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RESEARCH ARTICLE - ATMOSPHERIC & SPACE SCIENCES

The effect of climate warming on the seasonal variation of mortality in European countries

Michail Prevezanos[1] · Alexios Benos[2] · Nikolaos Zoumakis[1] · Nikolaos Papadakis[1]

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Abstract
Although several studies have concluded that excess winter deaths are not a suitable indicator of cold-related health impacts, the investigation of temporal fluctuation in mortality across many European countries could provide an insight into the seasonal variation of deaths at different climatic conditions. We investigated the evolution over time of the Excess Winter Deaths Index (EWDI) and the Summer-to-Winter Deaths ratio (S/W) for the period 1960–2018 and the temporal fluctuation of the Heating and Cooling Degree Days indices for the period 1979–2020. We found a clear spatial pattern of EWDI with statistically significant decreasing trends in Mediterranean countries and increasing trends in Nordic countries. On the other hand, S/W index shown increasing trends in Mediterranean region and decreasing trends in Nordic countries. Statistical analysis of Heating Degree Days index showed significant decreasing trends for all European countries, probably due to the appearance of milder winters. Also, the values of Cooling Degree Days index exhibited a statistically significant upward trend for Mediterranean countries, mainly due to increased frequency of warmer summers, as a result of climate change. This study shows that the differences in seasonal variation of mortality between European countries are likely to disappear, as the climate gets warmer. A possible explanation for our findings is that climate change already brings milder winters and hotter summers to the Mediterranean countries, while in the Nordic countries global warming causes less severe winters and more pleasant summers as shown from Heating and Cooling Degree Days analysis. In addition to providing a basis to investigate potential effects of global warming on human mortality, the findings of this study are likely to be crucial for climate change policy and developing relevant adaptation strategies in Europe.

Keywords Human mortality · Heating degree days · Climate change · Global warming

Introduction

Much debate exists even in the more recent literature about why certain countries have experienced higher excess winter mortality. Many recent studies indicated that countries with less severe cold weather in Southern Europe had higher levels of excess winter deaths than those countries with more severe winters in Northern Europe (McKee 1989; Laake and Sverre 1996; Clinch and Healy 2000; Healy 2003; Fowler et al. 2015). A possible explanation for these findings may be the better physiological, social and behavioral adaptation to cold climate in Northern European countries with severe winter weather. In particular, Northern European countries have lower levels of excess winter deaths because people are better protected from cold weather with warmer homes and more appropriate clothing. (Laake and Sverre 1996; The Eurowinter Group 1997; Clinch and Healy 2000). It is also obvious that populations in warmer regions tend to be vulnerable even to moderate cold conditions, and therefore, more people die during winter months. Several studies have concluded that EWDI is not an appropriate indicator of cold-related health impacts, because a significant proportion of cold-related deaths can occur outside of the winter season (Liddell et al. 2015; Hajat and Gasparrini 2016). Despite this limitation, any analysis of EWDI temporal fluctuation across

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✉ Michail Prevezanos
pmichail@auth.gr

1 Laboratory of Hygiene, Social and Preventive Medicine and Medical Statistics, Faculty of Medicine, Aristotle University of Thessaloniki, Thessaloniki, Greece

2 Laboratory of Primary Health Care, General Medicine and Health Research Services, Faculty of Medicine, Aristotle University of Thessaloniki, Thessaloniki, Greece

many European countries could provide an insight into the seasonal variation of mortality related to different climatic conditions (Gasparrini et al. 2015a; Gasparrini et al. 2015b).

Climate change is expected to bring milder winters, with lower excess winter deaths (Kinney et al. 2015). Moreover, increasing ambient temperatures are causing more frequent and intense heatwave episodes, which are responsible for elevated heat-related deaths (Gasparrini et al. 2015a, b; Gasparrini et al. 2016; Gasparrini et al. 2017). Accumulating evidence suggests that the climate change is already happening and represents one of the greatest environmental, social and economic threats facing the planet (Kinney et al. 2008; Twardosz and Kossowska-Cezak 2015; Twardosz, Kossowska-Cezak and Pelech 2016; Gasparrini et al. 2017). The IPCC reports that changes in many extreme weather and climate events, including a decrease in cold temperature extremes and an increase in warm temperature extremes, have been observed since about 1950 (IPCC 2014).

It is well known that climate and weather conditions affect human health (Fowler et al. 2015; Vardoulakis et al. 2015; Gasparrini et al. 2015b). Furthermore, both excess heat and excess cold weather conditions are associated with high mortality risk (Liddell et al. 2015; Gasparrini et al. 2017; Oudin Åström et al. 2018). Many studies have shown that temperature-related mortality patterns are expected to change throughout this century because of warming climate (Forzieri et al. 2017). The IPPC reports that the observed warming has increased heat-related human mortality and decreased cold-related human mortality in North America and Europe (IPCC 2014). One of the most notable impacts of climate change is that the number of cold days and nights has decreased and the number of warm days and nights has increased on the global scale (IPCC 2014; Twardosz and Kossowska-Cezak 2015; Twardosz, Kossowska-Cezak and Pelech 2016). In order to examine the effect of climate change conditions on human mortality, we used the Heating Degree Days (HDD) and Cooling Degree Days (CDD) to study the temporal fluctuations of extreme cold and extreme heat, respectively. HDD and CDD are useful to make cross-country comparisons but also monitor the temporal fluctuations of weather extremes for each country.

In this study, we examined the excess winter mortality indices (EWDI) in almost all European countries over the last 59 years, and the possible causal role of climate in shaping the seasonal mortality cycle. To the extent of our knowledge, this is the first study to make European comparisons of seasonal-mortality patterns using mortality data from 1960 to 2018. For each European country, mortality indices have been analyzed using regression models. Simple linear regression assumes that residuals are independent, normally distributed, with zero mean and constant variance, and unrelated to the predictor variable (Hamilton 1994; Box et al. 2008). To check the validity of these assumptions, we applied parametric statistical tests using SAS/ETS 14.3 (SAS Institute Inc. 2017). Our results show a significant decrease in excess winter mortality in Southern Europe, in accordance with global warming trends that exhibit a clear latitudinal gradient. Mediterranean countries are projected to experience a strong surge in heat-related excess mortality, while the cold component becomes progressively less important (Forzieri et al. 2017; Gasparrini et al. 2017). As the climate gets warmer, the differences in EWDI between European countries are likely to disappear (Fowler et al. 2015). Despite the fundamental criticisms that EWDI is not an appropriate indicator of cold-related health impacts (Hajat and Gasparrini 2016), there is a high degree of spatial consistency in the pattern of temporal trends across most European countries, suggesting that climate is a key factor in shaping the seasonal mortality cycle (The Eurowinter Group 1997; Fowler et al. 2015). Moreover, we studied the heat-related mortality by considering the Summer-to-Winter deaths ratio (S/W) for the years from 1960 to 2018. The results from the S/W index showed statistical significant increasing trends of heat-related mortality for Mediterranean countries probably due to global warming and increased heatwave episodes (IPCC 2014).

Methodology and data

Excess winter deaths and excess winter death index

Excess winter deaths (EWDs) describe the additional number of deaths that occurred in the winter months (December–March) compared to the average number of deaths that occurred in the non-winter months (preceding August–November and the following April–July) (Fowler et al. 2015). It is calculated as the difference between those two numbers.

We selected Excess Winter Deaths Index (EWDI) which is defined as the ratio of excess deaths in the winter period compared with deaths in the non-winter period (expressed as percentage), where a positive value indicates a winter excess mortality (McKee 1989; Healy 2003).

It can be calculated using the following formula:

$$\mathrm{EWDI}(\%) = \frac{(\text{Winter Deaths}) - \frac{(\text{Non-winter Deaths})}{2}}{\frac{(\text{Non-winter Deaths})}{2}} \cdot 100. \quad (1)$$

Summer/winter deaths ratio

Alternative to EWDI, we also defined the Summer-to-Winter deaths ratio (S/W) as the average number of daily deaths in summer (June, July, and August) compared with the average daily deaths in the four coldest months of the year (December–March):

$$S/W = \frac{\text{Summer Deaths}}{\text{Winter Deaths}}. \tag{2}$$

Definition of heating and cooling degree days

Heating Degree Days (HDD) and Cooling Degree Days (CDD) are weather-based technical indices designed to describe the need for heating and cooling energy requirements for buildings, respectively. These indices are calculated as the difference between average ambient temperature and an optimum (base) temperature (Agri4Cast Resource Portal 2021; Eurostat 2021b). High values of HDD and CDD indices are generally associated with exposure to temperature extremes, which can result from extreme cold and extreme hot weather conditions, respectively.

Statistical analysis

In recent decades, particularly as a result of climate change impacts on human health, considerable effort has been given to determine trends in excess mortality rates. Uncertainty arising from a small sample of observations should be seriously taken into consideration in the reliability of detecting trends (Hamilton 1994). The length of time series can vary, but many models require at the very least 50 observations for accurate estimation (McCleary et al. 1980).

For each European country, the EWDI, S/W, HDD and CDD indices have been analyzed by time series models. A linear decomposition model (Eq. 3) can be used to examine the relative influence of trend (T_t), seasonality (S_t) and random components (E_t) on time series data. The additive decomposition model describes each value of the EWDI, S/W, HDD and CDD time series (y_t) as the sum of these three components:

$$y_t = T_t + S_t + E_t. \tag{3}$$

In the case of time-series data with autocorrelated errors, the random component can be determined by the following autoregressive error model:

$$E_t = -\varphi_1 \cdot E_{t-1} - \varphi_2 \cdot E_{t-2} - \ldots - \varphi_m \cdot E_{t-m} + e_t \\ e_t \sim IN(0, \sigma^2), \tag{4}$$

where the random error term (e_t) is normally and independently distributed (with mean zero and variance σ^2) and ϕ_i are the autoregressive error model parameters. However, EWDI and S/W have not exhibited seasonal variation, because these indices were estimated from monthly mortality rates. So these indices show only trend and random variability (the irregular component). In this study, the regression coefficients and the autoregressive error model parameters (φ_m) were estimated by a regression model with autocorrelated errors (Eq. 4) (SAS Institute Inc. 2017).

The regression analysis was performed using statistical tests in AUTOREG procedure in SAS/ETS 14.3 (Cromwell et al. 1994; SAS Institute Inc. 2017) to investigate EWDI, S/W, HDD and CDD trends for the evaluated countries. Parametric trend tests, such as first-order regression analysis, are more powerful than nonparametric ones, but they are very sensitive to outliers, make stronger assumptions about the distribution of the data and require sufficiently long time series, often not available in mortality studies. In this study, we used parametric methods to test the basic assumptions of linear regression models. If p value is greater than the chosen significance level of 0.05 (for all statistical tests presented below), then the corresponding test fails to reject the null hypothesis.

The nonparametric Mann–Kendall and Sen's methods (Mann 1945; Sen 1968; Hamed and Rao 1998) were applied, using XLSTAT software (Addinsoft 2014), to determine slope and statistical significance of overall trends of the time series data. The KPSS test was applied to test for the presence of any stochastic trend (trend that is not constant and can change over time) in a time series, which assesses the null hypothesis of stationarity against the alternative of a non-stationary unit root process. The bandwidth selection for the KPSS test was derived using automatic procedures, such as the Bartlett kernel and the Quadratic Spectral kernel (Kwiatkowski et al. 1992; SAS Institute Inc. 2017). Furthermore, a p value above 0.05 means we have no evidence that a series is not trend stationary (at the usual 5% significance level) (Kwiatkowski et al. 1992; Newey and West 1994; Hobijn et al. 2004; SAS Institute Inc. 2017). The statistical tests for normality, such as the Anderson–Darling, Shapiro–Wilk and Jarque–Bera tests, are associated with the null hypothesis that the population (from which the sample is drawn) is normally distributed. When the p value is greater than the alpha risk threshold (in this case 0.05), the statistical analysis suggests normally distributed data (Anderson and Darling 1954; Shapiro and Wilk 1965; Jarque and Bera 1980, 1987; Royston 1992). The presence of heteroscedasticity was then tested by the White's test, the Breusch–Pagan test and autoregressive conditional heteroscedasticity models (Breusch and Pagan 1979; White 1980; Engle 1982; McLeod and Li 1983). Independence tests are widely used in model selection, residual analysis, and model diagnostics, because ordinary least squares (OLS) regression models are based on the assumption of independently distributed errors. The Wald–Wolfowitz test (or runs test for randomness) and turning point test are two widely used tests for independence. The statistics of both tests have approximately the standard normal distribution under the null hypothesis of independence (Wald and Wolfowitz 1940; SAS Institute Inc. 2017).

Since the runs test completely ignores the magnitudes of the observations, an alternative statistic is the rank version of the von Neumann ratio test (SRVN test statistic). In the case when the SRVN test statistic is less than the critical value of the test, the null hypothesis of independence is accepted (Bartels 1982; SAS Institute Inc. 2017). There is also a statistical assumption that the ordinary regression residuals are uncorrelated over time. The sample autocorrelation (ACF) and partial autocorrelation (PACF) plots were used to detect the presence of autocorrelation in the residuals. The Durbin–Watson test statistic (DW) tests the null hypothesis that the residuals are not autocorrelated against the alternative hypothesis that the residuals from an ordinary least-squares regression follow a first-order autoregressive process (a value of DW near 2 indicates non-autocorrelation) (Durbin 1969; White 1992). The Ljung–Box Q-statistics and the Breusch–Godfrey Lagrange multiplier (LM) test for high-order serial correlation were then used with the null hypothesis that there is no serial correlation in the residuals up to the specified order (Godfrey 1978a, 1978b). In the cases where there was some autocorrelation in the residuals, a first-order autoregressive error correction model was used to take into account the autocorrelation of the regression error terms (Eq. 4). The presence of heteroscedasticity in the residuals of the final model was also tested by all ARCH tests in the AUTOREG procedure (Engle 1982; McLeod and Li 1983; Lee and King 1993; Wong and Li 2011; Wooldridge 2013).

Furthermore, the Ramsey's RESET test, for the presence of nonlinear relationships between the independent and dependent variable, was used with the null hypothesis that the regression model is correctly specified (Ramsey 1969). When the regression model is nonlinear, a direct approach is to use simple transformations to linearize the regression function. Therefore, in this study in order to fit an adequate trend model, we adopted (Wooldridge 2013): (I) the simple linear regression model, (II) the log–linear regression model based on logarithmic transformation of the response variable to linearize an exponential function, (III) the log–log regression model based on logarithmic transformation of both sides of a power function to linearize regression relation, and (IV) the sqrt–sqrt regression model based on square root transformation of both variables. Details of the statistical analysis are described in the appendix.

Data

Based on the Eurostat database (Eurostat 2021a), we examined seasonal variations in mortality in almost all European countries over the period 1960–2018, using data on monthly all-cause mortality in the general population. We investigated the distribution over time of the Excess Winter Deaths Index (EWDI) and the Summer-to-Winter deaths ratio (S/W). Also, we examined the temporal fluctuation of the Heating and Cooling Degree Days indices for the period 1979–2020. Both Heating and Cooling Degree Days indices were calculated by the Joint Research Center's AGRI4CAST Resources Portal and re-published by Eurostat.

Results

Temporal distribution of EWDI is presented in Fig. 1. We found a clear spatial pattern of EWDI, using Mann–Kendall's trend test, with statistically significant decreasing trends in Greece, Italy, Spain, United Kingdom and Ireland, increasing trends in Denmark and Sweden, and insignificant (near-zero) trends in the other countries (Table 1). Conversely, by considering the Summer-to-Winter deaths ratio (S/W), we found significant ($p < 0.05$) increasing trends in the Mediterranean countries and decreasing trends in the Nordic countries (Fig. 2). Furthermore, for each country with statistical significant trend we used regression models to estimate the time trend equation (Table 2). In addition, we applied parametric statistical tests to validate the basic assumptions of normality, independence and homoscedasticity of residuals (Table 3).

Also, statistical analysis of HDD and CDD indices, shown that HDD exhibited statistical significant decreasing trends ($p < 0.01$ for Portugal and $p < 0.001$ for other countries) for all European countries (Fig. 3), probably due to the appearance of milder winters. On the other hand, as we move toward the Mediterranean region, the values of Cooling Degree Days index exhibited a statistically significant upward trend ($p < 0.1$ for Portugal and $p < 0.001$ for Spain, Italy and Greece), over the whole period of analysis, mainly due to the increased frequency of warmer summers, as a result of climate change. The statistical analysis of the HDD index for Greece is presented in Table 4 (the results for all indices are presented in the supplementary appendix).

Discussion and conclusions

Previous studies have shown that countries with very mild winters in Southern Europe had higher levels of excess winter deaths than those countries with more severe winters in Northern Europe (McKee 1989; Healy 2003; Fowler et al. 2015). Our findings reveal that the spatial patterns of excess winter mortality (Fig. 1, Table 1) indices may be reversed in the near future, probably because global warming effects show a clear latitudinal gradient, generally increasing toward Southern Europe (Forzieri et al. 2017) as it can be seen in Fig. 3, with statistical significant increasing trends for CDD index only for Mediterranean countries. A possible explanation for our findings is that climate change already

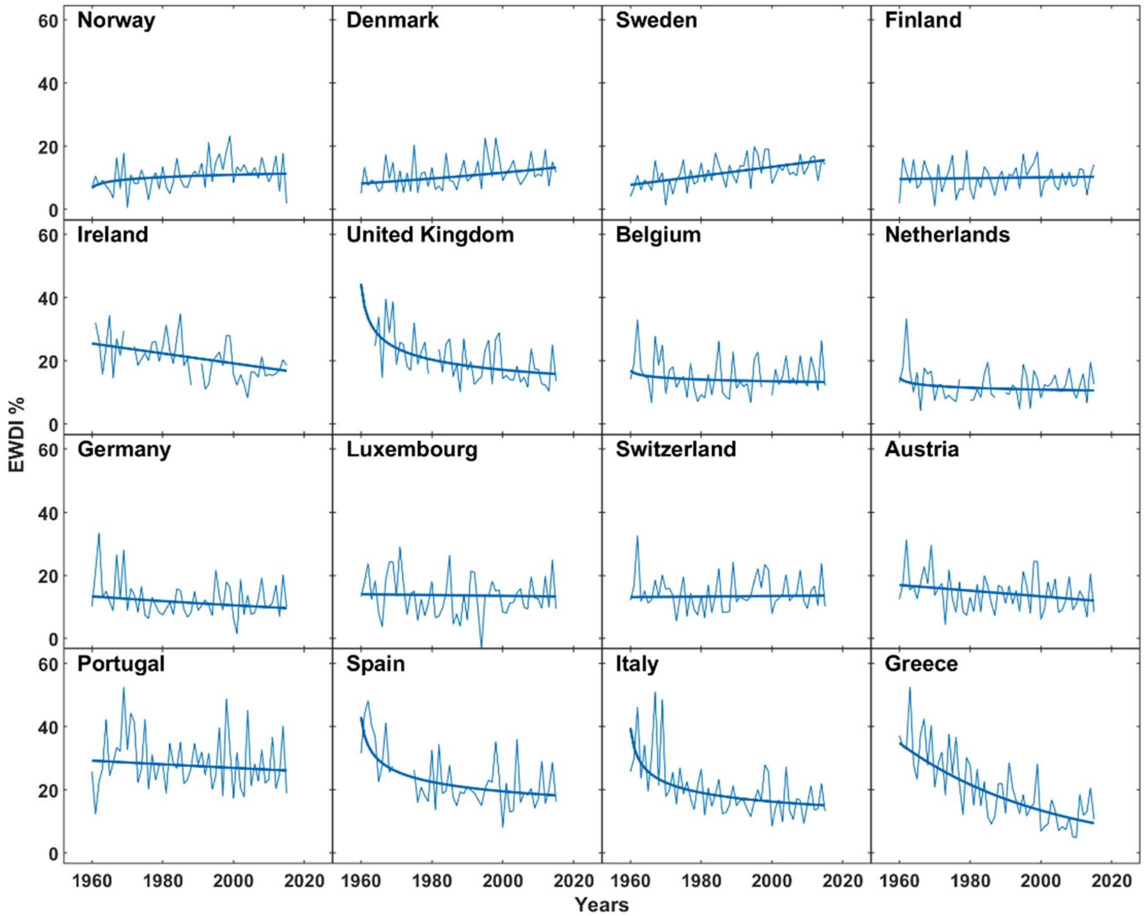

Fig. 1 Temporal distribution of EWDI for Mediterranean, Atlantic, Central, North and Nordic European countries (the lines represent time trends of EWDI index)

Table 1 Mann–Kendall trend test and Sen's slope values for Excess winter deaths index (EWDI) by country

Country	Mann–Kendall's trend test (*p*-value)	Sen slope
Greece	0.001	– 0.4555
Italy	0.001	– 0.1934
Spain	0.05	– 0.1892
United Kingdom	0.001	– 0.2447
Ireland	0.01	– 0.1677
Denmark	0.01	0.0943
Norway	0.1	0.078
Sweden	0.001	0.1433

brings milder winters and hotter summers to the Mediterranean countries, while in the Nordic countries global warming causes less severe winters and more pleasant summers (Aström et al. 2016; Oudin Åström et al. 2018).

Many epidemiological studies (Gasparrini et al. 2016; Gasparrini et al. 2017; Gasparrini et al. 2015b) have shown that winter warming contributes to lower cold-related mortality rates in all countries, while summer warming contributes to higher heat-related mortality rates in the Mediterranean region and, on the contrary, reduced mortality rates in the Nordic countries (Fig. 2). This study shows that the differences in EWDI between European countries are likely to disappear, as the climate gets warmer as shown in Fig. 3 with statistical significant decreasing trends of HDD index for all European countries and increasing trends for CDD index only for Mediterranean countries. There is a pronounced increase in the summer contribution to total mortality with decreasing EWDI trends and increasing S/W trends in Southern Europe, probably associated with a summer-dominant warming (Forzieri et al. 2017; Gasparrini et al. 2017, 2015a; Mora et al. 2017) and a more subdued decrease in the winter contribution to total mortality (Gasparrini et al. 2017). In the Nordic countries, any reduction in cold-related mortality is likely to be lower than the reduction in the non-winter mortality rates, finally resulting in increasing EWDI trends (Oudin Åström et al. 2018).

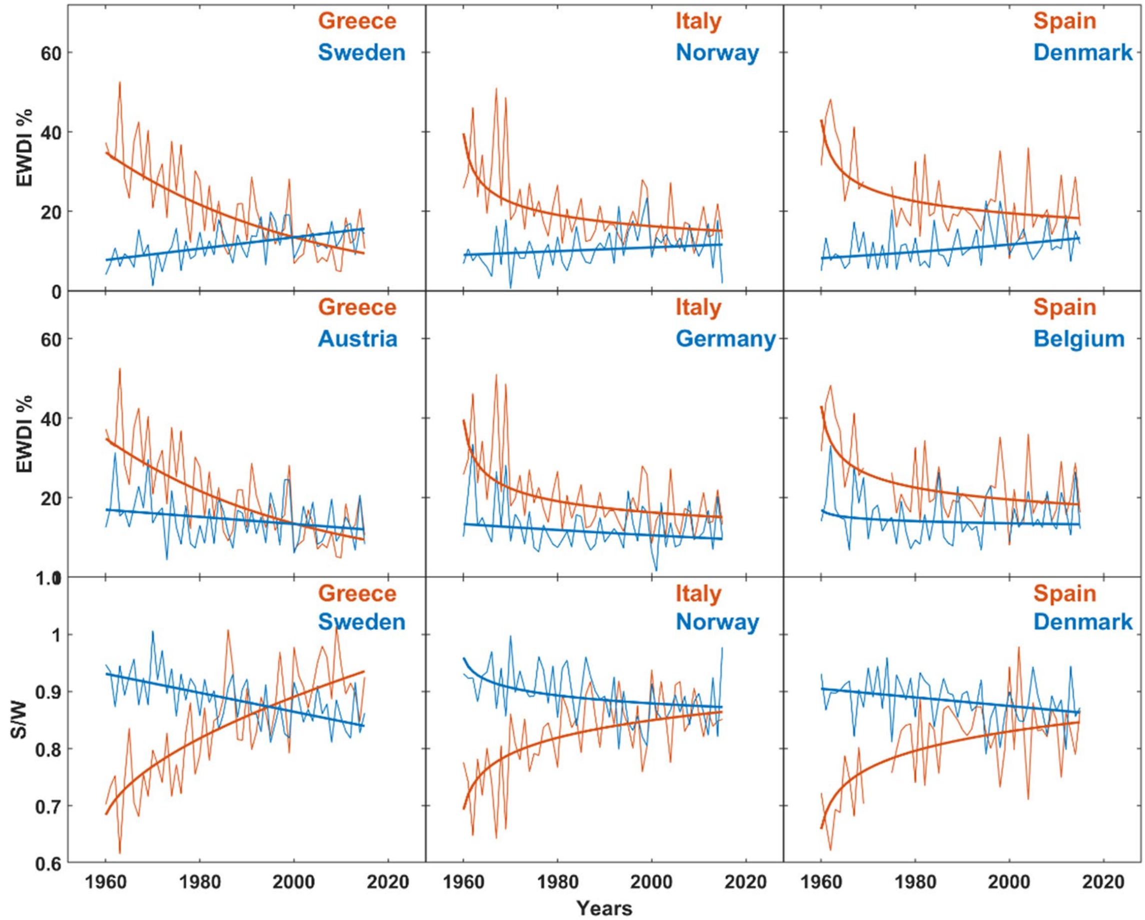

Fig. 2 Distribution over time for EWDI and S/W between Mediterranean, Scandinavian and Central European countries

The results for the temporal fluctuations of Heating and Cooling Degree Days indices show that global warming has brought changes in climate conditions, such as decreasing trends of excess cold weather for all European countries and increasing trends of excess heat for Mediterranean countries (Fig. 3). Analysis of Summer-to-Winter deaths ratio (S/W) shows that heat-related mortality for Mediterranean countries is increasing for the whole study period (Fig. 2), probably due to global warming and heatwave episodes (Mora et al. 2017; Gasparrini et al. 2015b). For Nordic countries, S/W ratio shows decreasing trends as global warming causes more pleasant summers.

In the present study, the Excess Winter Deaths Index (EWDI) was used to analyze the human mortality in Europe. The innovation of this study is the analysis of seasonal variation of mortality in European countries using time series models. Also, this work could provide a basis to investigate potential effects of global warming on human mortality, the findings of this study are likely to be crucial for climate change policy and developing relevant adaptation strategies in Europe. The results are generally consistent with those of a very recently published study (Gasparrini et al. 2017), in which the southern parts of Europe are projected to experience a pattern of decreasing trends in cold-related mortality and a rapid increase in the excess mortality associated with heat, as it can be seen in Fig. 2, under extreme scenarios of global warming. By contrast, the northern parts of Europe are projected to initially experience a low warming rate and a relatively high cold component, as it can be seen in Fig. 3 with decreasing trends of HDD index, resulting in a net reduction in temperature-related excess mortality, although this pattern could reverse during the course of the century (Gasparrini et al. 2017). However, it would be wise to note some of the obvious limitations on the use of EWDI as an indicator of health impacts associated with cold weather (Hajat and Gasparrini 2016). Among the limitations, the most noteworthy fact is that excess winter deaths are influenced by differences in the distribution of cold-related deaths across the colder months of the year. It is clear that cold season

Table 2 Trend equations for mortality indices by country

EWDI			
Greece	$\log(y) = 1.55 - 0.01 \cdot x + \varepsilon_t$	$p < 0.0001$	Semi-log model
Italy	$\log(y) = 1.60 - 0.24 \cdot \log(x) + \varepsilon_t$	$p < 0.0001$	Log–log model
Spain	$\log(y) = 1.63 - 0.21 \cdot \log(x) + \varepsilon_t$	$p < 0.0001$	Log–log model
United Kingdom	$\log(y) = 1.65 - 0.26 \cdot \log(x) + \varepsilon_t$	$p < 0.0001$	Log–log model
Ireland	$y = 25.68 - 0.16 \cdot x + v_t$ $v_t = 0.17 \cdot v_{t-1} + \varepsilon_t$	$p = 0.0057$	Linear model with autoregressive error correction
Denmark	$\log(y) = 0.91 + 0.00038 \cdot x + v_t$ $v_t = -0.36 \cdot v_{t-1} + \varepsilon_t$	$p < 0.0001$	Linear model with autoregressive error correction
Norway	$\log(y + 104.1) = 2.0451 + 0.01\log(x) + \varepsilon_t$	$p = 0.1331$	Log–log model
Sweden	$y = 7.65 + 0.14 \cdot x + \varepsilon_t$	$p < 0.0001$	Linear model
S/W			
Greece	$\mathrm{sqrt}(y) = 0.81 + 0.02 \cdot \mathrm{sqrt}(x) + \varepsilon_t$	$p < 0.0001$	Sqrt-sqrt model
Italy	$\log(y) = -0.16 + 0.05 \cdot \log(x) + \varepsilon_t$	$p < 0.0001$	Log–log model
Spain	$\log(y) = -0.18 + 0.06 \cdot \log(x) + \varepsilon_t$	$p < 0.0001$	Log–log model
United Kingdom	$\log(y) = -0.1787 + 0.57 \cdot \log(x) + \varepsilon_t$ $v_t = -0,26 \cdot v_{t-1} + \varepsilon_t$	$p < 0.0001$	Linear model with autoregressive error correction
Ireland	$y = 0.72 + 0.0014 \cdot x + \varepsilon_t$	$p < 0.0001$	Linear model
Denmark	$y = 0.91 - 0.00075 \cdot x + v_t$ $v_t = -0.31 \cdot v_{t-1} + \varepsilon_t$	$p = 0.0009$	Linear model with autoregressive error correction
Norway	$\log(y) = -0.02 - 0.02 \cdot \log(x) + \varepsilon_t$	$p = 0.0244$	Log–log model
Sweden	$y = 0.93 - 0.00166 \cdot x + v_t$ $v_t = -0.29 \cdot v_{t-1} + \varepsilon_t$	$p < 0.0001$	Linear model with autoregressive error correction

Table 3 Residuals and model diagnostics for trend equations by country

	Residuals diagnostics			Model diagnostics
	Normality: Shapiro–Wilk (p -value)	Serial correlation: Durbin-Watson (DW statistic)	Heteroscedasticity: White's test (p -value)	Misspecification test: Ramsey's RESET (p -value)
EWDI				
Greece	0.5579	1.8122	0.0106	0.0631
Italy	0.5491	2.3086	0.8221	0.4735
Spain	0.5979	2.2168	0.5501	0.6017
United Kingdom	0.0509	2.4075	0.6731	0.8348
Ireland	0.7880	1.8866	0.8392	0.2555
Denmark	0.0840	1.9405	0.1714	0.9076
Norway	0.5972	1.8850	0.1506	0.9721
Sweden	0.4979	2.3691	0.4119	0.4520
S/W				
Greece	0.8688	1.8864	0.8333	0.6918
Italy	0.0773	2.1469	0.0825	0.4612
Spain	0.8272	2.1741	0.7195	0.6938
United Kingdom	0.3479	1.9276	0.5665	0.7499
Ireland	0.4373	1.6829	0.7217	0.1480
Denmark	0.4803	1.9973	0.9064	0.9790
Norway	> 0.1500	1.7192	0.0672	0.6202
Sweden	0.4130	1.9491	0.8911	0.7898

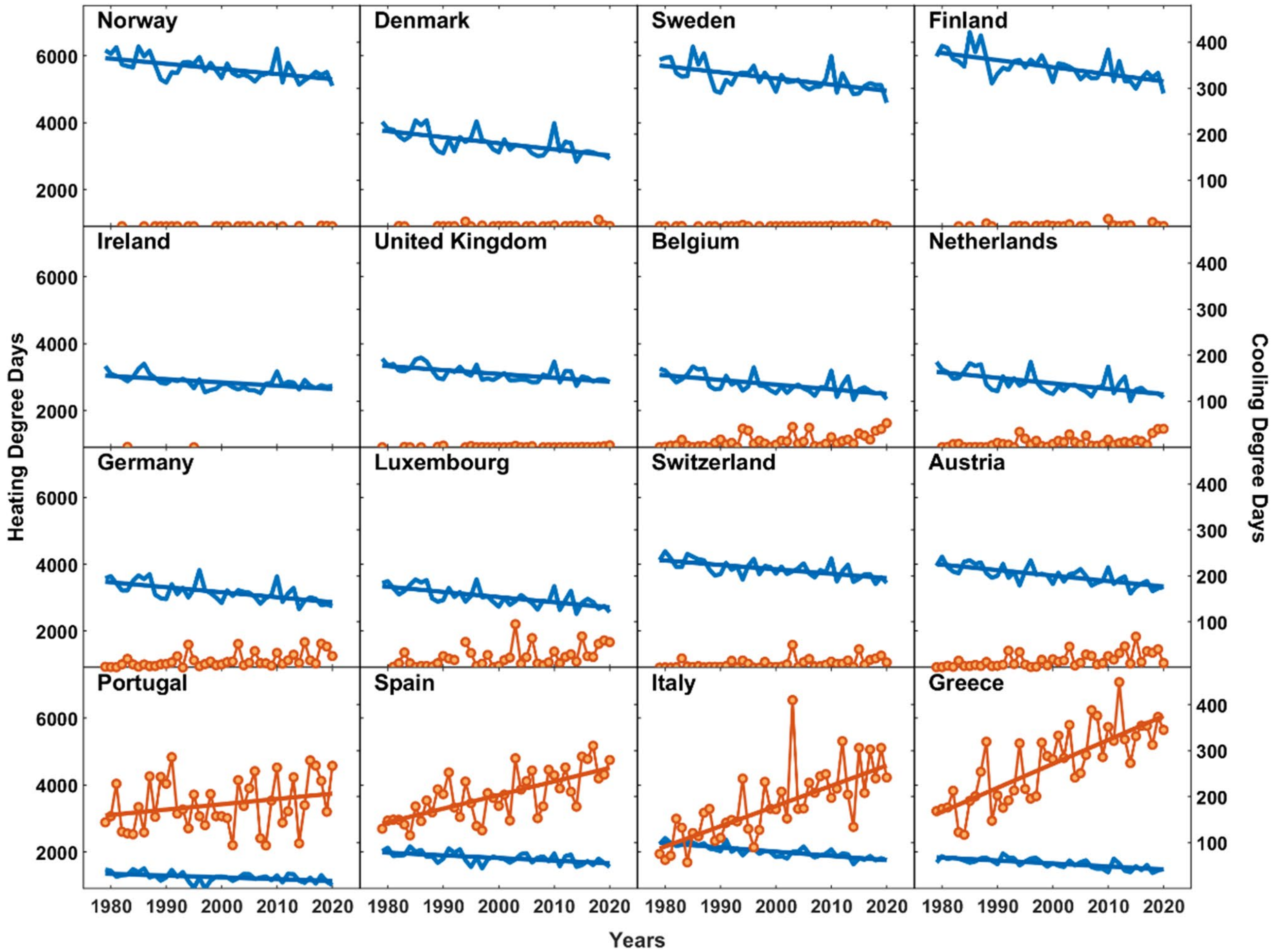

Fig. 3 Temporal distribution of Heating (blue lines) and Cooling (orange lines) Degree Days for Mediterranean, Atlantic, Central, North and Nordic European countries

lasts longer in the north than in the south of Europe, which may contribute to uncertainties in estimates of the differences in EWDI that exist between southern and northern European countries (The Eurowinter Group 1997; Liddell et al. 2015). This index can also be influenced by differences in the distribution of excess deaths due to seasonal infections such as influenza (or other seasonal factors unrelated to weather) across the winter. Despite the fundamental criticisms that EWDI is not an appropriate indicator of cold-related health impacts, there is a high degree of climatic consistency in the spatial pattern of temporal trends across most European countries (with different climates) regardless of the causal pathway that leads to excess winter deaths (Kinney et al. 2015; Hajat and Gasparrini 2016; Gasparrini et al. 2015a). This could explain the geographical shift seen in Fig. 1, probably suggesting that climate is a key factor in shaping the seasonal mortality cycle.

Adaptation can mitigate the adverse impacts of global warming (Gasparrini et al. 2016, 2017, 2015b), but its effectiveness is strongly dependent on the magnitudes and rates of climate change (IPCC 2014; Gasparrini et al. 2017). Despite a growing number of climate change mitigation policies, anthropogenic greenhouse gases have continued to increase over the last decades (IPCC 2014). Although an increasing threat to human life from global warming seems almost inevitable (Mora et al. 2017), most people in developed countries are reluctant to change their behavioral and lifestyle choices (IPCC 2014; Zoumakis et al. 2017). Therefore, it is necessary to realize that climate change is not only an environmental, economic, political and social crisis, but above all a cultural crisis.

Table 4 Statistical tests for identification and diagnostics checking for the HDD for Greece

Statistical test	p -values
Testing for stationarity	
KPSS (Bartlett kernel)	$p = 0.0764$
KPSS (quadratic spectral kernel)	$p = 0.2974$
Testing for normality	
Jarque—Bera test	$p = 0.4220$
Anderson—Darling test	$p > 0.2500$
Shapiro—Wilk test	$p = 0.3193$
Testing for statistical independence	
Turning points	$p = 0.3184$
Runs test	$p = 0.5214$
Rank version of von Neumann ratio	$p = 0.8494$
Testing for serial correlation	
Durbin—Watson test	$p > 0.05$
Godfrey's serial correlation test	$p > 0.05$
Testing for heteroscedasticity	
Breusch—Pagan	$p = 0.4021$
White's test	$p = 0.5282$
Tests for ARCH disturbances	$p > 0.05$
Testing for nonlinear dependence	
Ramsey's RESET	$p = 0.1725$

If p value is greater than 0.05 (for all statistical tests presented below), then t corresponding test fails to reject the null hypothesis

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11600-022-00809-4.

Declarations

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

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