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Spatiotemporal variability of meteorological drought in Romania using the standardized precipitation index (SPI)

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ABSTRACT: This study addresses the spatial and temporal variability of meteorological drought in Romania based on a standardized precipitation index (SPI) analysis over the period 1961–2010. The 1- and 3 mo SPI values from 124 meteorological stations were used to examine the duration, magnitude, intensity, and frequency of the drought spells. Empirical orthogonal function analysis supported the investigations on the variability of the SPI values both in time and space, and this was framed in relation to mesoscale patterns of meteorological variables like air pressure, humidity and temperature. The role of the North Atlantic Oscillation in the winter precipitation deficit, and the possible influence of the Atlantic Multidecadal Oscillation on summer droughts are revealed. The study indicates that large-scale atmospheric circulation is the major drought driver in Romania in winter, while thermodynamic factors (such as air temperature and humidity) are the major drivers in summer. The Carpathian mountain chain is the secondary regional factor influencing SPI spatial variability, triggering differences between the intra-Carpathian and extra-Carpathian regions in winter time.

KEY WORDS: Drought · Standardized precipitation index · Romania · Climate variability · NAO · AMO

1. INTRODUCTION

Drought can broadly be described as a water deficit situation that may occur in any geographical region and climate. Its onset can equally be very slow or abrupt, and a drought event may last more than any other natural hazard, being generated by complex factors. The assessment and prediction of drought have always been a climatological challenge, and a large number of definitions and indices have been implemented according to various needs. Meteorological, hydrological and agricultural droughts have different characteristics and impacts, so that the methodologies to be applied may consequently vary.

A large number of studies have been devoted to drought indices or to the evaluation of their performance (Guttman 1998, Keyantash & Dracup 2002, Vicente-Serrano et al. 2010). The standardized precipitation index (SPI) has proved to be one of the most competitive tools for assessing drought, and it is used nowadays for operational and research activities in more than 70 countries (WMO 2012). The pool of participants in the Inter-Regional Workshop on Indices and Early Warning Systems for Drought, held at the University of Nebraska-Lincoln, USA, in December 2009 agreed that the SPI is a universal meteorological drought index, and that it should be used by all national meteorological and hydrological services (Hayes et al. 2011). SPI was proposed by McKee et al. (1993, 1995), and many scholars have addressed the concept and methods (Edwards & McKee 1997, Guttman 1998, Wu et al. 2005, Bonsal et al. 2013), despite the main criticisms regarding the use of a single meteorological element for describing a complex event like drought. However, it has been demonstrated that precipitation amount is by far the

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major driver for meteorological droughts (Guttman 1998, Heim 2002, Gebrehiwot et al. 2011), and therefore many studies have examined these phenomena based on SPI solely (i.e. Capra & Scicolone 2012, Moreira et al. 2013).

While the standardization contained in the SPI's concept and its computation makes the comparison between the droughts in different locations meaningful, the spatial representation becomes problematic. Some applications have strived to bring more consistency to SPI interpolation, through gridding methods, derived indices more oriented to spatiality, or by implementing GIS-based monitoring and satellite imagery in regions with sparse meteorological networks (Bhuiyan et al. 2006; Gebrehiwot et al. 2011).

To the best of our knowledge, Lana et al. (2001) published the first SPI-based analysis of the temporal variability of drought, in a study focused on Catalonia (Spain). The majority of the journal articles cover decadal periods (Bordi et al. 2009, Viste et al. 2013), but longer analysis may extend to centuries (Bonsal et al. 2013).

There are only a few publications on the SPI-based drought research in Romania. Barbu & Popa (2003) investigated drought in forest areas, Cheval et al. (2003) tackled mainly methodological aspects, and Paltineanu et al. (2009) jointly analyzed the SPI and the water deficit at a national scale. Recently, Levanič et al. (2012) used the SPI for drought reconstruction in the south-western part of Romania over a period >300 yr. At the same time, drought-related hazards periodically generate costly damages to the Romanian economy, creating a need for early warning, accurate assessment, and long-term prediction.

Romania is situated in southeastern Europe, roughly between 20 and 29° E, and 43 and 48° N. It has a temperate climate with oceanic and Mediterranean influences in the western and southwestern areas, with Baltic intrusions in the north, summer African and Arabian air invasions in the south, and aridity signals in the eastern and southeastern regions. Average annual temperatures are between 8 and 11°C, while mean annual precipitation ranges between <400 mm (extreme southeast) and ~1200 mm (mountainous area).

This study contributes to an improved understanding of the temporal and spatial variability of drought, and our results underline the potential of the SPI as a tool in addressing this field of research. Focusing on the territory of Romania, the specific objectives of this study were: (1) to examine the spatial and temporal characteristics of meteorological drought, in terms of duration, magnitude, and intensity (2) to identify significant trends and shift points in temporal variability, and (3) to explore the possible causes for drought occurrence.

2. METHODOLOGY

2.1. Data sets

The study is based on monthly precipitation data from 124 meteorological stations with <10 % missing data over 1961–2010, coherently distributed over the territory of Romania (Fig. 1), and their coordinates (latitude, longitude, and altitude) may be found in Birsan & Dumitrescu (2014). The Multiple Analysis of Series for Homogenization (MASH) v3.03 method and software (Szentimrey 1999, Venema et al. 2012) was used to fill gaps in the data sets, and for quality control and homogenization. Seasonal SPI values were calculated for the 14 meteorological stations with complete precipitation data sets over the period 1901–2010; this part of the investigation was limited to only a few aspects, with the aim of validating the main analysis. Geographically, these 14 stations are well distributed over the country (Fig. 1), and they were used in a number of previous publications (Busuioc & von Storch 1996; Busuioc et al. 2010)

2.2. Standardized precipitation index

The results are based on 1 mo and 3 mo time scales, and refer to monthly and seasonal drought. The SPI computation methodology has been thoroughly described in a large number of publications (McKee et al. 1993, 1995 Edwards & McKee 1997, WMO 2012). SPI is a dimensionless index, and its computation for a given location and period is conducted after the following sequence: (1) precipitation data are fitted to a probability distribution function (PDF); (2) results are then used to find the cumulative probability of a precipitation event for a given month and time scale (Edwards & McKee 1997); (3) the cumulative probability distribution is transformed into a standard normal distribution, with a mean of zero and a variance of 1, representing the SPI value. The gamma PDF was used for fitting the precipitation data in this study (Edwards & McKee 1997):

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad (1)$$

where $\alpha > 0$ is a shape parameter, $\beta > 0$ is a scale parameter, Γ is the gamma function, and $x > 0$ is the

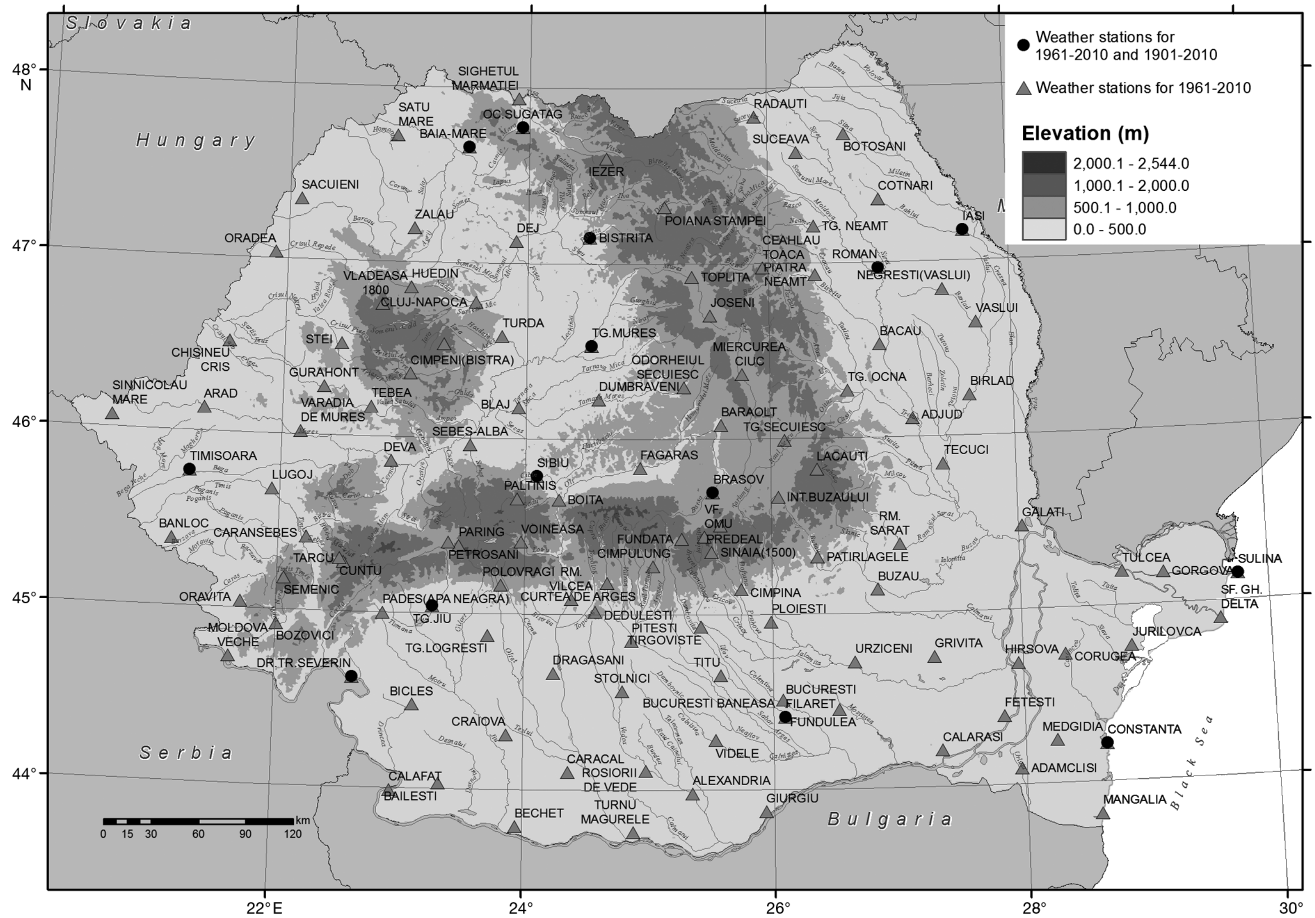

Fig. 1. Meteorological stations used in this study, and altitudinal context of Romania

precipitation totals over the time scale of interest. The SPI was calculated using the SPEI library, which consists of a set of functions implemented in the R language (R Core Team 2013) for computing potential evapotranspiration, and several widely used drought indices (Beguería & Vicente-Serrano 2013).

Table 1 shows the classification of the drought events according to the SPI values (McKee et al. 1993), and the associated probability of recurrence (WMO 2012). This study focuses on moderate, severe and extreme drought, so that the beginning of a drought spell is determined by a fall in SPI to below −1.00, while the end is marked by the SPI exceeding this value.

Table 1. Standardized precipitation index, SPI-based drought categories and associated probability of recurrence (McKee et al. 1993)

SPI	Drought category	Probability of recurrence (%)
0.00 to −0.99	Near normal/mild	24.0
−1.00 to −1.49	Moderate	9.2
−1.50 to −1.99	Severe	4.4
≤ −2.0	Extreme	2.3

2.3. Drought characteristics and their large-scale drivers

Magnitude, intensity, duration, spatial extension or frequency may be used for characterizing the drought events (Feng & Zhang 2005, Sharma & Panu 2012), but definitions may differ substantially. For example, McKee et al. (1993) and Edossa et al. (2010) consider that the drought magnitude is equal to the cumulated SPI values over a drought period. Feng & Zhang (2005) adopt a logarithmic formula combining the precipitation anomaly percentage, and the drought duration. For Sharma & Panu (2012), the drought magnitude is the product of its length and intensity. Vicente-Serrano & Cuadrat-Prats (2007), and Naresh Kumar et al. (2009) use only the SPI categories to characterize the drought intensity, while Edossa et al. (2010) define it as the ratio between magnitude and duration.

The main characteristics of SPI's spatial and temporal variability at different time scales over the period 1961–2010 analysed in the present study are: (1) spatial distribution of the mean and maximum duration of the drought spells; (2) long-term trends using the non-parametric Mann-Kendall (M-K) statistics (10% significance level) (Mann 1945; Kendall 1975); (3) regime shifts in the mean (10% significance level), and cut-off length of 10, using the regime shift index (RSI) (Rodionov 2004, Rodionov & Overland 2005); (4) empirical orthogonal functions (EOF) analysis (Barnett 1981, Wilks 1995, von Storch & Zwiers 1999); (5) connections with large-scale climate variability (i.e. sea level pressure, SLP; air temperature at 850 hPa, T850; specific humidity at 700 hPa, SH700; North Atlantic oscillation, NAO; and Atlantic multidecadal oscillation AMO).

EOF analysis is used to identify the spatial and temporal characteristics of regional and large-scale variability. EOF analysis is usually used as a data-filtering procedure to eliminate noise (although it can exclude potentially useful information). The main spatial features of climate variability in the analysed data set are given by the first few EOF patterns. The first EOF pattern (EOF1) is the most important and explains the largest part of the variance in the analysed data set, the second EOF pattern (EOF2) explains the second largest part and so on. The main characteristics of temporal variability (trends, shifts) are synthesized by the coefficient time series (principal components, PCs) associated with the most important EOFs, the most relevant being PC1 associated with EOF1.

Results from previous studies relating to mechanisms controlling the precipitation variability in Romania (Busuioc & von Storch 1996, Busuioc et al. 2010) found that the SLP area between 5–45° E and 30–55° N is the optimal driver for precipitation variability in Romania, in winter. For other climatic variables like T850, and SH700, the optimum area is 20–30° E, 40–50° N (Busuioc et al. 2010). The grid point monthly mean data sets of these predictors have been taken from the NCEP-NCAR reanalysis (Kalnay et al. 1996). More detailed selection of the optimum domain of the same predictors presented above, but related to other indices associated with precipitation and temperature extremes in Romania, is given in Busuioc et al. (2014). The large-scale/regional-scale predictors refer to dynamic variables (SLP) and thermodynamic ones (T850, SH700), and were found to be skilful in simulations of Romania's climate in previous studies, as shown mainly in statistical downscaling models (e.g. Busuioc et al. 2006, 2010). In the present study, PC1 calculated for SLP, SH700 and T850 was analyzed in connection with the SPI PC1 over Romania through the correlation coefficient between them. We also used a linear regression model between PC1 of SPI and the PC1 of SLP, T850 and SH700 to understand the relative importance of these predictors. SLP and SH700 are significantly negative correlated.

A few previous studies reported the NAO and AMO's influence on the climate of Romania (Bojariu & Paliu 2001, Rimbu et al. 2002, Ştefan et al. 2004; Tomozeiu et al. 2005; Ionita et al. 2012, 2013), and therefore we analyzed their links to the drought characteristics and variability. The NAO index is defined by SLP anomalies in key regions from the North Atlantic, either by the difference between standardised SLP anomalies at Lisbon (Azores Anticyclonic Centre) and Stykkisholmur/Reykjavik (Iceland Cyclonic Centre), or by the PC (PC1) associated with the first EOF pattern of SLP field over the North-Atlantic region (Hurrell et al. 2003). NAO index data were provided by the Climate Analysis Section, NCAR, Boulder, USA (Hurrell 1995, NCAR 2013). The AMO refers to the patterns of sea surface temperature (SST) variability in the North Atlantic, after removing linear trends. The AMO index based on the Kaplan SST V2 data (Kaplan et al. 1998) was provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA (ESRL 2013).

3. RESULTS AND DISCUSSION

3.1. Drought spells and drought frequency

The severity of a drought spell is directly related to the duration, magnitude and intensity of the water deficit, and here we report on the drought spell frequency in Romania, organized by their duration and the SPI-derived intensity. The maximum duration of mild drought spells ranges between 6 and 15 mo, moderate drought spells last 2 to 7 mo, most of the severe drought spells develop over 2 to 4 mo, and the extreme events may occur over 2 to 3 consecutive months at most (Fig. 2). For all drought categories, the drought spell length analysis did not reveal clear spatial patterns as the SPI is designed for drought monitoring under any climate conditions in terms of the standardized precipitation deviation against the climate (long term average) in each location. As a consequence of its normal distribution, the

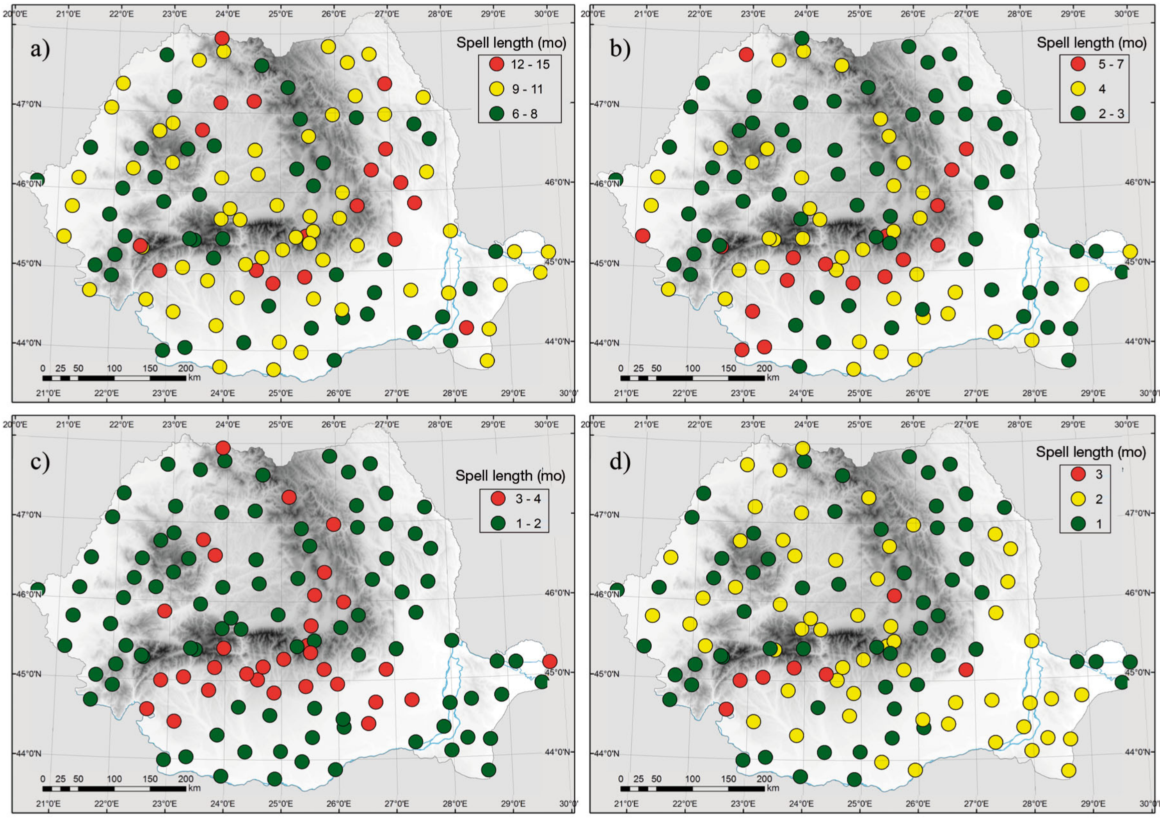

Fig. 2. Maximum continuous duration (in months) of (a) mild, (b) moderate, (c) severe, and (d) extreme drought spells

index values occur with similar frequencies at any location.

The drought spells lasting 2 or 3 mo are the most frequent, summing up >90% of the total drought cases as a country average (Table 2); moreover, at some stations the drought duration has never exceeded 2 mo, so that the contribution of droughts of this length to the total number of drought events reaches 100% (e.g. Semenic, Targu Mures, Bechet, Mangalia).

3.2. Temporal variability

Over 1961–2010, the M-K statistics revealed decreasing trends in annual drought frequency at 74 stations, versus positive trends at 40 stations, generally with no statistical significance ($p < 0.1$). At 10 stations the tendency is rather stationary. Fig. 3 shows a similar variability of the mean and maximum annual drought frequency averaged over the 124 stations included in this study. There are signs of a decadal pattern, in agreement with the findings reported by Ionita et al. (2012) at a European scale.

As regards the seasonal variability of the SPI values, we found a significant increasing tendency with a large spatial extent during the autumn, while values in the other seasons are less consistently positive or negative (Fig. 4). Results showed decreasing trends in spring in the Olteniei Plain (SW Romania), which is one of the major agricultural areas of the country. The findings are consistent with previous publications regarding seasonal precipitation trends (e.g. Busuioc et al. 2010).

The Rodionov RSI showed that negative changes in the means of the 3 mo SPI largely occur in the years 1971–1973 and 1989 for winter, and in 1982 for autumn, while positive shifts are less frequent overall, and occur only in spring, summer, and autumn (Table 3). The same test applied for a 3 mo NAO window detected significant changes around the winters of 1971 and 1972 (positive NAO), while other signals

Table 2. Frequency (%) of drought spells of different lengths in the total drought spell duration. Mean and maximum values over 124 stations in Romania

	2 mo	3 mo	4 mo	5 mo	6 mo	7 mo
Mean	73.8	17.8	6.0	2.1	0.2	0.1
Maximum	100.0	42.9	36.4	34.1	14.6	17.1

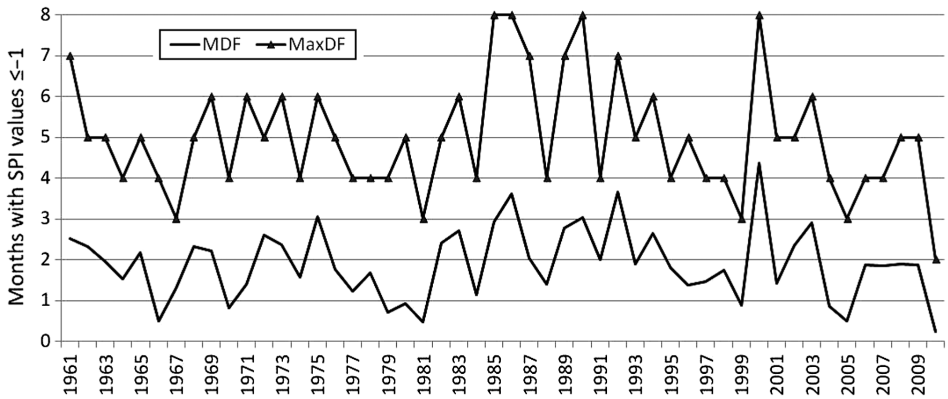

Fig. 3. Mean (MDF) and maximum (MaxDF) annual drought frequency over Romania. SPI: standardized precipitation index

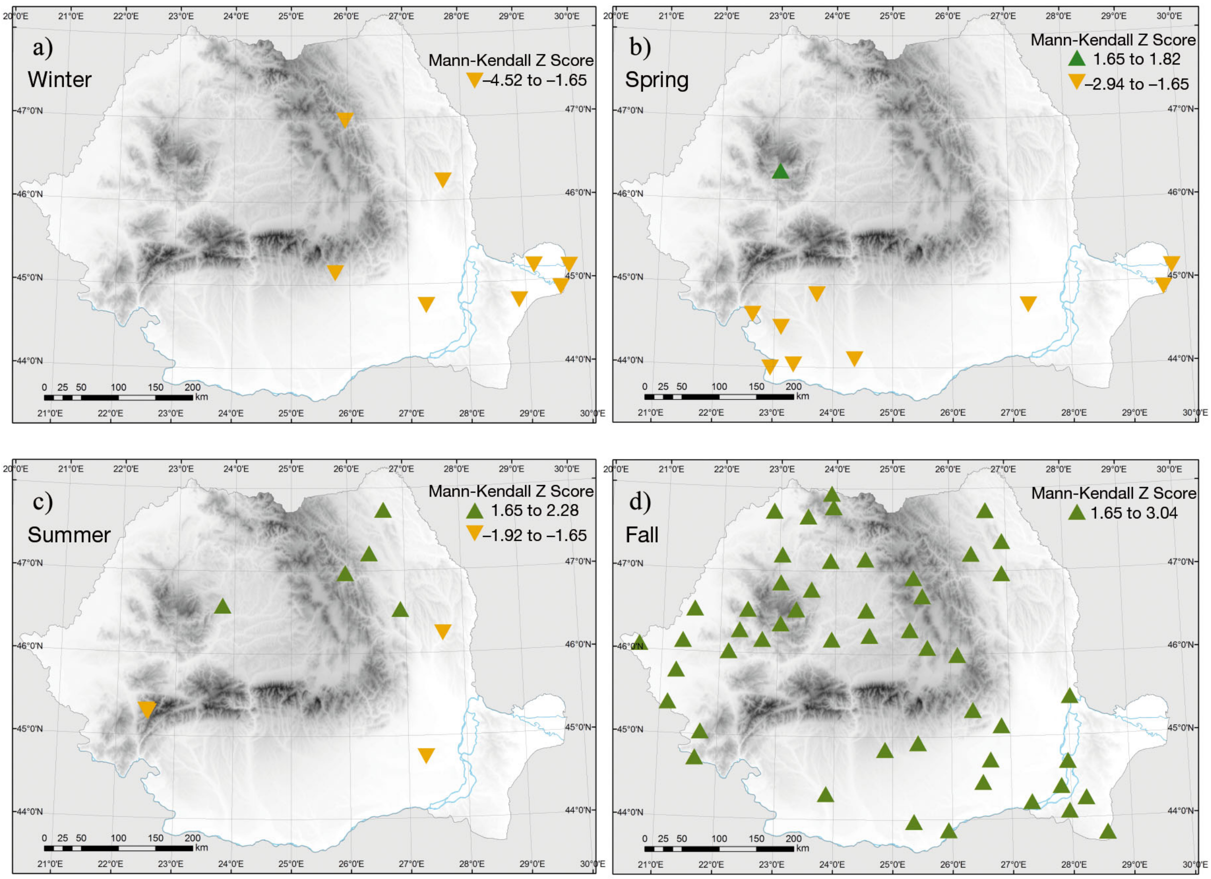

Fig. 4. Significant trends ($p < 0.1$) of the 3 mo standardized precipitation index values. Positive and negative trends are marked by the arrow direction

are less grouped in time. The results suggest possible influences of the NAO on drought in Romania (see Section 3.4 for more details), and they confirm previous reports. Thus, using a smaller number of stations (14), but a longer time interval (1901–1988), Busuioc & von Storch (1996) found a significant shifting point in winter precipitation around 1969–1970.

3.3. EOF analysis

The EOF analysis was applied for the seasonal SPI, SLP, T850 and SH700, and Figs. 5 and 6 show the first 2 EOF patterns of the SPI and SLP for winter and summer. For the SPI, EOF1 has returned explained variances of between 49 % (summer) and 60 % (au-

Table 3. Years with regime changes in the temporal variability of the seasonal standardized precipitation index (SPI), and the North Atlantic Oscillation (NAO), based on the Rodionov RSI test. Parentheses: number of stations with significant RSI ($p < 0.1\%$); (+) upward change; (–) downward change

	DJF	MAM	JJA	SON
SPI(+)	0	2004 to 2005 (24)	1969 (10) 2004 to 2005 (29)	1995 (23) 2001 (14)
SPI(–)	1971 to 1973 (95) 1989 (10)	0	0	1982 (32)
NAO	1972 (+)	0	0	0

tumn), and shows the same sign over the entire country, indicating that a large-scale mechanism controls its principal mode of spatial variability (Table 4). The EOF2 values emphasize regional patterns specific to each season. For example, a contrasting variability between the intra- and extra-Carpathian regions occurs in winter, revealing the role of the mountain chain in air mass flow. Winter precipitation in Romania is mostly advective (Busuioc & von Storch 1996, Busuioc et al. 1999, 2010), and this mechanism explains 13 % of the total observed SPI variability. In summer, there is a contrasting variability between the northern and southern regions of Romania, and this mechanism explains 8 % of the observed SPI variability. The influence of the Carpathians is considerably less important in summer, while other regional mechanisms are likely to control SPI variability. The highest number of spatial variability modes (16) represented by the number of EOF patterns explaining at least 1 % of observed variance occurs in summer. The PC1 integrates the main characteristics of temporal variability (trends, shifts). Fig. 5 presents the first 2 EOF patterns of SPI for winter and summer. The M-K test indicates a decreasing trend (not statistically significant) in winter, a highly significant increasing trend ($p < 0.05$) in autumn, and no significant trends

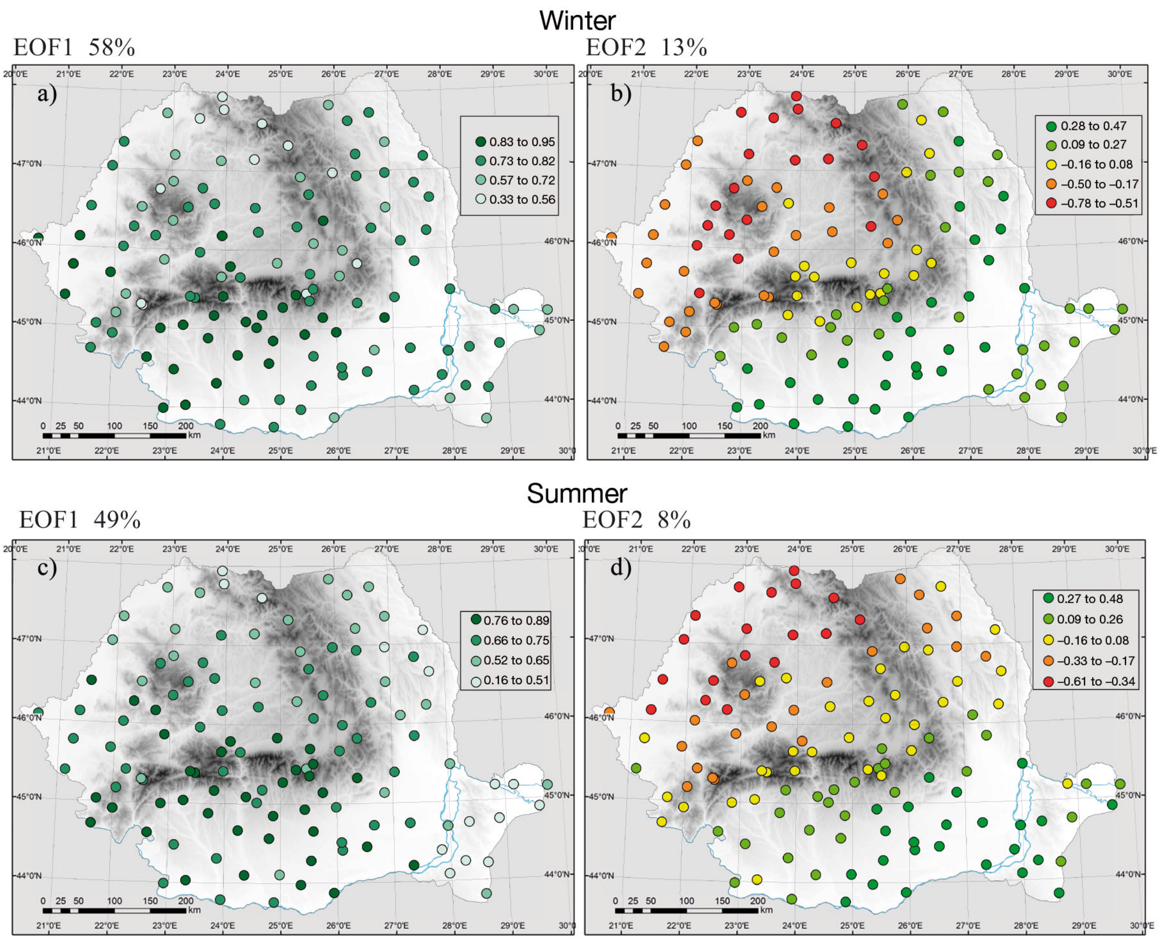

Fig. 5. The first 2 empirical orthogonal function (EOF) patterns of the standardized precipitation index for (a,b) winter and (c,d) summer (values multiplied by −1). Percentages are variance

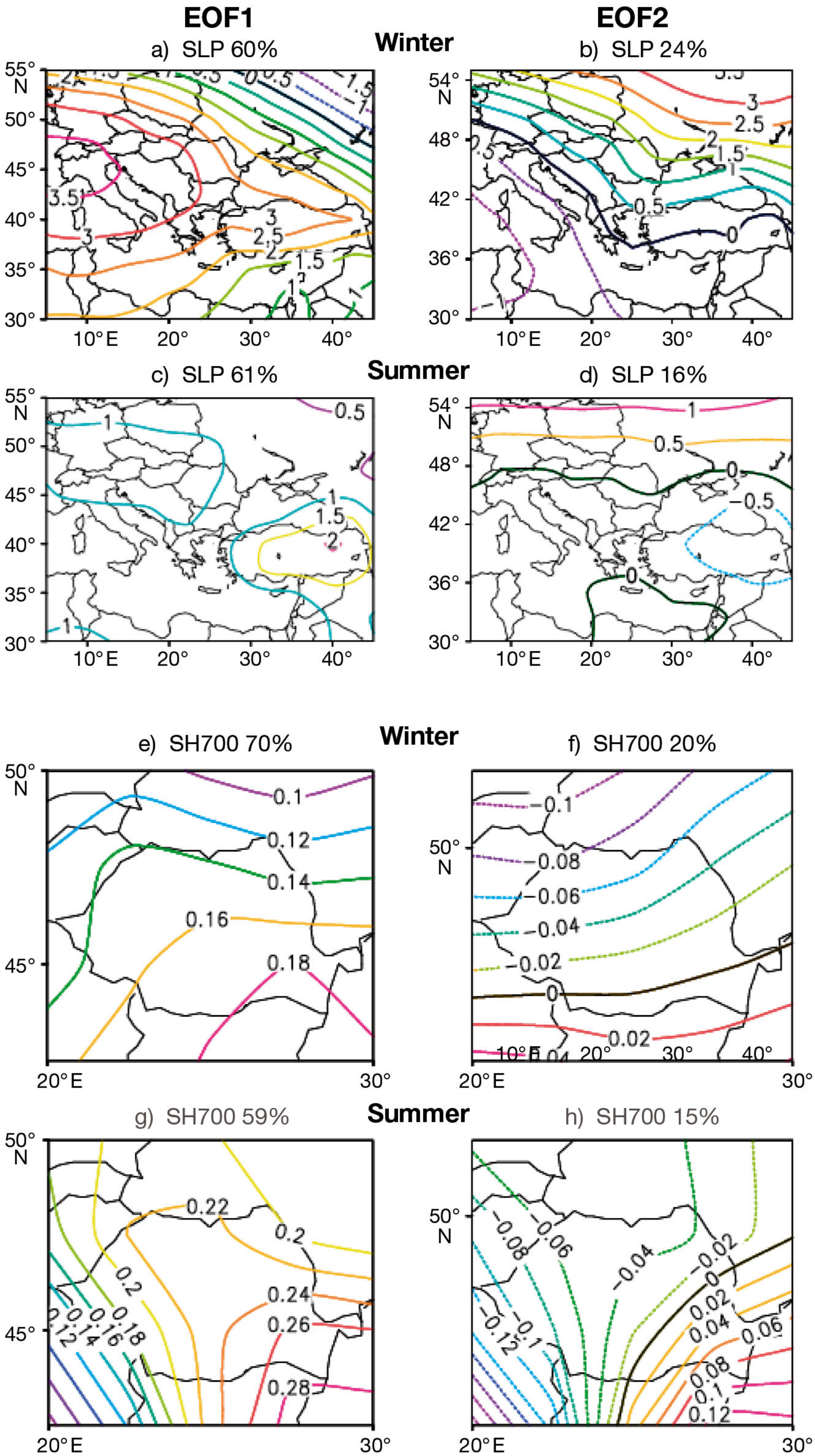

Fig. 6. The first 2 empirical orthogonal function (EOF) patterns (left: EOF1; right: EOF2) of the SLP (a–d) and SH700 (e–h) for winter, and summer. Percentages are variance

for the other seasons (Table 4), confirming the results presented in Section 3.2 at the station scale.

In order to explain the possible physical reasons for the characteristics of the seasonal SPI variability presented above, we applied the EOF analysis to the main large and regional scale climate variables, likely to be physically related to the SPI variability. In a recent national synthesis on climate variability and change in Romania, Busuioc et al. (2010) pointed out the dynamic (SLP) and thermodynamic (SH700, T850) parameters physically connected to precipitation variability in Romania. Table 5 presents the Pearson correlation coefficients between the first 2 PCs of the SPI for all seasons and the first 2 PCs of the 3 predictors. The values of Spearman's rank correlation, which is not sensitive to the presence of linear trends in data sets, are very similar to the Pearson's coefficients (not shown).

For all predictors, the first EOF patterns show the same sign over Romania (positive) and the second EOF patterns illustrate a dipole structure. As an example, Fig. 6 shows the first 2 EOF patterns for SLP and SH700. The SLP spatial variability is quite low in summer compared to winter (Fig. 6a–d). Both EOF1 and EOF2 have low summer anomalies (0.0–1.0 hPa), summing up 77 % of the explained variance, and no trend was identified in the PC values (Table 4). In the winter, the EOF1 (with 60 % explained variance) displays a strong cyclonic (anticyclonic) structure that induces a southwesterly (northwesterly) circulation over Romania. The SLP PC1 presents a significant increasing trend ($p < 0.05$), corresponding to the increase in frequency of anticyclonic structures that trigger reduced precipitation, which could explain the slight decrease in the SPI PC1 (Fig. 7);

Table 4. The explained variance (%) of the first 2 empirical orthogonal function (EOF) patterns of the seasonal standardized precipitation index (SPI) and the predictors SLP, T850, and SH700. Significance—**bold**: 5% level; *italics*: 10% level; arrows: linear trends. The number (n) of EOFs with explained variance >1% are also indicated. The second rows in each column show the significant shifts of the PCs and shift direction (+ for increasing and – for decreasing)

Parameters	Winter			Spring			Summer			Autumn		
	n	PC1	PC2	n	PC1	PC2	n	PC1	PC2	n	PC1	PC2
SPI	11	58 **1970–**	13	12	50	12	16	49	8	9	**60 ↑** **1994+**	14
SLP	5	**60 ↑** **1988+**	24	6	**52 ↑** **1975+**	**24** **1987–**	7	61	16	5	59 **1974+**	14
SH700	6	**70 ↓** **1988–**	12	8	**61 ↓** **1992–**	14	8	59	15	7	*58 ↓*	**13** **1986+**
T850	3	**81 ↑** **1985**	15	3	*86 ↑*	7	3	**78 ↑** **1985+**	13	3	76	**16** **1978+**

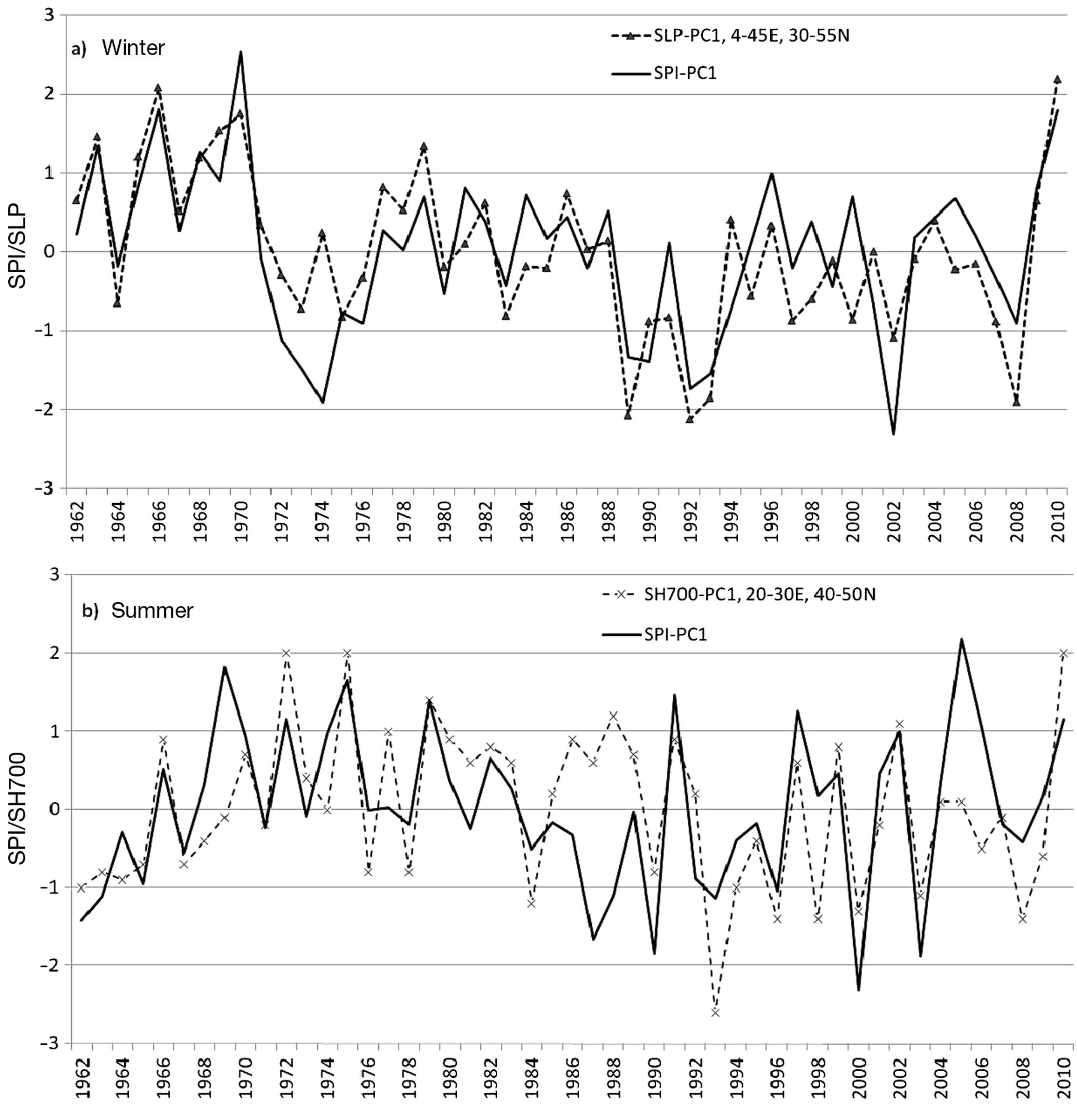

Fig. 7. Coefficient time series associated with the first empirical orthogonal function pattern (PC1) (a) for the SLP (values multiplied by −1) and standardized precipitation index for the winter season; correlation coefficient between the 2 time series is 0.76; (b) the same for summer, but in comparison with the PC1 for the SH700; correlation coefficient between the 2 time series is 0.57

Table 5. Pearson correlation coefficients between PC1/PC2 of the seasonal SPI and PC1/PC2 of various predictors. Statistical significance — **bold**: 5% level; *italic*: 10% level

Predictors		Winter		Spring		Summer		Autumn	
		PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2
SLP									
	PC1	**−0.76**		**−0.40**		0.02		−0.14	
	PC2		**0.54**		−0.21		**−0.31**		**0.40**
SH700									
	PC1	**0.68**		0.18		**0.57**		0.17	
	PC2		−0.10		−0.1		−0.15		*0.25*
T850									
	PC1	−0.23		**−0.32**		−0.04		**−0.31**	
	PC2		***−0.26***		**0.28**		*0.27*		**−0.47**

the SLP and SPI PC1 variations over 1962–2010 are very similar (but in opposite phase), with a Pearson correlation coefficient of −0.76 (Table 5). The SPI PC1 is also significantly correlated with the SH700 PC1 (0.68) that shows a significant decreasing trend, showing also a plausible mechanism: lower air humidity at 700 hPa level over Romania triggers less precipitation and consequently lower SPI values leading to drier conditions. These results show that the winter SPI variability in Romania is mainly controlled by the principal variability mode of the SLP and SH700 (e.g. dynamic factors represented by the enhanced/diminished moist air mass advection from the Mediterranean basin, and thermodynamic factors represented by the air humidity at the 700 hPa level) with dynamical factors dominanting. This result is also proved by the linear regression model showing a higher explained variance for the SLP PC1 compared to SH700 PC1 (57 vs. 44%). The SLP EOF2 (24% explained variance) shows a zone circulation over Romania that is modulated by the Carpathians into a northwest to southeast trajectory. The SLP PC2 revealed no significant linear trend, but it is significantly correlated with the SPI PC2 (0.54), representing the second major mechanism which controls winter SPI variability, thus explaining the bipolar pattern represented by the EOF2. Consequently, it can be concluded that the dynamic factor is dominant in winter SPI variability.

For the other seasons, the results presented in Table 4 show that the dry conditions in Romania are controlled by the surface circulation in spring (as principal mode but with a lower correlation) and in autumn (as secondary mode). In both seasons the thermodynamic factor represented by upper air temperature (850 hPa) is also important (higher temperatures are associated with drier conditions). Summer surface circulation is less important for drought phenomenon in Romania, while thermodynamic factors (represented by convection) become dominant (a significant correlation of 0.57 between SPI PC1 and SH700 PC1), as expected according to previous studies regarding precipitation variability in Romania (Busuioc et al. 2010). However, the PC2 of SPI (associated with EOF2, showing a bipolar structure with a north–south gradient, Fig. 6c,d) is 5% significantly correlated (-0.31) with the PC2 of SLP in summer associated with EOF2, showing a similar dipol pattern (Fig. 6g,h). These results are in agreement with those presented by Busuioc & von Storch (1996) and Busuioc et al. (2010), for which a more complex method based on canonical correlation analysis (CCA) was used to explain the precipitation variability in Romania. In the present study, we found that the analysis of seasonal time coefficients associated with the first 2 EOF patterns (explaining an important fraction of the total variance of the SPI and selected predictors) generally revealed a physically coherent explanation of mechanisms responsible for the spatial and interannual variability of drought conditions in Romania, as measured by the SPI index. The temporal variability on longer time scales (decadal or multi-decadal) is explained in Section 3.4.

3.4. NAO and AMO

Tomozeiu et al. (2005) linked the reduction of winter precipitation in Romania to the positive phase of NAO, and López-Moreno et al. (2011) observed a similar pattern was associated with the extended winter (DJFM). Ionita et al. (2012) showed that AMO can be regarded as a possible multi-decadal mechanism that modulates moisture variability over Europe in summer, and Ionita et al. (2013) demon-

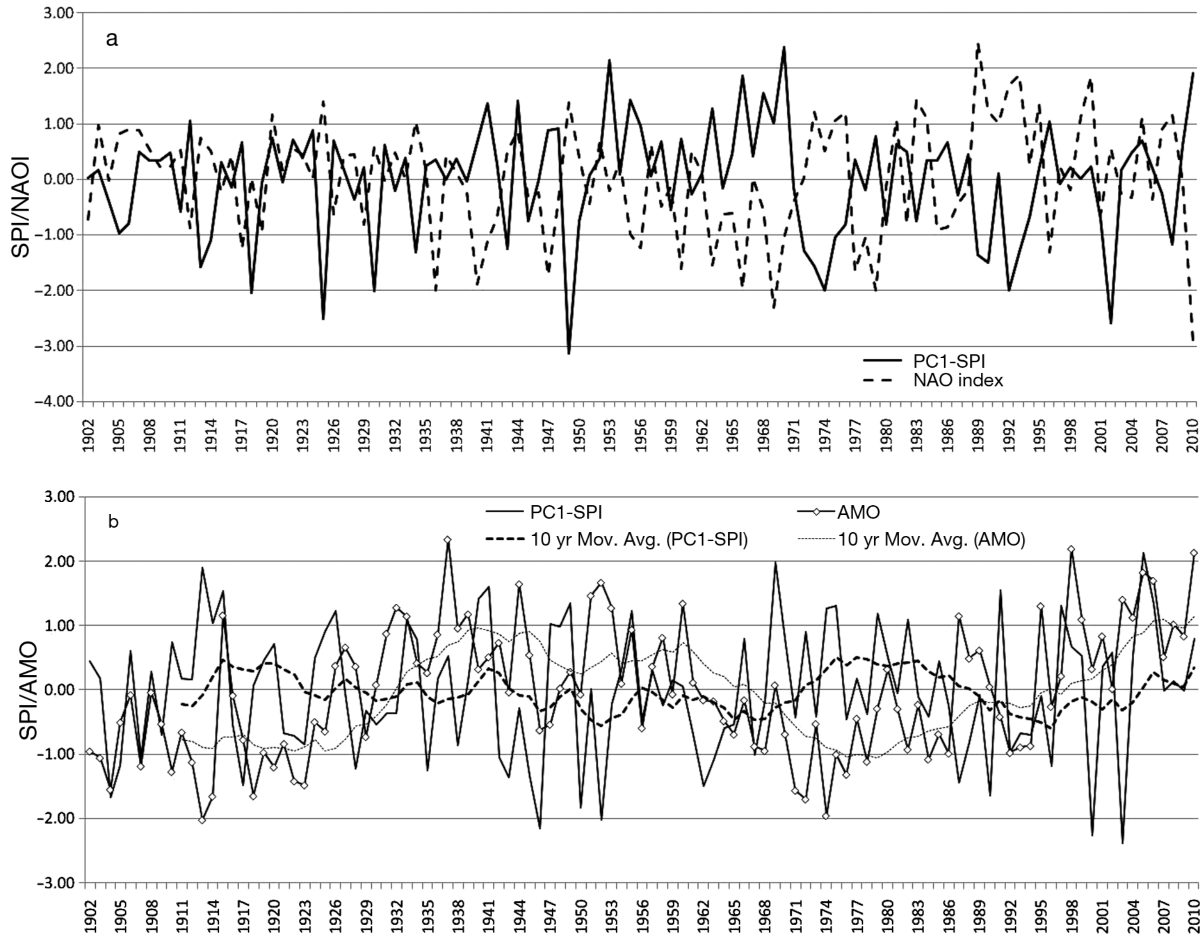

Fig. 8. Variability of (a) winter (DJF) and (b) summer (JJA) PC1 standardized precipitation index SPI averaged over 14 meteorological stations in Romania against (a) winter North Atlantic oscillation (NOA) index and (b) summer Atlantic multidecadeal oscillation (AMO), and normalised by standard deviation. Corresponding 10 yr moving averages also shown in (b)

strated the AMO's link to summer temperatures in Romania; thus one can assume a certain relationship with moisture.

The analysis of the 124 stations over 1961–2010 reveals that, at country scale, the winter SPI has a statistically significant negative correlation with NAO (–0.38), while relevant correlations are sparse during the other seasons (i.e. –0.31 between autumn SPI and August-September-October NAO; –0.35 between spring SPI and NAO), and no spatial pattern has been clearly substantiated. Longer time series (1902–2010) averaged over 14 stations have returned strong correlation coefficients between the PC1-SPI and NAO in winter (–0.57) (Fig. 8a). For the AMO, the correlation of the values is weak, but the 10 yr moving average has a greater correlation (–0.38) even if it is not so strong, emphasizing a possible link between AMO and the droughts occurring over Romania on a multi-decadal scale (Fig. 8b). The results are in agreement with other studies which show that multi-decadal variability of summer droughts at a European scale can be related to the AMO (Ionita et al. 2012), while winter variability can be associated with the NAO (Haylock & Goodess 2004). We expect that other, more complex, drought indices based on a combination between temperature and moisture conditions (e.g. the Palmer Drought Severity Index, PDSI; Standardised Precipitation-Evapotranspiration Index, SPEI) show a stronger relationship with the AMO on a multidecadal scale, but this was beyond the scope of this study.

4. CONCLUSIONS

To the best of our knowledge, this is one of the only analyses (and probably the most complex) of the spatial and temporal variability of meteorological drought in Romania, based on SPI outputs. Monthly and seasonal SPI values were used to characterize drought spells, and revealed poor spatial patterns over Romania, in agreement with previous studies (Paltineanu et al. 2009). There is no evidence showing that the drought frequency, magnitude, or intensity is more consistent in any one region than in others. This is probably due to the SPI's computational concept, but it also reflects a reality: drought may likewise affect areas with a low or high precipitation average, and can occur in mountains or lowlands.

During the period 1961–2010, significant trends are associated with temporal variability in autumn for the whole territory (positive), and in spring for southeastern Romania (negative). These results are in agreement with those derived for seasonal precipitation (Busuioc et al. 2010). The annual drought frequency appears to be characterized by multi-decadal variability.

In Romania, average drought spells generally last 2 to 3 mo; mild drought spells may extend from 6 to 15 consecutive months at most, and extreme events generally develop over 2 to 3 consecutive months. In accordance with previous studies that focused on precipitation, the SPI-based investigations revealed significant and spatially extended (increasing) trends ($p < 0.1$) only during the autumn.

Precipitation deficit leading to meteorological drought in Romania originates in large scale processes, while the Carpathian Mountains in combination with with local conditions influence the spatial drought distribution. EOF analysis has proved to be a powerful tool for the objective identification of the main characteristics of spatial and temporal variability: the winter SPI variability in Romania is mainly controlled by the principal variability mode of the SLP and SH700 (e.g. dynamic factors represented by moist air mass advection from the Mediterranean basin, and thermodynamic factors represented by the air humidity at 700 hPa level), while for summer the thermodynamic factor (represented by the SH700) is dominant, proving the advective character of precipitation in winter and a convective character in summer. In the other seasons (spring and autumn), the large-scale climate signal controlling dry conditions in Romania is less obvious: represented by the surface circulation in spring (as principal mode) and in autumn (as secondary mode); in both seasons the thermodynamic factor represented by air temperature at 850 hPa is also important, but the connection is not very strong. Although NAO has a lower influence, it may be considered a large-scale drought driver in the cold season. Moreover, the results reported in this study show that the NAO (AMO) could give a large-scale climate signal in winter (summer), but other regional climate processes (dynamic and thermodynamic) and local factors (e.g. Carpathian Mountain topography) prevail in controlling the drought conditions over Romania on an interannual scale, overlapping with the large-scale decadal or multi-decadal mechanisms that modulate them.

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