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Population vulnerability to extreme cold days in rural and urban municipalities in ten provinces in Spain

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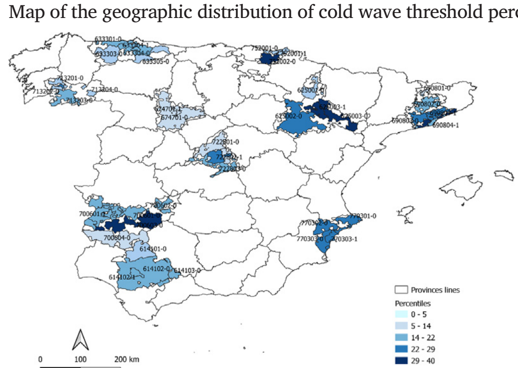
HIGHLIGHTS

- This study showed lower vulnerability to cold waves among rural areas.
- The vulnerability to cold waves increases with unemployment.
- Local adaptation and thermal inertia of dwellings help explain vulnerability to extreme cold.

GRAPHICAL ABSTRACT

Map of the geographic distribution of cold wave threshold percentiles.



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ABSTRACT

Background: The objective was to analyze whether there are differences in vulnerability to Extreme Cold Days (ECD) between rural and urban populations in Spain.
Methodology: Time series analysis carried out from January 1, 2000, through December 31, 2013. Municipalities with over 10,000 inhabitants were included from 10 Spanish provinces, classified into 42 groups by isoclimate and urban/rural character as defined by Eurostat criteria. The statistical strategy was carried out in two phases. First: It was analyzed the relationship between minimum daily temperature (Tmin) (source: AEMET) and the rate of daily winter mortality due to natural causes —CIE-10: A00 – R99— (source: National Statistics Institute). Then, It was determinated the threshold of Tmin that defines the ECD and its percentile in the series of winter Tmin (Pthreshold), which is a measure of vulnerability to ECD so that the higher the percentile, the higher the vulnerability. Second: possible explanatory variables of vulnerability were explored using Mixed Generalized Models, using 13 independent variables related to meteorology, environment, socioeconomics, demographics and housing quality.
Results: The average Pthreshold was 18 %. The final model indicated that for each percentage point increase in unemployment, the vulnerability to ECD increased by 0.4 (0.2, 0.6) points. Also, with each point increase in rurality index, this vulnerability decreased by −6.1 (−2.1, −10.0) points. Although less determinant, other factors that could contribute to explaining vulnerability at the province level included minimum winter daily temperatures and the percentage of housing with poor insulation.

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Conclusions: The vulnerability to ECD was greater in urban zones than in rural zones. Socioeconomic status is a key to understanding how this vulnerability is distributed. These results suggest the need to implement public health prevention plans to address ECD at the state level. These plans should be based on threshold temperatures determined at the smallest scale possible.

1. Introduction

Current global temperatures are an average of 1.2 °C greater than preindustrial levels (Romanello et al., 2021). Even in the context of global warming, extreme cold is an important risk factor in public health (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; Egondi et al., 2015; Son et al., 2016). Spain, in particular, could be one of the European countries with the greatest risk to health related to this temperature extreme (Carmona et al., 2016a; Carmona et al., 2016b). In fact, estimates for the 2021–2050 period suggest (in a moderate emission scenario of RCP4.5) that there could be between 175 and 286 cold-related death per year in Spain (IC95%), remaining practically constant compared to the baseline period 2000–2009 in case of non-adaptation (Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c).

These health risks associated with extreme cold show that the increase in global temperatures does not necessarily imply a decrease in this risk and their impacts. On the contrary, global warming could increase vulnerability to cold risks, and the evolution of minimum mortality temperatures could reflect this process. This indicator presents an increasing trend that suggests that populations are progressively adapting to higher temperatures (Åström, 2016; Chung et al., 2017; Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; Follos et al., 2020; Follos et al., 2021; Navas-Martín et al., 2022). In contrast, adaptation to cold could be worsening (Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c). In fact, there is a broad body of scientific evidence that confirms greater risks to health associated with extreme cold events than with extreme heat events (Allen and Sheridan, 2018; Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; Egondi et al., 2015; Goix et al., 2019; Linares et al., 2020; López-Bueno et al., 2021a; Son et al., 2016; Wang, 2017) and others have concluded that risks related to cold waves remain constant or grow (Linares et al., 2015).

Although it is difficult to reach a point of consensus in the literature on this issue because of the different approaches to the problem in terms of methodologies, definitions and population vulnerabilities, generating as much evidence as possible is essential to decide where to focus public health policies.

The influence of socioeconomic factors during episodes of extreme cold could be important factors enhancing extreme-cold-vulnerability (Benmarhnia et al., 2015; Gutierrez and LePrevost, 2016; Linares et al., 2020; Navas-Martín et al., 2022; Rohat et al., 2019; Vargo and Russell, 2016), given that they determine the level of exposure. For example, better housing conditions were associated with less severe impacts of extreme cold on health (López-Bueno et al., 2019; López-Bueno et al., 2021b; López-Bueno et al., 2021c).

In addition, this factor is not independent of income. The population with lower incomes tends to inhabit homes with worse thermal properties (Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015), which is linked to greater difficulties in maintaining a comfortable temperature in the interior of the home (Bouzarovski, 2018; Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015). It seems that better socioeconomic status allows people to better protect themselves from outdoor temperatures.

The socioeconomic and urban type factors that modulate the exposure to low temperatures can vary greatly between the rural and urban populations (Bouzarovski, 2018; Gutierrez and LePrevost, 2016; López-Bueno et al., 2021b; López-Bueno et al., 2021c; Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015; Svensson and Eliasson, 2002). Despite this, there are few studies on this topic in Spain and in the rest of the world. Those studies that do exist are usually related to the urban perspective. This is probably because there is no universal definition of "rurality", in addition to the fact that there are few appropriate environmental indicators for rural zones, which present obstacles to this type of investigation (Gartner et al., 2011; Goerlich et al., 2016; J and Martí, 2015; Lorenzo et al., 2021; Prieto-Lara and Ocaña-Riola, 2010).

Nevertheless, some studies have recently been published that analyze this issue in Spain (López-Bueno et al., 2021a; López-Bueno et al., 2021b; López-Bueno et al., 2021c). According to these studies, when controlling for the poverty index, people over age 65 and housing quality indicators, rurality was a protective factor against extreme cold in the province of Madrid (López-Bueno et al., 2021a). Thus it is important to generate new scientific evidence to evaluate whether the case of Madrid can be extrapolated to other zones in the country.

Despite the importance of cold as a risk factor, there are no ecological studies in the scientific literature that explore population vulnerability to extreme cold using vulnerability indices or other such measures. The principal objective of this study was to determine whether there are differences in vulnerability to Extreme Cold Days between the rural and urban populations in 10 provinces that are representative of Spain; and if so, whether these differences can be explained by environmental, meteorological, socioeconomic, demographic and urban type variables.

2. Material & methods

An exploratory, ecological study was carried out consisting of time series analysis of daily mortality from January 1, 2000, through December 31, 2013, in municipalities of over 10,000 inhabitants in 10 provinces that are representative of Spain (Díaz et al., 2019a; Díaz et al., 2019b). Particularly, these 10 provinces constitute the 20 % of the spanish provinces, the 19.89 % of the country's area and the 41.43 % of the population of Spain (INE, 1994; INE, 2021). Likewise, their distribution ensures the inclusion of the major climates of the country. Lastly, these same provinces have been studied in previous studies, which makes it possible to compare the results with equivalent studies.

2.1. Sample units

Each municipality was classified based on two criteria. They were first classified based in their rural/urban character. Urban municipalities were those considered as such based on Eurostat criteria (Eurostat, 2016; Eurostat, 2021). According to Eurostat urban "cities" are those with over 50,000 inhabitants and where the majority of the population lives in the urban center. — > 50 %— (Eurostat, 2021). In contrast, those municipalities that are not considered "city", which has been assimilated as urban cities in this study, are defined as rural. The geography and distribution of the included areas in the study are shown in the Fig. 1a.

Second, participating municipalities were classified based on their isoclimate zone of reference. These are areas of similar climate behavior defined by the State Meteorological Agency (AEMET) used for meteorological predictions (Carmona et al., 2017; Roldán et al., 2011) (Fig. 1b).

Based on these two criteria, the municipalities were placed (n = 1136) into 42 different groups that made up the sample units of the study. This study used data aggregated at this level.

2.2. Variables used

2.2.1. Mortality data

— Mortality rate *(MR)*: Daily mortality rate due to natural causes (ICD-10: A00-R99) between 01/01/2000 and 12/31/2013 at the study group level. Due to the mandatory registration of every death in Spain, this

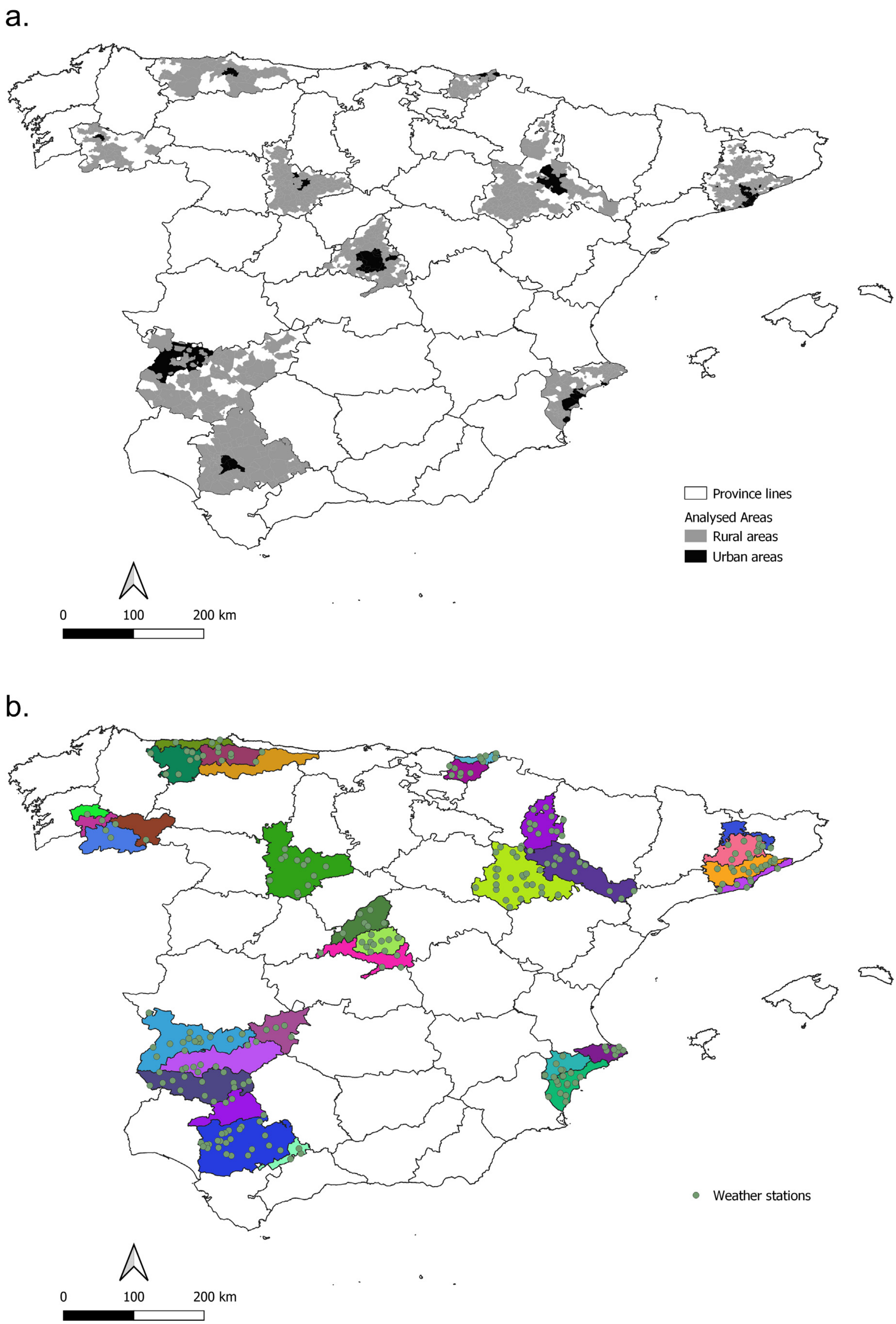

Fig. 1. Map of analyzed areas. a: urban areas are shaded black and rural are shaded grey. White areas were not analyzed as they did not meet with the inclusion requirements. b: different colors represent different isoclimatic areas.

indicator of health has the advantage of being the most accurately counted and diagnosed. Then, it is not being biased in relation to rural populations.

Given that there are great census differences between rural and urban populations, direct mortality counts are not directly comparable. Therefore, the MR variable was used. This was calculated as the number of deaths per million inhabitants for each group. Daily mortality counts were provided by the National Statistics Institute (INE) via an agreement for the concession of micro data subject to confidentiality. The population data came from the census and are available in the INE open database (INE, 2021).

2.2.2. Meteorological and environmental variables

—*Minimum Daily Temperature (Tmin)*: Minimum daily temperature stated in degrees Celsius from January 1, 2000, through December 31, 2013.

It corresponds to the average of the Tmin values registered in each of the AEMET meteorological observatories that are located in the same isoclimate zone. These data were provided by the State Meteorological Agency. The geographic distribution of the observatories can be seen in Fig. 1b.

Regarding why Tmin was selected as the exposure variable instead of mean or maximum daily temperature, some studies have established that, given the high correlation between different temperatures, there are no temperatures that are better indicators than others in this type of studies (Barnett et al., 2010).

However, other considerations must be taken into account when selecting the indicator variable for extreme cold exposure and others authors recommends to associate specifically winter mortality with Tmin due to their stronger statistical association (Díaz et al., 2005; Pyrgou and Santamouris, 2020).

Lastly, although the whole of temperatures —mean, minimum and maximum daily temperature— are increasing in Spain, these three temperature variables are behaving differently. In a report, AEMET recently find out that maximum daily temperature increases greater and faster than minimum daily temperature (AEMET, 2019), that is, the behavior of both extremes is not symmetrical. Therefore, although different temperature measurements are correlated, it is hardly acceptable that they are interchangeable.

—*Winter Tmin*: Average winter Tmin observations (November to March) during the study period for each group (Carmona et al., 2017; Díaz et al., 2005; López-Bueno et al., 2021a).

—*Predictive Positive Balance (BPP)*: Binomial variable that indicates where the water balance is positive, which is related to the absence of aridity. This variable was calculated on site by the National Geographic Institute (ING) as the difference between precipitation and potential evapotranspiration, using data from the years 1996–2016, available at (Atlas Nacional de España, 2019). This variable was transformed into a dichotomous variable such that, if the balance is negative BPP = 0, and therefore the group is located in an arid zone. On the contrary, BBP = 1 indicates that the zone has a positive water balance (not arid).

2.2.3. Variables related to the socioeconomic and demographic contexts

—*Deprivation:* The deprivation index was included as a poverty indicator, and it was calculated using data from the 2011 census, which is the latest recorded one by Duque et al. (2020, 2021). The variables that constitute this index are the following, and it also were considered as independent variables:

—Percentage of workers employed in manufacturing companies.
—Percentage of unemployed people
—Percentage of temporary workers
—Percentage of unskilled workers
—Percentage of unskilled young people
—Percentage of homes without access to the Internet

These data came from the open database of the Spanish Society for Epidemiology (Sociedad Española de Epidemiología (SEE), 2020).

—*Rurality*: a quantitative and multidimensional indicator that incorporates the economic and demographic structure of Spain's rural population at the census level based on annual census data from 2001, provided by INE. These data were provided directly by the authors (Prieto-Lara and Ocaña-Riola, 2010) and were aggregated by the average for each group studied.

—*Population over age 65* (65<): the average percentage of population over age 65 in each group between 2000 and 2013. These data were calculated based on the census data (INE, 2021).

2.2.4. Housing indicators

The following indicators were calculated based on data from the municipal registry:

—*Dwelling in decline (DD)* (%): Percentage of dwellings in decline for each group, that is, buildings in poor conditions but that have not been declared uninhabitable. These data were calculated based on official registries from the cadastre (Dirección General del Catastro, 2021).

—*Good thermal inertia* (GTI)(%): Percentage of housing with good thermal properties by group. According to the literature (Núñez-Peiró et al., 2021; Sanz Fernández et al., 2017) this type of housing tends to be constructed before 1941, due to the quality of the materials, or that built after 2007, when legislation required new housing construction to adhere to specific energy efficiency standards. Using this criteria, the GTI was determined based on official data from the cadastre (Dirección General del Catastro, 2021).

—*Deficient thermal inertia* (DTI)(%): Percentage of housing whose thermal inertia is deficient by group. A large part of the housing constructed between 1941 and 1980 took place in post-war circumstances and in absence of specific regulations for thermal properties for housing. Therefore, this housing is characterized by poor thermal inertia (Núñez-Peiró et al., 2021; Sanz Fernández et al., 2017). Again, this indicator was calculated based on official data from the cadastre (Dirección General del Catastro, 2021).

2.2.5. Control variables

—*Seasonality*: variables were generated with the sine and cosine functions, with periods of 365, 180, 120, 90, 60 and 30 days per period. These variables, 12 in total, served to control for seasonal variations in mortality caused by factors and confounding variables that were not directly considered.

The trend and autoregressive character of the series was also controlled for. In the first case, a counter n1 was used, whose value was 1 on the first day of the series, 2 on the second day, and so on. The autoregressive character was controlled for by introducing the first order autoregressive variable.

2.3. Determination of extreme cold day threshold temperatures

In the absence of a universally accepted definition of a cold spell, there are several validated definitions and study strategies in the literature. One of them consists of selecting a fixed threshold which must be surpassed several consecutive days (Carmona et al., 2016a; Carmona et al., 2016b; Chen et al., 2019; Labajo et al., 2014). With this approach, the vulnerability to the cold spell can be analyzed by comparing the Relative Risks among populations.

Although this approach is rigorous, it presents some critical limitations for this work, which is oriented towards the continuous updating and improvement of extreme-temperatures prevention plans. In particular, the definition of cold wave discussed is based on conventional temperature thresholds and consecutive days (Radinović and Ćurić, 2012), and therefore not based on the effects of extreme temperatures on health.

Instead, we select the threshold temperature of extreme cold by analysing the functional relationship mortality-temperature. This methodology is detailed in the Section 2.3.2. Moreover, as it has been demonstrated that isolated days of extreme cold have an influence on mortality (Díaz et al., 2005), the study was not restricted to events lasting several consecutive days. Therefore, it is a study of extreme cold days rather than a study of cold waves.

For this purpose, the threshold temperature (Tthreshold) that marks the beginning of a cold wave was determined. In terms of public health adaptation strategies, these are defined based on their effects on health (Sánchez-Martinez et al., 2019; WHO, 2021).

This methodology has been well described in the literature (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2005; Díaz et al., 2019b; Linares et al., 2021; López-Bueno et al., 2021a)* and is carried out in two steps described in the following.

2.3.1. Calculation of pre-whitened MR using ARIMA models

Time series of mortality and temperature follow common behavior described by seasonality, period, trend and the autoregressive component (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2005; Díaz et al., 2019a; Díaz et al., 2019b). Thus, the direct correlation of both variables can give rise to spurious associations that are statistically significant when this confusion is not adequately controlled for.

Therefore, the complete daily MR time series were adjusted for each group, using autoregressive integrated moving average models (ARIMA) (Cowpertwait and Metcalfe, 2009), and employing the control variables shown in Section 2.2 (*seasonality*).

The ARIMA models allow for describing the dependent variable based on the moving average, autoregressive component and trend parameters (Cowpertwait and Metcalfe, 2009). These three parameters depend only on the temporal evolution of the dependent variable, in this case the mortality rate.

The adjusted values of the model correspond to the component of mortality that is explained by the historical behavior of the data. In contrast, the residuals of the model collect all of the variability of the series that is not explained in this way.

This collection of residuals, called *pre-whitened daily mortality*, is the product of this first phase. Pre-whitened daily mortality was used because it has the advantage of being free from seasonality, trend and the autoregressive component. This ensures that the associations between mortality and temperature found is not spurious.

The methodology described here was carried out using the “arima” function of the SPSS basic package.

2.3.2. Determination of the extreme cold threshold temperature using dispersion diagrams showing pre-whitened mortality

In this study, threshold temperatures of extreme cold are defined as temperature below that mortality is statistically higher than the seasonal mortality (Carmona et al., 2017; Díaz et al., 2015; López-Bueno et al., 2021b; López-Bueno et al., 2021c).

The literature suggests that the effect of extreme cold on mortality takes place over the long and medium term (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2005). In particular, this effect tends to manifest in terms of two spikes: the first is between 2 and 7 days after a cold wave, and the second is between days 7 and 14 (Díaz et al., 2005).

In order to identify this first mortality spike, each value for minimum daily temperature (Tmin) was associated with average pre-whitened mortality in seven days. This temperature indicator was selected instead of the average or maximum daily value, because it presents a better statistical behavior related to winter mortality (Díaz et al., 2005; López-Bueno et al., 2021a; Pyrgou and Santamouris, 2020).

Later, observations were used from the winter months, that is, November through March (Barbieri and Bertini, 2020) and the following calculations were carried out:

a. The winter mean of the pre-whitened mortality in seven days (seasonal mortality).

b. The mean of the pre-whitened mortality by intervals of two degrees.

Corresponding 95 % probability confidence intervals were calculated for both estimates.

Threshold temperatures of extreme cold days (Tthreshold) were determined for each group based on these measures with the help of scatterplots. In these scatterplots Tmin was represented on the X-axis, and average pre-whitened mortality in seven days were represented on the Y-axes. The confidence interval of the seasonal average appears as a band centered on zero. In it, the threshold temperatures correspond with that interval of temperature associated with statically greater mortality than the seasonal mortality.

An example of these scatterplots can be seen in Fig. 2. In this illustrative example (group 633,304–0), the threshold temperature corresponds to 2 degrees Celsius.

This procedure was carried out for each of the study groups. This phase of the protocol was carried out using the basic package and the ggplot library of the free software R4.0.4.

2.4. Analysis of vulnerability to extreme cold days

Calculating the threshold temperatures provides knowledge about the most appropriate times to implement preventive actions against extreme temperatures. However, they are limited in that they cannot be compared directly to each other, because they depend on different local and climate factors in each study area (López-Bueno et al., 2021b; López-Bueno et al., 2021c).

The threshold temperatures calculated according to what has been described earlier (Section 2.3.2) can be translated into a measure of relative temperature (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2015; López-Bueno et al., 2019; López-Bueno et al., 2021a; López-Bueno et al., 2021c). In this study, they are expressed as a function of the percentile of minimum daily winter temperatures for each group. These temperature percentiles range from 0 to 100. Thus, although the threshold expressed in degrees Celsius is different between two zones, if the percentile coincides, the level of adaptation to the local temperature can be considered equivalent.

Thus, the closer the threshold temperatures percentiles are to zero, the more extreme are the minimum temperatures experienced by the population that do not result in significant increases in mortality.

Since these threshold percentiles mark the relative starting point of the increased mortality attributable to extreme cold, it can be directly interpreted as an epidemiological measure of the level of vulnerability to this environmental risk. And they have the advantage of being based directly on the relationship between mortality and temperature instead of other indirect variables which are supposed to be associated with higher vulnerability to extreme cold.

Thus, we analyzed which factors explained the distribution of this vulnerability by Generalized Mixed Models (link = identity), using the calculated threshold temperatures as the dependent variable. The meteorological, socioeconomic, demographic and urban indicators described in Section 2.1 (and shown in Table 2) were used as independent variables. Finally, given that the data possess a structure of geographic correlation and of territory typology, provinces and their rural/urban category were included as random effects factors.

In terms of the modeling strategy, variables were preselected that presented the best statistical behavior based on the descriptive analysis of the data and the results of the univariate models.

Using the preselected independent variables, multivariate models were adjusted by types of indicators: environmental, socioeconomic and housing-related.

Finally, all of the variables with p-values <0.05 in these intermediate models were selected for the general model. In this model, variables were sequentially discarded that did not reach statistical significance (p-value <0.05) using backward step regression.

The translation of threshold temperatures (°C) into threshold temperature percentiles (level of vulnerability) was carried out using the basic package of R 4.0.4. The “mixed” function of the StateBE 17 software was used to adjust the models.

3. Results

Table 1 shows descriptive statistics for the analyzed groups. In total, It were pooled information from 1136 municipalities in 42 groups, with an aggregated population of 17,826,646 inhabitants. It is especially interesting to compare the mortality by type of group. The average mortality rate in the

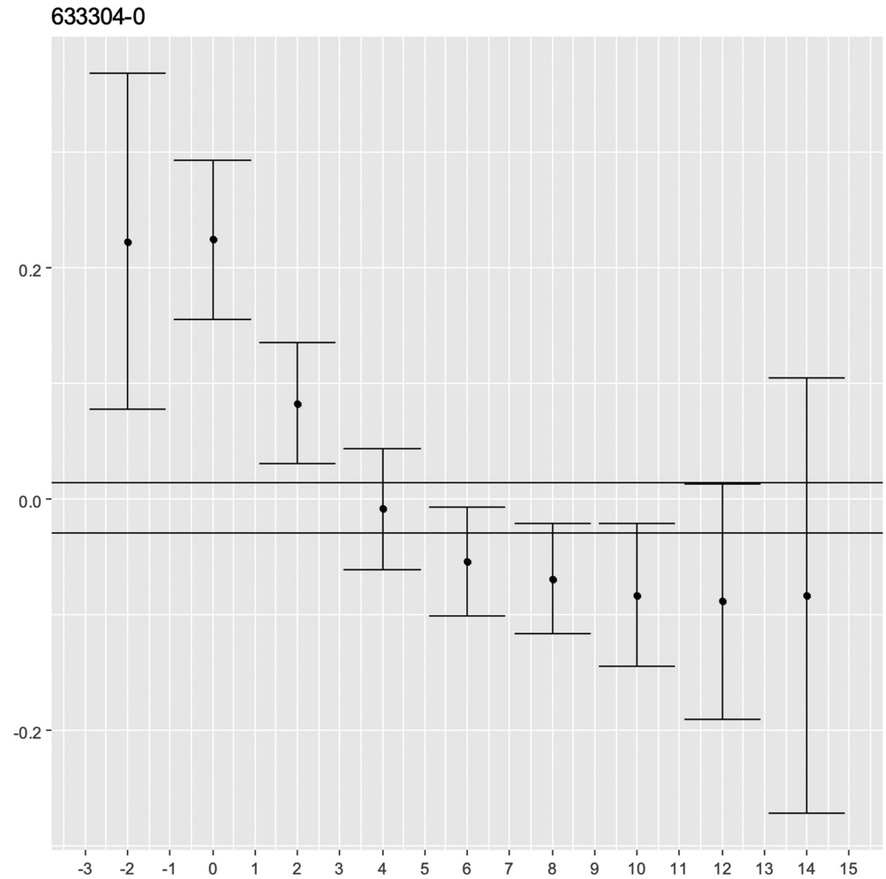

Fig. 2. Example of a dispersion graph of residuals used to determine Threshold Temperatures of Extreme Cold Days. The X-axis displays daily minimum temperatures in degrees Celsius. The Y axis displays pre-whitened average mobile mortality by temperature intervals. The center band represents confidence intervals for mobile pre-whitened mortality during the full winter period. In the title, the code identifies the analyzed group. The first part of the code is a meaningless numerical code that identifies the isoclimatic zone of the group. The second part indicates if the group is rural (0) or urban (1).

urban zones was 36.68 deaths per million inhabitants per day. This was statistically greater than the 21.67 deaths observed in rural areas (*t*-test, p-value = 0.0178).

Table 2 shows the levels of vulnerability due to Extreme Cold Days (ECD) —the geographic distribution is shown in Fig. 3—. There are only two groups in which there is no mortality increases in any of the temperature ranges (Pthreshold = 0). In contrast, there was no detected increase in mortality due to extreme heat in eight groups. On average, the vulnerability to extreme cold was 18 %.

Table 3a shows the descriptive statistics of the variables used in the linear mixed models. The percentage of unemployed people was high in all of the study groups (18 % – 48.36 %). The housing stock with poor thermal inertia was important in all of the groups analyzed (average DTI = 33.58 %). In terms of the population over age 65, the data indicate that this population group has an important presence in all of the groups analyzed (on average 21.83 %).

Table 3b shows the adjusted models. These models shows that the winter temperature (winter Tmin) was the only meteorological or environmental variable that was statistically significant, although it lost statistical significance in the final model. In terms of the direction of the coefficient ($\beta_{\text{Winter Tmin}} > 0$), we can see that in general, greater vulnerability to extreme cold was found where temperatures tend to be higher.

Among the sociodemographic factors (Table 3b), unemployment and rurality index reached statistical significance (p-value <0.005). Furthermore, these two variables displaced all of the others in the final model. In terms of their coefficients, rurality played a protective role against extreme cold ($\beta_{\text{Rurality}} = -6.1$) and unemployment contributed to greater vulnerability ($\beta_{\text{unemployment}} = 0.4$).

Finally, the supplemental material shows a comparison of the vulnerability found due to ECD and vulnerability due to extreme hot days reported in a prior study (López-Bueno et al., 2021b; López-Bueno et al., 2021c). It can be observed that the study population was on average 9.64 % more vulnerable to extreme cold than to extreme heat (p-value <0.005).

4. Discussion

The principal findings of this study are that population vulnerability to Extreme Cold Days (ECD) tends to be greater in urban areas than in rural ones, controlling for indicators related to economic status, housing and climate.

A possible protective role of rural areas is shown in Table 3b. With each percentage point increase in the rurality index, vulnerability to extreme cold decreased by 6.1 points. Furthermore, this was one of the most explanatory factors among the study variables, given that it was maintained in the final model.

These results agree with what has been reported in the past for the province of Madrid (López-Bueno et al., 2021a), where the same protective effect was observed in the rural areas of the province. The same has also been observed for heat waves (López-Bueno et al., 2021b; López-Bueno et al., 2021c).

In contrast, in some places such as Australia and Prague, greater risks due to extreme cold have been found for remote, rural populations (Jegasothy et al., 2017; Urban et al., 2014). However, these differences should be interpreted with caution, because the use of different methodologies can result in findings that are not truly comparable.

Table 1
Descriptive statistics of the study groups.

Group		Province	MR[c]		Tmin[d]		Mun[e]	Csta[f]	Pop[g]
Isocode[a]	Urban[b]		Mean	SD	Mean	SD			
614101	0	Sevilla	17.86	24.73	2.67	4.25	9	3	29,372
614102	0	Sevilla	14.72	4.77	6.95	3.42	68	23	859,300
614102	1	Sevilla	31.62	7.00	6.95	3.42	3	23	885,808
614103	0	Sevilla	14.70	16.31	5.66	3.65	14	3	57,862
625001	0	Zaragoza	20.12	30.90	2.69	3.58	13	11	21,213
625002	0	Zaragoza	25.10	15.38	2.31	3.58	139	26	110,824
625003	0	Zaragoza	17.37	15.08	3.36	3.60	32	13	84,000
625003	1	Zaragoza	30.34	7.50	3.36	3.60	1	13	652,456
633301	0	Asturias	24.72	17.06	7.02	3.09	9	3	88,526
633303	0	Asturias	33.48	33.20	3.86	3.36	6	8	30,224
633304	0	Asturias	27.31	11.21	4.45	3.20	16	6	229,391
633304	1	Asturias	46.14	15.18	4.45	3.20	1	6	215,936
633305	0	Asturias	31.86	26.70	3.79	3.80	5	1	46,923
674701	0	Valladolid	15.70	9.75	0.83	3.82	153	12	175,000
674701	1	Valladolid	29.06	10.15	0.83	3.82	1	12	307,082
690801	0	Barcelona	16.42	54.60	2.45	3.97	6	1	5440
690802	0	Barcelona	22.73	10.24	1.31	3.74	62	13	255,834
690803	0	Barcelona	12.34	4.42	4.10	3.57	84	13	739,175
690803	1	Barcelona	26.60	6.99	4.10	3.57	8	13	744,121
690804	0	Barcelona	13.52	5.36	6.66	3.09	43	7	608,934
690804	1	Barcelona	27.35	4.70	6.66	3.09	12	7	2,749,770
700601	0	Badajoz	24.21	12.78	5.34	3.53	36	16	165,160
700601	1	Badajoz	37.76	14.78	5.34	3.53	2	16	199,493
700602	0	Badajoz	31.25	53.90	4.74	3.26	5	4	11,505
700603	0	Badajoz	22.22	12.85	5.24	3.01	28	8	136,442
700604	0	Badajoz	25.83	18.03	5.34	3.03	32	14	83,329
713201	0	Ourense	21.23	17.88	1.72	4.49	7	1	29,136
713202	0	Ourense	51.84	46.50	4.28	4.36	8	1	30,507
713202	1	Ourense	54.74	24.43	4.28	4.36	1	1	108,158
713203	0	Ourense	27.85	20.47	2.28	4.10	21	2	65,821
713204	0	Ourense	31.39	66.80	2.02	3.52	3	2	7091
722801	0	Madrid	19.70	9.50	1.20	3.30	52	6	279,366
722802	0	Madrid	9.80	5.70	2.40	3.60	22	11	315,512
722802	1	Madrid	20.00	2.80	2.40	3.60	15	11	4,893,817
722803	0	Madrid	14.70	7.80	1.50	3.80	36	4	303,721
770301	0	Alicante	20.32	10.06	8.10	2.99	51	7	226,449
770302	0	Alicante	13.44	9.24	4.26	3.47	14	7	157,737
770303	0	Alicante	21.18	7.84	7.88	3.02	39	14	495,661
770303	1	Alicante	21.20	5.77	7.88	3.02	5	14	742,622
752001	0	Gipuzkoa	9.72	7.30	6.62	3.73	18	6	202,550
752001	1	Gipuzkoa	78.70	26.22	6.62	3.73	2	6	243,584
752002	0	Gipuzkoa	19.16	9.37	3.74	3.74	54	54	231,796
Counts	42								
Sum	11		1075.30	721.25	177.63	149.59	1136	422	17,826,646
Average			25.60	17.17	4.23	3.56	27	10	424,444
SD			13.1	14.8	2.1	0.4	34	9	842,418

[a] Isoclimatic code.
[b] 1:urban, 0: not urban.
[c] Winter mortality rate expressed in deaths per million inhabitants.
[d] Winter minimum daily temperature.
[e] Number of municipalities included per group.
[f] Number of weather stations per group.
[g] Average population over the period 2000–2013.

The description "rural" encompasses different areas whose levels of inequality, geographic isolation, infrastructure development and health system access is very heterogeneous between countries (Gutierrez and LePrevost, 2016). Therefore, these results cannot necessarily be extrapolated beyond countries that have a similar environment and with similar standards in terms of development.

Table 3 also shows that lower winter temperatures correlated with lower vulnerability to extreme cold. This behavior is along the lines of what would excepted in a context of local adaptation to cold and has been detected in prior studies (Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; Pyrgou and Santamouris, 2020). That is to say, in those zones where low temperatures are dominant, the built structures and lifestyles could be adapted to these circumstances, mitigating ECD's effects on health (Bobb et al., 2014). In any case, this variable was less determinant than the socioeconomic indicators, which displaced it in the final model (Table 3b).

In terms of the variables, the percentage of housing with poor thermal inertia was the most determinant of all of the urban type variables. This result agrees with the literature ((López-Bueno et al., 2019; López-Bueno et al., 2020a; Urban et al., 2014), p.), and establishes that these homes hardly maintain comfortable indoor temperatures (Bouzarovski, 2018; Núñez-Peiró et al., 2021; Sánchez-Guevara et al., 2015; Santamouris and Kolokotsa, 2015).

In relation to housing, the literature suggests that one of the causes of the protective effect of rurality against extreme temperatures is that rural housing presents better thermal properties than modern urban dwellings (Martin et al., 2010). These results partially agree with this hypothesis, in that both variables competed in the models. However, it is possible that

Table 2
Vulnerability due to Extreme Cold Days (ECD) in Spain. The value of vulnerability equals the threshold percentiles (Pthresold). *: mortality rates statistically higher than the seasonal average were not detected for any temperature range. In these cases, Pthreshold was assumed to equal 0.

Iscode	Urban	Vulnerability to cold waves (Pthresold)
614101	0	0*
614102	0	20
614102	1	20
614103	0	17
625001	0	0*
625002	0	25
625003	0	34
625003	1	34
633301	0	18
633303	0	3
633304	0	24
633304	1	24
633305	0	0*
674701	0	10
674701	1	10
690801	0	12
690802	0	18
690803	0	29
690803	1	29
690804	0	40
690804	1	19
700601	0	19
700601	1	19
700602	0	22
700603	0	35
700604	0	14
713201	0	4
713202	0	2
713202	1	31
713203	0	19
713204	0	1
722801	0	16
722802	0	12
722802	1	27
722803	0	18
752001	0	1
752001	1	5
752002	0	33
770301	0	25
770302	0	27
770303	0	28
770303	1	28
Average (SD)		18 (11)

there are other underlying factors, such as those related to the rurality index.

The protective effect of the rural environment could also be due to better health status of the rural population. This could be related to the way in which rural environments promote physical activity and lower levels of stress and air pollution (Bernard et al., 2007; 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 to lower levels of loneliness and elder abandonment (Dwyer et al., 1990; Wagenfeld, 1990). Regarding this, the average mortality rate of the urban zones analyzed was 36.68 deaths per million inhabitants per day. This was statistically greater than the 21.67 deaths observed in rural areas (*t*-test, p-value = 0.0178). Thus, it appears that the rural populations studied do have better health status.

In relation to this point, studying a cohort of people with metabolic syndrome over 5 years, Cabré vila et al. (2018) found a lower overall incidence of cardiovascular disease in the rural population, but a higher mortality rate. In contrast, Moreno-Lostao et al. (2019), studying the risk of mortality from cardiovascular causes according to the degree of urbanization, found a protective effect in rural areas, where there was also a lower prevalence of smoking, obesity and physical inactivity in men and obesity in women.

On the other hand, Errezola et al. (1989) found higher cancer mortality in rural areas. However, more recently, Domínguez-Berjón et al. (2016), adjusting for age, poverty and NO2, found higher lung cancer mortality in urban areas.

Although the results may seem contradictory and these comparisons should be made with caution because of the different approaches to rurality and cause specificity, some of these papers are consistent with the results found. Future studies could help confirm this hypothesis.

In addition to rurality index, unemployment was the other variable that contributed most to explaining vulnerability to cold (Table 3b). In this study, the percentile increased by 0.4 points for each percentage point increase in unemployment.

Unemployment is related to poverty, which is one of the primary risk factors associated with the impacts of climate change (Linares et al., 2020; MedECC, 2020; Romanello et al., 2021), and these results agree with what has been reported in prior literature (López-Bueno et al., 2020a; López-Bueno et al., 2021a; López-Bueno et al., 2021b; López-Bueno et al., 2021c).

Another aspect worth pointing out is that in this study the socioeconomic variables explained the distribution of vulnerability better than the percentage of population over age 65. These results also agree with the findings of other studies described in the bibliography (López-Bueno et al., 2021b; López-Bueno et al., 2021c).

In comparison to prior research, we found that vulnerability to ECD (Supplementary Table) was higher than vulnerability to extreme hot days. This is a pattern that has been confirmed in numerous studies in Spain and in other countries (Allen and Sheridan, 2018; Carmona et al., 2016a; Carmona et al., 2016b; Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; Egondi et al., 2015; López-Bueno et al., 2020a; López-Bueno et al., 2021a; López-Bueno et al., 2021b; López-Bueno et al., 2021c; MedECC, 2020; Wang, 2017). One related factor is that cold risks are associated with diffuse effects over the long term that make prevention difficult. For this reason, the perception of risk among patients and health professionals underestimates the lethal nature of extreme cold and hinders the implementation of public health action plans (WHO, 2021).

To make matters worse, there is no national prevention plan to address extreme cold events in Spain, which would be a key to mitigating the effects on health (Allen and Sheridan, 2018; Linares et al., 2020; Sánchez-Martinez et al., 2019; Sheridan et al., 2019). In this regard, Spain is not an exception in Europe, where there are contingency plans against cold waves but, with some exceptions, these are either generalized or focused on protecting health (UK Health Security Agency, 2021; WHO, 2013; WHO, 2018).

Applying health prevention plans has been shown to reduce mortality attributable to heat in Spain and in Europe (Díaz et al., 2018; Sánchez-Martinez et al., 2019). It is therefore urgent that they also be implemented to address extreme cold risks (Díaz et al., 2019a; Díaz et al., 2019b; Díaz et al., 2019c; López-Bueno et al., 2021a).

4.1. Study strengths and limitations

Fig. 1 shows that the studied areas are representative of the primary population and climate types that make up the country. The strengths of this study include that it used data from 1136 municipalities, an aggregated population of 17,826,646 inhabitants, and 422 meteorological observatories with a wide geographic dispersion (Table 1).

One of the traits that best differentiates urban zones from rural zones is population density (Eurostat, 2016; Goerlich et al., 2016; Prieto-Lara and Ocaña-Riola, 2010). This naturally leads to problems of jumps in scale of mortality recounts, which cannot really be compared directly between these populations. However, expressing this variable in terms of rates corrects these jumps in scale (Table 1).

This study shares the limitations of those with ecological designs (Morgenstern, 1995). These include that it is not possible to make individual inferences based on results that are found at the population level.

Also, the exposure variable, minimum daily temperature (Tmin), was not measured in the places where people were exposed. Furthermore, the

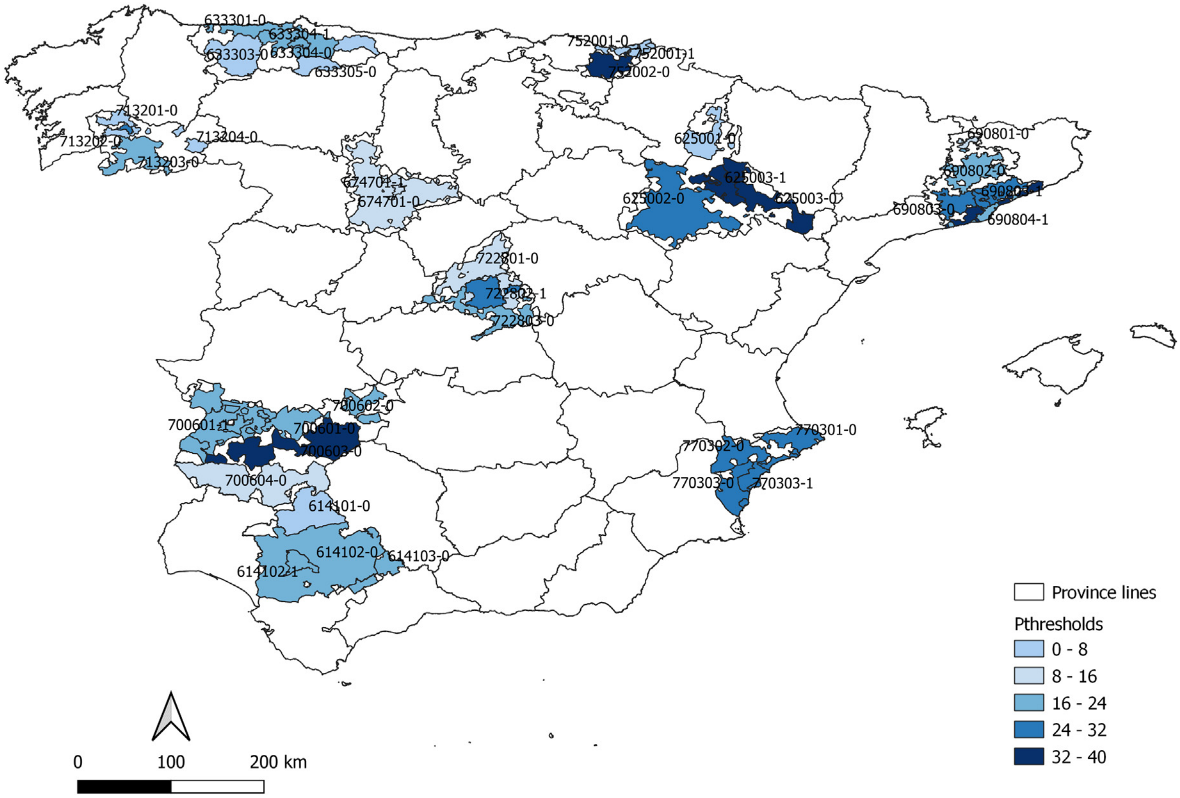

Fig. 3. Map of the geographic distribution of the extreme-cold threshold percentiles. The numbers are codes that identify the analyzed groups. The first part of the code is a meaningless numerical code that identifies the isoclimatic zone of the group. The second part indicates if the group is rural (0) or urban (1).

number of meteorological observatories was not equally distributed among the groups, which could have resulted in Tmin measurements not being equally precise among them. Meteorological indicators were specifically measured covering wide areas, which is associated with the Berkson error. However, given that the study population was divided into homogeneous climate groups, the associated errors related to this bias should be considered negligible (Roldán et al., 2011). This is a problem that is common in this type of study.

Table 3
Mixed generalized linear models.

a. Descriptive statistics of the variables included in the mixed generalized models.

Variable	UD	N	Mean	SD	Min	Max
Pthreshold	Non-dimensional	42	18	11	0	40
Winter tmin	° cesius	42	4.2	2.1	0.8	8.1
Manual jobs	%	42	63.32	10.91	44.30	82.02
Unemploiment	%	42	29.20	7.61	18.00	48.36
Temporary workers	%	42	29.51	9.14	20.46	56.36
Low education	%	42	29.53	8.67	14.24	47.07
Low youth education	%	42	12.00	3.99	4.31	21.76
without internet	%	42	51.15	13.48	23.83	79.64
Deprivation	1	42	0.08	0.67	−1.06	1.53
Rurality	Non-dimensional	42	−0.82	0.81	−2.21	0.77
65<	%	42	21.83	7.65	8.85	39.16
DD	%	39	2.02	2.82	0.03	11.79
DTI (1941–1980)	%	39	33.58	8.51	15.77	51.16
GTI (before 1940 & from 2007)	%	39	30.67	10.30	16.22	57.06
			0	1		
BPP	1: positive, 0: negative	42	31	11		

b. Models adjusted by types of variables and general fitted model.

	Percentile	β	SE	z	p > |z|	95%CI	
Model of weather variables	Winter Tmin	3.6	0.5	7.66	0.000	2.7	4.6
Socioeconomic variables model	Unemployment	0.4	0.1	5.11	0.000	0.3	0.6
	Rurality	−6.1	2.0	−2.98	0.005	−10.2	−2.0
Household model	DTI	0.5	0.0	11.65	0.000	0.5	0.6
General fitted model	Unemployment	0.4	0.1	5.11	0.000	0.3	0.6
	Rurality	−6.1	2.0	−2.98	0.005	−10.2	−2.0

Furthermore, it is important to take into account that all of the AEMET observatories in the studied provinces were used. Therefore, there are no available data of better quality than what was used.

Working with aggregated data at the group level is not free of MAUP type errors (Jelinski and Wu, 1996). These involve problems of scale and zoning and are especially relevant when working with socioeconomic variables, given that they present great heterogeneity (López-Bueno et al., 2020a; López-Bueno et al., 2020b). Working with census data would be ideal (Duque et al., 2021). However, working at this level implies the risk of inability to detect threshold temperatures due to lack of statistical power, such that the final selection of sample units is somewhat a compromise. It is important to note that this limitation is partially compensated for through the inclusion of provinces and the rural-urban typology as random effects factors (López-Bueno et al., 2021b; López-Bueno et al., 2021c).

In this study it was not possible to determine the potential confounding effect of chemical air pollution due to the absence of quality data outside of the principal cities in the country [89], and using data of this type can introduce instability into the models (Linares et al., 2014). This is another limitation that is common in this type of study (Eurostat, 2018; Linares et al., 2014). Nor was it possible to control for the flu, although other studies have shown the role of the flu as a confounding variable to be negligible (López-Bueno et al., 2020a); likewise with relative humidity.

The established definition of threshold temperature has some advantages. One, it constitutes a transformation of the exposure variable that linearises the temperature mortality relationship. On the other hand, it establishes an objective criterion for determining when extreme temperature preventive plans should be implemented based on the health impacts of extreme temperatures. Moreover, to the extent that this is a parameter that varies between populations, it is a good indicator of population adaptation to extreme temperatures. Finally, this definition has practical applications in Public Health, given that it is the method used to establish when to activate extreme temperature alerts in Spain.

However, this methodology also has a limitation. It does not allow studying the effect of moderate temperatures. In other words, the measures of epidemiological impact that can be given from this measure only refer to the temperature range considered extreme from the definition itself. Therefore, it does not allow estimating possible risks associated with temperatures before exceeding this threshold.

Finally, though the definition used to classify municipalities as rural or urban could precisely determine urban zones, it represents a poor approximation to rural zones (Eurostat, 2016; Eurostat, 2018; Eurostat, 2021). Therefore, in this study zones were classified as rural that really should be have been considered semi-urban, which could result in imprecise conclusions (Lourenço, 2012). In contrast, the limited nature of this definition was offset by including a quantitative rurality index. Thus, the impact of this limitation can also be considered minimal.

5. Conclusions

This study showed lower vulnerability to extreme cold among rural areas, and that this vulnerability increases with unemployment. Other factors that contributed to explaining greater effects of extreme cold on health included local adaptation to low temperatures and the quality of the thermal inertia of housing.

Furthermore, vulnerability to extreme cold seems to be higher than vulnerability to extreme heat. Therefore, the results of this study support the need to put prevention plans to address extreme cold events in place. The influence of local factors on threshold temperature values and on the associated impacts of extreme cold events make it necessary to articulate prevention plans at the smallest geographic scale possible, along the lines of what has been recommended by the WHO for heat waves.

CRediT authorship contribution statement

José A López-Bueno. Original idea of the study. Study design; Elaboration and revision of the manuscript.

Miguel Ángel Navas. Providing and Analysis of data; Elaboration and revision of the.

manuscript.

Julio Díaz. Original idea of the study. Study design; Elaboration and revision of the manuscript.

Isidro J Mirón. Providing and Analysis of data; Elaboration and revision of the manuscript.

Yolanda Luna. Providing and Analysis of data; Elaboration and revision of the manuscript.

Gerardo Sánchez-Martínez. Epidemiological study design. Elaboration and revision of the manuscript.

Dante Culqui. Epidemiological study design. Elaboration and revision of the manuscript.

Cristina Linares. Original idea of the study. Study design; Elaboration and revision of the manuscript.

Data availability

The data that has been used is confidential.

Declaration of competing interest

The researchers declare that they have no conflict of interest that would compromise the independence of this research work. The views expressed by the authors do not necessarily coincide with those of the institutions they are affiliated with.

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Appendix A. Supplementary data

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