INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. (2017)
Published online in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.5295

Recent changes in heat waves and cold waves detected based on excess heat factor and excess cold factor in Romania

Adrian Piticar, Adina-Eliza Croitoru,* Flavius-Antoniu Ciupertea and Gabriela-Victoria Harpa

Faculty of Geography, Babeş-Bolyai University, Cluj-Napoca, Romania

ABSTRACT: In this paper, we investigated changes in heat and cold waves in Romania over the period 1961–2015 by employing a new and superior approach. It consists in using excess heat factor to identify heat waves and excess cold factor to identify cold waves. Five indices were calculated and then analysed for both heat waves and cold waves resulting in a set of ten indices. Indices for heat waves were analysed for the extended summer season (May–September), whereas those for cold waves were assessed for the extended winter (November–March). The intensity threshold was set to be equal or above the 90th percentile for heat waves, and equal or below the 10th percentile for cold waves, while the duration threshold for both heat and cold waves was of at least three consecutive days. For a better comparison with other studies conducted worldwide, and to get more information from the data sets, the percentile thresholds for heat and cold waves identification were calculated based on three reference periods: 1961–1990, 1971–2000, and 1981–2010. Trends were calculated using ordinary least square method, whereas statistical significance was assessed by the *t*-test. The main results indicated that changes are more substantial in the case of indices calculated based on excess heat factor compared to those based on excess cold factor, suggesting that the warming process is more reflected in heat waves rather than in cold waves. Thus, heat waves became more frequent, longer, and more intense, while cold waves became less frequent, but more intense. When the reference period for percentile threshold calculation was changed from the earliest to the most recent ones, the frequency of increasing and significant increasing trends decreased for some of the heat wave indices, while for the cold wave indices the significant downward trends increased.

KEY WORDS climate changes; heat wave indices; cold wave indices; excess heat factor; excess cold factor; ordinary least square method; Romania

Received 10 April 2017; Revised 19 August 2017; Accepted 22 August 2017

1. Introduction

Among natural hazards, heat and cold waves cause a high number of casualties. Heat wave (HW) and cold wave (CW) events are factors of high stress to biological systems, especially elderly and young population, who are the most vulnerable and can be put at risk (Hartz *et al.,* 2012). Although the human body can be very effective in adapting its functions to environmental conditions and acclimatize, sudden exposure to extreme high or low temperatures may cause serious health problems or even death (Basarin *et al.,* 2016). The failing of the human body to adequately respond to HWs and CWs can lead to heat strokes, acute cerebrovascular accidents, contribute to thrombogenesis, and aggravate chronic cardiac and pulmonary conditions, kidney failure, hyperthermia and hypothermia, and other diseases (WHO, 2006; Basarin *et al.,* 2016). The risk of death during heat and cold episodes can also arise from indirect causes related to heat and cold such as drowning accidents or carbon monoxide intoxication (Kim *et al.,* 2016). Even though there is no simple relationship between air temperature and morbidity and mortality, high correlation between certain extreme temperatures and mortality has been demonstrated worldwide (Knowlton *et al.,* 2009; Barnett *et al.,* 2012). HWs cause more deaths all over the world than any other natural hazards (Unkaševic and Tošic, 2009; D'Ippoliti *et al.,* 2010; Peterson *et al.*, 2013; Shaposhnikov *et al.,* 2014; Liu *et al.,* 2015; Nairn and Fawcett, 2015; Kim *et al.,* 2016; Chen *et al.,* 2017). Some previous studies showed an increase in the number of deaths during HWs: between 3.0 and 7.8% in the United States of America (Medina-Ramón and Schwartz, 2007; Anderson and Bell, 2009; Peng *et al.,* 2011), 21.8% in the Mediterranean areas (D'Ippoliti *et al.,* 2010), 16.5% in Spain (Linares *et al.,* 2015), 5% in China (Ma *et al.,* 2015). At present, it is considered highly likely that anthropogenic effect on climate will double the risk of HWs of the same magnitude of that which occurred in Europe in 2003 and was characterized by a severe impact on population (Montero *et al.,* 2012). In coming years, changes in HWs are expected to have a greater impact on human mortality than CWs (Linares *et al.,* 2015; Wang *et al.,* 2016).

CWs also contribute to a wide range of impacts on human health, including death from respiratory and cardiovascular conditions (Barnett *et al.,* 2012). In Central and

* Correspondence to: A.-E. Croitoru, Department of Physical and Technical Geography, Faculty of Geography, Babeş-Bolyai University, 5-7, Clinicilor Street, 400006 Cluj-Napoca, Romania. E-mail: adina.croitoru@ubbcluj.ro; adina04@yahoo.com

Eastern Europe more than 800 deaths caused by hypothermia resulted after extremely cold conditions in the winter of 2011/2012 (Lhotka and Kyselý, 2015). The effect of CWs on mortality revealed an increase by 12.9% in Spain (Linares *et al.,* 2015), 10% in China and Russia (Revich and Shaposhnikov, 2016; Ryti *et al.,* 2016), and 2.1% in the United States of America (Wang *et al.,* 2016). Such substantial differences in the excess mortality during HWs and CWs around the world could be explained by the climate, adaptation, and socioeconomic status of each region in which it was reported (Wang *et al.,* 2016).

Climatologists worldwide have shown a significant increase in HWs number, duration, and intensity, and a decrease of the same parameters of CWs. These findings could explain the increase in HW-related mortality and the decrease in CW-related mortality (Radinović and Ćurić, 2012; Oleson *et al.,* 2015; Rusticucci *et al.,* 2015; Spinoni *et al.,* 2015; Wang *et al.,* 2016).

In terms of economic impact, changes in both HWs and CWs imply an important change in electricity production and demand (Parey and Hoang, 2015), and induce vulnerability in the electricity sector. They could also have a considerable impact on other sectors of human activity and environment.

HWs and CWs are described in a very wide range of definitions in which a heat or cold event is represented by a number of consecutive days which can vary from two to six or even more days when maximum air temperature (TX) or minimum air temperature (TN) registers values above or below a certain fixed or relative threshold. Some definitions take into consideration 1 or 2 days of no heat or cold wave conditions included within a longer event, while others eliminate or break it into two or more events. These definitions are good predictors of extreme heat or cold events, but they may be imprecise when it comes to related morbidity and mortality, and also to impacts on other specific sectors. Recently, a few studies have analysed HWs by using the excess heat factor (EHF) and showed that this approach is superior to other definitions and it can be used as a better indicator for HW-related mortality and morbidity compared to singular daily values of TX or TN (Langlois *et al.,* 2013; Nairn and Fawcett, 2013; Scalley *et al.,* 2015; Hatvani-Kovacs *et al.,* 2016). EHF quantifies the intensity of an HW event by factoring in the cumulative effect of high TX and TN in a 3-day period contrasted with a prior 30-day acclimatization period, in terms of temperature, and with the long-term normal climatic conditions (Nairn and Fawcett, 2013, 2015; Scalley *et al.,* 2015; WMO and WHO, 2015; Rohini *et al.,* 2016; Loughran *et al.,* 2017). Acclimatization involves a wide range of physiological adaptation processes, including changes in heart rate, stroke volume, plasma volume expansion, increased sweat rate and alternations in core body temperature (Scalley *et al.,* 2015). The acclimatization period used in the EHF formula considers all these physiological processes that may result in human body responses to HWs (Scalley *et al.,* 2015). Hatvani-Kovacs *et al.* (2016) indicated that EHF can predict 77% of excess morbidity during the most intense HW days and enables a more in-depth analysis of the HWs severity. This approach is also analogously applicable to CWs by employing the excess cold factor (ECF) (Nairn and Fawcett, 2013; Wang *et al.,* 2016). Thus, ECF identifies a 3-day period of unusual cold compared with long-term climate and short-term period needed for the human body to acclimatize, including behavioural changes and physiological adaptation (Wang *et al.,* 2016). One of the main advantages of using these definitions for measuring HWs and CWs is that it can be used in a variety of climates, since its value is relative to the local climate.

The main aims of this study were to detect and analyse changes in HWs and CWs in Romania by using a new and superior approach and find regional patterns of changes. For Romania some previous studies were conducted (Croitoru, 2014; Dragotă and Havriş, 2015; Spinoni *et al.,* 2015; Huştiu, 2016; Papathoma-Koehle *et al.,* 2016; Croitoru *et al.,* 2016a), but EHF and ECF have not yet been considered for the identification of HWs and CWs.

2. Data and methods

2.1. Study area

Romania is located in Eastern Europe between latitudes 43°40′N and 48°11′N and longitudes 20°19′E and 29°66′E (Figure 1). The analysed area has a temperate continental climate with general influences of dry air from east and moist air masses coming from west. There are some regional differences, mainly due to the presence of the Carpathian Mountains, which form a natural barrier in front of different types of air masses. Thus, the extra-Carpathian regions (eastern, southeastern, and southern regions) have similar characteristics and they are drier and hotter in summer and drier and colder in winter, whereas the intra-Carpathian regions (the western and central areas) have mild winters and they are wetter and cooler in summer.

Romania has a population of 20.1 mil inhabitants, 54% of them living in urban areas and 46% in rural settlements. Out of the total population, 20% are highly vulnerable to HWs and CWs in terms of age (approximately 1 mil children between 0 and 4 years and more than 3 mil adults, 65 or older). The increase of urban elder population is expected to bring a considerable higher impact during summer HWs (Papathoma-Koehle *et al.,* 2016), whilst the effects of CWs on human health are estimated to diminish.

2.2. Data

Data series of EHF and ECF were derived from TX and TN data sets recorded in 31 weather stations across Romania over a 55-year period (1961–2015). The spatial distribution and geographical coordinates of the considered weather stations are shown in Figure 1 and Table 1. Most of the data sets were freely downloaded from ECA&D database (Klein Tank *et al.,* 2002) (non-blend data over the period 1961–2009) and reconstructed from row synoptic messages available at www.meteomanz.com (for the period 2010–2015). In the case of five weather stations

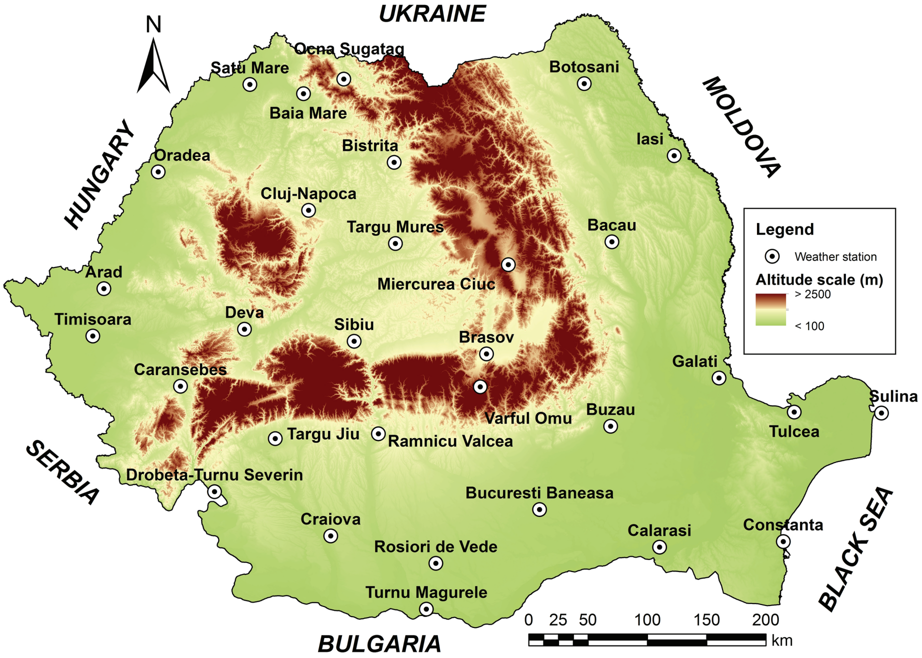

Figure 1. Study area and considered weather stations. [Colour figure can be viewed at wileyonlinelibrary.com].

(Brasov, Satu Mare, Oradea, Timisoara, and Targu Mures) data sets were provided by the Romanian National Meteorological Administration (RNMA). The 55-year period (1961–2015) was chosen in order to avoid as much as possible the inhomogeneities and gaps in the daily data that could be induced by some non-climatic factors, such as changes in the observation practices and timetable, or historical events, as the world wars (Croitoru *et al.,* 2015, 2016a). Also, the 55-year period is long enough for trend detection. So as to meet the World Meteorological Organization (WMO) requirements, we did not include stations that had more than 5% of missing data. Finally, each station used for this study had less than 2.2% of missing data (Table 1).

2.3. Methods

2.3.1. Data quality control

Before indices calculation, all the data were quality controlled by using ClimPACT2 software. As described in the *User guide*, the quality control (QC) consisted in a complex procedure based on seven tests (Alexander and Herold, 2016).

First, the interquartilic range (IQR) technique was employed at monthly time-scale to identify the potential outliers. The IQR is the difference between the 75th and the 25th percentile. All temperature data values falling outside the range defined by 25th - 3 and 75th + 3 IQR are considered outliers. This method has the advantage that the detection of percentile-based outliers is not affected by the presence of larger outliers.

The second step used for QC consisted in reporting the occurrence of four or more equal consecutive values in the temperature data series.

The third technique assessed and considered for elimination all values higher than 50.0 °C.

The fourth step of QC stage considered the cases in which temperature difference between two consecutive values was equal or higher than 20.0 °C.

The fifth technique detected all the cases when TN was higher than TX of the same day and fixed them.

The sixth step considered for elimination the values of TX and TN, which were more than four standard deviations away from their mean values.

The seventh technique evaluated the rounding problems. This test assessed how often each of the ten possible values (0.0–0.9) appeared after the decimal point. If one or more values are too or less frequent than others, one might consider to discharge the series or use a statistical approach to restitute the data. After QC assessment only a few errors were found in the data sets and they were eliminated.

2.3.2. Calculation of excess heat factor and excess cold factor

The two indices were calculated based on percentile values. The threshold percentiles were computed for each corresponding calendar day of the year (including those in the extended summer and extended winter seasons) using a 15-day running window. This calculation technique was implemented in the standardized software ClimPACT2 developed by expert team on Sector-specific Climate Indices (ET-SCI) of the WMO, Commission for Climatology (www.wmo.ch). Compared to some previous sources (Nairn and Fawcett, 2013; Perkins and Alexander, 2013), in this software the EHF has been updated and uses the 90th percentile of daily mean temperature for each calendar day using a 15-day running window (Alexander and Herold, 2016).

Table 1. Geographical coordinates of the weather stations considered.

No.	Weather station name[a]	Latitude (N)	Longitude (E)	Altitude (m)	Missing data (%)
1	Arad	46°08′15″	21°21′13″	117	0.0
2	Bacau	46°31′54″	26°54′45″	184	0.0
3	Baia Mare	47°39′40″	23°29′36″	224	0.0
4	Bistrita	47°08′56″	24°30′49″	367	0.0
5	Botosani	47°44′08″	26°38′40″	161	0.0
6	Brasov	45°41′46″	25°31′40″	535	0.0
7	Bucuresti Baneasa	44°31′00″	26°05′00″	90	0.0
8	Buzau	45°07′57″	26°51′05″	97	0.0
9	Calarasi	44°12′22″	27°20′18″	19	0.0
10	Caransebes	45°25′01″	22°13′30″	241	0.0
11	Cluj-Napoca	46°46′39″	23°34′17″	410	0.0
12	Constanta	44°12′49″	28°38′41″	13	0.0
13	Craiova	44°18′36″	23°52′00″	192	0.0
14	Deva	45°51′52″	22°53′55″	230	0.0
15	Drobeta-Turnu Severin	44°37′43″	22°37′33″	77	0.3
16	Galati	45°28′23″	28°01′56″	71	0.0
17	Iasi	47°10′15″	27°37′42″	102	0.0
18	Miercurea Ciuc	46°22′16″	25°46′21″	661	0.0
19	Ocna Sugatag	47°46′37″	23°56′25″	504	2.1
20	Oradea	47°02′10″	21°53′51″	136	0.0
21	Ramnicu Valcea	45°05′19″	24°22′45″	239	0.5
22	Rosiori de Vede	44°06′26″	24°58′42″	102	0.0
23	Satu Mare	47°43′18″	22°53′20″	128	0.0
24	Sibiu	45°47′21″	24°05′28″	444	0.0
25	Sulina	45°08′00″	29°45′00″	3	0.2
26	Targu Jiu	45°02′26″	23°16′35″	204	0.0
27	Targu Mures	46°32′01″	24°32′07″	317	0.0
28	Timisoara	45°46′17″	21°15′35″	86	0.0
29	Tulcea	45°11′26″	28°49′26″	4	0.1
30	Turnu Magurele	43°45′36″	24°45′41″	31	0.0
31	Varful Omu	45°26′45″	25°27′24″	2504	0.0

[a]Weather stations are arranged alphabetically.

The percentile thresholds for significant excess heat index (EHI_{sig}) and significant excess cold index (ECI_{sig}) were calculated over three reference periods (1961–1990, 1971–2000, and 1981–2010). This approach allows for a better comparison with other studies and provides useful extra information, since consistent differences were found among those three reference periods when percentile thresholds were calculated and analysed for the considered weather stations in Romania (Figures 2 and 3, and Figures S1–S6, Supporting information).

The reference period of 1961–1990 is recommended by the WMO in the latest update to *Guide to Climatological Practices*, as it should be used to compare climate change and variability across all countries relative to this standard reference period (WMO, 2016).

The other two reference periods were employed because the WMO also accepts the possibility of using more recent reference periods, since considering them allows for a slight improvement in ‘predictive accuracy’ for elements that show a secular trend (i.e. where the time series show a consistent rise or fall in their values when measured over a long-term period). Also, the percentile values calculated based on 1971–2000 or 1981–2010 reference periods would be viewed by many users as more ‘current’ than those calculated based on 1961–1990 period (WMO, 2011). Thus, we considered that the population could be more adapted to the ‘present’ temperatures represented by the last reference period. Even though it is the most ‘optimistic’ situation of changes in HWs, we still found evidence for important changes. Consequently, our study could be an important tool for local and national administration in order to adopt the most appropriate mitigation and adaptation measures.

2.3.2.1. Excess heat factor calculation: EHF is a new method to measure HWs and it is based on two excess heat sub-indices incorporating both TX and TN (Nairn and Fawcett, 2013; Alexander and Herold, 2016):

$$\mathrm{EHI}_{\mathrm{sig}} = \left[\left(Tm_i + Tm_{i-1} + Tm_{i-2}\right)/3\right] - Tm90i \tag{1}$$

and

$$\mathrm{EHI}_{\mathrm{accl}} = \left[\left(Tm_i + Tm_{i-1} + Tm_{i-2}\right)/3\right] \left[-\left(Tm_{i-3} + \cdots + Tm_{i-32}\right)/30\right] \tag{2}$$

where EHI_{sig} describes the anomaly over a 3-day period against the 90th percentile of the mean daily temperature (Tm) of the reference period, Tm_i represents the daily mean temperature for day i (Tm is calculated as average value of TX and TN of the same day i as $Tm = (\mathrm{TX} + \mathrm{TN})/2$), and $Tm90i$ is the 90th percentile of Tm for each calendar day within the user-specified reference period, using a

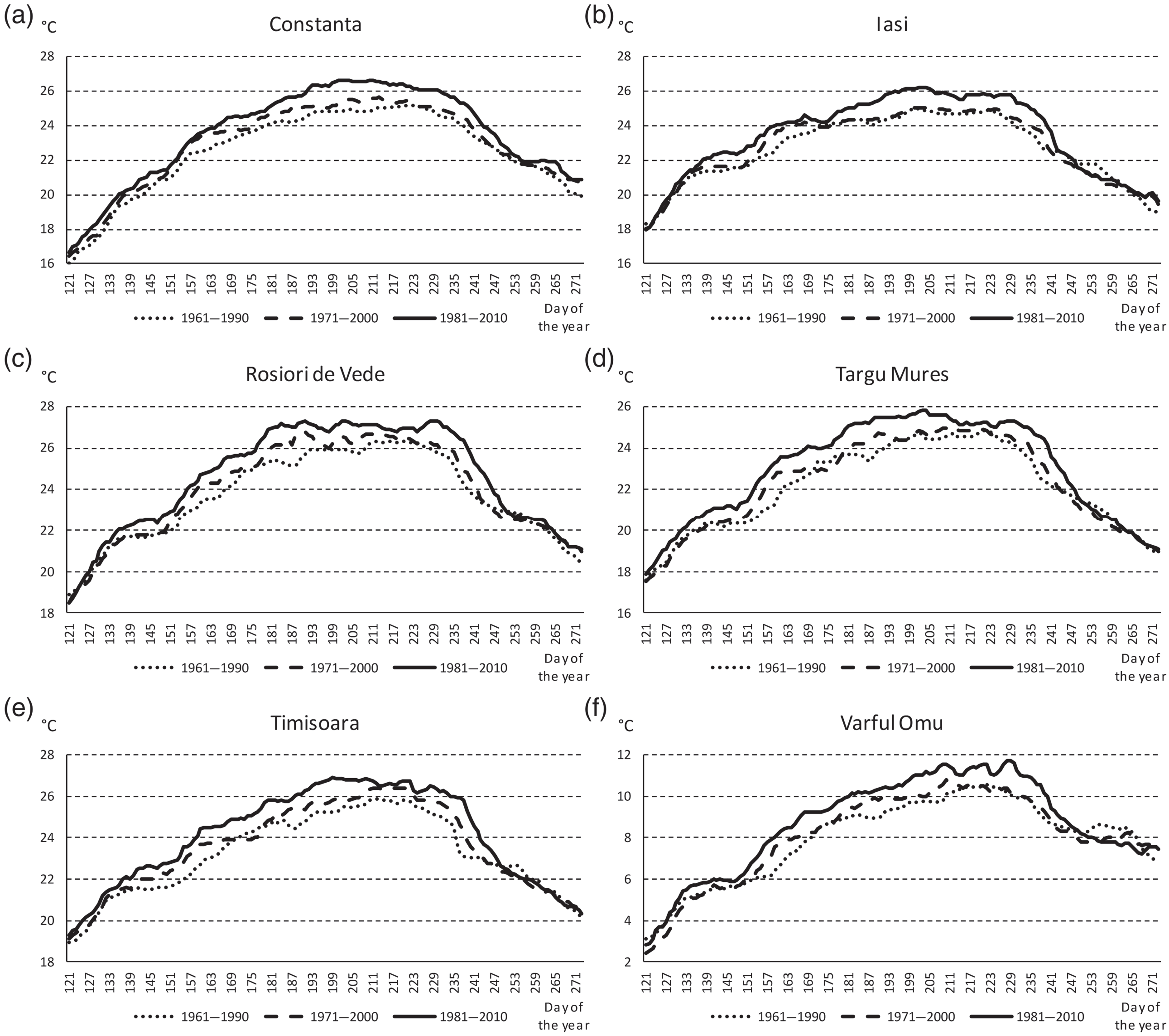

Figure 2. The 90th percentile of daily Tm for extended summer season for three reference periods at six representative weather stations in Romania.

15-day running window; EHI_{accl} is the excess heat index for acclimatization and it is defined as the anomaly of the same 3-day period against the preceding 30 days.

While EHI_{sig} sub-index refers to a significant excess heat against long-term climatic conditions, EHI_{accl} sub-index assesses human body acclimatization to its local climate in terms of air temperature, in 30 days; this takes into account the idea that people acclimatize (at least to some extent) to their local climate, with respect to the temperature variation across latitude and throughout the year, but they may not be prepared for a sudden rise in temperature above the value of the recent past (Nairn and Fawcett, 2015).

Equations (1) and (2) are then combined to obtain EHF:

$$\mathrm{EHF} = \max\left[1, \mathrm{EHI}_{\mathrm{accl}}\right] \times \mathrm{EHI}_{\mathrm{sig}} \tag{3}$$

where positive values of EHF define HW conditions for day *i*. Therefore, these conditions must persist for at least three consecutive days to allow identification of a HW event. Recently, a similar procedure has been successfully employed to study the impact of extreme heat events on human health and mortality (Langlois *et al.,* 2013; Perkins and Alexander, 2013; Hatvani-Kovacs *et al.,* 2016), but it is also efficient for studying the impact on other socio-economic sectors. More specifically, the ability of biological systems to recover from high heat load is dependent on the diurnal variation of temperature. A sufficient drop from TX during the day to TN by night will allow the heat to discharge. However, high TN will lead to an accumulation of heat load, causing excess heat (Nairn and Fawcett, 2013) with negative consequences on various systems. The EHF definition used in this study differs slightly from that stated by Nairn and Fawcett (2013). The main differences consist in using the 90th percentile instead the 95th percentile as intensity threshold for HWs and the calculation of the percentile is based on a 15-day window centred on each calendar day of the extended summer season instead of a single value calculated over the entire season (Alexander and Herold,

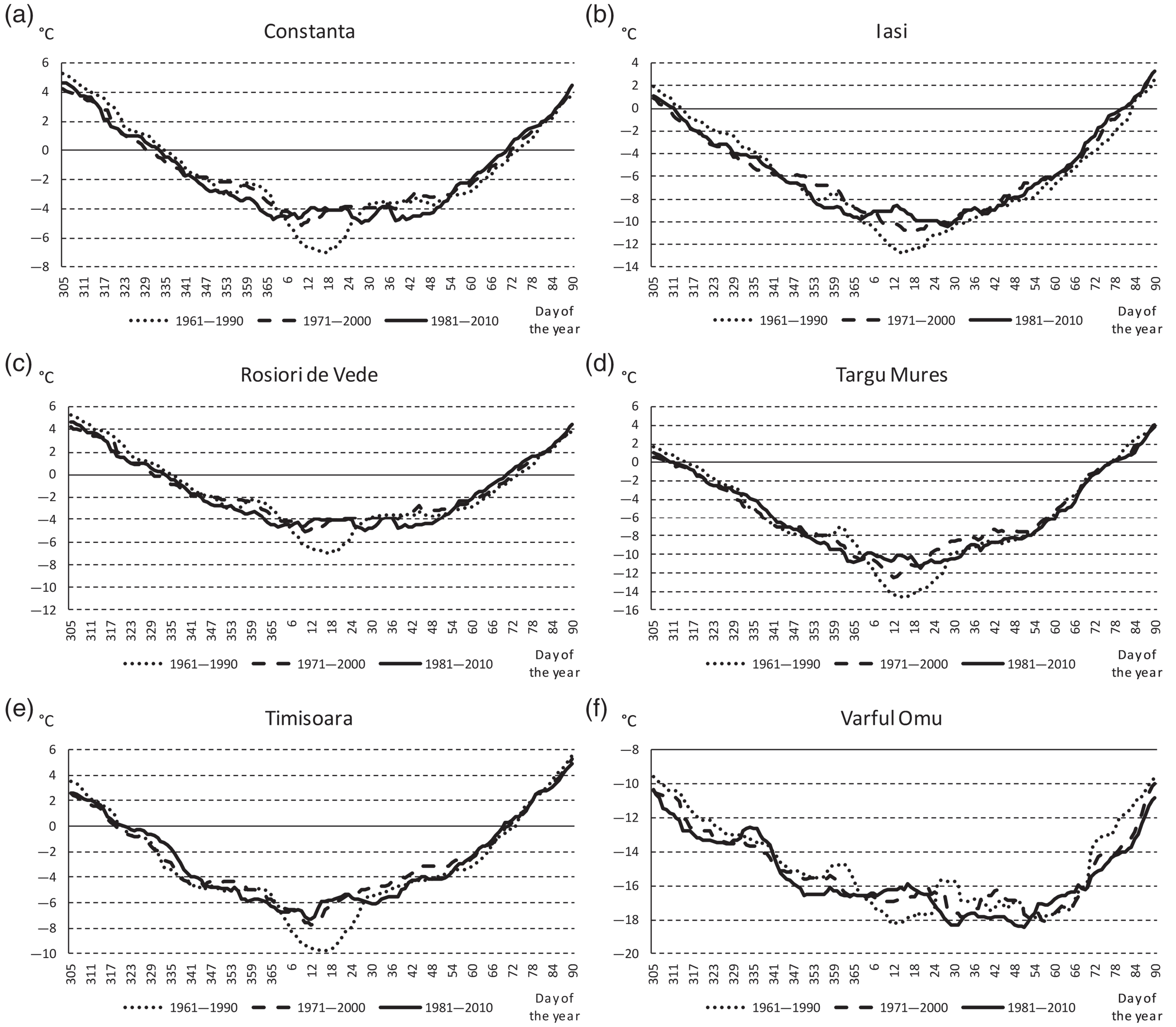

Figure 3. The 10th percentile of daily Tm for extended winter season for three reference periods at six representative weather stations in Romania.

2016). The advantage of using this approach lies in the fact that it can offer better comparisons with other studies which mostly used the 90th percentile for the identification of HWs.

2.3.2.2. Excess cold factor calculation: Similar to EHF, the ECF was developed to measure CWs. It is expressed by two excess cold sub-indices incorporating both TX and TN and it is calculated on the same principles as EHF, as it follows:

$$\mathrm{ECI_{sig}} = \left[\left(Tm_i + Tm_{i-1} + Tm_{i-2}\right)/3\right] - Tm10i \tag{4}$$

where Tm_i is the daily mean temperature of day i and $Tm10i$ is the 10th percentile of Tm calculated for each calendar day (day i) of the considered season (extended winter).

$$\mathrm{ECI_{accl}} = \left[\left(Tm_i + Tm_{i-1} + Tm_{i-2}\right)/3\right] \left[-\left(Tm_{i-3} + \cdots + Tm_{i-32}\right)/30\right] \tag{5}$$

The $\mathrm{ECI_{sig}}$ is the significant excess cold index and measures the significant excess cold against long-term climatic conditions, while the $\mathrm{ECI_{accl}}$ is the excess cold index for acclimatization and measures cold stress induced by short-term temperature contrast. Then ECF is derived from the two sub-indices as:

$$\mathrm{ECF} = -\mathrm{ECI_{sig}} \times \min\left(-1, \mathrm{ECI_{accl}}\right) \tag{6}$$

The negative values of ECF indicate CW conditions, and a period of at least three consecutive days defines a CW event.

The choice of at least three consecutive days for HW and CW indices calculation derived from studies on human responses to onset of extremely hot or cold weather. According to these, it takes three consecutive days of very hot or cold weather in order to rise significantly the mortality rate above its antecedent rate (Nairn and Fawcett, 2015; Wang *et al.*, 2016).

Although some sources state that the effects of CWs on mortality have been observed to be milder than those of

HWs (Ekamper *et al.*, 2009; Miron *et al.,* 2015), and it is recommended to use the more extreme threshold of 5th percentile for ECI_{sig}, we still used the 10th percentile in order to compare the results of CWs to those of HWs.

EHF-based indices were analysed for the extended summer season (May–September), while those based on ECF were assessed for the extended winter season (November–March).

2.3.3. *EHF and ECF indices*

To assess changes in HWs and CWs, five indices were calculated based on both EHF and ECF, resulting in a set of ten indices recommended by ET-SCI of the WMO Commission for Climatology and Indices (CCI) (Table 2):

i. The annual number of individual events in each extended summer for EHF (EHF_HWN) and each extended winter for ECF (ECF_CWN);
ii. The annual number of participating days when conditions for the occurrence of an event are met, as confirmed by definitions (EHF_HWF for EHF and ECF_CWF for ECF);
iii. The length of the longest event measured by EHF (EHF_HWD) and ECF (ECF_CWD) each year;
iv. The mean values of all HW or CW events magnitude in a year (EHF_HWM for EHF and ECF_CWM for ECF);
v. The amplitude is calculated as the highest daily value in the hottest HW (EHF_HWA) and respectively as the lowest daily value in the coldest CW (ECF_CWA).

All five indices were calculated for each extended summer for EHF and for each extended winter for ECF over the period 1961–2015 by employing ClimPACT2 software (Alexander and Herold, 2016) resulting in a total number of 930 time series that were analysed in this paper (10 indices calculated for 31 locations based on 3 reference periods).

2.3.4. *Trend detection*

Climate change has been detected worldwide by using a multitude of trend tests, designed to detect linear or nonlinear trends (Mann–Kendall test, ordinary least square (OLS) method, Pettitt test, change-point models with statistically dependent or independent errors, etc.). In our study, trends were calculated using OLS method, whereas statistical significance was assessed by employing the t-test. OLS method uses a linear model to estimate the magnitude of the slope. Slopes of time series were computed per decade. t-test follows a student's t-distribution. The statistical significance of the trends was assessed at the 5% level ($p < 0.05$). These methods have been used in the latest decades to document climate changes in different regions of the planet (Spinoni *et al.,* 2015; Anandhi *et al.,* 2016). Both methods are implemented in the ClimPACT2 software (Alexander and Herold, 2016) and in the earlier version of the same software (ClimPACT), which was successfully used by Keggenhoff *et al.* (2015) for HWs indices detection in Georgia.

In order to detect spatial patterns of changes, maps of spatial distribution of trend types were generated by using ArcGIS 10.2 software.

3. Results and discussions

3.1. Brief climatology of EHF and ECF indices

The climatological values of HWs and CWs indices based on EHF and ECF definitions for each of the three threshold sets employed for the Romanian territory are shortly presented in this section.

In Romania, on average, there were recorded between 1.7 and 2.9 HW events, corresponding to each threshold for the extended summer season (May–September) (Table 3). The number of CW events is higher than the number of HW events for all the thresholds considered. These results suggest that Romania is more exposed to CWs than to HWs. Also, ECF_CWD analysis reveals that the longest average length of the CWs is more than double compared to that of the HWs as assessed by EHF_HWD index. As it was expected, ECF_CWF index values are also higher than EHF_HWF since these indices are directly connected and have a direct influence on the number and length of CW and HW events. The HWs and CWs magnitude values (EHF_HWM and ECF_CWM indices) are quite similar when different reference periods are used to calculate the intensity threshold.

3.2. Overall changes

Changes in HWs and CWs indices were identified and analysed for all 930 time series generated. Our results revealed a generalized increase of HWs-related indices in most of the time series. Overall, HWs indices increased in 93.5% of the cases when the percentile threshold was calculated over the reference period 1961–1990. The upward trend was found statistically significant for 66.5% of all of the time series considered (Figure 4(a)). When 1971–2000 and 1981–2010 reference period thresholds were considered, the results showed a frequency of upward trends that slightly decreased but still remained high, while the frequency of downward trends increased (Figures 4(b) and (c)). The highest frequency of statistically significant increase is specific to EHF_HWN, EHF_HWF, and EHF_HWD indices. EHF_HWM and EHF_HWA also recorded upward trends for the majority of locations considered, yet statistically insignificant.

Most of the CWs data series generated based on ECF were found statistically insignificant. Trends detected had a general downward trend. Results showed a decreasing trend in about 80% of time series for all the reference periods considered (Figure 5). Statistically significant decrease covered 28–34%, depending on the reference period used for intensity threshold calculation. It has a higher frequency in case of ECF_CWN and ECF_CWF indices, especially when the threshold was calculated based on the recent reference periods (Figures 5(b)

Table 2. Heat and cold waves indices (after Alexander and Herold, 2016 and Loughran et al., 2017).

Index	Definition	Units
Heat wave indices		
EHF_HWN	The annual number of individual HWs calculated based on EHF that occur in each extended summer (May–September)	Events
EHF_HWF	The number of days that contribute to HWs as identified by EHF_HWN	Days
EHF_HWD	The length of the longest HW identified by EHF_HWN	Days
EHF_HWM	The magnitude is the average of all heatwave's averaged EHF values in a year identified by EHF_HWN calculated based on EHF	°C^2
EHF_HWA	The peak daily value in the hottest HW calculated based on EHF	°C^2
Cold wave indices		
ECF_CWN	The annual number of individual CWs calculated based on ECF that occur in each extended winter (November–March)	Events
ECF_CWF	The annual number of days that contribute to CWs as identified by ECF_CWN	Days
ECF_CWD	The length of the longest CW identified by EHF_CWN	Days
ECF_CWM	The magnitude is the average of all coldwave's averaged ECF values identified by ECF_CWN calculated based on ECF	°C^2
ECF_CWA	The lowest daily value in the coldest CW calculated based on ECF	°C^2

Table 3. Climatological values of EHF and ECF-based indices over the period 1961–2015.

Parameter	EHF					ECF				
	HWN (events)	HWF (days)	HWD (days)	HWM (°C^2)	HWA (°C^2)	CWN (events)	CWF (days)	CWD (days)	CWM (°C^2)	CWA (°C^2)
Reference period for percentile calculation: 1961–1990										
Mean[a]	2.9	15.4	7.1	5.6	16.6	3.9	32.0	14.6	−20.0	−94.0
Maximum[b]	8.4	64.1	17.7	15.2	47.8	8.1	71.4	35.3	−54.0	−276.0
Minimum[c]	0.0	0.0	3.0	0.9	1.9	0.6	2.6	3.6	−5.7	−12.3
Reference period for percentile calculation: 1971–2000										
Mean	2.5	12.9	6.6	5.6	15.9	4.0	33.8	15.2	−19.7	−96.0
Maximum	8.0	60.0	17.0	14.8	47.8	8.2	74.4	37.1	−54.2	−279.6
Minimum	0.0	0.0	3.0	0.9	1.7	0.7	3.2	3.9	−5.4	−12.8
Reference period for percentile calculation: 1981–2010										
Mean	1.7	8.1	5.7	5.5	14.1	4.0	33.6	15.2	−19.7	−95.7
Maximum	7.1	47.8	14.8	15.0	44.2	8.1	74.5	36.7	−54.5	−279.1
Minimum	0.0	0.0	3.0	0.8	1.6	0.7	3.1	3.8	−5.6	−13.1

[a]The mean values are calculated based on all stations values. [b]The maximum value is the highest value recorded in Romania (for the considered weather stations). [c]The minimum value is the lowest value recorded in Romania (for the considered weather stations).

and (c)). Statistically insignificant changes (both increasing and decreasing trends) were identified for the other three indices for the great majority of weather stations considered.

3.2.1. Analysis of changes detected in HWs indices

3.2.1.1. Heat wave number (EHF_HWN): The number of EHF-based HWs recorded an important change in Romania during the extended summer season over the period 1961–2015. Increasing trends were found in all data sets analysed, while significant increasing trends had a frequency of 97% when the first and the last reference periods were considered for calculation of the percentile threshold. The frequency slightly decreased (94%) in the case of 1971–2000 reference period (Figures 4 and 6).

The magnitude of change had an average value of 0.70 events decade^{-1} for the studied area using the first reference period (Table 4). Slopes recorded slightly lower values when the recent reference periods were used for percentile thresholds calculation (0.64 events decade^{-1} and 0.52 events decade^{-1}). The magnitude of change had low values (below 0.4 events decade^{-1}) only for few stations, while the most part of the Romania's territory was affected by higher values (above 0.7 events decade^{-1}) when 1961–1990 reference period threshold was employed (Table 4).

The magnitudes of EHF_HWN slopes were lower for the first two reference periods and higher for the last one compared to those detected for HWN calculated based on daily TX in a previous study (Croitoru *et al.,* 2016a). When compared to the weak magnitude of HWN identified based on daily TN by Croitoru *et al.* (2016a), our results revealed higher slopes for EHF_HWN for all reference periods. No decreasing trends were recorded for EHF_HWN in Romania, for the considered period.

These results indicated that EHF-HW events became more frequent in Romania during the extended summer season over the period 1961–2015. Such changes can have an important impact on society and environment due to the thermal stress caused to humans, plants, and

Table 4. Slopes of EHF-HWs indices over the period 1961–2015.

Parameter Unit	EHF_HWN Events decade^{-1}	EHF_HWF Days decade^{-1}	EHF_HWD Days decade^{-1}	EHF_HWM °C^2 decade^{-1}	EHF_HWA °C^2 decade^{-1}
Reference period for percentile calculation: 1961–1990					
Mean[a]	0.70	5.09	1.02	0.12	1.65
Maximum[b]	0.98	8.15	2.34	0.50	3.38
Minimum[c]	0.14	1.28	0.16	−0.42	−0.75
Reference period for percentile calculation: 1971–2000					
Mean	0.64	4.30	0.84	0.07	1.30
Maximum	0.95	6.77	1.76	0.52	2.97
Minimum	0.19	1.56	0.11	−0.42	−0.82
Reference period for percentile calculation: 1981–2010					
Mean	0.52	3.03	0.62	−0.11	0.76
Maximum	0.81	4.62	1.16	0.55	2.88
Minimum	0.12	1.23	0.23	−1.22	−1.11

[a]The mean values are calculated based on all stations values. [b]The maximum value is the highest value recorded in Romania (for the considered weather stations). [c]The minimum value is the lowest value recorded in Romania (for the considered weather stations).

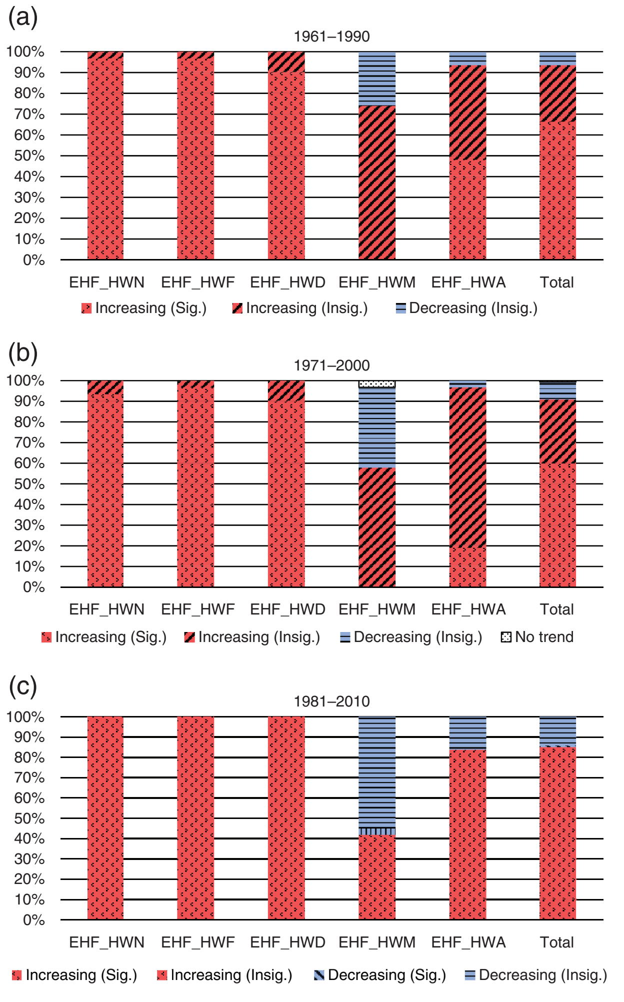

Figure 4. Trends frequency of EHF-based indices of HWs over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

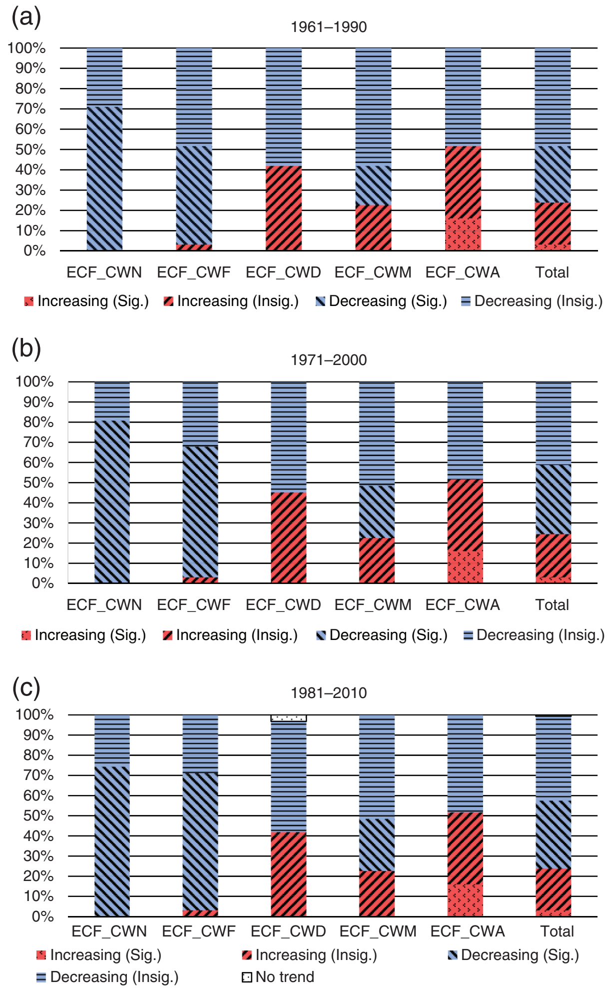

Figure 5. Trends frequency of ECF-based indices of CWs over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

animals. Quality of life can be considerably diminished by increasing morbidity and mortality, especially in the case of poor people who do not have air conditioning in their houses. Under these circumstances, the identification and implementation of the most appropriate adaptation measures should be of a high priority. Moreover, a wide range of specific sectors (e.g. food security and agriculture, water resources, electricity) should not neglect the changes in EHF_HWN as this index is highly relevant for different sectorial impacts.

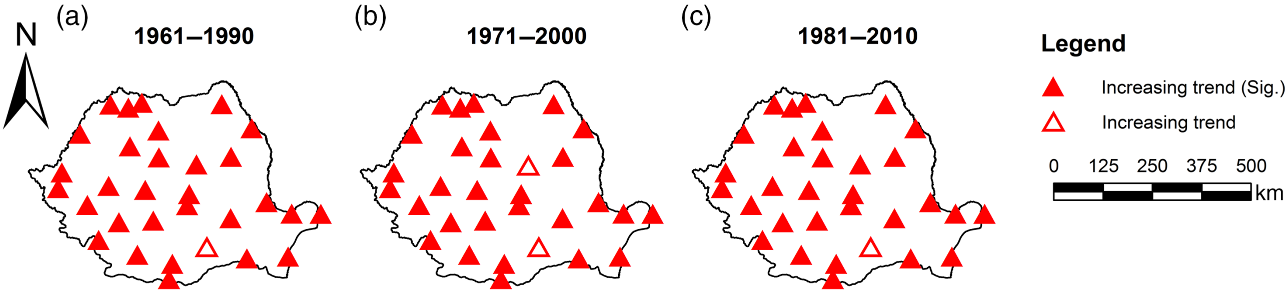

Figure 6. Spatial distribution of changes in EHF_HWN index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

3.2.1.2. Heat wave frequency (EHF_HWF): The results for the participating HW days quantified by EHF_HWF index are similar to those of EHF_HWN. EHF_HWF increased significantly in 97% of the weather stations considered for all three thresholds used (Figure 7). The magnitude of the significant increasing trends ranged between 1.28 and 8.15 days decade^{-1} in the case of 1961–1990 reference period chosen for threshold calculation (Table 4). As average value, EHF_HWF increased by 5 days decade^{-1} for the first reference period considered and had a slower rate of increase when the threshold was calculated based on the recent reference periods. As the number of contributing days for EHF-HWs increased significantly, this change can be reflected either in HWN or HWD, or in both cases. The results suggest that, among other factors, changes in EHF_HWF have considerably contributed to increasing trends in EHF_HWN. Out of all the analysed indices, EHF_HWF had the highest increase in terms of number of significant trends detected.

3.2.1.3. Heat wave duration (EHF_HWD): The duration of the longest HW of each year (EHF_HWD index) registered an important change for all reference periods considered for threshold calculation. Thus, 90% of the trends detected increased significantly when percentile thresholds were calculated based on the first two reference periods, while for the last one, significant increasing trends recorded a much lower frequency, of 65% (Figures 4 and 8). On average, EHF_HWD increased by 1.02 days decade^{-1} when 1961–1990 reference period was used (Table 4). The highest increase was recorded in southeastern Romania, on the Black Sea coastline (2.34 days decade^{-1} at Constanta weather station). When 1971–2000 and 1981–2010 reference periods were employed for threshold calculation, the slopes of EHF_HWD increased at a lower rate on average (0.84 and 0.62 days decade^{-1}). The spatial distribution of trends indicated that statistically insignificant trends were mostly found in the northwestern, central, southern, and southeastern areas, especially when the intensity threshold was calculated based on the most recent reference period (Figure 8).

There is a strong evidence indicating that the longer the HW spans in time, the higher the number of deaths (Gasparrini and Armstrong, 2011; Montero *et al.,* 2012; Miron *et al.,* 2015). It was found that for every 1-day increase in HWD, mortality risk increased by 0.38% in the United States of America (Anderson and Bell, 2011) and by 2.6% in Korea (Son *et al.,* 2012). Kim *et al.* (2016) used the maximum duration of HWs as a predictor of human deaths and showed that this index is even more alarming than the HWN. As the EHF_HWD significantly increased in Romania over the 55-year period considered, this could have a serious impact on human health and mortality. Moreover, it was found that the maximum duration of a HW had a major impact on water quality, which can induce indirect effects on human health and ecosystems (D'Ippoliti *et al.,* 2010; Liu *et al.,* 2015; Kim *et al.,* 2016).

3.2.1.4. Heat wave annual mean magnitude (EHF_HWM): From the oldest to the newest reference period, the number of increasing trends of EHF_HWM index diminished considerably. It recorded increasing trends in 74% of the locations, when 1961–1990 reference period was used and had lower values in the case of the last two reference periods used: 58% for 1971–2000 reference period and 45% for 1981–2010 reference period, respectively (Figure 4). None of the increasing trends were statistically significant. Increasing trends were slightly overcome by decreasing trends when EHF_HWM was calculated with 1981–2010 reference period threshold. The spatial distribution of EHF_HWM trends showed that positive slopes are mainly concentrated in the western half of Romania for all thresholds (Figure 9). Overall, the mean annual magnitude of HWs increased by 0.12 and 0.07 °C^2 decade^{-1} when the first two reference periods were used, and decreased by –0.11 °C^2 decade^{-1} when the most recent reference period was considered for percentile threshold calculation (Table 4). These results suggest that although EHF-HWs became longer and more frequent for the extended summer season in Romania, they did not record a significant change in terms of mean annual magnitude. Opposite to these results, Croitoru *et al.* (2016a) found significant increasing trends for HWM identified based on daily TX for most locations, but when using HWM based on TN significant increase was found only in the southwestern areas. This may be explained by the fact that EHF_HWs contains supplementary components such as the cumulative effect of TX and TN and the acclimatization (the impact of the preceding 30 days).

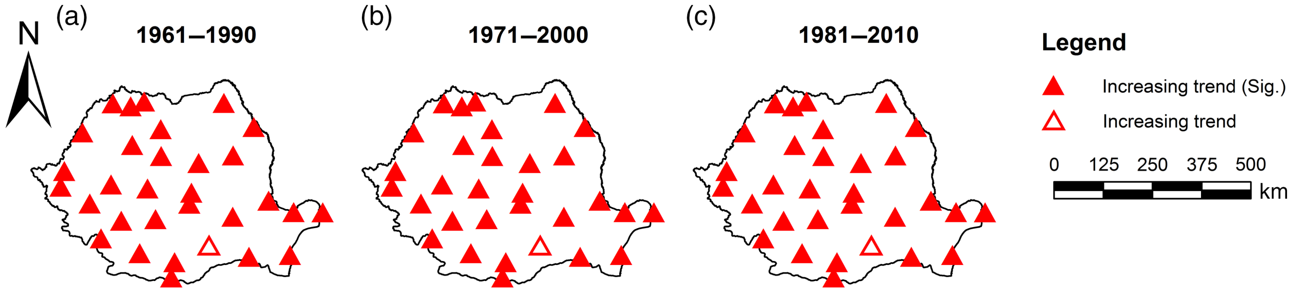

Figure 7. Spatial distribution of changes in EHF_HWF index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

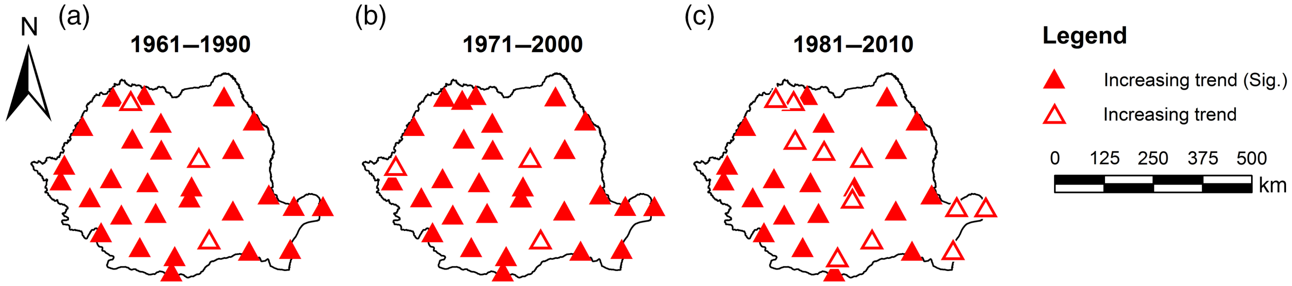

Figure 8. Spatial distribution of changes in EHF_HWD index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

They may not overlap with those identified based on TX and/or TN, because if the HW event occurs in a warm period, the magnitude of EHF will be reduced compared to a cool build up period.

3.2.1.5. Heat wave amplitude (EHF_HWA): The highest value of the hottest HW recorded each year during May–September season was evaluated by using EHF_HWA index. Results indicate that EHF_HWA increased more significantly in the western regions of Romania compared to the rest of the country when 1961–1990 and 1971–2000 reference period thresholds were employed for HW detection (Figures 10(a) and (b)). Only one weather station located in eastern Romania recorded a significant increasing trend for 1981–2010 reference period threshold (Figure 10(c)). Significant increasing trends had a frequency of 48% when 1961–1990 reference period threshold was considered (Figure 4).

When thresholds were calculated for 1971–2000 and 1981–2010 reference periods, significant increasing trends recorded a frequency of 19% and 3%, respectively. Insignificant decreasing trends were found in some locations in central and southeastern regions. The average slope value for Romania was 1.65 $°C^2$ decade^{-1} considering 1961–1990 reference period threshold, while lower values characterized change in amplitude when the threshold was calculated based on the most recent reference periods (Table 4). Because the last two reference periods were warmer than the first one, the percentile threshold values were higher and therefore a reduction in the number of identified HWs and their amplitude was detected. Thus, the trend and its statistical significance and magnitude were directly affected by changing the reference period threshold from the earliest interval to the most recent one. Statistical significance of increasing trends seemed to be the most sensitive to this change since the frequency of significant trends has considerably decreased by shifting from one to another reference period. The mean intensity of HWs expressed by EHF_HWM did not record any significant changes. However, the EHF_HWA, which measures the most intense event in a year, significantly increased especially in the western regions of Romania, especially for the first reference period threshold (Figure 10). Therefore, similarly to the other EHF-HWs indices, changes in EHF_HWA could amplify the negative impact of these events on environment and human society.

3.2.2. Analysis of changes detected in CWs indices

CWs still represent a concerning threat for temperate regions, including Romania, even under global warming conditions. Their importance derives from the high frequency of diseases associated with cold-related excess mortality (ischemic heart disease, cerebrovascular, or respiratory diseases) (Hassi, 2005). Although there has been less research on CWs, neglecting the effects generated by extreme cold events can cause serious impact on humans and society.

ECF takes into account how much the daily temperature exceeded a long-term temperature threshold, and it also adds some information about the cooling degree in the previous 30 days, which is related to short-term acclimatization including behavioural and physical adaptation (Anderson and Bell, 2009, cited by Wang *et al.,* 2016). Under these circumstances, it becomes an extremely important parameter to characterize the biometeorological impact of CWs.

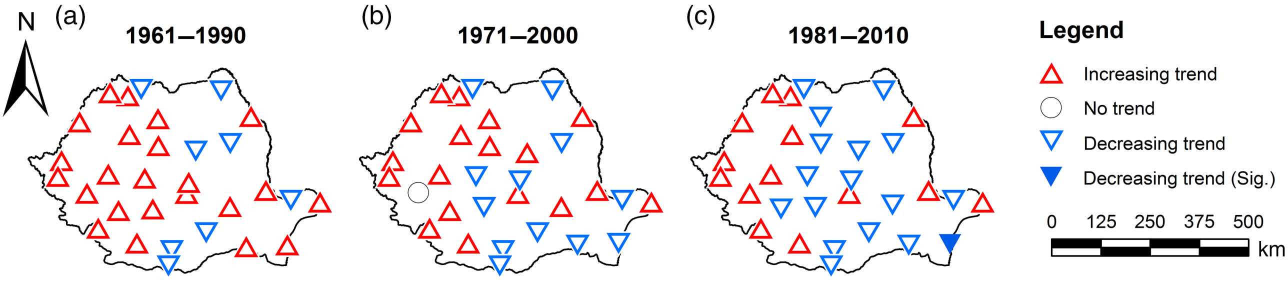

Figure 9. Spatial distribution of changes in EHF_HWM index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

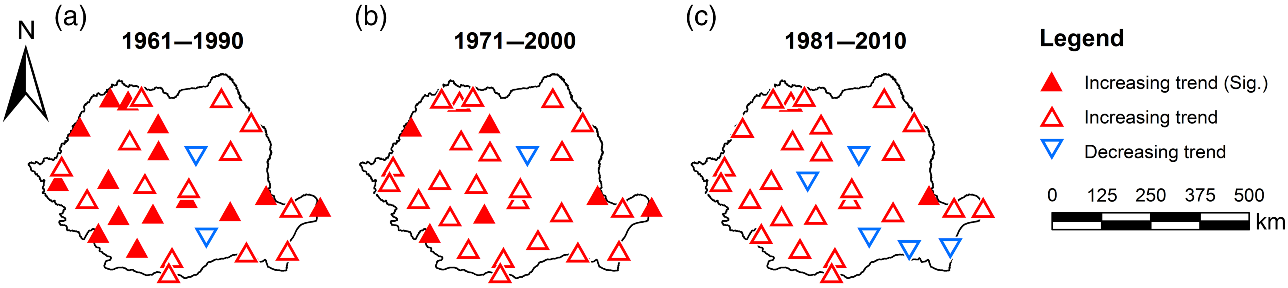

Figure 10. Spatial distribution of changes in EHF_HWA index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

3.2.2.1. Changes in cold wave number (ECF_CWN): The analysis of the number of CW events identified based on ECF (ECF_CWN index) for the extended winter season (November–March) showed that the great majority of locations considered experienced statistically significant decreasing trends for all three thresholds considered (Figure 5). Only a few weather stations, located in central and western regions of the country, recorded insignificant downward trends (Figure 11). Increasing or stationary trends were not identified for this index, thus suggesting that the CWs decreased homogenously for the entire Romanian territory. On average, for all the considered stations, the slopes of ECF_CWN were similar for all three reference periods thresholds: $-0.34 \ldots -0.37$ events decade^{-1} (Table 5). The great majority of significantly decreasing trends across all regions may indicate that in the near future, we can expect less CWs if this tendency continues. However, further investigations are needed to confirm this hypothesis by employing regional climate models outputs.

3.2.2.2. Changes in cold waves frequency (ECF_CWF): Similar to HWs, the ECF_CWF index is strongly related to ECF_CWN because the number of participating days to CW events is directly reflected in the number of events. Thus, when a change occurs in one of these indices, it is expected a similar change to occur in the other one, too. In terms of frequency of different types of trends and their spatial distribution, statistically significant downward trends were dominant in the number of participating days to CWs events (ECF_CWF index) over the studied area (Figures 5 and 12). Only one weather station experienced an upward trend, but it was found statistically insignificant. It is located on a mountain peak, at an altitude higher than 2500 m. Significant trends in ECF_CWF were recorded mostly in the western half of the country when 1961–1990 reference period was employed for intensity threshold calculation. For the other two reference periods thresholds, statistically significant decreasing trends were also recorded in the eastern and southern regions of Romania. The frequency of this trend type was higher compared to that calculated based on the first intensity threshold (Figure 5). Overall, ECF_CWF index had similar slopes for all three intensity thresholds employed and decreased by about -2.5 days decade^{-1} in Romania (Table 5). The most important decrease (more than 4 days decade^{-1}) was recorded in western Romania (Timisoara weather station).

3.2.2.3. Changes in cold waves duration (ECF_CWD): The duration of the yearly longest CW event, measured by ECF_CWD index did not record any significant change in Romania. Decreasing trends have a frequency of 58% when 1961–1990 reference period threshold was used for CWs detection, and it dropped to 55% when thresholds were calculated based on the other two reference periods (Figure 5). Increasing trends had a frequency of about 43%. Only one location recorded a stationary trend when 1981–2010 reference period threshold was used (Figures 5 and 13). Spatial distribution of trends indicated that positive slopes had a similar pattern for all the reference period thresholds and were found mainly in the southeastern half of the country (Figure 13). Overall, the slope magnitude of ECF_CWD was similar for all thresholds calculated for different reference periods and it decreased, on average, by -0.07 days decade^{-1} (Table 5). Wang *et al.* (2016) found that the duration of CWs measured by ECF was highly associated with an increase in mortality in 209 cities in the United States of America. Under these circumstances, we can consider that the general decreasing trends of ECF_CWD across Romania could have a positive effect

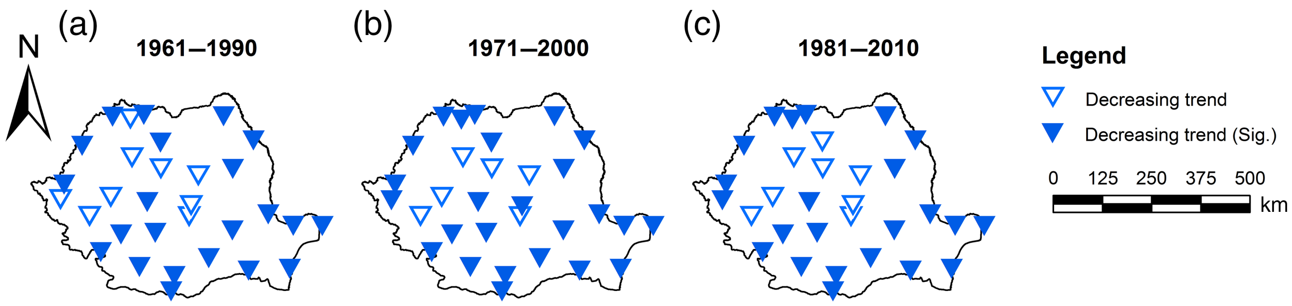

Figure 11. Spatial distribution of changes in ECF_CWN index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

Table 5. Slopes of ECF-CWs indices over the period 1961–2015.

Parameter Unit	ECF_CWN Events decade^{-1}	ECF_CWF Days decade^{-1}	ECF_CWD Days decade^{-1}	ECF_CWM °C^2 decade^{-1}	ECF_CWA °C^2 decade^{-1}
Reference period for percentile calculation: 1961–1990					
Mean[a]	−0.34	−2.54	−0.07	−1.01	1.62
Maximum[b]	−0.06	0.13	1.26	1.42	21.04
Minimum[c]	−0.52	−3.62	−1.69	−3.54	−10.72
Reference period for percentile calculation: 1971–2000					
Mean	−0.37	−2.78	−0.07	−0.99	1.76
Maximum	−0.14	0.20	1.25	1.53	20.53
Minimum	−0.53	−4.17	−1.61	−3.08	−10.61
Reference period for percentile calculation: 1981–2010					
Mean	−0.37	−2.79	−0.07	−1.00	1.63
Maximum	−0.09	0.13	1.25	1.51	20.56
Minimum	−0.57	−4.22	−1.61	−3.03	−10.63

[a]The mean values are calculated based on all stations values. [b]The maximum value is the highest value recorded in Romania (for the considered weather stations). [c]The minimum value is the lowest value recorded in Romania (for the considered weather stations).

on mortality associated with CWs if decreasing trend continues.

3.2.2.4. Changes in cold waves mean annual magnitude (ECF_CWM): ECF_CWM index was proposed to quantify the magnitude of all CWs measured by using ECF in the extended winter season. An upward trend of ECF_CWM index indicates a decrease in the mean annual magnitude of CWs, while a downward trend may be associated with an increase in mean annual magnitude. The analysis of changes in ECF_CWM data sets indicated a slightly different behaviour than in the case of the previous indices. Decreasing trends were found for the most weather stations considered and for all the reference period thresholds used (Figure 5), but only about 25% of them were found statistically significant. They are especially located in the southern, southeastern, and western regions of Romania (Figure 14). A few increasing trends were detected mainly in northwestern Romania, but none of them was identified as statistically significant. Overall, the slope of ECF_CWM decreased by −1.00 °C^2 decade^{-1} (Table 5). Generally, the results indicated that, on average, CWs became less intense in northern and western regions and more intense in the rest of the country. These results could be extremely important from the biometeorological perspective, since events frequency, duration, and number of contributing CW days decreased, and the mean annual intensity of CWs expressed by ECF_CWM index increased over the period 1961–2015. Even though this increase was not statistically significant for the greatest part of the country, it might be a good indicator for future conditions and if this trend would continue, it could have important negative consequences on human health and mortality, as well as on agriculture. The winter crops production could be affected by the increase in CWs intensity, since the most important areas where those crops are intensively cultivated experienced the above-mentioned conditions.

3.2.2.5. Changes in cold waves amplitude (ECF_CWA): The ECF_CWA index identifies the lowest temperature value of the most intense CW in the extended winter. The ECF_CWA index increased for the intra-Carpathian areas and decreased for the extra-Carpathian regions (Figure 15). Most of the significant increasing trends were concentrated in northern Romania. The frequency of trend types remained unchanged for all the stations when different reference periods thresholds were employed (Figure 5). Overall, the frequency of decreasing trends was 48.4%. The ECF_CWA positive slopes were higher compared to the negative ones, suggesting that the decrease of CWs intensity was at a higher rate than the increasing intensity (Table 5). Thus, one can say that CWs became more intense in the extra-Carpathian regions of Romania, and milder in the rest of the country, especially in the northwestern region where they significantly decreased (Figure 15).

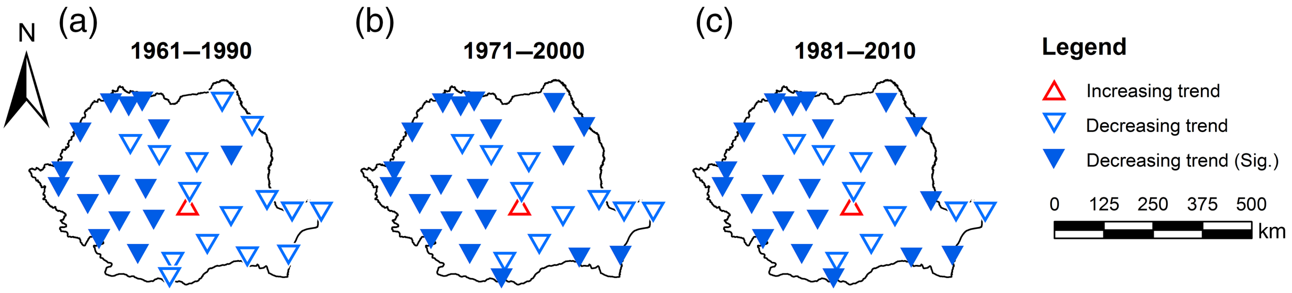

Figure 12. Spatial distribution of changes in ECF_CWF index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

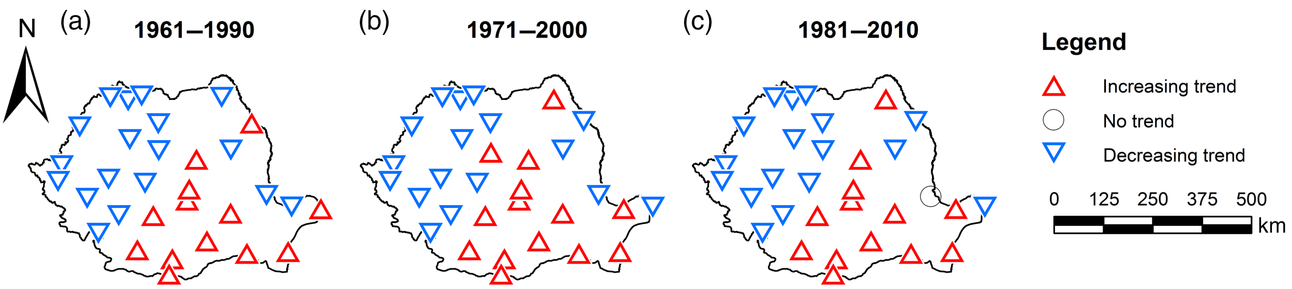

Figure 13. Spatial distribution of changes in ECF_CWD index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

4. Conclusions

This study reports the results of changes in HWs and CWs indices in Romania over a 55-year period (1961–2015) by employing a set of ten indices recommended by ET-SCI of CCI. HWs indices were computed based on EHF definition for the extended summer season (May–September), whereas CWs indices were computed based on ECF for the extended winter season (November–March). For each definition five indices were calculated. They describe some key features: number, frequency of participating days, the longest duration, magnitude, and amplitude of the heat and cold events. For a better comparison with other studies conducted worldwide, and to get more information from the data available, the percentile thresholds for HWs and CWs identification were calculated based on three reference periods: 1961–1990, 1971–2000, and 1981–2010.

The main results indicate that changes were more substantial in the case of EHF-based indices than in ECF-based indices, suggesting that the warming process was more reflected in HWs rather than in CWs. Analysis of changes in HWs revealed that number, frequency, and duration of HWs experienced a statistically significant increase for the great majority of locations. When analysing the EHF_HWM and EHF_HWA indices, which are related to HW intensity, the results revealed no statistically significant changes in the case of EHF_HWM index, while for EHF_HWA index significant trends had a low frequency and were mostly located in the western half of the country. When changing the reference period for percentile threshold calculation, the frequency of significantly increasing trends remained almost unchanged for the EHF_HWN, EHF_HWF, and EHF_HWD indices. For EHF_HWA and EHF_HWM indices, the frequency of upward trends decreased gradually when switching to a more recent reference period for threshold calculation. Although the procedure of HWs identification is fundamentally different than that employed by Croitoru *et al.* (2016a), the analysis of EHF-based indices generated similar results, especially for HWN, HWF, and HWD. Under these circumstances, we consider that the findings of the two papers present evidence of changes detected in HWs, and that appropriate mitigation and adaptation measures must be taken by authorities.

However, some differences were found in case of HWM and HWA indices. For HWM, trends were mostly increasing but statistically insignificant when 1961–1990 reference period threshold was employed. By changing the reference period for threshold calculation from the earliest to the more recent ones, the frequency of increasing trends gradually decreased. On the contrary, Croitoru *et al.* (2016a) found significant increasing trends for most of the Romanian territory when analysing HWM based on TX, and only in the western regions when HWM was identified based on TN. The frequency of trends type (increasing or decreasing) found by Croitoru *et al.* (2016a) for HWM remained almost constant when the reference period threshold was changed. In the case of HWA, significant increasing trends had a lower frequency than that identified based on TX. A comparison between our results and those found by Croitoru *et al.* (2016a) indicates that, considering the anomaly against previous 30 days (acclimatization component), it moderates the slopes of increasing trends and their statistical significance for some EHF-HW indices as compared to the results calculated for HW indices based on TX and TN analysis. The findings for CWs analysis indicate that, in general, these events became less frequent and shorter, but more intense. The

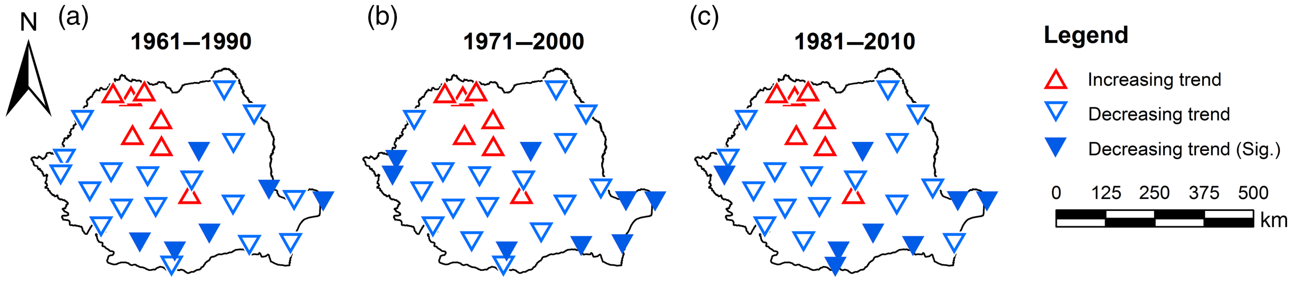

Figure 14. Spatial distribution of changes in ECF_CWM index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

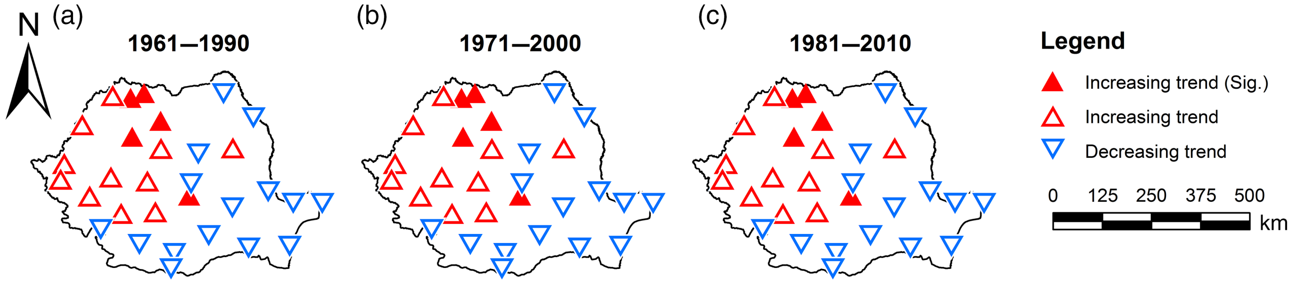

Figure 15. Spatial distribution of changes in ECF_CWA index over the period 1961–2015. [Colour figure can be viewed at wileyonlinelibrary.com].

duration of the longest yearly event in the extended winter period did not record any significant change, which may be beneficial for various sectors, but especially for human health.

Significant multi-decadal climate variability has been observed all over the world adding a level of complexity to the process of climate change detection and enhancing or masking the anthropogenic effects (Parker *et al.*, 2007; Farneti, 2017). Temperature extreme events also present multi-decadal variability (Tencer and Rusticucci, 2012). In a recent study, DelSole *et al.* (2011) stated that there is a global pattern of internal multi-decadal variability, separable from the anthropogenic signal of climate change and that it contributed significantly to the global warming trend of the recent decades (1977–2008). Thus, the resultant trends detected in EHF- and ECF-based indices could be considered as a combination of multi-decadal climate variability as well as induced anthropogenic climate change. In this context and considering that change points were detected for Romania in annual and mean seasonal temperature (Busuioc *et al.*, 2010; Croitoru *et al.*, 2012, 2014, 2016b), further analysis of HWs and CWs should focus on change point analysis and detecting trends by sub-periods.

The results of this research can provide valuable information for a wide range of sectors which could be affected by HWs and CWs and to develop an adaptation strategy to these changes. Thus, as the HW indices recorded significant changes in Romania and considering the absence of a detailed national strategic adaptation plan, our study could be of a crucial importance in developing rigorous plans for preventing negative impacts of HWs. As death and morbidity attributed to HWs and CWs can be readily prevented, the implementation of adequate adaptation strategies to changes in HWs and CWs should be a priority measure in order to minimize the side effects on humans.

This research will be continued by future studies that will explore the impact of EHF-HWs and ECF-CWs on human morbidity and mortality in Romania.

Acknowledgements

This research was developed under the framework of the research grant *Extreme weather events related to air temperature and precipitation in Romania* (project code: PN-II-RU-TE-2014-4-0736), funded by the Executive Unit for Financing Higher Education, Research, Development, and Innovation (UEFISCDI) in Romania. The authors acknowledge the daily temperature data provided by the European Climate Assessment & Dataset project (Klein Tank *et al.*, 2002), Meteomanz data base, and the National Meteorological Administration in Romania. The authors kindly acknowledge to Dr Diana Elena Alexandru for the English technical support. Special acknowledgements are given to the two anonymous reviewers for their valuable suggestions which helped us to improve the quality of this paper.

Supporting information

The following supporting information is available as part of the online article:

Figure S1. The 90th percentile of daily Tm for extended summer season for three reference periods at weather stations in Romania.

Figure S2. The 90th percentile of daily Tm for extended summer season for three reference periods at weather stations in Romania.

Figure S3. The 90th percentile of daily Tm for extended summer season for three reference periods at weather stations in Romania.

Figure S4. The 10th percentile of daily Tm for extended winter season for three reference periods at six representative weather stations in Romania.
Figure S5. The 10th percentile of daily Tm for extended winter season for three reference periods at six representative weather stations in Romania.
Figure S6. The 10th percentile of daily Tm for extended winter season for three reference periods at six representative weather stations in Romania.

References

Alexander L, Herold N. 2016. *ClimPACT2 Indices and Software*. University of South Wales: Sidney, Australia. https://github.com/ARCCSS-extremes/climpact2.

Anandhi A, Hutchinson S, Harrington J, Rahmani V, Kirkham MB, Rice CW. 2016. Changes in spatial and temporal trends in wet, dry, warm and cold spell length or duration indices in Kansas, USA. *Int. J. Climatol.* **36**: 4085–4101. https://doi.org/10.1002/joc.4619.

Anderson BG, Bell ML. 2009. Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. *Epidemiology* **20**: 205–213.

Anderson BG, Bell ML. 2011. Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. *Environ. Health Perspect.* **119**(2): 210–218. https://doi.org/10.1289/ehp.1002313.

Barnett AG, Hajat S, Gasparrini A, Rocklöv J. 2012. Cold and heat waves in the United States. *Environ. Res.* **112**: 218–224. https://doi.org/10.1016/j.envres.2011.12.010.

Basarin B, Lukić T, Matzarakis A. 2016. Quantification and assessment of heat and cold waves in Novi Sad, northern Serbia. *Int. J. Biometeorol.* **60**: 139–150. https://doi.org/10.1007/s00484-015-1012-z.

Busuioc A, Caian M, Cheval S, Bojariu R, Boroneant C, Baciu M, Dumitrescu A. 2010. *Variabilitatea si schimbarea climei in Romania*. Pro Universitaria Press: Bucharest.

Chen Y, Hu Q, Yang Y, Qian W. 2017. Anomaly based analysis of extreme heat waves in Eastern China during 1981–2013. *Int. J. Climatol.* **37**: 509–523. https://doi.org/10.1002/joc.4724.

Croitoru AE. 2014. Heat waves. Concept, definition and methods used to detect. *Riscuri si Catastrofe* **15**(2): 25–32.

Croitoru AE, Drignei D, Holobaca IH, Dragota CS. 2012. Change-point analysis for serially-correlated summit temperatures in the Romanian Carpathians. *Theor. Appl. Climatol.* **108**: 9–18.

Croitoru AE, Drignei D, Dragotă CS, Imecs Z, Burada DC. 2014. Sharper detection of winter temperature changes in the Romanian higher-elevations. *Glob. Planet. Change* **122**: 122–129.

Croitoru AE, Piticar A, Burada DC. 2015. Changes in precipitation extremes in Romania. *Quat. Int.* **415**: 325–335.

Croitoru AE, Drignei D, Burada DC, Dragotă CS, Imecs Z. 2016a. Altitudinal changes of summer air temperature trends in the Romanian Carpathians based on serially correlated models. *Quat. Int.* **415**: 336–343.

Croitoru AE, Piticar A, Ciupertea AF, Roşca CF. 2016b. Changes in heat waves indices in Romania over the period 1961–2015. *Glob. Planet. Change* **146**: 109–121.

DelSole T, Tippett MK, Shukla J. 2011. A significant component of unforced multidecadal variability in the recent acceleration of global warming. *J. Clim.* **24**: 909–926.

D'Ippoliti D, Michelozzi P, Marino C, De'Donato F, Menne B, Katsouyanni K, Kirchmayer U, Analitis A, Medina-Ramon M, Paldy A, Atkinson R, Kovats S, Bisanti L, Schneider A, Lefranc A, Iñiguez C, Perucci C. 2010. The impact of heat waves on mortality in 9 European cities: results from the EuroHEAT project. *Environ. Health* **9**(37): 1–9. https://doi.org/10.1186/1476-069X-9-37.

Dragotă CS, Havriş LE. 2015. Changes in frequency, persistence and intensity of extreme high-temperature events in the Romanian plain. In *Proceedings of the Conference on Air and Water. Components of the Environment,* 17–24.

Ekamper P, Van Poppel F, Van Duin C, Garssen J. 2009. 150 Years of temperature-related excess mortality in the Netherlands. *Demogr. Res.* **21**(14): 385–426.

Farneti R. 2017. Modelling interdecadal climate variability and the role of the ocean. *Clim. Change* **8**: 1–26. https://doi.org/10.1002/wcc.441.

Gasparrini A, Armstrong B. 2011. The impact of heat waves on mortality. *Epidemiology* **22**(1): 68–73. https://doi.org/10.1097/EDE.0b013e3181fdcd99.

Hartz DA, Golden JS, Sister C, Chuang W-C, Brazel J. 2012. Climate and heat-related emergencies in Chicago, Illinois (2003–2006). *Int. J. Biometeorol.* **56**: 71–83.

Hassi J. 2005. Cold extremes and impacts on health. In *Extreme Weather Events and Public Health Responses*. Springer-Verlag: Berlin and Heidelberg, Germany, 59–67. https://doi.org/10.1007/3-540-28862-7_6.

Hatvani-Kovacs G, Belusko M, Pockett J, Boland J. 2016. Can the excess heat factor indicate heatwave-related morbidity? A case study in Adelaide, South Australia. *Ecohealth* **13**: 100–110. https://doi.org/10.1007/s10393-015-1085-5.

Huştiu MC. 2016. Cold and heat waves in the Barlad plateau between 1961 and 2013. *Riscuri şi Catastrofe* **18**(1): 31–42.

Keggenhoff I, Elizbarashvili M, King L. 2015. Heat wave events over Georgia since 1961: climatology, changes and severity. *Climate* **3**: 308–328.

Kim DW, Deo RC, Chung JH, Lee JS. 2016. Projection of heat wave mortality related to climate change in Korea. *Nat. Hazards* **80**: 623–637. https://doi.org/10.1007/s11069-015-1987-0.

Klein Tank AMG, Wijngaard JB, Können GP, Böhm R, Demarée G, Gocheva A, Mileta M, Pashiardis S, Hejkrlik L, Kern-Hansen C, Heino R, Bessemoulin P, Müller-Westermeier G, Tzanakou M, Szalai S, Pálsdóttir T, Fitzgerald D, Rubin S, Capaldo M, Maugeri M, Leitass A, Bukantis A, Aberfeld R, van Engelen AFV, Forland E, Mietus M, Coelho F, Mares C, Razuvaev V, Nieplova E, Cegnar T, Antonio López J, Dahlström B, Moberg A, Kirchhofer W, Ceylan A, Pachaliuk O, Alexander LV, Petrovic P. 2002. Daily dataset of 20th-century surface air temperature and precipitation series for the European climate assessment. *Int. J. Climatol.* **22**: 1441–1453.

Knowlton K, Rotkin-Ellman M, King G, Margolis HG, Smith D, Solomon G, Trent R, Paul E. 2009. The 2006 California heat wave: impacts on hospitalization and emergency department visits. *Environ. Health Perspect.* **117**(1): 61–67. https://doi.org/10.1289/ehp.11594.

Langlois N, Herbst J, Mason K, Nairn J, Byard RW. 2013. Using the excess heat factor (EHF) to predict risk of heat related deaths. *J. Forensic Leg. Med.* **20**: 408–411.

Lhotka O, Kyselý J. 2015, 2015. Characterizing joint effects of spatial extent, temperature magnitude and duration of heat waves and cold spells over Central Europe. *Int. J. Climatol.* **35**: 1232–1244. https://doi.org/10.1002/joc.4050.

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

Liu G, Zhang L, He B, Jin X, Zhang Q, Razafindrabe B, You H. 2015. Temporal changes in extreme high temperature, heat waves and relevant disasters in Nanjing metropolitan region, China. *Nat. Hazards* **76**: 1415–1430. https://doi.org/10.1007/s11069-014-1556-y.

Loughran TF, Perkins-Kirkpatrick SE, Alexander LV. 2017. Understanding the spatio-temporal influence of climate variability on Australian heatwaves. *Int. J. Climatol.* **37**: 3963–3975. https://doi.org/10.1002/joc.4971.

Ma W, Zeng W, Zhou M, Wang L, Rutherford S, Lin H, Liu T, Zhang Y, Xiao J, Zhang Y, Wang X, Gu X, Chu C. 2015. The short-term effect of heat waves on mortality and its modifiers in China: an analysis from 66 communities. *Environ. Int.* **75**: 103–109.

Medina-Ramón M, Schwartz J. 2007. Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. *Occup. Environ. Med.* **64**: 827–833.

Miron IJ, Linares C, Montero JC, Criado-Alvarez JJ, Díaz J. 2015. Changes in cause-specific mortality during heat waves in central Spain, 1975–2008. *Int. J. Biometeorol.* **59**: 1213–1222. https://doi.org/10.1007/s00484-014-0933-2.

Montero JC, Mirón IJ, Criado-Álvarez JJ, 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.

Nairn J, Fawcett R. 2013. Defining heatwaves: heatwave defined as a heat-impact event servicing all community and business sectors in Australia. Technical Report No. 60, The Centre for Australian Weather and Climate Research, Melbourne, Australia.

Nairn JR, Fawcett RJB. 2015. The excess heat factor: a metric for heatwave intensity and its use in classifying heatwave severity. *Int. J. Environ. Res. Public Health* **12**: 227–253. https://doi.org/10.3390/ijerph120100227.

Oleson KW, Anderson GB, Jones B, McGinnis SA, Sanderson B. 2015. Avoided climate impacts of urban and rural heat and cold waves over de U.S. using large climate model ensembles for RCP8.5 and RCP4.5. *Clim. Change.* https://doi.org/10.1007/s10584-015-1504-1.

Papathoma-Koehle M, Promper C, Bojariu R, Cica R, Sik A, Perge K, Lászlo P, Czikora EB, Dumitrescu A, Turcus C, Birsan MV, Velea L, Glade T. 2016. A common methodology for risk assessment and mapping for south-east Europe: an application for heat wave risk in Romania. *Nat. Hazards* **82**: 89–109. https://doi.org/10.1007/s11069-016-2291-3.

Parey S, Hoang TTH. 2015. Changes in distribution of cold waves in France in the middle and end of the 21st century with IPSL-CM5 and CNRM-CM5 models. *Clim. Dyn.* **47**: 879–893. https://doi.org/10.1007/s00382-015-2877-6.

Parker D, Folland C, Scaife A, Knight J, Colman A, Baines P, Dong B. 2007. Decadal to multidecadal variability and the climate change background. *J. Geophys. Res.* **112**: D18115.

Peng RD, Bobb JF, Tebaldi C, McDaniel L, Bell ML, Dominici F. 2011. Toward a quantitative estimate of future heat wave mortality under global climate change. *Environ. Health Perspect.* **119**: 701–706.

Perkins SE, Alexander LV. 2013. On the measurement of heat waves. *J. Clim.* **26**: 4500–4517. https://doi.org/10.1175/JCLI-D-12-00383.1.

Peterson TC, Heim RR, Hirsch R, Kaiser DP, Brooks H, Diffenbaugh NS, Dole RM, Giovannettone JP, Guirguis K, Karl TR, Katz RW, Kunkel K, Lettenmaier D, McCabe GJ, Paciorek CJ, Ryberg KR, Schubert S, Silva VB, Stewart BC, Vecchia AV, Villarini G, Vose RS, Walsh J, Wehner M, Wolock D, Wolter K, Woodhouse CA, Wuebbles D. 2013. Monitoring and understanding changes in heat waves, cold waves, floods, and droughts in the United States: state of knowledge. *Bull. Am. Meteorol. Soc.* **94**: 821–834. https://doi.org/10.1175/bams-d-12-00066.1.

Radinović D, Ćurić M. 2012. Criteria for heat and cold wave duration indexes. *Theor. Appl. Climatol.* **107**: 505–510.

Revich BA, Shaposhnikov DA. 2016. Cold waves in southern cities of European Russia and premature mortality. *Stud. Russ. Econ. Dev.* **27**(2): 210–215.

Rohini P, Rajeevan M, Srivastava AK. 2016. On the variability and increasing trends of heat waves over India. *Sci. Rep.* **6**: 26153. https://doi.org/10.1038/srep26153.

Rusticucci M, Kyselý J, Almeira G, Lhotka O. 2015. Long-term variability of heat waves in Argentina and recurrence probability of the severe 2008 heat wave in Buenos Aires. *Theor. Appl. Climatol.* **124**: 679–689. https://doi.org/10.1007/s00704-015-1445-7.

Ryti NR, Guo Y, Jaakkola JJ. 2016. Global association of cold spells and adverse health effects: a systematic review and meta-analysis. *Environ. Health Perspect.* **124**: 12–22.

Scalley BD, Spicer T, Jian L, Xiao J, Nairn J, Robertson A, Weeramanthri T. 2015. Responding to heatwaves intensity: excess heat factor is a superior predictor of health service utilisation and a trigger for heatwaves plans. *Aust. N. Z. J. Public Health* **39**: 582–587. https://doi.org/10.1111/1753-6405.12421.

Shaposhnikov D, Revich B, Bellander T, Bedada GB, Bottai M, Kharkova T, Kvasha E, Lezina E, Lind T, Semutnikova E, Pershagen G. 2014. Mortality related to air pollution with the Moscow heat wave and wildfire of 2010. *Epidemiology* **25**(3): 359–364. https://doi.org/10.1097/EDE.0000000000000090.

Son JY, Lee JT, Anderson B, Bell M. 2012. The impact of heat waves on mortality in seven major cities in Korea. *Environ. Health Perspect.* **120**(4): 566–571.

Spinoni J, Lakatos M, Szentimrey T, Bihari Z, Szalai S, Vogt J, Antofie T. 2015. Heat and cold waves trends in Carpathian region from 1961 to 2010. *Int. J. Climatol.* **35**: 4197–4209. https://doi.org/10.1002/joc.4279.

Tencer B, Rusticucci M. 2012. Analysis of interdecadal variability of temperature extreme events in Argentina applying EVT. *Atmosfera* **25**(5): 327–337.

Unkaševic M, Tošic I. 2009. An analysis of heat waves in Serbia. *Glob. Planet. Change* **65**: 17–26. https://doi.org/10.1016/j.gloplacha.2008.10.009.

Wang Y, Shi L, Zanobetti A, Schwartz JD. 2016. Estimating and projecting the effect of cold waves on mortality in 209 US cities. *Environ. Int.* **94**: 141–149.

WHO (World Health Organization). 2006. *Preventing harmful health effects of heat-waves*. World Health Organization, Copenhagen, Denmark.

WMO (World Meteorological Organization). 2011. *Guide to climatological practices*. WMO-No. 100. http://www.wmo.int/pages/prog/wcp/ccl/guide/documents/WMO_100_en.pdf (accessed 22 January 2017).

WMO (World Meteorological Organization). 2016. *Normals. Guide to climate*. Update to guide to climatological practices. WMO-No. 100. http://www.wmo.int/pages/prog/wcp/ccl/guide/documents/Normals-Guide-to-Climate-190116_en.pdf (accessed 22 January 2017).

WMO and WHO (World Meteorological Organization and World Health Organization). 2015. *Heatwaves and health: guidance on warning-system development*. WMO-No. 1142, Geneva, Switzerland.

