USE OF BIOMETEOROLOGICAL INDICES IN ASSESSING HEAT WAVE-RELATED MORTALITY IN VIGO, SPAIN

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RESUMEN
En el contexto actual de cambio climático, las olas de calor se han convertido en un problema importante para la salud humana. La ausencia de un índice biometeorológico estandarizado para evaluar la intensidad de las olas de calor y su influencia sobre la mortalidad ha demostrado tener un fuerte efecto en la planificación de la salud pública. Este trabajo evalúa los efectos de los días de ola de calor en la población de Vigo, durante el período comprendido entre 1980 y 2014. Para ello, se han utilizado dos índices; la temperatura aparente máxima y el factor de exceso de calor (EHF). Se han identificado un total de 534 días que cumplen con los criterios de EHF durante ese período. Se ha comprobado la existencia de una relación no lineal en forma de U entre la mortalidad y la temperatura aparente máxima. En el caso del EHF, se encontró una relación no lineal en forma de J entre la mortalidad y el índice EHF. Este estudio encontró que el EHF es un indicador más específico para la mortalidad relacionada con el calor que la temperatura aparente máxima. Además, se ha demostrado que los períodos de ola de calor no presentan el mismo grado de severidad en un período de temperaturas extremas. Por lo tanto, la intensidad de una ola de calor es un importante indicador de riesgo de mortalidad durante estos eventos. En lo que respecta a la vulnerabilidad humana al calor, las condiciones respiratorias y cardiovasculares preexistentes representan las tasas más altas de mortalidad.

Palabras clave: efectos del calor, temperatura aparente, mortalidad, Vigo, intensidad, Excess Heat Factor.

ABSTRACT
In the current context of climate change, heat waves have become a significant problem for human health. The lack of a standardised biometeorological index to assess the intensity of heat waves and their effects on mortality has proved to have a strong effect on Public Health planning. This paper assesses the effects of heat wave days on the human population in Vigo, Spain, during the period between 1980 and 2014. To this end, two indices have been used; the maximum apparent temperature and the Excess Heat Factor (EHF). A total of 534 days meeting the EHF criteria have

been identified during that period. The dependence shows a non-linear U-shaped relationship between mortality and maximum apparent temperature. In the case of the EHF, a non-linear J-shaped relationship between mortality and the EHF was found. This study found that the EHF is a more specific indicator for heat-related mortality than maximum apparent temperature. Furthermore, it has been demonstrated that heat wave periods do not present the same degree of severity over a period of days. Thus, the intensity of a heat wave is an important mortality risk indicator during heat wave days. As far as human vulnerability to heat is concerned, pre-existing respiratory and cardiovascular conditions account for the highest rates of mortality.

Key words: heat effects, Apparent Temperature, mortality, Vigo, intensity, Excess Heat Factor.

1. INTRODUCTION

Climate change has become a significant concern for the health of the global population. Climate projections show an increase in global surface temperatures of between 1.8ºC and 4ºC by 2100 (IPCC, 2014; Sheridan and Allen, 2015). Furthermore, this increase in temperature has effects on the frequency and intensity of extreme weather events (IPCC, 2014; Schleussner et al, 2017). Consequently, projections show more intense and frequent extreme heat events in Europe in the future, with a higher impact in the Iberian Peninsula and Mediterranean Regions (Fischer and Schär, 2008; IPCC, 2014).

Understanding the impact of temperature on health is critical, particularly when aspects such as a changing climate and an ageing population are taken into account. Furthermore, it has been proven that the combination of social and thermal environmental factors affect human health (Tobías et al, 2012; Loughnan et al, 2014; Quinn et al, 2014; Basu, 2009; Xu et al, 2013). As a consequence, it is expected that heat-related deaths will most likely evolve in a similar way to heat waves (IPCC, 2014; Chen et al, 2014; Li et al, 2016; Hanna and Tait, 2015).

However, when analyzing the impact of the thermal environment, and heat waves in particular, one must address certain difficulties regarding the definition of what a heat wave is. Previous authors have discussed the definition of heat waves by focusing on climatological and public health criteria (Díaz et al, 2015a; Perkins and Alexander, 2013; Nairn and Fawcett, 2015; Radinović and Ćurić, 2011; Montero et al, 2013; Li et al, 2015; Steadman, 1984; Ye et al, 2011). However, strictly climatological definitions of heat waves do not target any health impacts. Therefore, other authors have defined heat waves from a public health perspective in order to measure the implications of heat waves on health. Nevertheless, there is no standard public health definition (Montero et al, 2013; Quinn et al, 2014). Perkins and Alexander (2013) addressed the difficulties of the definition of heat waves by comparing the existing heat indices. Using different definitions of heat waves has led to varying results between previous research studies (Xu et al, 2016). However, it should be noted that, regardless of the definition, scientific evidence has proven that an excessive increase in ambient temperature has direct consequences on both mortality and morbidity (Díaz et al, 2015b; Xu et al, 2016; Taracido-Trunk et al, 2009; Basagaña et al, 2011).

Earlier studies have not satisfactorily succeeded in comparing the intensity of heat waves over heat wave days themselves (Son et al, 2014). In this study, the Excess Heat Factor (EHF) will be used (Nairn and Fawcett, 2015). This heat wave index incorporates the aspect of intensity, which is not included in many of the previous heat indices used to assess heat-related mortality (Xu et al, 2016). Likewise, there is no universal definition for intensity itself. Several studies have used a combination of temperature as it is directly related to intensity (Gao et al, 2013). Thus, the EHF could prove particularly useful in demonstrating another perspective of the impact of heat waves on human health.

Moreover, the thermal environment is composed of different atmospheric variables, such as solar radiation, humidity and wind speed, which influence human health in combination with air temperatures. Therefore, in this research, the apparent temperature as a biometeorological index will be used both to estimate the EHF and as an exposure variable. This will provide a clearer view of the effects of heat on human health and will help to assess the best index for the prediction of mortality during heat waves.

Consequently, this paper focuses on the short-term effects of heat wave-related mortality in the urban area of Vigo (Northwest Spain), between 1980 and 2014 from a biometeorological perspective. Moreover, this study specifically addresses the intensity of the effects of heat waves on human health.

2. METHODOLOGY

2.1. Data Sources

Meteorological data

The meteorological data was obtained from the European Climate Assessment and Dataset Project (ECA&D, http://eca.knmi.nl/). The weather station selected for this research is located at the airport of Vigo-Peinador, which lies 9 km to the east of the city center. The weather station is located within the limits of a municipality bordering the city. Therefore, it is better able to record the average weather patterns in the study area. The altitude of the weather station is 261m. The average altitude of the study area is 184 m. The data collected comprises daily maximum, mean and minimum temperatures, daily mean humidity and daily mean wind velocity for the period 1980-2014.

Mortality data

Data on daily mortality in the study area was obtained from the official registers of the Epidemiological Service, General Assistant Manager of Health Information and Epidemiology, SERGAS. Daily deaths have been classified according to natural causes (ICD-10: A00-Y99), cardiovascular diseases (ICD- 10: I00-I99) and respiratory diseases (ICD-10: J00-J99).

2.2. Biometeorological Indices

Apparent Temperature

This biometeorological index was developed by Steadman (1984), in which apparent temperature is based on the combination of air temperature, humidity and wind speed.

From these meteorological variables, the daily maximum and mean apparent temperatures (ATmx, ATmean) were estimated for the shade according to Steadman (1984) (Eq. 1):

$AT = -2.7 + 1.047 \cdot T + 2.0 \cdot P_v - 0.65 \cdot v_{10}$, (1)

where T is the temperature in ºC, P_v is the vapor pressure (hPa) and v_{10} is the wind velocity 10 meters above the ground. P_v can be estimated with the Equation 2:

$P_v = (rh/100) \cdot 6.105 \cdot e^{(17.27 \cdot T)/(237.7+T)}$, (2)

where rh is the relative humidity expressed as a percentage.

Excess Heat Factor

The Excess Heat Factor (EHF) is a recent measure of heat wave intensity (Nairn and Fawcett, 2015). The index is based on a three-day average daily mean temperature. The three-day period is motivated by studies of human responses to the onset of extremely hot weather. The main reason for measuring heat wave intensity is to identify those heat waves which may inflict severe consequences on the population (Langlois et al, 2013; Nairn and Fawcett, 2015; Scalley et al, 2015).

The EHF is divided into two components. The first is the comparison of the three-day average daily mean temperature with the annual temperature threshold in that specific location. If the average of the daily mean temperature during the three-day period is higher than the 95th climatological percentile for the daily mean temperature, then this three-day period falls under heat wave conditions. This component is called the significance index (EHIsig) (Eq. 3). If it is positive, the period is deemed to be unusually warm compared with the local annual climate.

The second component of the EHF is a measure of the temperatures reached during the three-day period compared with the recent past (the previous 30 days). This second component is the acclimatization index (EHIaccl) (Nairn and Fawcett, 2015) (Eq. 4).

$$EHI_{sig} = \frac{(T_i+T_{i+1}+T_{i+2})}{3} - T_{95} \ , \qquad (3)$$

$$EHI_{accl} = \frac{(T_i+T_{i+1}+T_{i+2})}{3} - \frac{(T_{i-1}+\cdots+T_{i-30})}{30} \ , \qquad (4)$$

Where T_i is the average daily mean temperature for each period of three days. According to Nairn and Fawcett (2015), in order to calculate the EHF, previous indices should be multiplied as shown in the following formula (Eq. 5):

$$EHF = EHI_{sig} \cdot max(1, EHI_{accl}) \qquad (5)$$

For the purpose of this research, mean apparent temperature has been used instead of mean temperature. In order to identify a heatwave as such, the EHF value should be positive. Furthermore, a positive acclimatization EHI increases its impact upon the EHF calculation (Nairn and Fawcett, 2015)

Statistical Design

The non-linear relationship between the exposure and response variables was modeled using a distributed lag non-linear model (dlnm). The dlnm framework simultaneously describes complex non-linear and delayed effects of an environmental variable on a response variable with any family distribution and link function within Generalized Linear Models (GLM), Generalized Additive Models (GAM) or Generalized Estimating Equations (GEE) (Gasparrini and Armstrong, 2011; Gasparrini et al, 2015b). The possible lagged response on human health is a well-known phenomenon and expresses the temporal change at risk following a specific exposure event. In order to model the maximum apparent temperature, with the added effect of heat waves and the intensity of heat waves on mortality for this study, a Quasi-Poisson regression with GAM was fitted (Eq. 6) (Hastie and Tibshirani, 1990; Wood, 2006).
The first model structure corresponds to the maximum apparent temperature as the main exposure variable controlling the heat wave effect by the hw:

$$Y_t \; Quasi - Poisson(\mu_t)$$
$$log(\mu_t) = \alpha + \beta_1 Eat_{t,l} + \beta_2 Ehw_{t,l} + s(Trend, 75) + \eta dow_t \text{ , (6)}$$

The second model structure for the intensity of heat waves is as follows:

$$Y_t \; Quasi - Poisson(\mu_t)$$
$$log(\mu_t) = \alpha + \beta_1 Eehf_{t,l} + \beta_2 Eat_{t,l} + s(Trend, 75) + \eta dow_t \text{ , (7)}$$

where t is the day of the observation; Y_t is the observed daily mortality on day t; α is the intercept; $Eat_{t,l}$, $Eehf_{t,l}$ and $Ehwt,l$ are matrices obtained by applying the DLNM to ATmx, EHF and HW. Heat Wave is encoded as 1 for heat wave day (EHF > 0) and with 0 for EHF ≤ 0, respectively. β_i are vectors of coefficients for these matrices, and l is the lagged effect in days. s(. . .) is a thin plate regression spline. Trend is the long-term trend and seasonality with 75 df. *dow* is the day of the week on day t, and η are the vectors of coefficients. Sunday is the reference day for the day of the week. The selection of the degrees of freedom (df) was made using the Akaike Information Criterion (AIC).
In order to model the non-linear and lagged effects of apparent temperature and heat wave intensity, a cubic B-spline with 4 and 6 df was used. It is widely known that the effects of heat on morbi-mortality are quasi-direct with a delay of a few days (Ye et al, 2011). Therefore, in order to include possible harvesting effects and heat-related excesses of mortality followed by deficits (Guo et al, 2011), a maximum lag of 14 days was used to model the effects of ATmx and EHF on mortality.
A reference value to calculate the relative risk threshold of minimum mortality was estimated with the method applied by Tobías et al (2017). In the case of the intensity of the heat wave (EHF) the reference value of 0 $ºC^2$ was used, as values above this threshold indicate the presence of a heat wave. A specific explanation of the statistical details regarding the distributed lag non-linear model can be found in Bhaskaran et al

(2013) or Gasparrini et al (2015b). All models, statistical analyses and graphic results were performed with the free software environment R (R Core Team, 2016), version 3.3. The models used in this study have been estimated through packages mgcv, version 1.8-15, and dlnm, version 2.2.6.

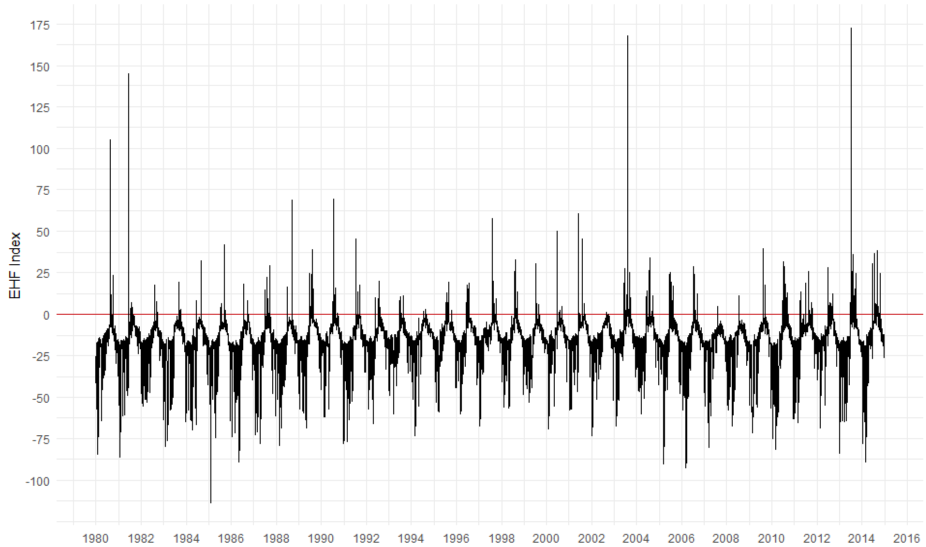


Fig. 1: EHF index and components time series from 1980 to 2014.

3. RESULTS

Over the course of the study period, 1980-2014, a total of 135,525 deaths due to natural, respiratory and cardiovascular causes were recorded. Natural deaths account for 68.49%, cardiovascular deaths for 24.62% and respiratory deaths for 6.89% of the total. When age group is taken into account, people over 64 years of age normally show a higher degree of vulnerability to heat. In this way, 80% of total deaths due to natural causes and 89% of total deaths related to both respiratory and cardiovascular conditions affected people over 64 years of age. Figure 1 shows the time series of the EHF calculation, including the significance of its components and acclimatization index. It is important to remember that as the EHF is the result of the product between two temperatures, it is expressed in ºC2. Each peak of EHF over 0ºC2 represents a heat wave day. Thus, during the period between 1980 and 2014, a total of 534 days meeting the EHF heat wave criteria have been identified. Figure 2 represents the number of heat wave days per year with the categorized EHF intensity index. Despite there being more heat wave days during 2013, the 2003 heat wave shows a higher intensity with more days in the highest percentiles. As shown in the figure, heat wave days present a high variability of intensities. Figure 1 confirms the same trend; the highest peaks represent the highest intensity of heat waves. Thus, 2003 and 2013 show the highest degrees of intensity.

	Natural	Respiratory	Cardiovascula
	RR (95% CI)	RR (95% CI)	RR (95% CI)
Atmx (Q90 to 99%, 24.81 to			
Current Day Effect	1.14 (1.11 –1.11	(1.01–1.17	(1.01 –
Overall Effect (0–14lag)	1.25 (1.10 –1.56	(1.03 –1.27	(1.28 –
EHF (Q75 to 95%, 16.87 to	1.43)	2.37)	1.91)
Current Day Effect	1.05 (1.03 –1.10	(1.05 –1.10	(1.07 –
Overall Effect (0–14lag)	1.18 (1.06 –1.35	(0.99 –1.31	(1.10 –

Table 1: Relative risks of heat wave mortality by cause when EHF and maximum apparent temperature values increase from the 90th to the 99th percentile and from the 75th to the 95th, respectively

Figure 3 shows the three-dimensional plots of the relationship between maximum apparent temperature and cause-specific mortality over lags of 14 days. The dependence shows a non-linear U-shaped relationship between mortality and maximum apparent temperature. Furthermore, there is a greater effect on mortality due to higher temperatures. Moreover, cold temperature effects could be identified, especially as far as respiratory causes are concerned. The minimum mortality for natural, respiratory and cardiovascular causes was reached at 19.4 ºC (95% CI: 16.6-25.2), 18.9 ºC (95% CI: 15.5-30.4) and 22.5 ºC (95% CI: 17.7-43.8) respectively, regarding the overall effects (lag 0-14). Higher temperatures show a quasi-direct lag effect. Nevertheless, the heat effect decreases considerably with each lag as can be observed in Figure 5a. Table 1 presents a summary of current day and overall effects from the 90th to 99th percentiles for maximum apparent temperature; and from the 75th to 95th percentiles for the EHF. A significant heat effect on mortality for all cause-specific mortality is reflected. A significant increase in mortality risk on the same day was found. Indeed, the maximum apparent temperature shows a 14% (95% CI: 10.63%-16.79%) rise in mortality due to natural causes. For respiratory and cardiovascular causes, excess mortality is 10.52% (95% CI: 1.31%-20.55%) and 17% (95% CI: 1.16%-22.50%). Furthermore, when the maximum apparent temperature rises from the 90th to the 99th percentile from 24.81 ºC to 33.18 ºC, the risk of mortality due to natural causes undergoes a 25.12% (95% CI: 9.61% -42.81%) increase. For respiratory and cardiovascular causes the increase is 56.42% (95% CI: 3.19%-137.10%) and 26.97% (95% CI: 1%-59.61%), respectively. Hence, current day effects are higher particularly for cardiovascular causes, followed by natural and respiratory causes. As far as the overall effect is concerned, there is a greater effect on respiratory causes, followed by cardiovascular and natural causes. The results obtained regarding the relationship between cause-specific mortality and heat wave intensity provided by the EHF can be seen in Figure 4. In a similar manner to the results for the maximum apparent temperature, the three-dimensional plots show a non-linear J-shaped relationship between the EHF and cause-specific mortality. The effects of intensity on mortality increase exponentially as EHF values rise. Moreover, the effect of heat intensity decreases with each lag, with the strongest effect occurring on the same day, as shown in Figure 5b. Even though the EHF has been conceived to identify heat wave intensity, negative EHF values show a slight, yet significant, increase in cause-specific mortality, which can reflect thermal effects beyond heat wave conditions. However, there are no previous experiences documented on the use of the EHF during cold spells and further research is needed in this area. Consequently, on the same day when EHF values rose from the 75th to the 95th percentile, (from 16.87 ºC2 to 46.22 ºC2), a significant increase in risk of mortality due to respiratory causes, 10.41% (95% CI 5.09%-16.02%), followed by 10.19% (95% CI 7.05%-13.42%) increase due to cardiovascular mortality and finally, a 5.38% (95% CI 3.52%-7.27%) increase in risk of mortality due to natural causes were found when applying the EHF index reflecting the heat wave intensity. As far as the overall heat effect is concerned, an increase was observed in the risk of mortality of 34.72% (95% CI 0.8%-82.95%) due to respiratory causes followed by a 31.38% (95% CI 9.67% - 57.40%) and a 17.93% (95% CI 6.46% - 30.46%) increase due to cardiovascular and natural causes, respectively.

The cumulative heat effect (lag 0-2 days) on respiratory and cardiovascular causes follows a similar trend, albeit with a different magnitude, as previously described (Figure 3). In fact, there is a significant increase in mortality related to natural causes on heat wave days, although the magnitude of this effect can be observed more clearly in the maximum apparent temperature. The effects of cold days can be seen in Figures 3 and 4. However, the magnitude of the cold effect is shown more clearly by the maximum apparent temperature. A considerable rise in mortality due to natural and respiratory causes under heat wave conditions on the same day was observed. Thus, the risk of mortality due to natural causes increases 6% (95% CI 0.68%-11.64%) while for respiratory causes it increases 23.30% (95% CI 4.61%-45.33%). The risk of mortality due to cardiovascular causes was the least observed effect with an increase of 4.61% (95% CI -13.30%-26.20%). In addition, the heat wave's cumulative effect (lag 0-2 days), of a 4.62% (95% CI -1.56%-11.93%) increase in the risk of mortality due to natural causes was observed. Regarding respiratory and cardiovascular causes, the increase identified was 29.32% (95% CI 6.61%-56.86%) and 3.03% (95% CI -7.25%-14.45%), respectively. The risk of mortality for cardiovascular conditions on the same day and on lag 0-2 proved not to be statistically significant, as was also the case for natural causes. As far as a possible harvesting effect is concerned, in the case of the apparent maximum temperature a slight effect was found for natural and cardiovascular causes. In fact, there was a decreasing risk from 20 ºC between lags 6-12. Moreover, for cardiovascular causes the threshold was found at 23 ºC between lags 7-11. Respiratory mortality does not show a harvesting effect. Harvesting effects were not identified as far as the EHF was concerned.

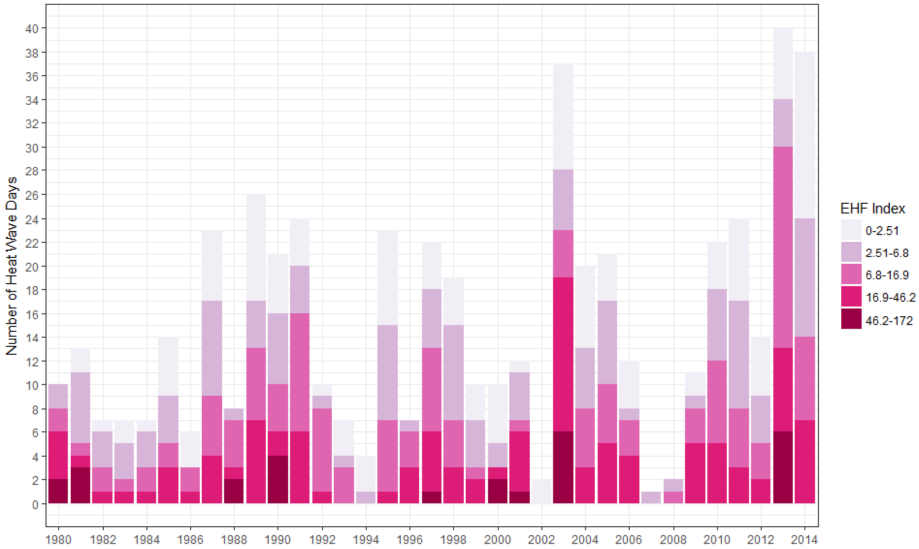


Fig. 2: EHF index intensity according to number of heat wave days.

4. DISCUSSION

The results of this study demonstrate the strong relationship between human health and the effects of heat through heat wave intensity and the biometeorological index. The results obtained especially highlighted the effects of heat on the same day and 1-3 days following a heat event; respiratory mortality rises considerably under extreme heat conditions for both apparent maximum temperature and the EHF.

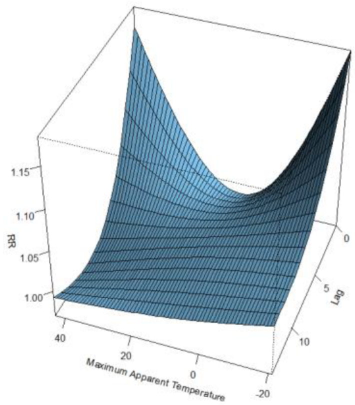
In line with previous studies, this research found a dose-response relationship between heat and mortality (Basu, 2009; Lee et al, 2015; Tobías et al, 2014; Monteiro et al, 2013; Li et al, 2016; Heudorf and Schade, 2014; Kenney et al, 2014; Hajat and Kosatky, 2009; Zhang et al, 2014). Therefore, in this research the maximum apparent temperature and the EHF present a non-linear shaped relationship with mortality for all specific causes. While the EHF showed a non-linear J-shaped relationship with mortality, the maximum apparent temperature showed a non-linear U-shaped relationship. Moreover, other authors have also found a non-linear U or V-shaped relationship between mortality and ambient temperature (Gasparrini et al, 2015a; Díaz et al, 2015a; Taracido-Trunk et al, 2009). This research identified higher comfort temperatures than previous studies in the same area (Taracido-Trunk et al, 2009). Even though the methodology in both studies was different, a possible reason for the different temperature thresholds identified may be related to the use of the maximum apparent temperature adopted in this study. Similar temperatures for minimum mortality to those mentioned above have also been identified in China. In that study, the daily mean temperature, humidity rate and wind speed were all taken into consideration for their calculations. Therefore, 21ºC was identified as the temperature at which the lowest mortality risk was found on the 40-day lag applied in the study (Zeng et al, 2016).

Both heat and cold waves have been shown to cause negative health impacts (Seltenrich, 2015). However, the effects of cold waves on health can be delayed for up 4 weeks, while heat wave effects are almost immediate and may last up to 4 days (Gasparrini et al, 2015b; Tobías et al, 2012). This research showed that heat effects were different on heat wave days. It proved that heat intensity differs within a heat wave period. For instance, as Mirón et al (2014) identified in the case of Spain, the first 2 days have a higher impact on human mortality for all causes. Other studies have confirmed the same observation on an international scale (Yang et al, 2012; Ha et al, 2011). Ha et al (2011) studied the lag effect over a 30-day period, proving that effects from heat gradually diminish and all heat effects decrease significantly after day 12. However, even though our study found heat effects on mortality on the 0-2 lags when comparing heat wave days with non-heat wave days, these effects showed no statistical significance for cardiovascular-related mortality for maximum apparent mortality. Moreover, our study has confirmed that heat effects on mortality tend to decrease over lags for both cases if the indices are used. In this research, a harvesting effect was found for maximum apparent temperature but not for the EHF. As a result of the EHF calculation itself, any possible harvesting affect may not be registered. This could be caused by the definition of EHF. Our research includes a measurement of heat wave intensity following the EHF criteria. As far as we know, previous studies have not applied a non-lineal distributed model with the EHF as an exposure variable and heat wave indicator.

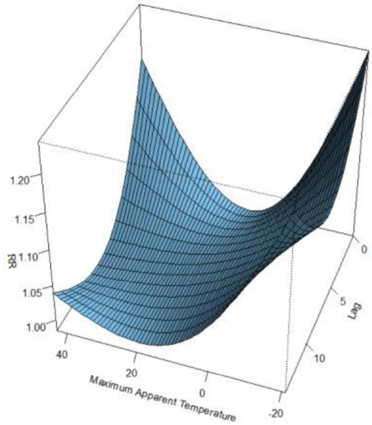
As Nairn and Fawcett (2015) has stated, heat wave intensity upholds a continuum in which low intensity heat waves show less impact on human health and other community sectors whereas more intense heat waves appear to have more serious consequences. Therefore, the methodology used in this study can help to predict and prevent the effects of intense heat days, not only on human health but also on business sectors. This confirms the results found by Langlois et al (2013), whose research has demonstrated that hot days over a heat wave period showed different degrees of severity and different risks of mortality. Further research on the application of the EHF in other places is needed. Results found in this study could not be compared with previous studies since this is the first time this methodology has been put into practice.

5. CONCLUSION

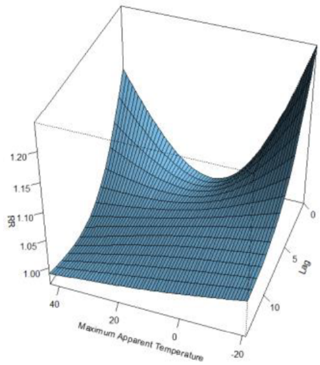
As mentioned above, the EHF would appear to be a better indicator than the maximum apparent temperature as far as heat-related mortality is concerned. It is important to acknowledge the fact that heat wave periods do not show the same degree of severity every day. Heat wave intensity is an important indicator of the increase in the risk of mortality during heat wave days. Consequently, this knowledge could be used for the prevention of heat wave mortality. As far as human vulnerability is concerned, natural causes account for the highest degree of mortality, in addition to the fact that those with respiratory and cardiovascular conditions are more vulnerable to heat wave days. Thus, mortality prevention should particularly focus on respiratory and cardiovascular conditions among the elderly as they are the group at highest risk. Since heat wave



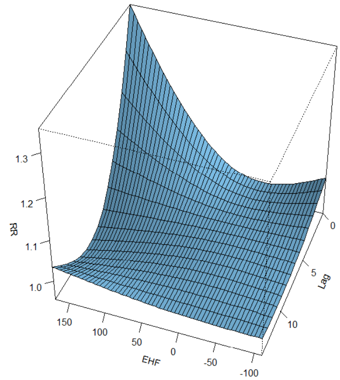
(a) Natural mortality (ATmx)



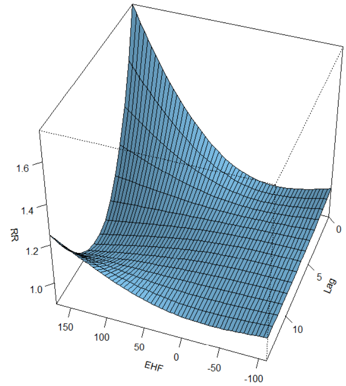
(b) Respiratory mortality (ATmx)



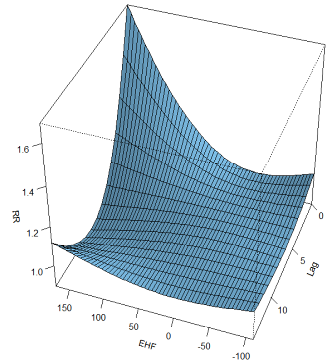
(c) Cardiovascular mortality (ATmx)



(d) Natural mortality (EHF)

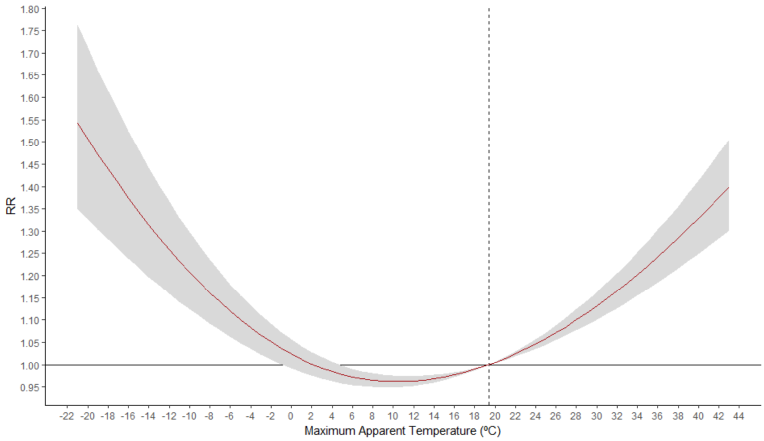


(e) Respiratory mortality (EHF)

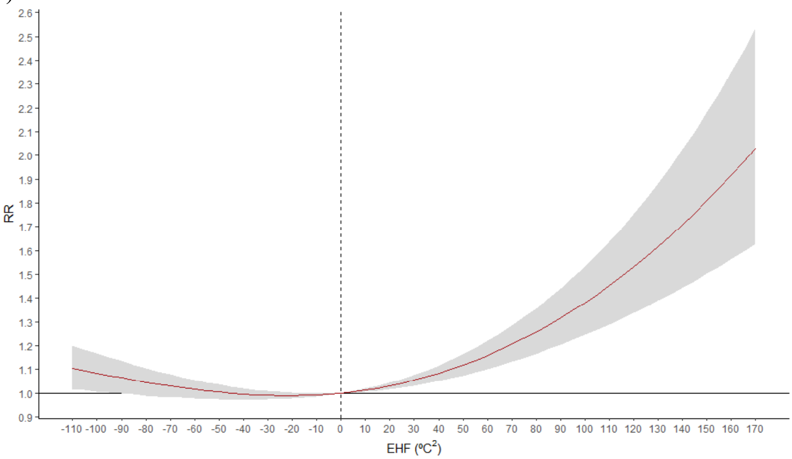


(f) Cardiovascular mortality (EHF)

Fig. 3: Relative risks of cause-specific mortality by maximum apparent temperature due to cause-specific mortality over 14-day lags.



(a)



(b)

Fig. 5: Cumulative effects of mortality due to natural causes by maximum apparent temperature (a) and EHF (b) over 0-2 day lags.

mortality decreases over lags, special attention should be paid to the first week after the highest severity heat wave event. The maximum apparent temperature showed a different threshold for each minimum cause-specific mortality at a specific temperature. Consequently, these results raise awareness regarding the different temperature threshold effects on heat-related mortality. For instance, a practical way to reduce the rate of mortality during heat waves could be the establishment of this comfort temperature in hospitals and retirement homes to better protect this especially vulnerable population. This fact should be taken into consideration when drafting a heat prevention plan. Due to the low number of studies on the EHF as a heat wave severity indicator and heat-related mortality and morbidity, further research is required to validate its application in other geographic areas and focus populations.

Further assessment of human vulnerability to heat is necessary, especially in the current context of an ageing population and global warming.

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