.11 (0.89, 1.38)
SET	8.6 (°C)*	Sex	Male	0.96 (0.84, 1.11)	1.1 (0.92, 1.32)	1.15 (0.93, 1.41)	1.12 (0.89, 1.42)	1.1 (0.85, 1.43)	1.12 (0.84, 1.49)
			Female	1.01 (0.85, 1.19)	1.19 (0.95, 1.47)	1.27 (0.99, 1.63)	1.27 (0.95, 1.68)	1.22 (0.89, 1.68)	1.17 (0.83, 1.66)
		Age	≥ 65	0.98 (0.84, 1.15)	1.13 (0.93, 1.37)	1.21 (0.97, 1.51)	1.24 (0.96, 1.60)	1.27 (0.95, 1.69)	1.33 (0.97, 1.82)
			< 65	0.98 (0.84, 1.14)	1.14 (0.94, 1.38)	1.17 (0.94, 1.47)	1.11 (0.86, 1.43)	1.02 (0.77, 1.36)	0.97 (0.71, 1.32)
		Total	–	0.98 (0.88, 1.09)	1.14 (0.99, 1.30)	*1.19 (1.02, 1.40)*	1.18 (0.98, 1.41)	1.14 (0.93, 1.40)	1.14 (0.91, 1.42)
	− 4.2 (°C)**	Sex	Male	0.94 (0.75, 1.18)	1.17 (0.86, 1.57)	1.27 (0.88, 1.83)	1.27 (0.82, 1.95)	1.24 (0.76, 2.03)	1.24 (0.72, 2.15)
			Female	0.82 (0.62, 1.07)	0.84 (0.59, 1.21)	0.92 (0.59, 1.44)	1.01 (0.6, 1.7)	1.06 (0.59, 1.92)	1.06 (0.55, 2.06)
		Age	≥ 65	0.75 (0.59, 0.96)	0.91 (0.65, 1.26)	1 (0.67, 1.48)	1.03 (0.65, 1.64)	1.06 (0.62, 1.80)	1.13 (0.62, 2.04)
			< 65	1.03 (0.81, 1.32)	1.12 (0.81, 1.55)	1.21 (0.81, 1.80)	1.25 (0.78, 2.00)	1.24 (0.72, 2.11)	1.15 (0.64, 2.10)
		Total	–	0.88 (0.74, 1.05)	1.02 (0.81, 1.28)	1.11 (0.84, 1.47)	1.15 (0.83, 1.60)	1.16 (0.79, 1.69)	1.16 (0.76, 1.77)

*Cool

**Cold

temperature on morbidity and mortality. They found that heat exposure seems to have an adverse effect on mortality in the elderly. Son et al. (2016) conducted a study in a subtropical city in Brazil and observed mortality was higher among females after heat effects and was higher among older persons after heat and cold effects. The higher prevalence of comorbidities and medication use in the elderly population may be the cause for some of the heat-related deaths in this population. Laboratory-based physiological examinations have shown that the ability to sense heat and to manifest appropriate behavioral (especially fluid intake) and physiological (e.g., blood distribution, sweating) responses during exposure to heat may be compromised in otherwise healthy older individuals (Kenny et al. 2010). Susceptibility of women to death in high thermal stress may be due to the social status of elderly females, who often live alone and, because of their specific thermoregulatory and physiological conditions, are unable to respond to extreme heat-related stress (Li et al. 2017; Marí-Dell'Olmo et al. 2018; Onozuka and Hagihara 2015). In addition, many women wear black veils in Iran, even in the warm seasons and this leads to more heat absorption.

Another finding of our study was that the strongest heat-related mortality association was in lag 0 and this effect was more severe than cold stress in the same lag. Cold stress seems to show its effects in later lags (lags 5–8). The more immediate effect of heat (versus cold) has been observed in many previous studies that focused on air temperature (Ma et al. 2014; Wang et al. 2014; Wu et al. 2013). Some studies have found that cold shows its effect after 1 or more weeks of lag and indicate that longer lags are needed to capture the effects of cold on mortality. Also, using similar lag structures for cold and heat effects is not suitable and using inappropriate short lags may underestimate the effect of cold (Anderson and Bell 2009; Guo et al. 2011). Our result showed the use of short lags cannot sufficiently capture the effect of cold stress and it probably ignores mortality displacement (the harvesting effects) in heat stress as well. Therefore, longer lags are required to evaluate the cold and heat stress effects. In our study, 24 days was probably enough to cover both cold and heat stress effects.

4.1 Strengths and limitation

One of strengths of our study was using three indices that can be applied for both outdoor and indoor environments. Another strength was using the DLNM. This model evaluates the effects of thermal comfort on mortality using a two-dimensional function.

We used the cut point of indices' range or extreme stress instead of percentiles. This might be a limitation of our study. However, some authors such as Rothman (2014) say that using percentiles is a poor method for choosing category boundaries and makes results incomparable with other studies.

There might be potential interactions between thermal comfort indices and air pollutants. But the conventional investigation of these effects in time series regression analysis depends on hard-to-verify modeling assumptions, which can be computationally unwieldy (Armstrong 2003), especially in our study in which we simultaneously assessed both exposure-outcome and lagged exposure-outcome non-linear relations. However, we assessed some interactions by using generalized additive models in which both linear (parametric) and non-linear (non-parametric) coefficients were assessed. The results showed that there was no significant linear interaction between thermal comfort indices and air pollutants, but the non-linear interactions were significant for all interaction terms. However, this method cannot accommodate non-linear lag-outcome relations and more advanced statistical methods need to be developed.

5 Conclusion

This study revealed that heat stress had a more apparent adverse effect on mortality than cold stress, in Kerman, Iran, and the elderly and females were more vulnerable than others. This suggests that the human body may not be able to adapt to atmospheric parameters like extreme high temperature. Therefore, people, especially high-risk individuals, should be warned on hot days. Considering that the most apparent effect of heat stress was seen in lag 0 and the middle lags (0–12), interventions should be implemented from the first days of heat strikes.

Acknowledgments The authors thank the Kerman Bureau of Meteorology and the Deputy of Health of Kerman University of Medical Sciences for providing the data for this study.

Funding information This study was financially supported by Kerman University of Medical Sciences through Grant No. 96000792.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Aboubakri O, Khanjani N, Shoraka H (2018) Ambient temperature and mortality due to external causes: a systematic review. Occup Dis Environ Med 6:81–94. https://doi.org/10.4236/odem.2018.63007

Aboubakri O, Khanjani N, Jahani Y, Bakhtiari B (2019a) Attributable risk of mortality associated with heat and heat waves: a time-series study in Kerman, Iran during 2005–2017. J Therm Biol 82: 76–82. https://doi.org/10.1016/j.jtherbio.2019.03.013

Aboubakri O, Khanjani N, Jahani Y, Bakhtiari B (2019b) The impact of heat waves on mortality and years of life lost in a dry region of Iran (Kerman) during 2005–2017. Int J Biometeorol 64:1–11. https://doi.org/10.1007/s00484-019-01726-w

Akaike H (1998) Information theory and an extension of the maximum likelihood principle. In: Selected Papers of Hirotugu Akaike. Springer, pp 199–213. https://doi.org/10.1007/978-1-4612-1694-0_15

Akaike H (2011) Akaike's information criterion. In: International encyclopedia of statistical science. Springer, pp 25–25. https://doi.org/10.1007/978-3-642-04898-2_110

Anderson BG, Bell ML (2009) Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiology (Cambridge, Mass) 20:205–213. https://doi.org/10.1097/EDE.0b013e318190ee08

Armstrong BG (2003) Fixed factors that modify the effects of time-varying factors: applying the case-only approach. Epidemiology 14:467-472. https://doi.org/10.1097/01.ede.0000071408.39011.99

Atapour H (2015) Geochemistry of potentially harmful elements in topsoils around Kerman city, southeastern Iran. Environ Earth Sci 74: 5605–5624. https://doi.org/10.1007/s12665-015-4576-

Basu R (2009) High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ Health 8:40–53. https://doi.org/10.1186/1476-069X-8-40

Cheng Y, Niu J, Gao N (2012a) Thermal comfort models: a review and numerical investigation. Build Environ 47:13–22. https://doi.org/10.1016/j.buildenv.2011.05.011

Cheng V, Ng E, Chan C, Givoni B (2012b) Outdoor thermal comfort study in a sub-tropical climate: a longitudinal study based in Hong Kong. Int J Biometeorol 56:43–56. https://doi.org/10.1007/s00484-010-0396-z

Coccolo S, Kämpf J, Scartezzini J-L, Pearlmutter D (2016) Outdoor human comfort and thermal stress: a comprehensive review on models and standards. Urban Clim 18:33–57. https://doi.org/10.1016/j.uclim.2016.08.004

Dadbakhsh M, Khanjani N, Bahrampour A (2015) Death from respiratory diseases and air pollutants in Shiraz, Iran (2006-2012). J Environ Pollut Hum Health 3:4–11. https://doi.org/10.12691/jephh-3-1-2

Dadbakhsh M, Khanjani N, Bahrampour A (2016) Death from cardiovascular diseases and air pollution in Shiraz, Iran (March 2006-March 2012). J Epidemiol Prev Med 2:114–121

Dadbakhsh M, Khanjani N, Bahrampour A, Haghighi PS (2017) Death from respiratory diseases and temperature in Shiraz, Iran (2006–2011). Int J Biometeorol 61:239–246. https://doi.org/10.1007/s00484-016-1206-z

Dadbakhsh M, Khanjani N, Bahrampour A (2018) The relation between death from cardiovascular diseases and temperature in Shiraz, Iran. ARYA Atheroscler 14:149–156. https://doi.org/10.22122/arya.v14i4.1341

Daneshvar MRM, Bagherzadeh A, Tavousi T (2013) Assessment of bioclimatic comfort conditions based on physiologically equivalent temperature (PET) using the RayMan model in Iran. Cent Eur J Geosci 5:53–60. https://doi.org/10.2478/s13533-012-0118-7

Dastoorpoor M, Idani E, Khanjani N, Goudarzi G, Bahrampour A (2016) Relationship between air pollution, weather, traffic, and traffic-related mortality. Trauma Mon 21. https://doi.org/10.5812/traumamon.37585

Dastoorpoor M, Goudarzi G, Khanjani N, Idani E, Aghababaeian H, Bahrampour A (2018a) Lag time structure of cardiovascular deaths attributed to ambient air pollutants in Ahvaz, Iran, 2008-2015. Int J Occup Med Environ Health 31:459–473. https://doi.org/10.13075/ijomeh.1896.01104

Dastoorpoor M, Khanjani N, Bahrampour A, Goudarzi G, Aghababaeian H, Idani E (2018b) Short-term effects of air pollution on respiratory mortality in Ahvaz, Iran. Med J Islam Repub Iran 32:30–39. https://doi.org/10.14196/mjiri.32.30

Dehghan A, Khanjani N, Bahrampour A, Goudarzi G, Yunesian M (2018) The relation between air pollution and respiratory deaths in Tehran, Iran-using generalized additive models. BMC Pulm Med 18:49

Farajzadeh H, Matzarakis A (2009) Quantification of climate for tourism in the northwest of Iran. Meteorol Appl 16:545–555. https://doi.org/10.1002/met.155

Gasparrini A (2013) Distributed lag linear and non-linear models for time series data. Document is available at R project: https://cran.R-Project.org/web/packages/dlnm/. (Accessed: 4 May 2015) http://143107 212

Gulyás Á, Matzarakis A (2009) Seasonal and spatial distribution of physiologically equivalent temperature (PET) index in Hungary. Időjárás 113:221–231

Guo Y, Barnett AG, Pan X, Yu W, Tong S (2011) The impact of temperature on mortality in Tianjin, China: a case-crossover design with a distributed lag nonlinear model. Environ Health Perspect 119:1719–1725. https://doi.org/10.1289/ehp.1103598

Hajat S, Vardoulakis S, Heaviside C, Eggen B (2014) Climate change effects on human health: projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s. J Epidemiol Community Health 68:641–648. https://doi.org/10.1136/jech-2013-202449

Hamzeh MA, Aftabi A, Mirzaee M (2011) Assessing geochemical influence of traffic and other vehicle-related activities on heavy metal contamination in urban soils of Kerman city, using a GIS-based approach. Environ Geochem Health 33:577–594. https://doi.org/10.1007/s10653-010-9372-0

Honjo T (2009) Thermal comfort in outdoor environment. Glob Environ Res 13:43–47

Höppe P (1999) The physiological equivalent temperature–a universal index for the biometeorological assessment of the thermal environment. Int J Biometeorol 43:71–75. https://doi.org/10.1007/s004840050118

Huang F, Zhao A, Chen RJ, Kan HD, Kuang XY (2015) Ambient temperature and outpatient visits for acute exacerbation of chronic bronchitis in Shanghai: a time series analysis. Biomed Environ Sci 28:76–79. https://doi.org/10.3967/bes2015.008

Humphreys M, Roaf S, Sykes O (2015) Standards for thermal comfort: indoor air temperature standards for the 21st century. Routledge

Kalankesh LR, Mansouri F, Khanjani N (2015) Association of temperature and humidity with trauma deaths. Trauma Mon 20:1–5. https://doi.org/10.5812/traumamon.23403

Katzschner L, Mayer H, Drey C, Bruse M (2007) Strategies and concepts for thermal comfort discussions in urban planning to mitigate the impacts of climate extremes. In: Proceedings of the sun, wind and architecture—The 24th International Conference on Passive and Low Energy Architecture, PLEA, pp 103-108

Kenny GP, Yardley J, Brown C, Sigal RJ, Jay O (2010) Heat stress in older individuals and patients with common chronic diseases. Can Med Assoc J 182:1053–1060. https://doi.org/10.1503/cmaj.081050

Khanjani N, Bahrampour A (2013) Temperature and cardiovascular and respiratory mortality in desert climate. A case study of Kerman, Iran. Iran J Environ Health Sci Eng 10:11–17. https://doi.org/10.1186/1735-2746-10-11

Khanjani N, Ranadeh Kalankesh L, Mansouri F (2012) Air pollution and respiratory deaths in Kerman, Iran (from 2006 till 2010). Iran J Epidemiol 8:58–65

Kim H, Ha J-S, Park J (2006) High temperature, heat index, and mortality in 6 major cities in South Korea. Arch Environ Occup Health 61:265–270. https://doi.org/10.3200/AEOH.61.6.265-270

Li J, Xu X, Yang J, Liu Z, Xu L, Gao J, Liu X, Wu H, Wang J, Yu J, Jiang B, Liu Q (2017) Ambient high temperature and mortality in Jinan, China: a study of heat thresholds and vulnerable populations. Environ Res 156:657–664. https://doi.org/10.1016/j.envres.2017.04.020

Lin T-P (2009) Thermal perception, adaptation and attendance in a public square in hot and humid regions. Build Environ 44:2017–2026. https://doi.org/10.1016/j.buildenv.2009.02.004

Lin T-P, Tsai K-T, Hwang R-L, Matzarakis A (2012) Quantification of the effect of thermal indices and sky view factor on park attendance. Landsc Urban Plan 107:137–146. https://doi.org/10.1016/j.landurbplan.2012.05.011

Ma W, Chen R, Kan H (2014) Temperature-related mortality in 17 large Chinese cities: how heat and cold affect mortality in China. Environ Res 134:127–133. https://doi.org/10.1016/j.envres.2014.07.007

Ma W, Wang L, Lin H, Liu T, Zhang Y, Rutherford S, Luo Y, Zeng W, Zhang Y, Wang X, Gu X, Chu C, Xiao J, Zhou M (2015) The temperature–mortality relationship in China: an analysis from 66 Chinese communities. Environ Res 137:72–77. https://doi.org/10.1016/j.envres.2014.11.016

Marí-Dell'Olmo M, Tobías A, Gómez-Gutiérrez A, Rodríguez-Sanz M, García de Olalla P, Camprubí E, Gasparrini A, Borrell C (2018) Social inequalities in the association between temperature and mortality in a South European context. Int J Public Health 64:1–11. https://doi.org/10.1007/s00038-018-1094-6

Matzarakis A (2007) Climate, thermal comfort and tourism. Climate change and tourism-assessment and coping strategies:139-154

Matzarakis A, Rutz F, Mayer H (2006) Modelling the thermal bioclimate in urban areas with the RayMan Model. In: International Conference on Passive and Low Energy Architecture, vol 2006. Citeseer, pp 449-453

Matzarakis A, Rutz F, Mayer H (2007) Modelling radiation fluxes in simple and complex environments—application of the RayMan model. Int J Biometeorol 51:323–334. https://doi.org/10.1007/s00484-006-0061-8

Mohammadi B, Karimi S (2017) The relationship between thermal sensation and the rate of hospital admissions for cardiovascular disease in Kermanshah, Iran. Theor Appl Climatol 134:1101–1114. https://doi.org/10.1007/s00704-017-2332-1

Morabito M, Crisci A, Messeri A, Capecchi V, Modesti PA, Gensini GF, Orlandini S (2014, 2014) Environmental temperature and thermal indices: what is the most effective predictor of heat-related mortality in different geographical contexts? The Scientific World Journal. https://doi.org/10.1155/2014/961750

Nastos PT, Matzarakis A (2012) The effect of air temperature and human thermal indices on mortality in Athens, Greece. Theor Appl Climatol 108:591–599. https://doi.org/10.1007/s00704-011-0555-0

Oliveira S, Andrade H (2007) An initial assessment of the bioclimatic comfort in an outdoor public space in Lisbon. Int J Biometeorol 52: 69–84. https://doi.org/10.1007/s00484-007-0100-0

Onozuka D, Hagihara A (2015) Variation in vulnerability to extreme-temperature-related mortality in Japan: a 40-year time-series analysis. Environ Res 140:177–184. https://doi.org/10.1016/j.envres.2015.03.031

Rothman K.J (2014) Six Persistent Research Misconceptions. J Gen Intern Med 29 :1060-1064. https://doi.org/10.1007/s11606-013-2755-z

Sharafkhani R, Khanjani N, Bakhtiari B, Jahani Y, Tabrizi JS (2018) Physiological equivalent temperature index and mortality in Tabriz (The northwest of Iran). J Therm Biol 71:195–201. https://doi.org/10.1016/j.jtherbio.2017.11.012

Son J-Y, Gouveia N, Bravo MA, de Freitas CU, Bell ML (2016) The impact of temperature on mortality in a subtropical city: effects of cold, heat, and heat waves in São Paulo, Brazil. Int J Biometeorol 60:113–121. https://doi.org/10.1007/s00484-015-1009-7

Song X, Wang S, Hu Y, Yue M, Zhang T, Liu Y, Tian J, Shang K (2017) Impact of ambient temperature on morbidity and mortality: an overview of reviews. Sci Total Environ 586:241–254. https://doi.org/10.1016/j.scitotenv.2017.01.212

Spagnolo J, De Dear R (2003) A field study of thermal comfort in outdoor and semi-outdoor environments in subtropical Sydney Australia. Build Environ 38:721–738. https://doi.org/10.1016/S0360-1323(02)00209-3

Thach T-Q, Zheng Q, Lai PC, Wong PPY, Chau PYK, Jahn HJ, Plass D, Katzschner L, Kraemer A, Wong CM (2015) Assessing spatial associations between thermal stress and mortality in Hong Kong: a small-area ecological study. Sci Total Environ 502:666–672. https://doi.org/10.1016/j.scitotenv.2014.09.057

Tian Z, Li S, Zhang J, Jaakkola JJ, Guo Y (2012) Ambient temperature and coronary heart disease mortality in Beijing, China: a time series study. Environ Health 11:56–63. https://doi.org/10.1186/1476-069X-11-56

Urban A, Kyselý J (2014) Comparison of UTCI with other thermal indices in the assessment of heat and cold effects on cardiovascular mortality in the Czech Republic. Int J Environ Res Public Health 11:952–967. https://doi.org/10.3390/ijerph110100952

Wang C, Chen R, Kuang X, Duan X, Kan H (2014) Temperature and daily mortality in Suzhou, China: a time series analysis. Sci Total Environ 466-467:985–990. https://doi.org/10.1016/j.scitotenv.2013.08.011

Wu W, Xiao Y, Li G, Zeng W, Lin H, Rutherford S, Xu Y, Luo Y, Xu X, Chu C, Ma W (2013) Temperature–mortality relationship in four subtropical Chinese cities: a time-series study using a distributed lag non-linear model. Sci Total Environ 449:355–362. https://doi.org/10.1016/j.scitotenv.2013.01.090

Xi T, Li Q, Mochida A, Meng Q (2012) Study on the outdoor thermal environment and thermal comfort around campus clusters in subtropical urban areas. Build Environ 52:162–170. https://doi.org/10.1016/j.buildenv.2011.11.006

Yang J, Ou C-Q, Ding Y, Zhou Y-X, Chen P-Y (2012) Daily temperature and mortality: a study of distributed lag non-linear effect and effect modification in Guangzhou. Environ Health 11:63–72. https://doi.org/10.1186/1476-069X-11-63

Yarahmadi J (2003) The integration of satellite images, GIS and CROPWAT model to investigation of water balance in irrigated area. In. ITC

Yi W, Chan APC (2015) Effects of temperature on mortality in Hong Kong: a time series analysis. Int J Biometeorol 59:927–936. https://doi.org/10.1007/s00484-014-0895-4