DTU Library

Analysis of vulnerability to heat in rural and urban areas in Spain

What factors explain Heat's geographic behavior?

López-Bueno, J. A.; Navas-Martín, M. A.; Díaz, J.; Mirón, I. J.; Luna, M. Y.; Sánchez-Martínez, G.; Culqui, D.; Linares, C.

Published in:
Environmental Research

Link to article, DOI:
10.1016/j.envres.2021.112213

Publication date:
2022

Document Version
Peer reviewed version

ARTICLE IN PRESS

Environmental Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Analysis of vulnerability to heat in rural and urban areas in Spain: What factors explain Heat's geographic behavior?

J.A. López-Bueno [a,*], M.A. Navas-Martín [a], J. Díaz [a], I.J. Mirón [b], M.Y. Luna [c], G. Sánchez-Martínez [d], D. Culqui [a], C. Linares [a]

[a] Escuela Nacional de Sanidad, Instituto de Salud Carlos III, Madrid, Spain
[b] Consejería de Sanidad, Junta de Comunidades de Castilla la Mancha, Toledo, Spain
[c] Agencia Estatal de Meteorología, Madrid, Spain
[d] DTU Partnership, Copenhagen, Denmark

ARTICLE INFO

Keywords:
Heat waves
Poverty
Urban
Rural
Vulnerability

ABSTRACT

Introduction: There is currently little knowledge and few published works on the subject of vulnerability to heat in rural environments at the country level. Therefore, the objective of this study was to determine whether rural areas are more vulnerable to extreme heat than urban areas in Spain. This study aimed to analyze whether a pattern of vulnerability depends on contextual, environmental, demographic, economic and housing variables.
Methods: An ecological, longitudinal and retrospective study was carried out based on time series data between January 01, 2000 and December 31, 2013 in 42 geographic areas in 10 provinces in Spain. We first analyzed the functional relationship between the mortality rate per million inhabitants and maximum daily temperature (Tmax). We then determined the summer temperature threshold (Pthreshold) (June–September) at which increases in mortality are produced that are attributable to heat. In a second phase, based on Pthreshold, a vulnerability variable was calculated, and its distribution was analyzed using mixed linear models from the Poisson family (link = log). In these models, the dependent variable was vulnerability, and the independent variables were exposure to high temperatures, aridity of the climate, deprivation index, percentage of people over age 65, rurality index, percentage of housing built prior to 1980 and condition of dwellings.
Results: Rurality was a protective factor, and vulnerability in urban areas was six times greater. In contrast, risk factors included aridity (RR = 5.89 (2.26 15.36)), living in cool summer zones (2.69 (1.23, 5.91)), poverty (4.05 (1.91 8.59)) and the percentage of dysfunctional housing (1.13 (1.04 1.24)).
Conclusions: Rural areas are less vulnerable to extreme heat than the urban areas analyzed. Also, population groups with worse working conditions and higher percentages of dwellings in poor conditions are more vulnerable.

1. Introduction

Heat Health Action Plans (HHAP) are public health strategies that have reduced mortality attributable to heat waves in many countries (Allen and Sheridan, 2018; Linares et al., 2020; Sánchez-Martinez et al., 2019; Sheridan et al., 2019). However, their efficiency has been somewhat heterogeneous (Sánchez-Martinez et al., 2019), and exposure to extreme heat is becoming more intense (Díaz et al., 2019a, 2019b; Linares et al., 2020).

HHAP should be continuously evaluated and updated in order to conserve and improve their positive impact on health (Sánchez-Martinez et al., 2019; WHO, 2021). Thus, an area of improvement recently proposed by the WHO (2021) is their application at the local level. Although there might be important differences in small-scale application in rural vs. urban areas, little is known about the vulnerability to extreme heat in rural areas. The inexistence of a common definition of rurality, and a lack of available data (Gartner et al., 2011; Goerlich et al., 2016; Lourenço, 2012; Prieto-Lara and Ocaña-Riola, 2010), has meant that studies of the effect of heat waves on health have focused primarily on urban areas (Chen et al., 2020; Gasparrini et al., 2015; Guo et al., 2017;

* Corresponding author. C/Monforte de Lemos, 5, 28029, Unidad de Referencia en Cambio Climático, Salud y Medio Ambiente Urbano, Escuela Nacional de Sanidad, Instituto de Salud Carlos III, Madrid, Spain.
E-mail address: joseanlo@ucm.es (J.A. López-Bueno).

https://doi.org/10.1016/j.envres.2021.112213
Received 10 August 2021; Received in revised form 21 September 2021; Accepted 11 October 2021
Available online 16 October 2021

Odame et al., 2018).

Even so, some studies have aimed to determine which type of population group is more vulnerable to extreme heat, though without conclusive results (Odame et al., 2018). On one hand, some studies indicate that rural zones are more vulnerable (Azhar et al., 2017; Chen et al., 2016; Eurostat, 2016; Hu et al., 2019; Lee et al., 2016; Li et al., 2017; Madrigano et al., 2015; Sheridan and Dolney, 2003). Others, however, indicate that urban areas are more vulnerable (Nayak et al., 2018; Reid et al., 2009; Wang et al., 2018; Wolf and McGregor, 2013).

This could be explained by the fact that both urban and rural territories present risk factors that can be determinants based on their social, economic and demographic contexts. For example, rural populations are generally older and therefore more vulnerable based on this variable (Benmarhnia et al., 2015; Díaz et al., 2002; Eurostat, 2016; Linares and Díaz, 2008; Yu et al., 2012). Also, in general, the rural population has more difficulty in accessing social and health services (Douthit, 2015; Gutierrez and LePrevost, 2016). Dedication to the agriculture sector also constitutes another risk factor (Earle-Richardson et al., 2015; Prieto--Lara and Ocaña-Riola, 2010), given the greater exposure to adverse meteorological conditions and greater physical hardship (Mac and McCauley, 2017). In addition, there is generally a greater incidence and prevalence of chronic conditions among rural populations (Disler et al., 2020; Dwyer et al., 1990; Miller and Vasan, 2021).

Other factors operate in the opposite direction. For example, rural areas imply lower exposure to environmental risks and higher levels of physical activity, including among those with chronic conditions (Dwyer et al., 1990; Husk et al., 2016; Oleson et al., 2018; Peen et al., 2010; Pitkänen et al., 2020; Wagenfeld, 1990; Zhu et al., 2016; Zhuori et al., 2019). In addition, social relationships in these populations are stronger, and there is greater cooperation and lower social isolation among the elderly (Dwyer et al., 1990; Wagenfeld, 1990).

Economic status (Benmarhnia et al., 2015; Bernard et al., 2007; López-Bueno et al., 2020; Reid et al., 2009; Rohat et al., 2019; Shi et al., 2011) and quality of housing (Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015) can result in very heterogeneous distributions of vulnerability in both urban (López-Bueno et al., 2019, 2020; Rinner et al., 2010) and rural areas (Dwyer et al., 1990; Earle-Richardson et al., 2015; Etowa et al., 2007; Hunter, 2007).

Therefore, in each case it is important to determine which type of population is most vulnerable through local studies. The primary objective of this work was to analyze the distribution of vulnerability to extreme heat in rural and urban areas in Spain, and to establish those climatological, meteorological and sociodemographic variables that permit understanding the distribution of vulnerability.

2. Material and methods

2.1. Study type, area and period

This study was an ecological, longitudinal and retrospective study of time series data from January 1, 2000 through December 31, 2013.

Ten representative provinces were selected using demographic and geographic criteria (Díaz et al., 2019a, 2019b; Díaz et al., 2018). Municipalities that had over 10,000 inhabitants were included. Each of these municipalities was classified as urban or non-urban following Eurostat's DEBURGA classification (Eurostat, 2016, 2018, 2021). At the same time, municipalities were also classified based on their isoclimatic zone (Carmona et al., 2017; Roldán, J, 2011). Isoclimatic zones are areas of equivalent climatological behavior determined by AEMET for the purposes of meteorological prediction and allow us to assign representative temperatures to each group. Based on these classification criteria —rurality and isoclimatic area— the municipalities included in the study were grouped into 42 different groups, which constitute the sample units of the study. Fig. 2 performs the geographic pattern resulted by this classification.

Once the study groups were defined, we designed a two-phase statistical strategy. The first phase determined the percentile in maximum daily temperatures in summer (June–September) that corresponded to the beginning of a heat wave in each analyzed area (Pthreshold). In the second phase we analyzed the vulnerability associated with these Pthreshold. Both phases are described in detail in sections 2.3 and 2.4, respectively.

2.2. Databases and variables used

A separate database was used for each of the two phases. Both are described as follows:

Database of time series data used in Phase 1:

Dependent variable.

- Rate of daily mortality (MR): We worked with the mortality due to natural causes (CIE-10: A00–R99). Rural and urban groups are characterized by different censuses. This means that the direct counts of daily mortality are not comparable between the two types of zones. Therefore, we used the MR per million inhabitants. This rate was calculated based on the daily counts of deaths at the municipal level and the data from the census. Then, this variable was aggregated at the unit levels. Thus, the final dependent variable was daily mortality rates per group. Both, mortality counts and census, variables were provided by the National Statistics Institute (INE by its initials in Spanish).

Independent variable.

- Maximum daily temperature (Tmax): Maximum daily temperature, which has been shown in prior studies that have a broader relationship with mortality than average and minimum daily temperatures, was used as an indicator of temperature (Díaz et al., 2015a, 2015b). This value was quantified in degrees Celsius and was determined by aggregating the averages of the values registered in all of the observatories found in the same isoclimatic zone. These data were provided by AEMET.

Control variables.

- Trend: A counter variable was generated and used to control the trend of the mortality rate. This variable takes the value of "1" on the first day of the series, "2" on the second, and continues successively until the end of the data series.
- Seasonality: Given that mortality and temperature follow markedly seasonal behavior patterns, seasonalities must be controlled for in order to ensure that the statistical association between them is free of confusion. To this end, a collection of variables was generated with the sine and cosine functions, each with oscillations for the annual, biannual, quadrimestral, trimestral, bimonthly and monthly periods.
- Time: The factor type variables *month* and *year* were also included as control variables. This added an additional control for seasonality and the trend in the time series of data.
- Ar1: The literature establishes that the temporal evolution of mortality includes an autoregressive component of order 1 (Alberdi et al., 1998). Therefore, a lag variable of order 1 was generated for MR.

Phase II of the analysis used a database with the following variables:

Independent variable.

- Vulnerability: A dimensionless variable that quantifies the susceptibility of the population to heat waves by their effects on MR. This variable was determined based on the results obtained in phase I of the analysis and is explained in depth in section 2.3.

Short-term meteorological exposure variables.

The following variables indicate exposure to heat during the period analyzed.

- Summer Temperature (Summer T): This variable was used to control for exposure to high temperatures. It corresponds to the value of Tmax (°C) by group during the summer months (June–September) of the time period analyzed.
- Summer extreme temperature (Summer P95): This variable was used to control for exposure to extreme heat. It corresponds to the 95th percentile of summer daily maximum temperatures (°C) during the period analyzed.

Climate variables.

In contrast to the variables mentioned, these variables were used to control for the long-term behavior of climate during the decades prior to the study period. These variables can influence culturally inherited habits among generations, the type of housing and even the physiological changes over the long term.

- Cool summer: This is a variable that indicates whether the climate in an analyzed group is characterized by cool summers. It is a dichotomous indicator that takes the value "1" in climates with cool summers and "0" in climates with moderate or hot summers (AEMET, 2011). It was determined using the Koppen classification carried out by AEMET (Chazarra et al., 2018) using climate data registered for the 1981–2010 period.
- Water Balance (WB): This variable indicates whether the precipitation surpasses evapotranspiration in the groups. It is related to aridity and depends on diverse meteorological factors (radiation, temperature, humidity of the air and wind), edaphic factors, and the characteristics of the ground coverage. In this case, the indicator included in the models is another binomial type variable that takes the value "1" when the balance is positive (precipitation > evapotranspiration) and "0" when the balance is negative (precipitación < evapotranspiration). This information was calculated based on the climate registries for the 1996–2016 period and is available in the open data repository of the National Center for Geographic Information (Atlas Nacional de España, 2019).

Economic, demographic and territorial variables:

- Deprivation: this index condenses six indicators related to laboral precariousness and material deprivation registered in the year 2011: the population working in manual labor, temporary working population, unemployment, insufficient instruction and homes without internet access. For each of the analyzed groups, its value was calculated by aggregating the average values at the section census level in the original data. A deprivation = 0 indicates an average level of poverty of the national territory. As this index surpasses zero, it indicates an increase in poverty; on the contrary, as it becomes negative, it indicates a decrease in poverty. The indicator was designed in the framework of the MEDEA project (Duque et al., 2020, 2021), and can be found in the open data bank of the Spanish Society of Epidemiology (Sociedad Española de Epidemiología, 2020).
- Rurality: Due to the difficulty in establishing the rural/urban character of the population using categorical classifications (Gartner et al., 2011; Goerlich et al., 2016; Prieto-Lara and Ocaña-Riola, 2010), this study included an indicator of the rural character of the territory based on different sociodemographic indicators. This indicator was composed of the percentage of elderly population; economic dependency; population employed in agriculture, ranching and fishing; self-employment; percentage of second residences; population density; immigration and perception of noise and pollution in the environment. Growth in the indicator reflects a more rural environment; as rurality goes below zero the environment is more urban. This indicator was supplied and developed by Ocaña-Riola Prieto-Lara and Ocaña-Riola, (2010).
- Elderly: Given that population ageing is a biological risk factor associated with heat waves (Díaz et al., 2015a, 2015b; Díaz et al., 2002; Pyrgou and Santamouris, 2020; Reid et al., 2009; Yu et al., 2012), the models controlled for the percentage of population over age 65. This variable was calculated based on the census data which is available at INE (2020).

Housing variables.

- Older Dwelling (OD): The percentage of older housing present in each municipality. An older dwelling was that which was built before 1980, based on prior literature (López-Bueno et al., 2019). Percentages were calculated based on data available directly from the general building census (Dirección General del Catastro, 2021).
- Dwelling in decline (DD): This variable was quantified as the percent of housing or dwellings in a state of dysfunction, for each group. Again, these data were calculated directly based on information from the general building census (Dirección General del Catastro, 2021).

2.3. Phase I: determination of the heat wave threshold percentiles

The starting point for this study was the WHO's recommended definition of a heat wave, based on the effect on health (2021). From this perspective, the threshold temperature of a heat wave is that for which mortality (MR) is statistically greater than the seasonal average for the period analyzed. Therefore, the objective of the first phase of the study was to determine the threshold temperature for each area and establish a percentile for the series of Tmax of the summer months.

To establish Tmax percentiles, we followed the recommended methodology described in the literature (Carmona et al., 2016, 2017; Díaz et al., 2018; Linares et al., 2016; López-Bueno et al., 2021a, 2021b; Mirón et al., 2015). First ARIMA models were fitted to the full mortality rate time series, so that 5114 days were include in each model, and an ARIMA model was calculated to each province. The ARIMA regression model are, in the general form:

$$Y_t = b + \beta_{1p}\varphi_{pt} + \beta_{2q}\theta_{qt} + \beta_{3P}s\varphi_{Pt} + \beta_{4Q}s\theta_{Qt} + \beta_5 n1_t + \beta_{6\alpha}\cos(\alpha t) + \beta_{7\alpha}sen(\alpha t) + \varepsilon_t;$$
$$\varepsilon_t \sim N(0, \sigma)$$

where Y_t is mortality on day t; b is the intercept; β are the coefficient of each variable in each case; φ is the no-seasonal autoregressive parameter of order p on day t; θ is the non-seasonal mobile average of order q on day t; $s\varphi$ is the seasonal autoregressive parameter of order P on day t; $s\theta_{Qt}$ is the seasonal mobile average of order Q on day t; n1 is the trend on day t; $\cos(\alpha t)$ *and* $sin(\alpha t)$ are seasonal functions of α {365, 180, 120, 90, 60, 30} periods on day t; and ε is the residuals which performs a normal distribution of mean = 0, and σ is the standard deviation of the ε. Since trend was included as an independent variable, the integrated parameter was I = 0.

These models were controlled by the *control variables* described in section 2.2 – trend and seasonality -. Associated with fitted values, models generate a time series of residuals, which corresponds to the difference between the observed values and fitted values. Then, we retained these residuals as new variable called *residuals*. This new variable had the advantage (compared to mortality rate) of being free from seasonality, trend and autoregressive components. Therefore, its association with Tmax reflects a true mortality-temperature relationship that is free of seasonal confusion. Next, summer observations (June–September) were kept in memory, and the dispersion of *residuals* was analyzed in temperature ranges with the help of an abscissa graph. Values on the X axis represent Tmax (°C), and the Y axis represents the average of *residuals,* grouped into 2-degree intervals, together with the corresponding confidence intervals. In these groups the confidence interval corresponding to the seasonal average of the *residuals* is shown, represented as a band centered on y = 0. All of the intervals mentioned were calculated with a confidence interval of 95 percent statistical significance. Fig. 1 shows an example of this type of graph.

The dispersion graphs of the residuals show temperatures at which the mortality rate of the interval is statistically higher than the seasonal MR. These can be recognized as those temperature ranges in which the *residuals* are elevated above zero, until the point at which their confidence intervals do not overlap with the central band.

In this work our interest is centered on the percentile of summer Tmax represented by these threshold temperatures. Thus, these threshold percentiles (Pthreshold) represent the relative temperature level at which a heat wave begins for each group, based on the epidemiological criterion considered. In this way, they represent a direct measure of the adaptation to heat, given that Pthreshold temperatures indicate that the population can tolerate relatively higher temperatures before manifesting associated health impacts.

This procedure was carried out independently for each of the 42 groups analyzed and used the software IBM SPSS Statistics 27. The dispersion graphs of the *residuals* were generated using the ggplot2 package of the free software R 4.0.4. Finally, the maps shown in the results were generated using the free software QGIS 3.18.2.

2.4. Phase II: analysis of vulnerability

The second phase of the study analyzed whether vulnerability to heat could be explained by different meteorological, climatological, socio-demographic and urban indicators.

Vulnerability was defined as the opposite of adaptation, based on the following equation:

[1] vulnerability = 100 – Pthreshold.

In those cases in which no threshold was detected, a complete adaptation was assumed (Pthreshold = 100).

The use of percentiles as a measure of impact of heat has been previously reported (López-Bueno et al., 2019; López-Bueno et al., 2021a, 2021b). This definition has the advantage of being a direct result of the

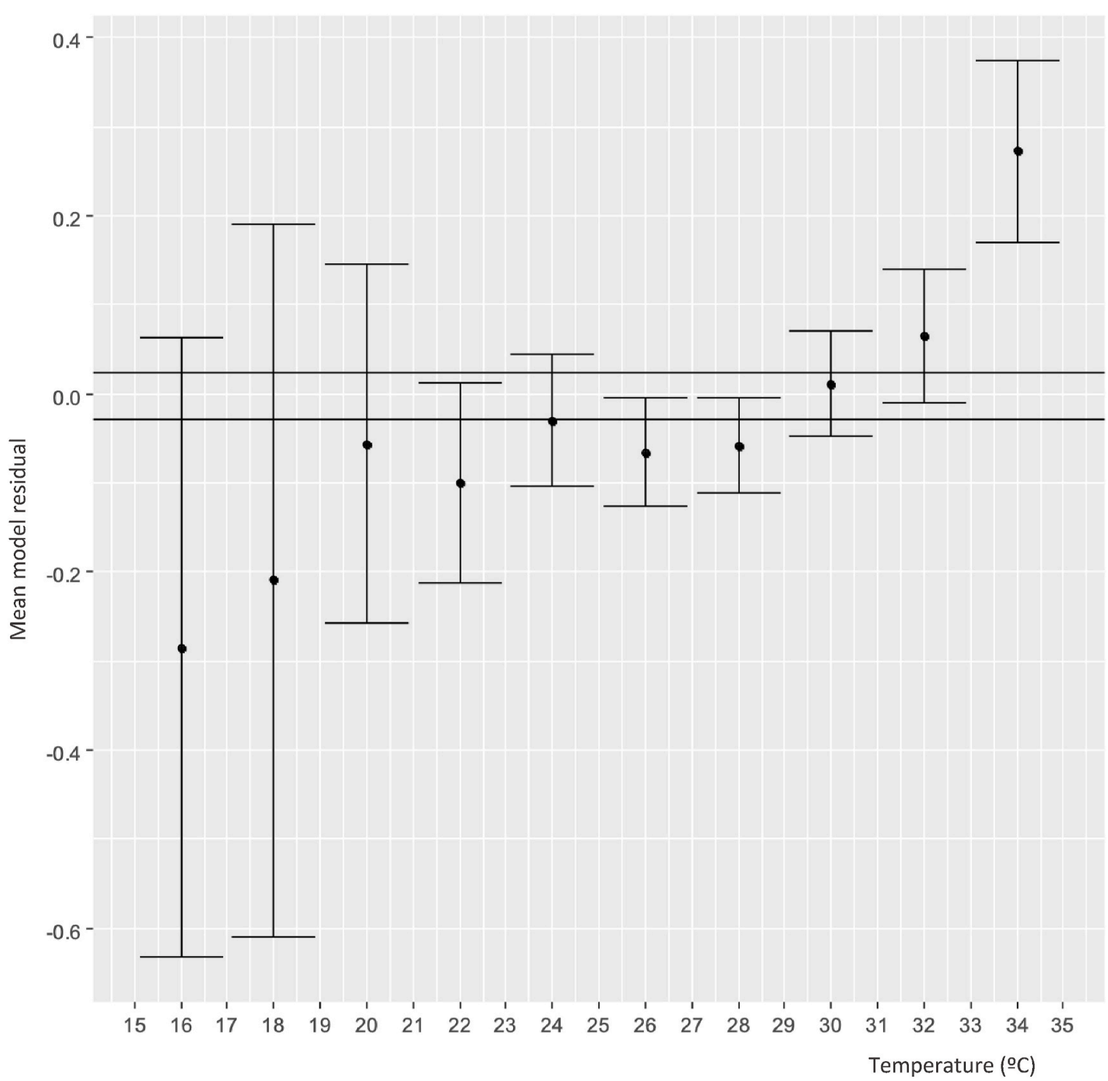

Fig. 1. Dispersion graph of pre-whitened mortality. The X axis represents temperatures in degrees Celsius. The Y axis is the average of the residuals calculated using ARIMA models in the time series of the summer months.

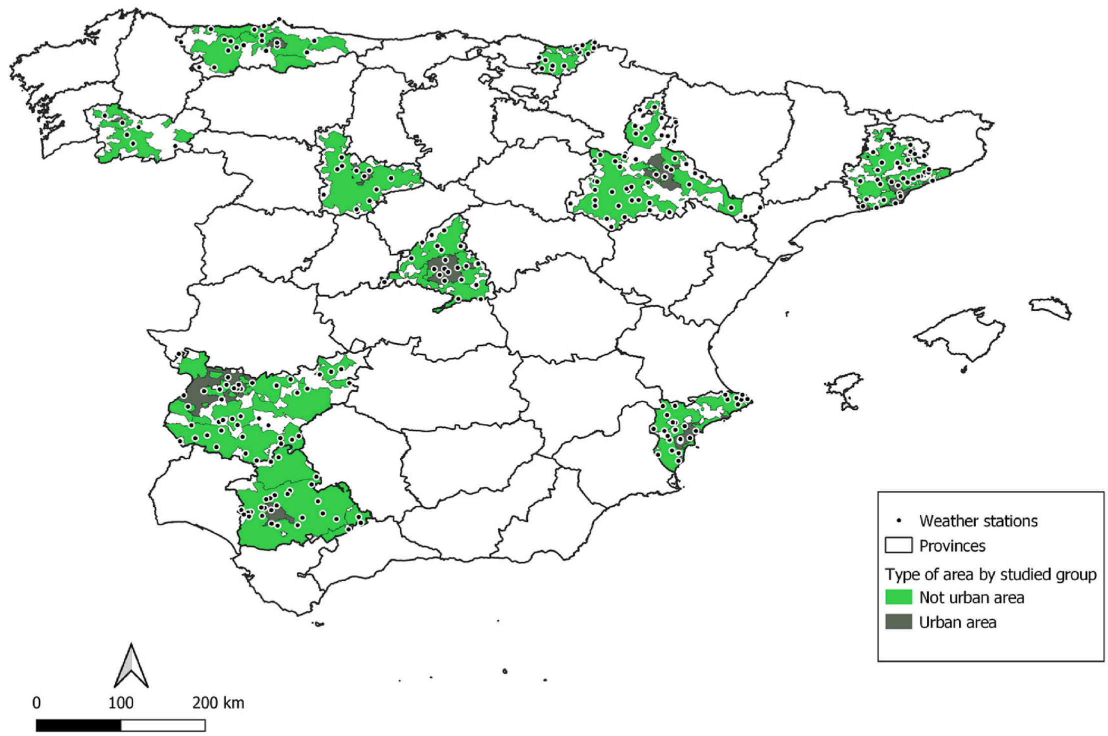

Fig. 2. Map of the groups and meteorological observatories considered in the study. In white: territory not included in the study.

mortality-temperature relationship, a key difference with respect to the vulnerability indices generated using the analysis of principal components available for other countries in the literature (Chen et al., 2016; Nayak et al., 2018; Wolf and McGregor, 2013).

In addition, a new variable was generated as a categorical transformation of deprivation. This variable took on a "low" level in those subgroups situated below the first quantile of the variable *deprivation*, "medium" for those groups in quantiles 1 and 3, and "high" for groups whose deprivation was above the 3rd quantile.

A mixed general linear model was adjusted, using vulnerability as the dependent variable. Given that this followed a Poisson distribution –non-negative values with asymmetric distribution whose histogram is displaced towards the zero value.-, a generalized model was adjusted with link = log. In this case, the dependent variable was considered to present a correlation structure at the geographic (princince) level, at the population level (urban/non-urban) and based on *socioeconomic level* (SEL), which were employed as factors of random effects in the model. The variables noted in section 2.2 were used as dependent variables. The equation of the model was as follows:

$$log(y) = \alpha + \beta_1 SummerT_i + \beta_2 SummerP95_i + \beta_3 CoolSummer_i + \beta_4 PWR_i + \beta_5 IP_i + \beta_6 Ageing_i + \beta_7 OD_i + \beta_8 DD_i \quad [2]$$

where i {1, …,43} denotes the observations of the groups, *y* is *vulnerability*; α is the intercept of the model and $\beta_{1\ \ldots\ 8}$ the coefficients of the fixed effects of the model for each of the independent variables.

The final model was defined using a backward stepwise method, that is, the variables were selected based on the biological significance of their coefficients and in descending order of the p-value until a model whose variables were all statistically significant was reached (p-value < 0.05). Based on the coefficients of the final model, relative risks (RR) could be easily calculated by using the following expression:

$$RR = e^{\beta}$$

The variables that ended up being protective factors were calculated based on the absolute value of the beta coefficient, in order to avoid RR less than zero.

These models were calculated using the"glmer()" function of the Ime4 package of the free software R 4.0.4.

3. Results

Table 1 shows the marginal sums indicating that the area of the study includes 1136 municipalities and an aggregate average population of over 17 million inhabitants. At the population level, two urban groups stand out: the metropolitan area of Madrid, with an average of around 5 million inhabitants, followed by the metropolitan area of Barcelona, with around 3 million. No other population group reached the average of 900,000 inhabitants.

Even though large differences can be found between the groups at the population level, this does not translate into spikes in MR (Table 1). In terms of urban/rural typology, 10 of the 42 groups analyzed are urban, and the average MR among them is 29.97 deaths per million inhabitants (sd = 14.59), greater than the average MR of 17.64 deaths per million inhabitants (sd = 6.76) among non-urban groups.

The temperature data (Tmax) (Table 1) were monitored by 374 meteorological stations, with an average of 9 observatories per group. Fig. 2 shows the geographic distribution of these data. There were wide variations in the values of Tmax, such that there was a difference of 12.6 °C between the coldest (633301 in Asturias) and warmest (614102 in Sevilla) areas. This provides a picture of the environmental and climatological diversity of the Iberian Peninsula.

The values of Pthreshold indicate that the average adaptation was around the 91st percentile. In nine of the 42 groups analyzed, there was complete adaptation (percentile = 100), that is, there were no observed statistically significant increases in any temperature interval. Of these nine groups, only one was urban (674701–1, Valladolid).

At the descriptive level, higher levels of Pthreshold were found where there is greater exposure (Table 1). For example, in Badajoz, Ourense, Madrid, Guipuzkoa and Alicante the highest percentiles were found in the warmest areas. On the other extreme, in Zaragoza, Asturias

Table 1
Descriptive statistics of the groups and resulting pthresholds. Summer months include the months of June, July, August and September//*: There was not detected threshold temperature for the start of a heat wave, thus complete adaptation was assumed Pthreshold = 100.

Group		Province	TM[c]		Tmax[d]		SEL[e]	Mun[f]	Csta[g]	Pop[h]	Pthreshold
Isocode[a]	Urban[b]		mean	sd	mean	sd					
614101	0	Sevilla	15.4	22.8	33.4	4.3	Low	9	3	29,372	*
614102	0	Sevilla	11.2	4.0	33.9	4.1	Low	68	23	859,300	95
614102	1	Sevilla	25.1	5.8	33.9	4.1	medium	3	23	885,808	84
614103	0	Sevilla	11.1	14.0	31.2	4.1	Low	14	3	57,862	96
625001	0	Zaragoza	17.8	28.5	28.6	4.4	medium	13	11	21,213	*
625002	0	Zaragoza	21.9	14.5	28.8	4.5	medium	139	26	110,824	73
625003	0	Zaragoza	15.6	13.8	30.6	4.3	medium	32	13	84,000	91
625003	1	Zaragoza	24.9	6.7	30.6	4.3	High	1	13	652,456	98
633301	0	Asturias	21.1	15.8	21.3	2.6	medium	9	3	88,526	96
633303	0	Asturias	27.9	30.4	24.0	3.9	medium	6	8	30,224	87
633304	0	Asturias	21.3	10.0	23.6	3.6	medium	16	6	229,391	95
633304	1	Asturias	38.1	13.4	23.6	3.6	High	1	6	215,936	95
633305	0	Asturias	25.7	23.9	22.8	3.7	medium	5	1	46,923	92
674701	0	Valladolid	14	9.0	28.2	4.5	medium	153	12	175,000	90
674701	1	Valladolid	24.1	9.3	28.2	4.5	medium	1	12	307,082	*
690801	0	Barcelona	12.1	46.8	26.3	4.9	medium	6	1	5440	*
690802	0	Barcelona	18.1	8.9	27.7	3.9	medium	62	13	255,834	87
690803	0	Barcelona	10	3.9	29.1	3.5	High	84	13	739,175	78
690803	1	Barcelona	21.3	5.8	29.1	3.5	medium	8	13	744,121	93
690804	0	Barcelona	11.2	4.7	27.2	2.9	High	43	7	608,934	96
690804	1	Barcelona	22.3	3.8	27.2	2.9	High	12	7	2,749,770	84
700601	0	Badajoz	18.8	10.7	32.9	4.3	Low	36	16	165,160	97
700601	1	Badajoz	30.4	12.7	32.9	4.3	medium	2	16	199,493	75
700602	0	Badajoz	28.1	52.0	33.2	4.6	Low	5	4	11,505	*
700603	0	Badajoz	17.9	11.7	32.5	4.2	Low	28	8	136,442	93
700604	0	Badajoz	20.3	15.5	32.2	4.3	Low	32	14	83,329	80
713201	0	Ourense	15.5	22.8	28.1	5.0	Low	7	1	29,136	*
713202	0	Ourense	40.2	40.8	29.7	4.6	medium	8	1	30,507	*
713202	1	Ourense	44.2	21.3	29.7	4.6	medium	1	1	108,158	90
713203	0	Ourense	22.2	18.5	26.0	4.4	Low	21	2	65,821	99
713204	0	Ourense	21.9	55.4	25.1	4.8	Low	3	2	7091	*
722801	0	Madrid	17.7	8.7	27.8	4.4	High	52	6	279,366	83
722802	0	Madrid	9.0	5.5	30.8	4.4	High	22	11	315,512	98
722802	1	Madrid	16.3	2.3	30.8	4.4	High	15	11	4,893,817	74
722803	0	Madrid	12.7	7.3	30.7	4.4	High	36	4	303,721	76
752001	0	Gipuzkoa	7.6	6.3	23.5	3.8	High	18	6	202,550	93
752001	1	Gipuzkoa	65.9	23.6	23.5	3.8	High	2	6	243,584	89
752002	0	Gipuzkoa	14.5	8.1	24.4	5.3	medium	54	6	231,796	98
770301	0	Alicante	17.6	9.1	29.8	2.8	medium	51	7	226,449	*
770302	0	Alicante	11.1	8.5	30.3	3.6	Low	14	7	157,737	87
770303	0	Alicante	17.5	6.7	30.5	2.7	medium	39	14	495,661	71
770303	1	Alicante	17.2	5.0	30.5	2.7	medium	5	14	742,622	*
Mean			20.9	15.4	28.7	4		27	9	424444	91
Σ								1136	374	17,826,646	

[a] Isoclimatic zone code.
[b] 1: Urban, 0: Not urban.
[c] Summer mortality rate expressed in deaths per million inhabitants.
[d] Summer maximum daily temperature.
[e] Socioeconomic level.
[f] Number of municipalities included in the study per group.
[g] Number of climatological stations per group.
[h] Average population over the period.

and Guipuzkoa we found that the lowest percentiles were in the coldest areas.

In the same way, Pthreshold levels tend to be lower in urban areas. Thus, in the provinces of Seville, Badajoz, Ourense, Madrid and Guipuzkoa there were lower percentiles among urban groups.

Fig. 3 illustrates the geographic dispersion of these percentiles. In this case, the intensity of heat is inversely proportional to the Pthreshold level, or, where heat is more intense, Pthreshold is lower. Table 3 shows that lower percentiles tend to occur in provinces allocated in the interior area of the Iberian Peninsula.

Table 2 shows the descriptive statistics of the database used to adjust the generalized linear mixed model. The table shows that the behavior of Tmax differs among the extremes (Summer P95) and the average (Summer T). Specifically, it can be observed that the range of variation in Summer P95 (14.4 °C) is greater than that of Summer T (12.6). On the other hand, warm summer is dominant among the groups analyzed, and the Water Balance (WB) is negative in 28 of the 42 groups analyzed. In terms of the socioeconomic and urban variables, it is worth noting that 51.4 percent of dwellings was built before 1980 (variable OB) and the average population at risk was 21.8 percent (variable Elderly).

Finally, Table 3 shows the final adjusted model and the RR calculated. WB (RR = 1.83) and rurality (RR = 1.29) were protective factors, and on the contrary, areas of cool summer (RR = 2.69), deprivation (RR = 4.05) and with dwellings in decline (RR = 1.13) were risk factors.

4. Discussion

The information shown in Tables 1 and 2 provides a picture of the population analyzed. At the population level, census imbalances are to be expected in a comparison of urban and rural areas (Prieto-Lara and

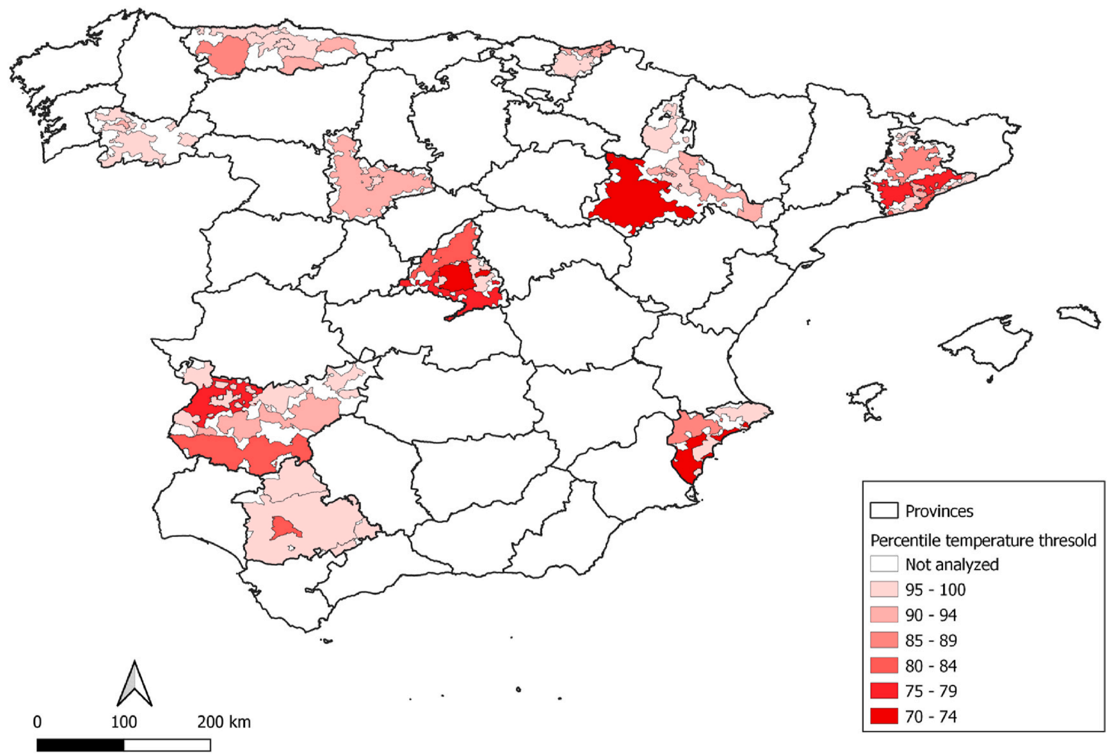

Fig. 3. Map of the distribution of vulnerability to heat in the provinces analyzed.

Table 2
Descriptive statistics of the database for analysis of the distribution of percentiles.

Variable	ud	N	Mean	Std. Dev.	Min	Max
Vulnerability	adimentional	42	8.74	8.82	0	29
Summer T	°C	42	28.7	3.4	21.3	33.9
Summer P95	°C	42	35.0	3.3	25.6	40.0
Privation	adimentional	42	0.08	0.67	−1.06	1.53
Rurality	adimentional	42	0.82	0.81	−2.21	0.77
Elderly	%	42	21.8	7.6	8.9	39.2
Older dweling	%	39	51.4	13.9	21.5	76.6
Dwelling in decline	%	39	2.0	2.8	0.0	11.8
			Frequency			
			0	**1**		
Cool summer		42	39	3		
Water Balance		42	28	14		

Ocaña-Riola, 2010). However, in relation to the census, mortality (MR) is comparable among groups.

These imbalances give rise to mortality recounts that are not comparable amongst themselves. However, MR do not experience jumps in scale and remain stable. Therefore, this does reflect a measure that is comparable among groups.

On the other hand, the area covered in this study presents a varied climate that must be closely controlled and is reflected in the descriptive values of Tmax (AEMET, 2011) (Table 1). The observation of a certain tendency to reach a greater Pthreshold where exposure is greater has been observed and discussed in previously published literature (Carmona et al., 2017; López-Bueno et al., 2021a, 2021b). Thus, it is a phenomenon that is related to physiological adaptation, culture and adaptation to high temperatures (Follos et al., 2020, 2021).

In terms of quantification, Carmona et al. (2017) determined thresholds for heat waves for 51 Spanish province capitals using the same methodology used here. In that study, the average percentile hovered around the 91st percentile (sd = 4), which coincides with the results in Table 1.

On the other hand, these Pthreshold values are situated below the 95th percentile that is traditionally used to define heat waves (WHO, 2021). In consequence, the calculation of epidemiological thresholds—based on the mortality-temperature relationship— allows Heat Health Action Plans (HHAP) to be put into place in time to reduce avoidable mortality due to extreme temperatures (Carmona et al., 2016; Díaz et al., 2019a, 2019b; WHO, 2021). On the contrary, in using a fixed, universal and arbitrary threshold —such as the 95th percentile— there is a part of the population that remains unprotected.

In terms of the distribution of these percentiles (Table 1 and Fig. 2), the visual representation indicates that they tend to be lower in interior areas, therefore, with worse adaptation. These interior areas are characterized by arid climates, mild or hot summers and water stress like has been stablished in previous climatological studies (AEMET, 2011;

Table 3
Table of risks calculated for the groups analyzed.

variable	Rol	Estimate	Std. Error	z value	Pr(>|z|)	RR	IC95	
Water Balance	Protective Factor	−1.7731	0.48912	−3.625	0.00	5.89	2.26	15.36
Rurality	Protective Factor	−0.34646	0.13208	−2.623	0.01	1.41	1.09	1.83
Cool summer	Risk Factor	0.99079	0.40061	2.473	0.01	2.69	1.23	5.91
Deprivation	Risk Factor	1.39794	0.38384	3.642	0.00	4.05	1.91	8.59
Dwelling in decline	Risk Factor	0.12471	0.04573	2.727	0.01	1.13	1.04	1.24

ATLAS CLIMÁTICO DIGITAL DE LA PENÍNSULA IBÉRICA, s. f.).

In this case, the adjusted model confirms the descriptive exploration (Table 3). Thus, in arid areas, where the water balance is negative, vulnerability is nearly six times greater (RR = 5.89) than in areas where the potential retention of water is positive. In contrast, the lack of adaptation to high temperatures is shown in the zones whose climates are characterized by cool summers, where vulnerability is nearly triple (RR = 2.69) that of mild and hot summers. This is related to greater habituation to extreme temperatures where exposure is more intense and frequent (Montero et al., 2012).

In contrast to the climatological variables, the *short-term meteorological variables* (Summer T and Summer P95) were displaced from the model. The same occurred with the percentage of population over age 65 (Elderly). This suggests that, in the process of adaptation to extreme heat, these are not the most determinant variables. On the contrary, the socioeconomic and demographic variables better explain the distribution of vulnerability to extreme heat.

Deprivation was associated with RR = 4.05, and the percentage of dwellings in decline with RR = 1.13. The role in risk played by these variables agree with what has been established in the literature (Duque et al., 2021; López-Bueno et al., 2019; López-Bueno et al., 2021a, 2021b; Reid et al., 2009; Santamouris and Kolokotsa, 2015). Although both variables are related to the inability to be isolated from exterior temperatures, they reflect different realities. On one hand, the labor precariousness indicators included in the deprivation variable could be more associated with difficulties in paying the electricity bill, which could also lead to a lack of air conditioning. On the other hand, dwellings in decline is probably more related to the consequences of living in dwellings whose passive thermal properties are not good (López-Bueno et al., 2020; Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015).

Finally, the model indicates that the rurality of the population is a protective factor against exposure to heat (Table 3), as has been observed in the province of Madrid (López-Bueno et al., 2021a, 2021b). Decreases of one point in this index correspond to increases of 41 percent in vulnerability.

This result is contrary to what has been found in the USA (M. Lee et al., 2016; Madrigano et al., 2015; S. Sheridan and Dolney, 2003), in China (K. Chen et al., 2016; Hu et al., 2019), and in India (Azhar et al., 2017). These studies explain their results in terms of worse health status of the rural population, higher levels of poverty and geographic and economic barriers in accessing health systems. Comparing the rural population in Spain to these countries is difficult (Disler et al., 2020). First of all, MR was statistically higher among the urban groups analyzed than among the rural. Thus in at least one aspect of mortality, the health of the rural population is superior to that of the urban population in the zones analyzed. Second, Spain differs from the aforementioned countries in that it provides free, universal access and broad-based healthcare coverage.

However, comparing results with the literature is limited by the absence of a universally accepted methodology to address the issue. The previous reports base their results on different methods, such as comparing different relative risks attributable to temperature on health or estimating vulnerability index by Principal Component Analysis methods. Hence, these comparisons should be interpreted cautiously.

Although it would seem that rural areas are more vulnerable to heat in general, there is controversy in the scientific evidence on this topic. There are also studies found in the literature that indicate greater vulnerability to heat in urban areas in the USA (Nayak et al., 2018), UK (Wolf and McGregor, 2013) and China (K. Chen et al., 2016; Hu et al., 2019).

Also, it is important to consider that in the studies mentioned, there could be confusion between the rural population, income levels and the demographic influence of the elderly population. In contrast, in this study the protective effect of rurality was controlled by these variables (Table 3). Therefore, it should be explained based on the idiosyncrasies that characterize the rural population.

Various factors could explain the differences found. First, traditional housing in rural areas could have better thermal properties than in urban areas (Martin et al., 2010), independently of its conditions. This means that comfort temperatures might be reached with less energy consumption due to their thicker walls. Also, rural areas can be conducive to an active lifestyle for the elderly (Bouchama et al., 2007; Zhang et al., 2017) and lower levels of social isolation (Lin et al., 2019; Reid et al., 2009; Wolf and McGregor, 2013; Zhang et al., 2017). In this way, rural environments are more natural and less exposed to environmental risks such as noise and different types of pollution (Díaz et al., 2020; Jimenez et al., 2011).

In terms of mitigation and adaptation policies regarding heat waves, these results show that vulnerability presents great local variations. This has been widely observed in the literature in many countries (Allen and Sheridan, 2016, 2018; Carmona et al., 2016, 2017; S. Chen et al., 2020; Díaz et al., 2018; Follos et al., 2020, 2021; W. Lee et al., 2018; Linares et al., 2020; López-Bueno et al., 2019, 2020). Therefore, in order to reduce mortality attributable to heat waves in the future, it is necessary to adjust Heat Health Action Plans (HHAP) in time and space. This involves planning at the local level to establish zones that are environmentally and socioeconomically homogeneous (Sánchez-Martinez et al., 2019; WHO, 2021). In this sense, our results indicate that the rural or urban character of the population is one of the factors that should be taken into account in these plans.

In addition to defining vulnerable population groups, it is important that HHAP establish specific measures for them (WHO, 2021). This could involve promoting a culture of heat in areas that are not accustomed to heat and among vulnerable population groups making use of the opportunities of new technologies (Abrahamson et al., 2008; Bobb et al., 2014; Sánchez-Martinez et al., 2019), guaranteeing access to housing rehabilitation and air conditioning systems among impoverished groups (Follos et al., 2021; López-Bueno et al., 2019; Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015), as well as poverty prevention by improving deprivation indicators (Stringhini et al., 2017) and developing programs for dependence and loneliness (Lin et al., 2019; Zhang et al., 2017).

There are several limitations that need to be considered in relation to this study, among which are the limitations of all ecological studies (Morgenstern, 1995). On one hand, population level analyses can not be extrapolated to individuals. On the other, the measures of Tmax and exposure take place in different locations, such that the population is not truly exposed to the temperatures described. In this way, the results found here for the social, economic and housing variables should be interpreted with caution due to the ecological fallacy effect.

Nevertheless, in phase II we associated vulnerability at study group level with the explicative variables aggregated at the same level. Thus, this work is not free of 'Modifiable Areal Unit Problem' (MAUP). MAUP involves scale problems and zoning problems (Jelinski and Wu, 1996). As we have aggregated "rurality" and "deprivation" variables from municipalities and census sections level, both may be the variables mainly affected by this kind of biases, because they are the more heterogeneous variables. Zoning problems are handled in our work for the climatological and meteorological variables, but it only have been partially limited grouping by provinces and urban nature. These biases should be avoided designing homogenous and small sample units, for example by districs. However, phase I is the limiting step of our research because estimating Temperatures Thresholds needs that mortality rate be enough in numbers. Moreover, in this case deprivation would still be associated with scale problems, since cities' districts are heterogeneous. Likely, a fair unit to deprivation is the census sections, but only Madrid City has 2443 of them. Moreover, taking smaller units in our study, like municipalities or districts, increase problems of temperature misclassification.

In addition, there is an imbalance in the number of meteorological observatories among the groups. This could give rise to greater precision of temperatures in places where there are more meteorological stations. Furthermore, although the number of observatories per group is greater than in the majority of studies found in the literature, there are few in terms of the geographical areas they cover. In consequence, this study is not free of Berkson type error. However, we consider that having worked with zones of similar climatological behavior, these limitations were minimized. On the other hand, there is no measure that is more precise than that which we used in this study, given that it used the registries of all of the meteorological stations that exist in the studied areas.

It was also not possible to determine the potential effect of air pollution because of the lack of representative data needed to disaggregate, especially in terms of the non-urban groups analyzed (AEMET, 2011; MITECO, 2019). This is a common limitation in research that analyzes the health risks due to heat waves (Barceló et al., 2016; Linares et al., 2015, 2020; López-Bueno et al., 2020). Employing these data with insufficient quality can introduce instability into the models (Linares et al., 2014), and this is even more the case if we take into account that the quality of data varies among provinces and between the urban and rural environments. In consequence, it is possible that part of the effect of pollution was collected along with the *rurality* variable and with the *urban* random effects factor. In any case, the statistical methodology employed to determine Tthreshold in part minimizes the short-term impact of these unconsidered variables in such a way that they are negligible (Linares et al., 2014).

In the classification of groups into urban and non-urban, it is difficult to document the true nature of the population in a precise way. An inadequate classification can give way to erroneous, confusing or imprecise results (Lourenço, 2012). In this work, this may lead to include semi-urban municipalities as rural ones, which would result in an over-estimation of the rural vulnerability.

However, it is important to point out that this is a recurring problem in studies of rural environments (Prieto-Lara and Ocaña-Riola, 2010). Also, the Eurostat definition, which was used as a reference in this work, is better than the classical criteria based on arbitrary thresholds of the population (Eurostat, 2018). Finally, Ocaña's rurality index, which groups various demographic and socioeconomic indicators, allowed us to complement the limitations with the initial classification of the groups by including variables that are more broadly related to the social and economic structure of the rural population.

5. Conclusions

European Countries has been developing prevention plans against extreme temperatures, mainly heat waves. Recently, the WHO has assessed the Heat-Health Action Plans (HHAP) in Europe and exposed some conclusions (WHO, 2021). These prevention plans have been useful to prevent premature deaths associated with the extreme heat. However, the results of these plans has been unequal by countries and they should to be adapted to deal with scenarios of a worsening Global Warming. Since heat-health risks changes over time and at local level, WHO propose to update these plans periodically. Nevertheless, developing HHAP at local level is currently hardly because health problems associated with temperatures have been studied traditionally over populations from big-urban areas.

Our results suggest that the urban population is more vulnerable to extreme heat than the rural population in Spain. The causes of this vulnerability could lie in factors related to the built environment, lifestyles and the cultural differences between both types of populations. In particular, indicators related to social class and quality building seems to be key drivers of extreme-heat vulnerability"

The type of climate, deprivation in terms of economic resources, and the state of dwellings could also explain the distribution of heat vulnerability in Spain. The findings suggest the need to update local heat adaptation plans, as well as, further investigations to identify the drivers of vulnerability to extreme temperatures in different population groups.

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.

Acknowledgements

The researchers are very grateful for the grants received from the projects ENPY 107/18, ENPY 376/18 and ENPY 304/20 of the Institute of Health Carlos III.

References

Abrahamson, V., Wolf, J., Lorenzoni, I., Fenn, B., Kovats, S., Wilkinson, P., Adger, W.N., Raine, R., 2008. Perceptions of heatwave risks to health: interview-based study of older people in London and Norwich, UK. Journal of Public Health (Oxford, England) 31 (1), 119–126. https://doi.org/10.1093/pubmed/fdn102.

AEMET, 2011. Atlas Climático Ibérico. AEMET. https://www.aemet.es/documentos/es/conocermas/recursos_en_linea/publicaciones_y_estudios/publicaciones/Atlas-climatologico/Atlas.pdf.

Alberdi, J.C., Díaz, J., Montero, C., Mirón, I., 1998. Daily mortality in Madrid community 1986-1992: relationship with meteorological variables. Eur. J. Epidemiol. 14, 571–578. https://doi.org/10.1023/a:1007498305075.

Allen, M.J., Sheridan, S.C., 2016. Spatio-temporal changes in heat waves and cold spells: an analysis of 55 U.S. cities. Phys. Geogr. 37 (3–4), 189–209. https://doi.org/10.1080/02723646.2016.1184078.

Allen, M.J., Sheridan, S.C., 2018. Mortality risks during extreme temperature events (ETEs) using a distributed lag non-linear model. Int. J. Biometeorol. 62 (1), 57–67. https://doi.org/10.1007/s00484-015-1117-4.

ATLAS CLIMÁTICO DIGITAL DE LA PENÍNSULA IBÉRICA. (s. f.). Recuperado 4 de febrero de 2021, de. http://www.opengis.uab.es/wms/iberia/mms/index.htm.

Atlas Nacional de España, 2019. Evapotranspiración y balance de humedad. Instituto Geográfico Nacional. http://atlasnacional.ign.es/wane/Clima.

Azhar, G., Saha, S., Ganguly, P., Mavalankar, D., Madrigano, J., 2017. Heat wave vulnerability mapping for India. Int. J. Environ. Res. Publ. Health 14 (4), 357. https://doi.org/10.3390/ijerph14040357.

Barceló, M.A., Varga, D., Tobias, A., Diaz, J., Linares, C., Saez, M., 2016. Long term effects of traffic noise on mortality in the city of Barcelona, 2004-2007. Environ. Res. 147, 193–206. https://doi.org/10.1016/j.envres.2016.02.010.

Benmarhnia, T., Deguen, S., Kaufman, J., Smargiassi, A., 2015. Review article: vulnerability to heat-related mortality: a systematic review, meta-analysis, and meta-regression analysis. Epidemiology 26 (6), 781–793. https://doi.org/10.1097/EDE.0000000000000375.

Bernard, P., Charafeddine, R., Frohlich, K.L., Daniel, M., Kestens, Y., Potvin, L., 2007. Health inequalities and place: a theoretical conception of neighbourhood. Soc. Sci. Med. 65 (9), 1839–1852. https://doi.org/10.1016/j.socscimed.2007.05.037.

Bobb, J.F., Peng, R.D., Bel, M.L., Dominici, F., 2014. Heat-related mortality and adaptation to heat in the United States. Environ. Health Perspect. 122 (8), 811–816.

Bouchama, A., Dehbi, M., Mohamed, G., Matthies, F., Shoukri, M., Menne, B., 2007. Prognostic factors in heat wave-related deaths: a meta-analysis. Arch. Intern. Med. 167 (20), 2170–2176. https://doi.org/10.1001/archinte.167.20.ira70009.

Carmona, R., Díaz, J., León, I., Luna, Y., Mirón, I., Ortiz, C., Linares, C., 2016. Temperaturas umbrales de disparo de la mortalidad atribuible al frío en España en el periodo 2000-2009. Comparación con la mortalidad atribuible al calor. Instituto de Salud Carlos III, Escuela Nacional de Sanidad.

Carmona, R., Linares, C., Ortiz, C., Mirón, I.J., Luna, M.Y., Díaz, J., 2017. Spatial variability in threshold temperatures of heat wave mortality: impact assessment on prevention plans. Int. J. Environ. Health Res. 27 (6), 463–475. https://doi.org/10.1080/09603123.2017.1379056.

Chazarra, A., Flórez, E., Peraza, B., Tohá, T., Lorenzo, B., Criado, E., Moreno, J., Romero, R., Botey, R., 2018. Mapas climáticos de España (1981-2010) y ETo (1996-2016). https://www.aemet.es/es/conocermas/recursos_en_linea/publicaciones_y_estudios/publicaciones/detalles/MapasclimaticosdeEspana19812010.

Chen, K., Zhou, L., Chen, X., Ma, Z., Liu, Y., Huang, L., Bi, J., Kinney, P.L., 2016. Urbanization level and vulnerability to heat-related mortality in jiangsu province, China. Environ. Health Perspect. 124 (12), 1863–1869. https://doi.org/10.1289/EHP204.

Chen, S., Xiao, Y., Zhou, M., Zhou, C., Yu, M., Huang, B., Xu, Y., Liu, T., Hu, J., Xu, X., Lin, L., Hu, R., Hou, Z., Li, J., Jin, D., Qin, M., Zhao, Q., Gong, W., Yin, P., Ma, W., 2020. Comparison of life loss per death attributable to ambient temperature among various development regions: a nationwide study in 364 locations in China. Environ. Health 19 (1), 98. https://doi.org/10.1186/s12940-020-00653-3.

Díaz, J., Jordán, A., García, R., López, C., Alberdi, J., Hernández, E., Otero, A., 2002. Heat waves in Madrid 1986-1997: effects on the health of the elderly. Int. Arch. Occup. Environ. Health 75 (3), 163–170. https://doi.org/10.1007/s00420-001-0290-4.

Díaz, J., Carmona, R., Mirón, I., Ortiz, C., León, I., Linares, C., 2015a. Geographical variation in relative risks associated with heat: update of Spain's Heat Wave Prevention Plan. Environ. Int. 85, 273–283. https://doi.org/10.1016/j.envint.2015.09.022.

Díaz, J., Carmona, R., Mirón, I., Ortiz, C., Linares, C., 2015b. Comparison of the effects of extreme temperatures on daily mortality in Madrid (Spain), by age group: the need for a cold wave prevention plan. Environ. Res. 143, 186–191. https://doi.org/10.1016/j.envres.2015.10.018.

Díaz, J., Carmona, R., Mirón, I.J., Luna, M.Y., Linares, C., 2018. Time trend in the impact of heat waves on daily mortality in Spain for a period of over thirty years (1983–2013). Environ. Int. 116 (January), 10–17. https://doi.org/10.1016/j.envint.2018.04.001.

Díaz, J., Carmona, R., Mirón, I.J., Luna, M.Y., Linares, C., 2019a. Time trends in the impact attributable to cold days in Spain: incidence of local factors. Sci. Total Environ. 655, 305–312. https://doi.org/10.1016/j.scitotenv.2018.11.254.

Díaz, J., Sáez, M., Carmona, R., Mirón, I.J., Barceló, M.A., Luna, M.Y., Linares, C., 2019b. Mortality attributable to high temperatures over the 2021–2050 and 2051–2100 time horizons in Spain: adaptation and economic estimate. Environ. Res. 172, 475–485. https://doi.org/10.1016/j.envres.2019.02.041.

Díaz, J., López-Bueno, J.A., López-Ossorio, J.J., Gónzález, J.L., Sánchez, F., Linares, C., 2020. Short-term effects of traffic noise on suicides and emergency hospital admissions due to anxiety and depression in Madrid (Spain). Sci. Total Environ. 710, 136315. https://doi.org/10.1016/j.scitotenv.2019.136315 (Journal Article).

Dirección General del Catastro, 2021. Servicios INSPIRE de Cartografía Catastral. http://www.catastro.minhap.gob.es/webinspire/index.html.

Disler, R., Glenister, K., Wright, J., 2020. Rural chronic disease research patterns in the United Kingdom, United States, Canada, Australia and New Zealand: a systematic integrative review. BMC Publ. Health 20 (1). https://doi.org/10.1186/s12889-020-08912-1. Scopus.

Douthit, N., 2015. Exposing some important barriers to health care access in the rural USA. Publ. Health 129, 10. https://doi.org/10.1016/j.puhe.2015.04.001.

Duque, I., Domínguez-Berjón, M.F., Cebrecos, A., Prieto-Salceda, M., Esnaola, S., Sánchez, M.C., Marí-Dell'Olmo, M., 2020. Manual del Índice de privación 2011 de la Sociedad Española de Epidemiología. https://www.seepidemiologia.es/documents/dummy/ManualIP2011.pdf.

Duque, I., Domínguez-Berjón, M.F., Cebrecos, A., Prieto-Salceda, M.D., Esnaola, S., Calvo Sánchez, M., Marí-Dell'Olmo, M., 2021. Índice de privación en España por sección censal en 2011. Gac. Sanit. 35 (2), 113–122. https://doi.org/10.1016/j.gaceta.2019.10.008.

Dwyer, J.W., Lee, G.R., Coward, R.T., 1990. The health status, health services utilization, and support networks of the rural elderly: a decade review. J. Rural Health 6 (4), 379–398. https://doi.org/10.1111/j.1748-0361.1990.tb00679.x.

Earle-Richardson, G., Scribani, M., Scott, E., May, J., Jenkins, P., 2015. A Comparison of health, health behavior, and access between farm and nonfarm populations in rural New York State. J. Rural Health 31 (2), 157–164. https://doi.org/10.1111/jrh.12098. Scopus.

Etowa, J., Wiens, J., Bernard, W.T., Clow, B., 2007. Determinants of black women's health in rural and remote communities. Can. J. Nurs. Res. 39 (3), 56–76 (Scopus).

Eurostat, 2016. Rural Development Statistics by Urban-Rural Typology—Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Rural_development_statistics_by_urban-rural_typology&oldid=294503#Population_structure.

Eurostat, 2018. Methodological Manual on Territorial Typologies, vol. 132. https://doi.org/10.2785/930137. Edition 2018.

Eurostat, 2021. Cities (urban audit). Spatial units. https://ec.europa.eu/eurostat/web/cities/spatial-units.

Follos, F., Linares, C., Vellón, J.M., López-Bueno, J.A., Luna, M.Y., Sánchez-Martínez, G., Díaz, J., 2020. The evolution of minimum mortality temperatures as an indicator of heat adaptation: the cases of Madrid and Seville (Spain). Sci. Total Environ. 747, 141259. https://doi.org/10.1016/j.scitotenv.2020.141259 (Journal Article).

Follos, F., Linares, C., López-Bueno, J.A., Navas, M.A., Culqui, D., Vellón, J.M., Luna, M. Y., Sánchez-Martínez, G., Díaz, J., 2021. Evolution of the minimum mortality temperature (1983–2018): is Spain adapting to heat? Sci. Total Environ. 784, 147233. https://doi.org/10.1016/j.scitotenv.2021.147233.

Gartner, A., Farewell, D., Dunstan, F., 2011. Rural/urban mortality differences in England and Wales and the effect of deprivation adjustment. Soc. Sci. Med. 72 (10), 1685–1694.

Gasparrini, A., Guo, Y., Hashizume, M., Kinney, P.L., Petkova, E.P., Lavigne, E., Zanobetti, A., Schwartz, J.D., Tobias, A., Leone, M., Tong, S., Honda, Y., Kim, H., Armstrong, B.G., 2015. Temporal variation in heat–mortality associations: a multicountry study. Environ. Health Perspect. 123 (11), 1200–1207. https://doi.org/10.7916/d8tq620t.

Goerlich, F.J., Reig, E., Cantarino, I., 2016. Construcción de una tipología rural/urbana para los municipios españoles. Investigaciones Regionales (35), 151–173.

Guo, Y., Gasparrini, A., Armstrong, B.G., Tawatsupa, B., Tobias, A., Lavigne, E., Coelho, M., Pan, X., Kim, H., Hashizume, M., Honda, Y., Guo, Y.-L.L., Wu, C.-F., Zanobetti, A., Schwartz, J.D., Bell, M.L., Scortichini, M., Michelozzi, P., Punnasiri, K., Tong, S., 2017. Heat wave and mortality: a multicountry, multicommunity study. Environ. Health Perspect. 125 (8), 087006 https://doi.org/10.1289/EHP1026.

Gutierrez, K.S., LePrevost, C.E., 2016. Climate justice in rural southeastern United States: a review of climate change impacts and effects on human health. Int. J. Environ. Res. Publ. Health 13 (2). https://doi.org/10.3390/ijerph13020189. Scopus.

Hu, K., Guo, Y., Hochrainer-Stigler, S., Liu, W., See, L., Yang, X., Zhong, J., Fei, F., Chen, F., Zhang, Y., Zhao, Q., Chen, G., Chen, Q., Zhang, Y., Ye, T., Ma, L., Li, S., Qi, J., 2019. Evidence for urban–rural disparity in temperature–mortality relationships in zhejiang province, China. Environ. Health Perspect. 127 (3), 37001. https://doi.org/10.1289/ehp3556.

Hunter, E., 2007. Disadvantage and discontent: a review of issues relevant to the mental health of rural and remote Indigenous Australians. Aust. J. Rural Health 15 (2), 88–93. https://doi.org/10.1111/j.1440-1584.2007.00869.x. Scopus.

Husk, K., Lovell, R., Cooper, C., Stahl-Timmins, W., Garside, R., 2016. Participation in environmental enhancement and conservation activities for health and well-being in adults: a review of quantitative and qualitative evidence. Cochrane Database Syst. Rev. (5) https://doi.org/10.1002/14651858.CD010351.pub2. Scopus 2016.

INE, 2020. Cifras oficiales de población de los municipios españoles: Revisión del Padrón Municipal. Resultados. https://www.ine.es/dyngs/INEbase/es/categoria.htm?c=Estadistica_P&cid=1254734710984.

Jelinski, D.E., Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. Landsc. Ecol. 11 (3), 129–140. https://doi.org/10.1007/BF02447512.

Jimenez, E., Linares, C., Martinez, D., Diaz, J., 2011. Particulate air pollution and short-term mortality due to specific causes among the elderly in Madrid (Spain): seasonal differences. Int. J. Environ. Health Res. 21 (5), 372–390. https://doi.org/10.1080/09603123.2011.560251.

Lee, M., Shi, L., Zanobetti, A., Schwartz, J.D., 2016. Study on the association between ambient temperature and mortality using spatially resolved exposure data. Environ. Res. 151, 610–617. https://doi.org/10.1016/j.envres.2016.08.029.

Lee, W., Choi, H.M., Lee, J.Y., Kim, D.H., Honda, Y., Kim, H., 2018. Temporal changes in mortality impacts of heat wave and cold spell in Korea and Japan. Environ. Int. 116, 136–146. https://doi.org/10.1016/j.envint.2018.04.017 (Journal Article).

Li, Y., Odame, E., Silver, K., Zheng, S., 2017. *Comparing Urban And Rural Vulnerability To Heat-Related Mortality: A Systematic Review And Meta-Analysis* [PhD Thesis]. https://dc.etsu.edu/etsu-works/14.

Lin, Y.-K., Maharani, A.T., Chang, F.-T., Wang, Y.-C., 2019. Mortality and morbidity associated with ambient temperatures in Taiwan. Sci. Total Environ. 651, 210–217. https://doi.org/10.1016/j.scitotenv.2018.09.161.

Linares, C., Díaz, J., 2008. Temperaturas extremadamente elevadas y su impacto sobre la mortalidad diaria de acuerdo a diferentes grupos de edad. Gac. Sanit. 22 (2), 115–119 https://doi.org/DOI: 10.1157/13119318.

Linares, C., Carmona, R., Díaz, J., 2014. Análisis del impacto a corto plazo de los extremos térmicos y de otros factores ambientales sobre la mortalidad diaria en la ciudad de Madrid en el periodo 2001–2009. *Reports I and II prepared for the European Commission under the BASE (Bottom-up Climate Adaptation Strategies Towards a Sustainable Europe) Project.* 7th Research Framework Programme.

Linares, C., Diaz, J., Tobías, A., Carmona, R., Mirón, I.J., 2015. Impact of heat and cold waves on circulatory-cause and respiratory-cause mortality in Spain: 1975–2008. Stoch. Environ. Res. Risk Assess. 29 (8), 2037–2046. https://doi.org/10.1007/s00477-014-0976-2.

Linares, C., Martinez-Martin, P., Rodríguez-Blázquez, C., Forjaz, M.J., Carmona, R., Díaz, J., 2016. Effect of heat waves on morbidity and mortality due to Parkinson's disease in Madrid: a time-series analysis. Environ. Int. 89–90, 1–6. https://doi.org/10.1016/j.envint.2016.01.017.

Linares, C., Díaz, J., Negev, M., Sánchez-Martínez, G., Debono, R., Shlomit, P., 2020. Impacts of climate change on the public health of the Mediterranean Basin population—current situation, projections, preparedness and adaptation. Environ. Res. 182, 109107. https://doi.org/10.1016/j.envres.2019.109107.

López-Bueno, J.A., Díaz, J., Linares, C., 2019. Differences in the impact of heat waves according to urban and peri-urban factors in Madrid. Int. J. Biometeorol. 63 (3), 371–380. https://doi.org/10.1007/s00484-019-01670-9.

López-Bueno, J.A., Díaz, J., Sánchez-Guevara, C., Sánchez-Martínez, G., Franco, M., Gullón, P., Peiró, M.N., Valero, I., Linares, C., 2020. The impact of heat waves on daily mortality in districts in Madrid: the effect of sociodemographic factors. Environ. Res. 190, 109993. https://doi.org/10.1016/j.envres.2020.109993.

López-Bueno, J.A., Navas-Martín, M.Á., Díaz, J., Mirón, I.J., Luna, M.Y., Sánchez-Martínez, G., Culqui, D., Linares, C., 2021a. The effect of cold waves on mortality in urban and rural areas of Madrid. Environ. Sci. Eur. 33 (1), 72. https://doi.org/10.1186/s12302-021-00512-z.

López-Bueno, J.A., Navas-Martín, M.A., Linares, C., Mirón, I.J., Luna, M.Y., Sánchez-Martínez, G., Culqui, D., Díaz, J., 2021b. Analysis of the Impact of Heat Waves on Daily Mortality in Urban and Rural Areas in Madrid. Environmental Research. https://doi.org/10.1016/j.envres.2021.110892, 110892.

Lourenço, A.E.P., 2012. The meaning of «rural» in rural health: a review and case study from Brazil. Global Publ. Health 7 (1), 1–13. https://doi.org/10.1080/17441692.2011.552513. Scopus.

Mac, V.V.T., McCauley, L.A., 2017. Farmworker vulnerability to heat hazards: a conceptual framework. J. Nurs. Scholarsh. 49 (6), 617–624. https://doi.org/10.1111/jnu.12327.

Madrigano, J., Jack, D., Anderson, G.B., Bell, M.L., Kinney, P.L., 2015. Temperature, ozone, and mortality in urban and non-urban counties in the northeastern United States. Environ. Health 14 (1), 3. https://doi.org/10.1186/1476-069x-14-3.

Martin, S., Mazarron, F.R., Canas, I., 2010. Study of thermal environment inside rural houses of Navapalos (Spain): the advantages of reuse buildings of high thermal inertia. Construct. Build. Mater. 24 (5), 666–676. https://doi.org/10.1016/j.conbuildmat.2009.11.002.

Miller, C.E., Vasan, R.S., 2021. The southern rural health and mortality penalty: a review of regional health inequities in the United States. Soc. Sci. Med. 268 https://doi.org/10.1016/j.socscimed.2020.113443. Scopus.

Mirón, I., Díaz, J., Linares, C., Montero, J., Criado, J., 2015. Changes in cause specific mortality during heat waves in Castile–La Mancha: Spain. Int. J. Biometeorol. 59, 1213–1222.

MITECO, 2019. Evaluación de la calidad del aire en españa. https://www.miteco.gob.es/images/es/informeevaluacioncalidadaireespana2019_tcm30-510616.pdf.

Montero, J.C., Mirón, I.J., Criado-Álvarez, J.J., Linares, C., Díaz, J., 2012. Influence of local factors in the relationship between mortality and heat waves: castile-La Mancha (1975–2003). Sci. Total Environ. 414, 73–80. https://doi.org/10.1016/j.scitotenv.2011.10.009.

Morgenstern, H., 1995. Ecologic studies in Epidemiology: concepts, principles, and methods. Annu. Rev. Publ. Health 21.

Nayak, S.G., Shrestha, S., Kinney, P.L., Ross, Z., Sheridan, S.C., Pantea, C.I., Hsu, W.H., Muscatiello, N., Hwang, S.A., 2018. Development of a heat vulnerability index for New York State. Publ. Health 161, 127–137. https://doi.org/10.1016/j.puhe.2017.09.006.

Odame, E., Li, Y., Zheng, S., Vaidyanathan, A., Silver, K., 2018. Assessing heat-related mortality risks among rural populations: a systematic review and meta-analysis of epidemiological evidence. Int. J. Environ. Res. Publ. Health 15 (8), 1597. https://doi.org/10.3390/ijerph15081597.

Oleson, K.W., Anderson, G.B., Jones, B., McGinnis, S.A., Sanderson, B., 2018. Avoided climate impacts of urban and rural heat and cold waves over the US using large climate model ensembles for RCP8.5 and RCP4.5. Climatic Change 146, 377–392. https://doi.org/10.1007/s10584-015-1504-1, 3-4, SI.

Peen, J., Schoevers, R.A., Beekman, A.T., Dekker, J., 2010. The current status of urban-rural differences in psychiatric disorders. Acta Psychiatr. Scand. 121 (2), 84–93. https://doi.org/10.1111/j.1600-0447.2009.01438.x.

Pitkänen, K., Lehtimäki, J., Puhakka, R., 2020. How do rural second homes affect human health and well-being? Review of potential impacts. Int. J. Environ. Res. Publ. Health 17 (18), 1–16. https://doi.org/10.3390/ijerph17186748. Scopus.

Prieto-Lara, E., Ocaña-Riola, R., 2010. Updating rurality index for small areas in Spain. Soc. Indicat. Res. 95 (2), 267–280 (https://doi.org/medec).

Pyrgou, A., Santamouris, M., 2020. Probability risk of heat- and cold-related mortality to temperature, gender, and age using GAM regression analysis. Climate (Basel) 8 (3), 40. https://doi.org/10.3390/cli8030040.

Reid, C.E., O'Neill, M.S., Gronlund, C.J., Brines, S.J., Brown, D.G., Diez-Roux, A.V., Schwartz, J., 2009. Mapping community determinants of heat vulnerability. Environ. Health Perspect. 117 (11), 1730–1736. https://doi.org/10.1289/ehp.0900683.

Rinner, C., Patychuk, D., Bassil, K., Nasr, S., Gower, S., Campbell, M., 2010. The role of maps in neighborhood-level heat vulnerability assessment for the city of toronto. Cartogr. Geogr. Inf. Sci. 37 (1), 31–44. https://doi.org/10.1559/152304010790588089.

Rohat, G., Wilhelmi, O., Flacke, J., Monaghan, A., Gao, J., Dao, H., Maarseveen, M. van, 2019. Characterizing the role of socioeconomic pathways in shaping future urban heat-related challenges. Sci. Total Environ. 695, 133941. https://doi.org/10.1016/j.scitotenv.2019.133941.

Roldán, J.D., Gómez, E., Pino, M.R., Esteban, M., 2011. Determinación de zonas isoclimáticas y selección de estaciones meteorológicas representativas en Aragón como base para la estimación del impacto del cambio climático sobre la posible relación entre la mortalidad y temperatura. Rev. Esp. Salud Publica 85, 603–610.

Sánchez-Guevara, C., Fernández, A.S., Aja, A.H., 2015. Income, energy expenditure and housing in Madrid: retrofitting policy implications. null 43 (6), 737–749. https://doi.org/10.1080/09613218.2014.984573.

Sánchez-Martinez, G., Linares, C., Ayuso, A., Kendrovski, V., Boeckmann, M., Diaz, J., 2019. Heat-health action plans in Europe: challenges ahead and how to tackle them. Environ. Res. 176, 108548. https://doi.org/10.1016/j.envres.2019.108548.

Santamouris, M., Kolokotsa, D., 2015. On the impact of urban overheating and extreme climatic conditions on housing, energy, comfort and environmental quality of vulnerable population in Europe. Energy and Buildings; Renewable Energy Sources and Healthy Buildings 98, 125–133. https://doi.org/10.1016/j.enbuild.2014.08.050.

Sheridan, S., Dolney, T., 2003. Heat, mortality, and level of urbanization: measuring vulnerability across Ohio, USA. Clim. Res. 24, 255–265. https://doi.org/10.3354/cr024255.

Sheridan, S.C., Lee, C.C., Allen, M.J., 2019. The mortality response to absolute and relative temperature extremes. Int. J. Environ. Res. Publ. Health 16 (9), 1493. https://doi.org/10.3390/ijerph16091493.

Shi, W., Chongsuvivatwong, V., Geater, A., Zhang, J., Zhang, H., Brombal, D., 2011. Effect of household and village characteristics on financial catastrophe and impoverishment due to health care spending in Western and Central Rural China: a multilevel analysis. Health Res. Pol. Syst. 9 (1), 16. https://doi.org/10.1186/1478-4505-9-16.

Sociedad Espanola de Epidemiologia, (SEE), 2020. GRUPO DE TRABAJO SOBRE DETERMINANTES SOCIALES DE LA SALUD. https://seepidemiologia.es/determinantes-sociales-de-la-salud/.

Stringhini, S., Carmeli, C., Jokela, M., Avendaño, M., Muennig, P., Guida, F., Ricceri, F., d'Errico, A., Barros, H., Bochud, M., Chadeau-Hyam, M., Clavel-Chapelon, F., Costa, G., Delpierre, C., Fraga, S., Goldberg, M., Giles, G.G., Krogh, V., Kelly-Irving, M., Zins, M., 2017. Socioeconomic status and the 25 × 25 risk factors as determinants of premature mortality: a multicohort study and meta-analysis of 1·7 million men and women. Lancet 389 (10075), 1229–1237. https://doi.org/10.1016/S0140-6736(16)32380-7.

Wagenfeld, M.O., 1990. Mental health and rural America: a decade review. J. Rural Health 6 (4), 507–522.

Wang, C., Zhang, Z., Zhou, M., Wang, P., Yin, P., Ye, W., Zhang, L., 2018. Different response of human mortality to extreme temperatures (MoET) between rural and urban areas: a multi-scale study across China. Health Place 50, 119–129. https://doi.org/10.1016/j.healthplace.2018.01.011.

WHO, 2021. Heat and Health in the WHO European Region: Updated Evidence for Effective Prevention. https://www.euro.who.int/en/health-topics/environment-and-health/Climate-change/publications/2021/heat-and-health-in-the-who-european-region-updated-evidence-for-effective-prevention-2021.

Wolf, T., McGregor, G., 2013. The development of a heat wave vulnerability index for London, United Kingdom. Weather and Climate Extremes 1, 59–68. https://doi.org/10.1016/j.wace.2013.07.004.

Yu, W., Mengersen, K., Wang, X., Ye, X., Guo, Y., Pan, X., Tong, S., 2012. Daily average temperature and mortality among the elderly: a meta-analysis and systematic review of epidemiological evidence. Int. J. Biometeorol. 56 (4), 569–581. https://doi.org/10.1007/s00484-011-0497-3.

Zhang, Y., Nitschke, M., Krackowizer, A., Dear, K., Pisaniello, D., Weinstein, P., Tucker, G., Shakib, S., Bi, P., 2017. Risk factors for deaths during the 2009 heat wave in Adelaide, Australia: a matched case-control study. Int. J. Biometeorol. 61 (1), 35–47. https://doi.org/10.1007/s00484-016-1189-9.

Zhu, W., Chi, A., Sun, Y., 2016. Physical activity among older Chinese adults living in urban and rural areas: a review. Journal of Sport and Health Science 5 (3), 281–286. https://doi.org/10.1016/j.jshs.2016.07.004. Scopus.

Zhuori, N., Cai, Y., Yan, Y., Cui, Y., Zhao, M., 2019. Does social support affect the health of the elderly in rural China? A meta-analysis approach. Int. J. Environ. Res. Publ. Health 16 (18). https://doi.org/10.3390/ijerph16183471. Scopus.