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Evaluation of the ERA5 reanalysis-based Universal Thermal Climate Index on mortality data in Europe

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ABSTRACT

Air temperature has been the most commonly used exposure metric in assessing relationships between thermal stress and mortality. Lack of the high-quality meteorological station data necessary to adequately characterize the thermal environment has been one of the main limitations for the use of more complex thermal indices. Global climate reanalyses may provide an ideal platform to overcome this limitation and define complex heat

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UTCI
Thermal stress
Heat
Cold

and cold stress conditions anywhere in the world. In this study, we explored the potential of the Universal Thermal Climate Index (UTCI) based on ERA5 – the latest global climate reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF) – as a health-related tool. Employing a novel ERA5-based thermal comfort dataset ERA5-HEAT, we investigated the relationships between the UTCI and daily mortality data in 21 cities across 9 European countries. We used distributed lag nonlinear models to assess exposure-response relationships between mortality and thermal conditions in individual cities. We then employed meta-regression models to pool the results for each city into four groups according to climate zone. To evaluate the performance of ERA5-based UTCI, we compared its effects on mortality with those for the station-based UTCI data. In order to assess the additional effect of the UTCI, the performance of ERA5-and station-based air temperature (T) was evaluated. Whilst generally similar heat- and cold-effects were observed for the ERA5-and station-based data in most locations, the important role of wind in the UTCI appeared in the results. The largest difference between any two datasets was found in the Southern European group of cities, where the relative risk of mortality at the 1st percentile of daily mean temperature distribution (1.29 and 1.30 according to the ERA5 vs station data, respectively) considerably exceeded the one for the daily mean UTCI (1.19 vs 1.22). These differences were mainly due to the effect of wind in the cold tail of the UTCI distribution. The comparison of exposure-response relationships between ERA5-and station-based data shows that ERA5-based UTCI may be a useful tool for definition of life-threatening thermal conditions in locations where high-quality station data are not available.

1. Introduction

Associations between ambient thermal conditions and human health are well documented in many geographical areas (Gasparrini et al., 2015; Guo et al., 2016; Di Napoli et al., 2018; Kim et al., 2019). So far, air temperature has been the most commonly used exposure metric in studies assessing relationships between thermal (heat and cold) stress and mortality (Son et al., 2019), although thermal indices calculated from a combination of meteorological variables may describe the thermal environment better (Błażejczyk et al., 2012). Over the past century, many thermal indices have been developed to assess thermal conditions for humans. The earlier simple biometeorological indices (such as heat index, apparent temperature, etc.; McGregor, 2011) were based exclusively on meteorological parameters such as air temperature, humidity and/or wind speed. Later, more advanced thermal indices were based on human heat balance equation (Parsons, 2010). Currently, Physiologically Equivalent Temperature (PET) (Mayer and Höppe, 1987; Höppe, 1999), the Universal Thermal Climate Index (UTCI) (Jendritzky et al., 2012) and Wet-Bulb Globe Temperature (WBGT) (Yaglou and Minard, 1957) have been among the most widely used indices in thermal perception studies (Potchter et al., 2018). The UTCI, in particular, has been designed as a universal thermal indicator, possible to use in all climates and all biometeorological applications, including epidemiological studies (Jendritzky et al., 2012).

Compared to the simple indices, however, the UTCI requires additional weather parameters (i.e. wind velocity, radiation and/or cloudiness) that often are not available from station observations. The lack of proper in situ observations represents the main limitation for a wider use of thermal indices (such as the UTCI) in epidemiological studies. Whilst these mostly rely on ground-based observations that are collected at location-specific stations, historical time series of station data are often incomplete due to lack of capacity for maintaining routine record-keeping (Colston et al., 2018). This is particularly the case when variables other than temperature and humidity (such as cloud cover, wind velocity, and solar radiation) are required for the calculation of thermal indices. Furthermore, high-quality professional stations are often located at city airports and do not necessarily represent environmental conditions of epidemiological surveillance sites within cities (Colston et al., 2018).

Climate reanalyses constitute a possible way to overcome these limitations: they provide multiple meteorological variables that can be used to retrieve simple indices and compute thermal indices as gridded parameters having the same resolution (Buzan et al., 2015; Di Napoli et al., 2020a). Reanalysis datasets are often freely available and provide temporally and spatially homogeneous data (Colston et al., 2018). For example, the latest reanalysis by the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 (Copernicus Climate Change Service (C3S), 2017), provides estimates of surface and atmospheric parameters at resolution over Europe approximately 28 × 28 km, which is the highest possible resolution of a global climate reanalysis (Dee et al., 2016; Hersbach et al., 2020). Although such resolution may not capture all meso- and micro-scale variations, especially in areas with a complex orography (Luo et al., 2019), it allows the assessment of relationships between ambient thermal conditions and mortality at the urban level (e.g., Royé et al., 2020). Evidence remains limited, however, as to the suitability of reanalysis data when meteorological variables other than air temperature are required to assess conditions of heat and cold stress. Based on ERA5 reanalysis, a novel ERA5-HEAT dataset has been introduced (Di Napoli et al., 2020a). This dataset provides a complete historical reconstruction of the UTCI (hourly data since 01/01/1979) and therefore allows for the assessment of biometeorological conditions across the globe in the same resolution and time span as ERA5 (28 × 28 km).

In this study, we explore for the first time the suitability of the novel ERA5-HEAT dataset as a source of thermal comfort data for epidemiological studies. The aim is to evaluate the relationship between mortality and the thermal environment, with the latter described by the UTCI. The performance of ERA5-based UTCI as a thermal metric affecting mortality is investigated and compared with the station-based UTCI. As air temperature (T) is the most used thermal exposure metric in epidemiological studies, its performance is also assessed and compared with the station-based T. The study was carried out for 21 cities across 9 European countries and used daily mortality data from European members of the Multi-City Multi-Country (MCC) Collaborative Research Network. Distributed lag nonlinear models (DLNM) were used to analyse exposure-response relationships between mortality, the UTCI, and T in each city. The city-specific exposure-response curves were pooled into four groups according to climate zones by the meta-analytic approach, and results for these groups were compared.

2. Materials and methods

2.1. Population under study

The MCC network (http://mccstudy.lshtm.ac.uk) is an international collaboration of research teams producing epidemiological evidence on the association between weather and health across the globe. For Europe the MCC network currently gathers mortality data from 17 countries. Thus, it provides an ideal platform for continent-wide studies on the association between environmental stressors and mortality. MCC data are available for different time intervals in individual cities, and the time period used in the present analysis varies between the cities. Since station data of a sufficient quality were not available for all locations in the MCC database (see Section 2.4 and Supplementary Material details on the station data quality control), weather and mortality data from 21 cities in 9 European countries across the overall time span 1990–2015 were included into the analysis (Table 1, Fig. 1). Mortality data were obtained from local authorities within each country or region included in the MCC network (Table S1 in Supplementary Material). Causes of death were classified according to the 9th or 10th version of International Classification of Diseases (ICD) codes wherever these were available. In each location mortality is represented by daily counts of either all-cause or non-external causes only (ICD-9: 0–799; ICD-10: A0–R99).

2.2. Definition of UTCI

In order to describe thermal environment that affects human health, we employed the Universal Thermal Climate Index (UTCI). The UTCI is defined as the air temperature (°C) of a reference environment that would elicit in the human body the same physiological response (sweat production, shivering, skin wittedness, skin blood flow and rectal, mean skin and face temperatures) as the actual environment (Fiala et al., 2012). The reference environment is described as a condition of calm air, i.e. wind speed 0.5 m/s at 10 m above the ground, no additional thermal radiation, i.e. mean radiant temperature equal to air temperature, 50% relative humidity (water vapour pressure capped at 20 hPa for air temperatures above 29 °C) where an average person walks at 4 km/h, generating a metabolic rate equal to 135 W/m2 $\simeq$ 2.3 MET (Błażejczyk et al., 2012). For better comprehensibility of the study, we compared results for the UTCI with air temperature (T, °C) at 2 m above surface. The offset between the UTCI and T depends on the actual values of T, mean radiant temperature, wind speed and humidity (Bröde et al., 2012). Two different types of datasets were used to express the UTCI and T (see Sections 2.3 and 2.4).

2.3. Climate reanalysis data

The ERA5 reanalysis is a climate dataset that merges a global climate model (i.e. a numerical representation of the physical processes and energy fluxes occurring in the Earth's atmosphere, oceans, and land surfaces) with in situ and satellite observations (Hersbach et al., 2020). ERA5 data, currently spanning from 1979 to the present date, are provided on regular latitude–longitude grids at approximately 28 km × 28 km resolution (0.25 ° × 0.25 °) and up to 1-h frequency. ERA5-HEAT is a novel dataset derived from the ERA5 reanalysis (Di Napoli et al., 2020a). It is a historical dataset of bioclimate variables related to human thermal stress. It stores the gridded dataset of UTCI as computed via a six-order polynomial equation from ERA5-retrieved air temperature, humidity, wind, and radiation (Bröde et al., 2012). ERA5-HEAT is freely available from the Copernicus Climate Data Store (https://doi.org/10.24381/cds.553b7518), which has been developed as part of the Copernicus Climate Change Service implemented by ECMWF (https://cds.climate.copernicus.eu/).

The gridded datasets of T and the UTCI were retrieved from ERA5 and ERA5-HEAT, respectively, for the 1990–2015 period at a 3-h step. For each of the cities considered in the study, the corresponding T and UTCI time series was obtained by extracting the corresponding value across the study period from the grid cell where the city centre point is located. This applies also to cities larger than one grid cell. From the T and UTCI 3-hourly time series, daily mean temperature (Tmean) and UTCI (UTCImean) values were computed.

2.4. Station data

In order to compare results from the ERA5 and ERA5-HEAT datasets, respectively, with corresponding station-based data, weather observations were collected for the 21 cities considered in the study. High-quality observations of air temperature, dew point temperature, wind speed, and cloud cover/global radiation were obtained for Rome, Tallinn, and Zürich from their respective national weather providers (Centro Nazionale di Meteorologia e Climatologia Aeronautica Militare Italiana (CNMCA), Estonian Meteorological and Hydrological Institute, and MeteoSwiss). For the other cities, information about air temperature, dew point temperature, wind speed, and total cloud cover were retrieved from the UK Met Office Integrated Data Archive System (MIDAS, Met Office, 2006). For each city, meteorological observations measured at the closest weather station (within 31 km radius from the city centre) were retrieved at 3-hourly intervals, namely at 0:00, 3:00, 6:00, 9:00, 12:00, 15:00, 18:00, and 21:00 Coordinated Universal Time (UTC). The time periods covered by data for selected cities are as reported in Table 1. To obtain reasonably long time series, missing values were identified via an extensive data quality control and cleaning procedure and treated as described in Supplementary Material.

Table 1
Characteristics of the cities selected to the study. *Lat* and *Long* denote latitude and longitude in decimal degrees. *Clim. zone* denotes a climate zone according to the updated Köppen-Geiger classification map (Beck et al., 2018). *Temp.* and *UTCI* indicate the station-based mean annual temperature and Universal Thermal Climate Index. *Time span* indicates the period of mortality and temperature data analysed in each city and *Total deaths* is number of deaths analysed during this period.

City	Acronym	Country	Lat	Long	Clim. zone	Temp. (°C)	UTCI (°C)	Region	Time span	Total deaths
Helsinki	Hel	Finland	60.17	24.94	Dfb	5.7	−2.7	Northern Europe	1994–2012	138,020
Tallinn	Tal	Estonia	59.44	24.75	Dfb	6.4	0.4	Northern Europe	1997–2015	84,052
Berlin	Ber	Germany	52.52	13.40	Dfb	10.2	4.4	Central Continental	1993–2015	811,051
Dresden	Dres	Germany	51.05	13.74	Dfb	9.6	2.2	Central Continental	1993–2015	125,866
Leipzig	Lei	Germany	51.34	12.39	Dfb	9.8	2.3	Central Continental	1993–2015	152,861
Stuttgart	Stu	Germany	48.78	9.18	Dfb	9.8	6.5	Central Continental	1993–2015	138,878
Prague	Pra	Czechia	50.08	14.44	Dfb	10.2	4.5	Central Continental	1994–2015	287,518
Zürich	Zü	Switzerland	47.38	8.54	Dfb	9.7	7.7	Central Continental	2004–2013	34,809
Bremen	Bre	Germany	53.07	8.81	Cfb	9.7	2.5	Central Oceanic	1993–2015	150,608
Düsseldorf	Dü	Germany	51.22	6.78	Cfb	10.9	4.6	Central Oceanic	1993–2015	160,069
Frankfurt	Fra	Germany	50.11	8.68	Cfb	10.9	6.1	Central Oceanic	1993–2015	168,417
Hamburg	Ham	Germany	53.55	9.99	Cfb	9.6	2.9	Central Oceanic	1993–2015	445,338
Hannover	Han	Germany	52.37	9.73	Cfb	9.9	3.5	Central Oceanic	1993–2015	279,125
Köln	Kö	Germany	50.93	6.95	Cfb	10.6	6.0	Central Oceanic	1993–2015	229,457
London	Lon	UK	51.43	−0.09	Cfb	11.6	6.1	Central Oceanic	1993–2006	847,362
Lyon	Lyo	France	45.75	4.85	Cfb	12.5	8.5	Central Oceanic	2000–2010	77,106
Paris	Par	France	48.87	2.33	Cfb	11.9	6.3	Central Oceanic	2000–2010	455,426
Madrid	Mad	Spain	40.40	−3.68	Csa	14.8	11.3	Southern Europe	1995–2014	513,115
Valencia	Val	Spain	39.47	−0.38	Csa	16.4	13.4	Southern Europe	1995–2014	139,180
Zaragoza	Zar	Spain	41.65	−0.88	BSk	17.6	14.5	Southern Europe	1995–2014	113,367
Rome	Rom	Italy	41.90	12.50	Csa	15.4	9.4	Southern Europe	2000–2015	358,879

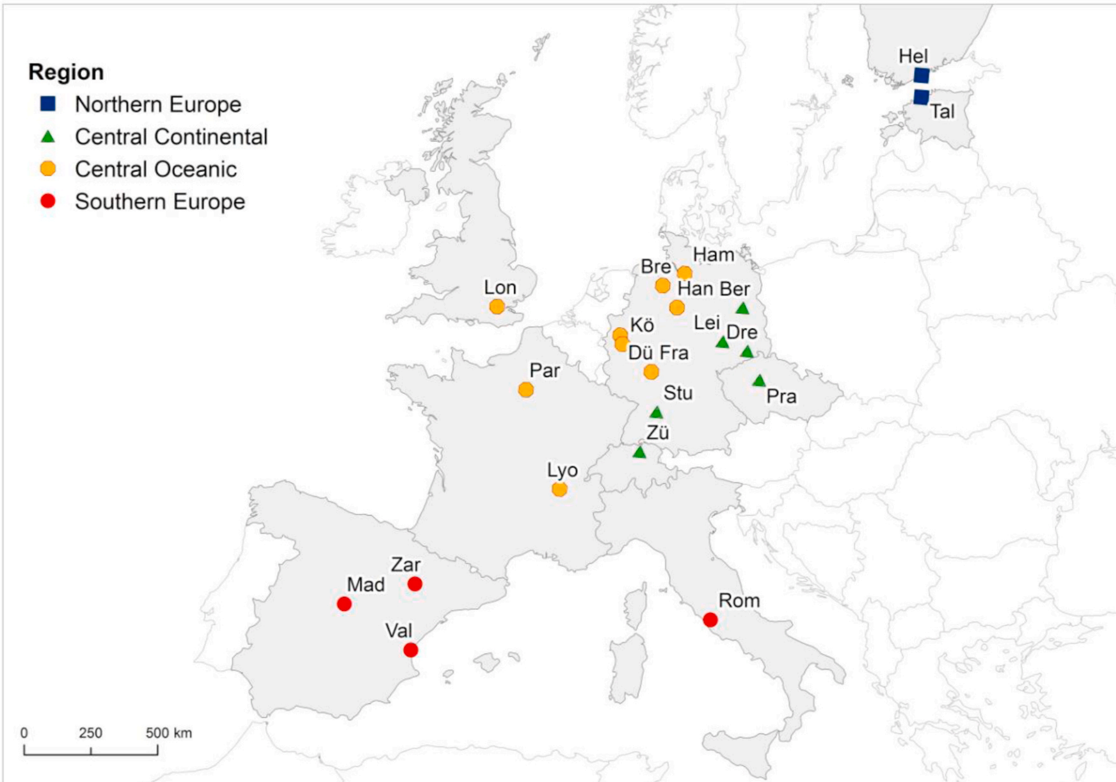

Fig. 1. Location of the 21 European cities considered in the study. Name acronyms are as in Table 1.

Quality-controlled, cleaned data were input into the RayMan Pro software (Version 2.1), a model that enables calculation of radiation fluxes and thermo-physiologically relevant indices using only basic meteorological variables (air temperature, air humidity, wind speed, and cloud cover; Matzarakis et al., 2007, 2010). Using this software, we calculated UTCI in 3-h time steps at individual stations. Station-based UTCImean and Tmean were computed for each location.

Although there have been studies about the importance of both minimum and maximum temperature for temperature-related mortality (e.g., Ragettli et al., 2017), the best predictor often differs for various populations, various health outcomes and at different time (Zhang et al., 2014; Petitti et al., 2016). According to the authors' experience, the mean temperature provides the most consistent results as it represents the whole-day exposure to the heat/cold better than any of the extremes. For these reasons we employed daily mean T and UTCI in the analysis.

2.5. Statistical analysis

All exposure-response modelling was conducted using R software (version 3.5.1). We adopted a two-stage time series analysis consistent with previous papers analysing similar data (e.g., Gasparrini et al., 2015; Vicedo-Cabrera et al., 2018).

2.5.1. First-stage time series analysis

A standard time-series quasi-Poisson regression was performed separately at each location to estimate location-specific exposure-response associations. These associations were reported as relative risk (RR), which means the ratio of the probability of dying in the exposed versus unexposed population. To take into consideration the delayed effects of thermal conditions on mortality, the exposure-response association was modelled using a distributed lag nonlinear model (DLNM) via the *dlnm* R package (Gasparrini et al., 2010). This approach is based on the definition of a 'cross-basis' function, which is a two-dimensional matrix of functions that defines the shape of the relationship between RR and thermal conditions with respect to its lagged effects (Gasparrini et al., 2010).

The cross-basis function was defined by a quadratic B-spline with three internal knots placed at the 10th, 75th, and 90th percentiles of location-specific distributions of the UTCI and T. The lag-response curve was defined with a natural cubic B-spline having an intercept and three internal knots placed at equally spaced values in the log scale. We extended the lag period to 21 days to include the long delay of the effects of cold and to exclude deaths that were advanced by only a few days (i.e. mortality displacement; Qiao et al., 2015). The cross-basis function was included into a generalized additive model (GAM; via the *mgcv* R package – Wood, 2006), defined by a natural cubic B-spline with 8 degrees of freedom (df) per year controlling for seasonal and long-term trends, and a categorical variable indicating day of the week. The number of degrees of freedom (df) was selected based on a comparison of the generalized cross-validation (GCV) score of models with 5–10 df. The GCV score is a measure of goodness of fit in GAMs that takes into account the effective degrees of freedom of the model (Wood, 2006). The adopted choice of knot placement is based on previous studies, which undertook time-series analyses on datasets comparable to those considered in the present study (e.g., Gasparrini and Armstrong, 2013; Gasparrini et al., 2015; Royé et al., 2020).

2.5.2. Second-stage meta-analysis

City-specific estimates were pooled through a single multivariate meta-analysis model using the *mixmeta* R package (Sera et al., 2019). Specifically, the cumulative association between thermal conditions and the mortality risk in each city was used to fit a multivariate meta-analytic model including the mean and range of the city-specific UTCImean and Tmean distribution. An alternative meta-analytic model including a categorical variable for the four groups of cities was tested in a sensitivity analysis. The final model's choice was made

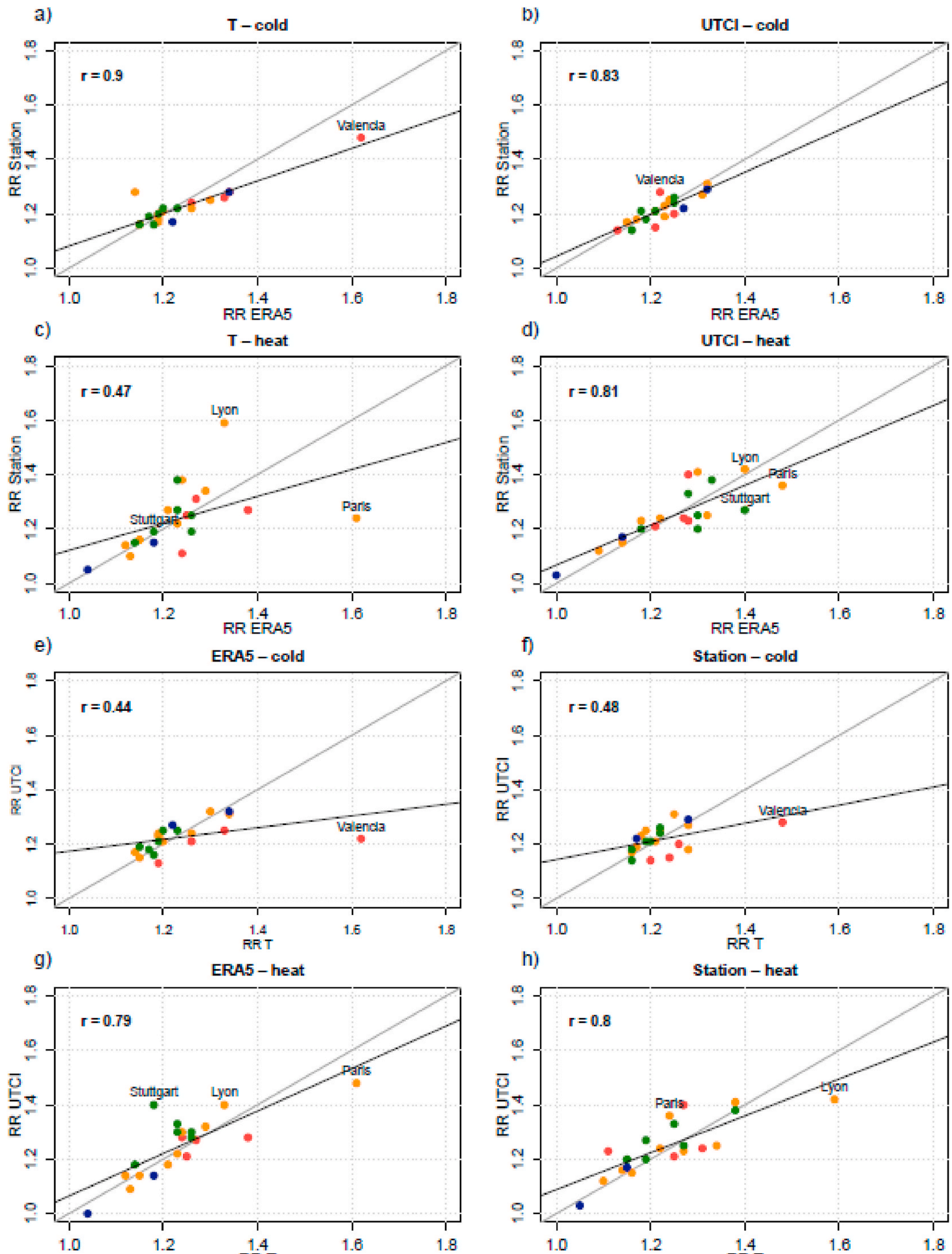

Fig. 2. Scatterplots of cumulative relative risks (RRs) at the 1st (a,b) and 99th (c,d) percentile of daily mean T (UTCI) vs minimum mortality T (UTCI) of best linear unbiased predictions (BLUPs) for individual cities. Panels a–d compare RRs based on T and the UTCI, respectively, calculated from station and ERA5 data. Panels e–h compare RRs at the 1st (e,f) and 99th (g,h) percentile of daily mean T (UTCI) when calculated from modelled (e,g) and observed (f,h) data, respectively. Black lines represent linear regression trend lines of compared variables and r values represent correlation coefficient of compared variables. Point colours indicate the four groups of cities as defined in Fig. 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

according to the Akaike information criterion (AIC; Akaike, 1974; Tong, 1975) and the Bayesian information criterion (BIC, Schwarz, 1978). Lower AIC and BIC values indicate better models. Consequently, the meta-analysis models were used to extract the best linear unbiased predictions (BLUPs) of the exposure-response association for each city while centring the spline at the city-specific Tmean (UTCImean) of minimum mortality (MMT) (i.e., the value for which the RR of dying from thermal stress is lowest). BLUPs represent a trade-off between the location-specific association provided by the first-stage regression and the pooled association. This approach enables more robust estimates of RRs in individual cities compared to location-specific models.

2.5.3. Comparison of regional differences

In the last step of the analysis, four groups of cities were defined, to compare the performance of individual thermal datasets in different European regions (Fig. 1). Four cities from Southern Europe and two cities from Northern Europe were assigned to their groups according to geographical locations. The 15 remaining cities from the central part of Europe were split into two groups – Central Oceanic and Central Continental – corresponding to the Cfb and Dfb climate zones, respectively, according to the updated Köppen-Geiger classification map with high spatial resolution (Beck et al., 2018). Examples of the time series of daily mortality (with a 91day filter), and station-based average UTCI and T (both with a 31day filter) in one city per category (Helsinki, Prague,

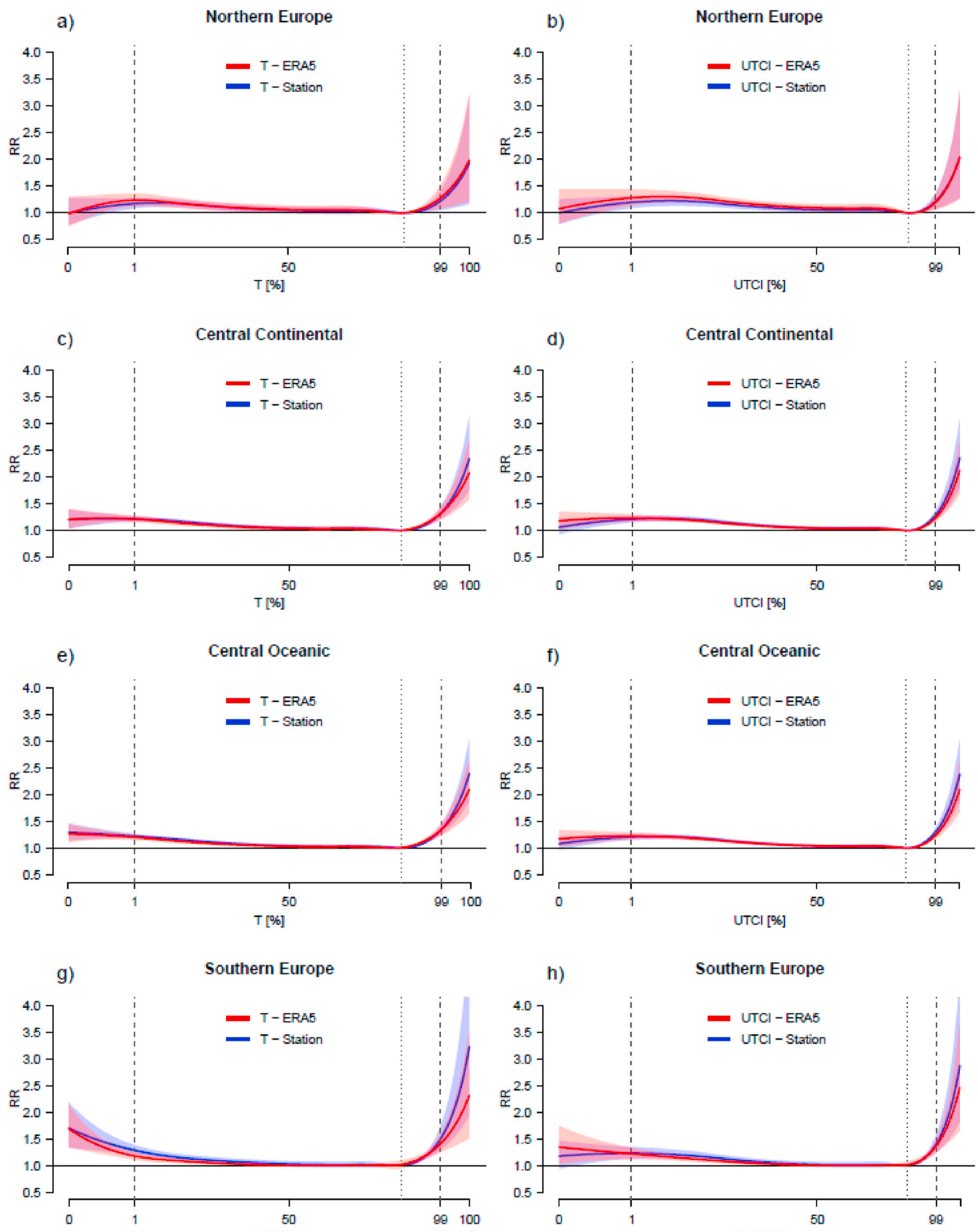

Fig. 3. Pooled estimates of the exposure–response relationships in relative risk (RR) between daily mean T (left), UTCI (right) and mortality in the four city groups considered in the study. The x-axes represent percentiles of the T (UTCI) distribution. Vertical dotted line indicates minimum mortality T (UTCI) and vertical dashed lines represent the 1st and 99th percentile of daily mean T and UTCI, for a given group of cities. See Table S2 for the specific RR values.

London and Madrid) are presented in Fig. S1. Pooled exposure-response curves and RRs of mortality at the 1st, 2.5th, 97.5th, and 99th percentiles of the T and UTCI distribution versus the MMT were derived for each group of cities from the meta-analysis models. These thresholds were chosen as they have been often used as a proxy for moderate (2.5th and 97.5th percentile) and extreme (1st and 99th percentile) cold and heat stress, respectively (Son et al., 2019). We considered RRs at the cold- and heat-effect thresholds versus the city-specific MMT.

3. Results

3.1. Evaluation of datasets

Fig. S2 represents strong correlation between ERA5 and station data. The correlation coefficient between aggregated ERA5 and station data from the 21 cities reached 0.99 for Tmean and 0.98 for UTCImean. The correlation was slightly weaker when UTCI and T datasets were compared (0.94 for both ERA5 and station data). The weaker correlation was mainly due to the effect of other variables on the cold tail of the UTCI distribution. Fig. S1 demonstrates larger differences between the station-based UTCImean and Tmean during the winter season. These differences can be explained by the effect of wind. Clear association

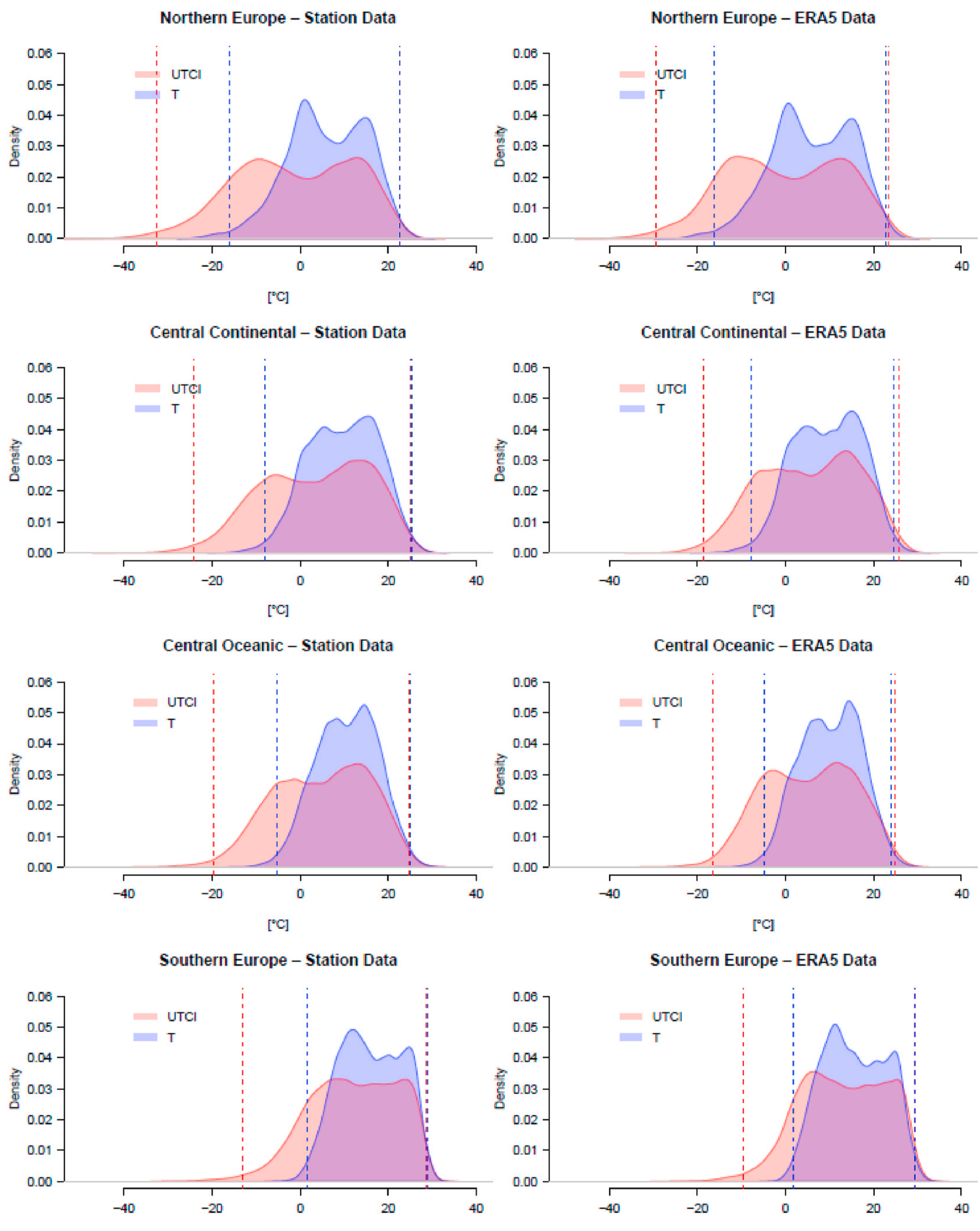

Fig. 4. Predicted density functions of station- and ERA5-based daily mean T and UTCI values in the four city groups considered in the study. Vertical lines denote the 1st and 99th percentile of T (UTCI) distribution.

between the average annual wind speed and the difference between the station-based average annual UTCI and T is shown in Fig. S3.

3.2. City-specific exposure-response patterns

Regardless of the region or city analysed, minor differences were in general observed between exposure-response curves modelled for ERA5 and station data. Generally a good agreement was found also between results for UTCImean and Tmean. The similarity between results for individual datasets is illustrated in Fig. 2, comparing cumulative RRs at the 1st (cold effect) and 99th (heat effect) percentile of Tmean (UTCI-mean) vs MMT, estimated from BLUPs for individual cities (Figs. S4–S11 in Supplementary Material).

As for the cold effect, the correlations between station- and ERA5-based RR estimates were stronger for Tmean than for UTCImean (r = 0.90 vs. 0.83, respectively, Fig. 2 a,b). The association was considerably weaker, when the two thermal indices were compared between each other (r = 0.44 for ERA5 and 0.48 for station data, respectively) (Fig. 2e and f). The differences in r were, however, generally insignificant, as they were mainly caused by a few outliers in the datasets. In particularly in Valencia, the cold effect estimated by Tmean was considerably stronger than for the UTCI (cf. Figs. S10–11).

For the heat effect, the correlation between the Tmean and UTCI-mean RR estimates was stronger than for the cold effect (r = 0.79 for ERA5 and 0.80 for station data, respectively), suggesting small differences in the impact of hot environment on mortality when characterised by Tmean and UTCImean (Fig. 2g and h). On the other hand, a weaker correlation between ERA5-and station-data was observed when the two thermal indices were considered separately (Fig. 2c and d). This was true especially for the comparison of ERA5 vs station-based Tmean RRs (r = 0.47), which was affected by outliers in Paris and Lyon, due to the extraordinary impact of the 2003 heat wave.

3.3. Pooled exposure-response patterns

A strong correlation between ERA5-and station-based UTCImean and Tmean is illustrated also in Fig. 3, displaying the pooled estimates of exposure-response curves for the four groups of cities. As suggested already in Section 3.2, the main differences between RR estimates appeared at the cold extreme, when results for UTCImean and Tmean are compared. This is true especially in Southern Europe (Fig. 3g and h). A well pronounced U shape of the exposure-response curve, with a constant increase in RR for temperatures below the 1st percentile of T, is typical for cities in this region (see also Figs. S10 and S11), whilst a flattened cold-related RR was observed for UTCImean in Southern Europe (Fig. 3h) as well as for Tmean and UTCImean in groups from higher latitudes. In Southern European cities, mild winters with lowest daily temperatures slightly below 0 °C and a sharp increase of RR at these temperatures are typical (Fig. 4 and Fig. S10–11). This pattern is especially pronounced in Valencia, Spain, and other Southern European cities, but a similar pattern was revealed also for some cities in the Central Oceanic region, namely London, Hamburg, Bremen (Fig. 3e,f and Figs. S8–9). On the contrary, the RR reaches its maximum at values around the 1st percentile of UTCImean (and Tmean) in colder regions, followed by a decrease in RR (Fig. 3a–d,f,h).

The exact RR estimates at the cold- and heat-effect thresholds (1st, 2.5th, 97.5th and 99th percentile of Tmean and the UTCI) in the four groups of cities are presented in Table S2 and Fig. 5. Models employing the UTCImean estimate in general slightly larger RRs than those with Tmean, regardless of the source of data (station or ERA5) and whether the heat or cold effect is considered. This is not the case, however, when the cold effect in the Southern European group is assessed. In this group, the largest difference between the two thermal indices was observed, with the cold effect estimated by Tmean (1.30 [95% confidence interval (CI): 1.20, 1.41] vs 1.29 [1.21, 1.38] at the 1st percentile according to the ERA5 vs station data, respectively) being considerably larger than for UTCImean (1.19 [1.12, 1.27] vs 1.22 [1.14, 1.31]). This was related to the rapid increase of RR at low temperatures illustrated in Fig. 3 (g,h).

Reported RRs for the cold effect in Southern Europe also show that the RR estimates modelled by the station data were larger than for ERA5. This was true also for other regions, except for the Northern European group of cities. However, the differences between ERA5 and station

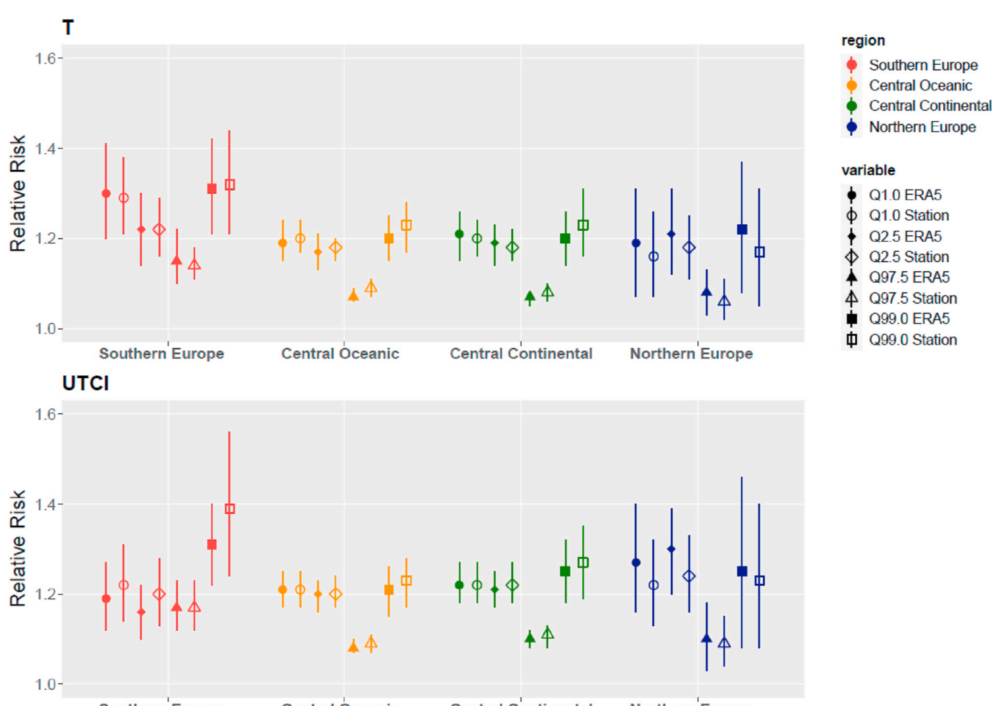

Fig. 5. Pooled estimates of cumulative relative risk (RR) of mortality at daily mean T and UTCI percentiles (*variable*) with respect to minimum mortality T (UTCI) in the four city groups considered in the study (*region*).

datasets were mostly small.

4. Discussion

In this study, we assessed the relationships between thermal stress and mortality in 21 cities from 9 European countries by comparing two sources of thermal stress data – climate reanalysis and station-based records. The novel ERA5-HEAT dataset was used here for the first time to provide a pan-European perspective on the relationship between human mortality and thermal conditions, with the latter represented by the UTCI. Performance of the ERA5-based UTCI was compared with results for the station-based UTCI. As a term of reference, performance of ERA5-based air temperature was also compared with results for station-based air temperature. Overall, we observed strong agreement between modelled exposure-response curves, regardless of whether comparing the results for (i) station and ERA5 data, (ii) the UTCI and T, (iii) individual cities, and/or (iv) the four groups of cities as defined in this study. Our findings complement previous work from the United States (Adeyeye et al., 2019) and Spain (Royé et al., 2020) and outline the great potential of climate reanalyses to provide comprehensive information about thermal conditions for studies modelling weather-health relationships. Gridded-observation products, such as PRIMS and Daymet in the United States (Spangler et al., 2018; Weinberger et al., 2019) and European E-OBS (Cornes et al., 2018), may have a similar potential. But these products do not provide all variables necessary for the calculation of thermal indices.

4.1. Evaluation of ERA5-HEAT

ERA5/ERA5-HEAT datasets are so valuable because they provide a comprehensive weather dataset, including wind and radiation. Wind is essential for estimating the wind chill effect on thermal comfort and hence for wind-dependent biometeorological indices such as the UTCI. Although wind is one of the most problematic weather variables to calculate in weather and climate models (Pappenberger et al., 2015), ERA5 near-surface wind measures show the best agreement with in situ observations in comparison to other global reanalyses (Ramon et al., 2019).

Radiation is also challenging to represent in models (e.g., Schreier et al., 2013). Model dynamics, physical parameterization, resolution, and cloudiness are some of the sources of uncertainty in relation to radiation as a reanalysis product. Recent improvements in how these aspects are considered in numerical models have nevertheless helped reduce such uncertainty, thereby allowing radiation to be used in applications studies, such as the present one, where the radiant environment represented plays an important role (Di Napoli et al., 2020b).

Although systematic errors exist in ERA5/ERA5-HEAT datasets, the advantages of homogenized, gridded, and freely available reanalyses considerably outweigh their disadvantages. Collecting station data is always fraught with difficulties (Colston et al., 2018). Most MCC members could not provide high-quality ground observation data necessary for the UTCI calculation. Thus, the required variables were retrieved from the MIDAS database by collecting surface observations from the SYNOP messages provided automatically by meteorological stations. Because these records contain errors and significant gaps at many locations (e.g., Estévez et al., 2011; Steinacker et al., 2011), we were not able to run the final analysis in all cities for which mortality data were available via the MCC network. Therefore, the final results are limited by the lack of high-quality ground observations at the MCC locations. This demonstrates another reason why using climate reanalysis data is preferable in continent-wide studies (Colston et al., 2018).

4.2. Definition of UTCI

Although generally good agreement between results for different datasets and thermal indices was found, several important differences appeared. The main discrepancies between exposure-response patterns occurred when effects of the daily mean UTCI (UTCImean) and temperature (Tmean) were assessed. Whilst similar heat effects on mortality were generally observed for the two thermal indices, differences between cold effects were much larger. This was true especially in the Southern European group of cities, but similar patterns were found also in other cities (London, Hamburg, Bremen). While the estimate of the cold effect in this region was clearly the largest among the city groups at the 1st percentile of the Tmean distribution, it was comparable with or even lower than estimates in other regions when UTCImean was considered. As these results were consistent for ERA5-and station-based data, we may assume that these differences were caused due to the effect of other variables in the UTCI definition.

As stated above (Section 2.2), the overall thermal stress shown by the UTCI is defined as a combination of air temperature, mean radiant temperature, humidity, and wind speed. Wind speed considerably affects the UTCI in cold environment (Błażejczyk et al., 2012; Novák, 2013; Urban and Kyselý, 2014), resulting in a much heavier cold tail of the UTCImean distribution compared to that of Tmean (see Fig. 4). A comparison of the UTCI and T time series with wind measurements (Figs. S1–S3) suggests that windier cities show larger differences between the distributions of T and UTCI in the cold environment. This phenomenon is especially important for the exposure-response patterns in Southern European cities, where the lowest daily temperatures rarely drop below 0 °C while daily UTCI can decline to −20 °C. In such cities, the RRs increase sharply for Tmean below the 1st percentile, whilst the cold effect is flattened at low UTCImean values because of the long left tail of the distribution (compare Figs. S10–S11).

A similar pattern with sharp increase of mortality at the lowest percentiles of the temperature distribution was observed also in some Central Oceanic cities, e.g., London. A great percentage increase in mortality at low temperatures in regions with relatively mild winters has been well documented in previous studies (Eurowinter Group, 1997; Gasparrini et al., 2015). Absence of central heating and poor housing standards have been hypothesized as possible reasons for such strong cold-related mortality effect in these countries (e.g., Laake and Sverre, 1996; Eurowinter Group, 1997). On the other hand, the flattened cold-related RR (with its maximum in moderately cold weather) in cities from higher latitudes is in accordance with findings from a previous Multi-City Multi-Country study (Gasparrini et al., 2015).

The interpretation of the cold effect on mortality is very complex and depends on many factors (Kinney et al., 2015). More specifically, the shape of the exposure-response curve may strongly depend on model parameters. However, our results as well as previous studies (Gasparrini et al., 2015) suggest that death risk is generally larger at moderately than extremely cold conditions. The difference between moderately and extremely cold days is even more evident when the UTCI is used for the definition of cold days. This might be due to the emphasised effect of wind on the UTCI (Novák, 2013; Urban and Kyselý, 2014; Pappenberger et al., 2015). More specifically, the UTCI tends to overestimate the wind chill effect, especially on days with extreme wind speeds (Novák, 2013). Moreover, results by Urban and Kyselý (2014) suggest that urban populations are less vulnerable to the effect of wind than rural populations. Considering this, days with strong wind but moderately cold conditions might be defined as extremely cold by the UTCI, although they do not necessarily have to be as risky as days with both lower wind speed and lower temperature.

4.3. Strengths and limitations

Several limitations of this study need to be acknowledged. Firstly, as suggested above, the robustness of the study was affected by a lack of high-quality ground observations at some locations and extensive cleaning procedure as described in Supplementary Material. Therefore, many locations (where mortality data were available via the MCC network) had to be discarded from the analysis due to a considerable amount of missing meteorological data. In cities that were finally used in this study, however, the amount of missing data was not larger than 1.5%. Therefore, we believe that the results are representative for climate conditions typical in individual cities.

The different classification, length and time span of mortality datasets available for individual countries represents another limitation. A previous study using similar datasets documented that replacing all-cause with non-external mortality has a marginal effect on results (Gasparrini et al., 2015). The other factors, on the other hand, might have contributed to the over- or under-estimation of the cold- and heat-effects in some regions compared to others. This was true especially for French cities (Lyon and Paris). The French mortality time series spanned the period 2000–2010, which was the second shortest time period analysed (after Zürich's). In addition, results for French cities were affected to an unprecedented extent by the 2003 heat wave (D'Ippoliti et al., 2010). Therefore, the estimates of the heat effect in these two French cities are extremely high compared to other cities (Fig. S8–9) and they might have affected also results for the Central Oceanic group of cities. Because the data for Paris and Lyon represent a very real phenomenon, however, we decided to keep them in the dataset.

As mentioned above, the shape of the exposure-response curve may strongly depend on model parameters. It is worth noting that the present analysis uses a lag of 21 days, which is a common lag window to consider for both the acute heat effect (and related harvesting effect) and the delayed cold effect (Kinney et al., 2015; Gasparrini et al., 2015; Gasparrini, 2016; Vicedo-Cabrera et al., 2018). As such it does not quantify the separate effects of heat and cold. Future work could achieve that by modelling heat and cold effects separately, e.g., by dividing the study period into warm and cold seasons and assigning different lag days to different temperature exposures (e.g. Fonseca-Rodríguez et al., 2019).

The main strength of this study is the use of a novel climate reanalysis product. ERA5-HEAT provides information about near-surface thermal conditions in a regular grid for the whole world with the highest possible resolution (Dee et al., 2016). This is especially important for heat and/or cold warning systems wherein forecasted data are usually derived from and/or shown as maps (Novák, 2013; Pappenberger et al., 2015; Vitolo et al., 2019).

The spatial resolution (28 km) and the land surface scheme (urban tile not included; Balsamo et al., 2009) of the ERA5 and ERA5-HEAT datasets might not capture all meso- and micro-scale variations of thermal conditions, especially in areas with a complex orography (Luo et al., 2019). Even at the smallest grid cell, a reanalysis is a collection of values averaged over an area whereas station measurements are values collected at one specific point. The difference between the two values depends on the grid cell size, the terrain complexity and the type of surface. However, work is in progress to overcome these uncertainties (Hogan, 2019). This is opening the pathway to more advanced, high-resolution climatological datasets from which the UTCI may be calculated at a scale closer to the city level.

Several European weather services have recently developed systems to operationally forecast human biometeorological conditions via the UTCI (cf. Di Napoli et al., 2021). Although the national systems are able to forecast the UTCI with a higher resolution, developing continental-wide systems that integrate weather forecasts of a thermal comfort indicator with the corresponding epidemiologically defined relative risk, would represent a step forward in health action planning against heat and cold extremes. This is particularly valuable for those regions where very few such warning systems exist (Singh et al., 2019), but it is important also for revision of existing national heat–health warning systems which differ in definition of heat–health warning thresholds and methodology (Lowe et al., 2016; Casanueva et al., 2019). While local meteorological datasets in some regions remain often sparse and underfunded, the use of climate reanalyses offers many practical advantages (e.g., Colston et al., 2018). In this study, we have demonstrated the potential of the ERA5-HEAT dataset that may serve as a proxy for observations when developing a continental-wide health-related thermal hazard warning system based on a comprehensive description of thermal environment.

5. Conclusions

Analysing daily mortality data from 21 cities across 9 European countries, we explored the potential of the ERA5-based UTCI as a health-related tool. Distributed lag nonlinear models (DLNM) were employed to assess exposure-response relationships for ERA5 and station-based UTCI. For this purpose, a novel ERA5-HEAT dataset was used for the first time. In addition, the same associations were analysed for ERA5- and station-based air temperature as this is the most commonly used variable in environmental epidemiology. Meta-regression models were employed to pool the results for each city into four groups according to climate zones.

The main findings of our analysis are as follow:

- Generally consistent exposure-response relationships for the ERA5- and station-based UTCI confirm the suitability of the ERA5-HEAT dataset in health-related studies.
- Strong correlation was found between results for the UTCI and air temperature in all groups of cities when assessing heat effects on mortality.
- The role of wind in the UTCI definition, on the other hand, resulted in larger differences between the UTCI and air temperature when cold effects on mortality were assessed.

We demonstrate that the ERA5-HEAT dataset provides a useful tool for climate and health studies, especially in locations where high-quality station data are not available. These findings are important for further development of continent-wide health-related warning systems. Analysis of the cold effect on mortality highlights the importance of further investigation of the wind chill effect in cold exposure assessments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2021.111227.

Credit author statement

AU, CDN, JK, FS, AG: Conceptualization, Methodology. AU, CDN:

Investigation, Visualisation, Writing- Original draft preparation. HLC, JK, FP, FS, RS, AMV, FA, MSR, CI, AT, EI, HO, JJKJ, NRIR, MP, VH, AS, FD, PM, AG: Data curation, Result interpretation, Writing- Reviewing and Editing. AG, JK, HLC, FP, FS, AMV: Supervision.

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