The Standardized Precipitation Index – an overview

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Abstract. At twenty years after its launch, the Standardized Precipitation Index (SPI) is intensively used both in fundamental studies and practical applications. It is implemented operationally in numerous Hydrological and Meteorological Services, being considered a universal drought index. This overview covers the interval 1993-2012, it focuses mainly on the publications in international journals, and reports on the conceptual and methodological developments (a), topics approached (b), operational status (c), and perspectives (d). The overview demonstrates the reasons which have made the SPI a powerful tool for drought studies, namely robust concept, simple calculation and understanding, temporal flexibility, spatial meaning, and wide applicability. Besides, the recent Lincoln Declaration on Drought Indices urges for further advancements of the SPI, and this overview makes up a support for such a growth.

Keywords: Standardized Precipitation Index; drought; wetness; precipitation; drought indices; drought overview.

1. INTRODUCTION

The atmospheric precipitations turn out environmental changes, damages and casualties either by extreme high or low amounts fallen over a certain territory within a time interval. Scientists from various domains have proposed numerous methodologies for assessing the magnitude of the
precipitation excess and deficit, and a few of them have been used more intensively. Overviews of the drought concepts, definitions and methodologies were tackled within scientific meetings and publications (Heim, 2002; Redmond, 2002; Mishra and Singh, 2010; Vicente-Serrano et al., 2012), and many studies were devoted to promote drought indices or to evaluate their performances (Bhalme and Mooley, 1979; Guttman, 1998, 1999; Vicente-Serrano et al., 2010). This paper overviews the development of the Standardized Precipitation Index (SPI) at 20 years after its launch.

In 2004, the SPI was considered a relatively new index and applied occasionally, whereas nowadays it seems to get the universal applicability predicted by some scholars (Tsakiris and Vangelis, 2004). The SPI is widely used in research or operational activities in more than 70 countries (WMO, 2012), approaching both fundamental studies and applications (i.e. agriculture, forestry, hydrology). In 2009, the participants at the Inter-Regional Workshop on Indices and Early Warning Systems for Drought held at the University of Nebraska-Lincoln issued “The Lincoln Declaration on Drought Indices” (Hayes et al., 2011). The document acknowledges the value of drought monitoring, and recommends explicitly using the SPI for characterizing meteorological droughts. Besides, the World Meteorological Organization (WMO) is urged to promote the implementation of the SPI in operational use at the National Meteorological and Hydrological Services (NMHSs). As a consequence, WMO sponsored the recent publication of a comprehensive SPI user manual (WMO, 2012). In its turn, the Joint Research Centre (JRC) supported a study on predicting the SPI-based drought (Singleton, 2012), while many stakeholders and public authorities have chosen the index for practical needs (Carbone et al., 2008).

The summaries of the SPI development are limited to methodological or regional aspects (Hayes, 2000; Lloyd-Hughes and Saunders, 2002; Karavitis et al., 2011; Bonsal et al., 2011, 2012). At a decade after the first SPI publication, Lloyd-Hughes and Saunders (2002) presented in-depth its concept, calculation, advantages and limits, and the drought climatology for Europe. Redmond (2002) supplied strong reasons for applying the SPI both in practical scope and fundamental studies, i.e. solid theoretical background, extensive and careful examination of its proprieties over almost 1200 stations. However, no comprehensive overview does exist so far. While a vast bibliography refers to the SPI in various manners, this paper is based on almost 300 articles published in journals within the main scientific international stream of English language –with very few exceptions– between 1993 and 2012.

The overview presents the significant aspects regarding the SPI’s conceptual framework and calculation methodology (a), its strengths and limitations (b), a summary of the topics approached (c), considerations on the operational use (d), and future developments (e). Only the main assumptions tackled in the SPI journal publications are summarized, aiming
to illustrate as widely as possible the methodology, the applications, the geographical coverage, and the perspectives.

2. SPI CONCEPTUAL FRAMEWORK AND CALCULATION METHODOLOGY

This section addresses the concept supporting the SPI functionality, calculation procedure, time scales, significance of the thresholds, and drought types, as derived from international journal publications.

2.1. Concept and calculation

At the beginning of the 1990s, Thomas B. McKee, Nolan J. Doesken, and John Kleist, researchers at the Colorado State University, developed the SPI with the intention to “propose an indicator and definition of drought which could serve as a versatile tool in drought monitoring and analysis” (McKee et al., 1993). At that time, the Palmer Drought Severity Index (PDSI) was the most widely used drought index in the U.S.A. (Hayes et al., 1999), despite caveats like inadequacy in mountain areas or spatial inconsistency. The theoretical framework of the SPI described by McKee et al., (1993, 1995) was substantially enhanced in the following years. Edwards and McKee (1997) and Guttmann (1999) provided detailed methodology for computation—including the Fortran source code—and applications of the index. Furthermore, the concept and the calculation procedure are tackled more or less detailed in most publications.

The SPI is a dimensionless probability index, and its computation for a given location and period is conducted after the following sequence:

(a) Data sets are fitted to a probability density function (PDF). The selection of the parametric distribution determines the accuracy of the SPI values (Singleton, 2012). McKee et al. (1993) recommended gamma, but other distributions perform at least similarly. Several options have been tested for different applications, i.e. Pearson III (Guttman, 1999; Vicente-Serrano, 2006b; Blain, 2011); Weibull (Livada and Assimakopoulos, 2007); log-normal (Angelidis et al., 2012); geometric (Cebrián and Abaurrea, 2012), but no universal agreement has been reached. The gamma PDF is defined as (Edwards and McKee 1997; Angelidis et al. 2012):

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

where \( \alpha > 0 \) is a shape parameter, \( \beta > 0 \) is a scale parameter, \( \Gamma \) is the gamma function, and \( x > 0 \) is the precipitation amount. Different formulas apply for
other PDFs.
(b) The results are then used to find the cumulative probability of a precipitation event for a given month and time scale (Edwards and McKee, 1997).
(c) Further, the cumulative probability distribution is transformed into a standard normal distribution, with mean of zero and variance of one, which is the SPI value (Sönmez et al., 2005; Angelidis et al. 2012).
Parry et al. (2011) illustrate eloquently the methodological flowchart from raw precipitation to SPI values showing the differences between two distinct climates in Europe (Figure 1). The precipitation pattern in an area may change over time, so that the shape and scale parameters of the PDFs change accordingly. Ntale and Gan (2003) assert that even a reasonably long calibration period provide results that would be affected significantly by a prolongation of the period.

At present, the SPI executables and manuals are available for Windows, Fortran, and R users (spi-support.blogspot.ro/p/software.html). Turgu (2008) report on the SPI program developed within the Turkish State Meteorological Service, capable to illustrate cumulative probability versus precipitation, and to display drought categories at the selected time scales.

Figure 1. Standardized Precipitation Index applied to summer three-month accumulations (JJA) for Madrid and London, 1901-2005 (Parry et al., 2011)
2.2. Time scale and length of data series

McKee et al. (1993, 1995) used the probability of the precipitation occurrence for 3, 6, 12, 24, 48 months, and recommended at least 30 years of data sets. Both the significance of the time steps and the length of the records were extensively scrutinized (Sönmez et al., 2005; Wu et al., 2005; WMO, 2012), and used in various ways. The short timescales proved their utility in meteorological and agricultural drought, while the longer are applied in hydrology (Guttman, 1998; Szalai and Szinell, 2000; Heim, 2002; Seiler et al., 2002; Łabedzki 2007). Sub-monthly scales are infrequently used. Wu et al. (2005) found that the length of the records becomes highly significant for computation only in regions where the precipitation pattern changes along time.

2.3. Thresholds

Beginning right with the original scale (McKee et al., 1993), the SPI has been often used in a simplistic way by considering precipitation surplus for SPI>0, and dry conditions for SPI<0, as Agnew (2000), Bhuiyan et al., (2006), or Ali and Lebel (2008) criticized. Most usual, the neutral conditions are defined around zero SPI.

Some authors proposed drought categories different than the original one, in terms of denominations (Hayes et al., 1999; Svoboda et al., 2002), thresholds (Agnew, 2000; Lloyd-Hughes and Saunders, 2002), or both (Michaelidis and Pashardis, 2008) (Figure 2). The neutral conditions are named ‘no drought’ (Agnew, 2000; Li et al., 2012), ‘average’ (Zsákovics et al., 2007), ‘normal’ (Vicente-Serrano et al., 2004; Liu et al., 2009; Zhai and Feng 2009), or ‘near normal’ (Hayes et al., 1999; Lana et al., 2001; Bonsal and Regier 2006; Zhang et al., 2009a). For some authors, the ‘mild drought’ begins immediately below zero (McKee et al., 1993, 1995; Liu et al., 2009; Zhai and Feng, 2009). The drought severity and wetness are divided in 3 to 5 categories, namely ‘abnormally’, ‘moderate’, ‘severe’ or ‘very’, ‘extremely’ and ‘exceptionally’ (Svoboda et al. 2002; Michaelidis and Pashardis, 2008). The precipitation deficit is named either ‘dry’ or ‘drought’, while the excess is generally named ‘wetness’.

Many studies provide the corresponding probability of occurrence for each category (Lloyd-Hughes and Saunders, 2002; Vicente-Serrano et al., 2004; Zhang et al., 2009a). Manatsa et al., (2008) propose a 3-digits SPI scale, probably too finely tuned for practical purposes. There is no universal recommendation for using the thresholds, and the operational needs are the main regulator.
2.4. Drought types

The SPI was initially designed to assess the meteorological drought, so that the first scale referred only to negative precipitation anomalies, although McKee and his colleagues acknowledged that the index could monitor both wet and dry periods (McKee et al., 1993). Nowadays, the SPI has become the most powerful and widely used of the simple drought indices (Bordi and Sutera, 2008; Angelidis et al., 2012), while publications regarding both the water deficit and surplus are much more rare (Krepper and Zucarelli, 2010; Yan et al., 2012), and no article dedicated to the excess only has been identified along this study. Most studies refer to a single type of drought (meteorological, agricultural or hydrological), but joint approaches are also useful (Mo, 2008; Caparrini and Manzella, 2009; Tabrizi et al., 2010; Vidal et al., 2010, 2012).

3. STRENGTHS AND LIMITATIONS

This section presents a succinct summary of the SPI’s benefits and disadvantages, acknowledging that most publications tackle the topic, and a few of them details it. One can remark that some characteristics may be interpreted both as strength and limitations (i.e. simplicity).

3.1. Strengths

1. Simplicity. The computation uses only atmospheric precipitation. However, despite its simplicity, Paulo and Pereira (2006) were capable to define the main features of the meteorological drought, such as lead-time, duration, severity, magnitude and intensity based on the SPI values, and the comparisons with indices of higher complexity demonstrate its efficiency (Bonsal and Regier, 2007; Sims et al., 2002; Vicente-Serrano et al., 2012).

2. Flexibility. It can be used to identify and assess both wet and dry periods (Dai et al., 2011).

3. It has the same efficiency for solid or liquid precipitation.

4. The standardization of the index triggers meaningful comparison between locations (Dai et al., 2011) and periods, undertaking consistency in interpretation. Nevertheless, the dry climate should be treated cautiously (see the SPI limitations).

5. Temporal versatility. SPI can be calculated over any timescale, depending on the user’s interest (WMO, 2012). The conceptual edifice of the SPI holds the idea that a region can be simultaneously in excess and in deficit, depending on the time scale approached (Redmond, 2011). While Hayes et al. (1999) advise avoiding the use of the 1, 2, or 3-month SPI in low precipitation climates, Guttman (1999), Vicente-Serrano (2006b), and
Champagne et al. (2011) argues that the SPI provide reliable results only up to 24-month periods. Sub-monthly periods are not recommended (Roudier and Mahe, 2010; WMO, 2012), but several studies were performed. For example, Anctil et al. (2002) found the 5-day SPI useful for predicting the end of ongoing droughts, Sims et al. (2002) calculated the daily, weekly, and bi-weekly SPI, while Wu and Wilhite (2004) pledged for the weekly scale in agricultural drought risk studies.

6. Monitor/operational use. SPI is capable to identify the drought onset very early. Bordi et al. (2001a, b) promoted the SPI for a monthly bulletin to monitor drought in Italy, and Carbone et al. (2009) developed a regional-scale dynamic drought index tool for North and South Carolina.

7. The topography does not bias the results.

3.2. Limitations

1. The SPI uses a single meteorological element for describing a complex event (Caparrini and Manzella, 2009). However, precipitation is the major driver at least for the meteorological drought (Guttman, 1998; Heim, 2002; Gebrehiwot et al., 2011).

2. The raw precipitation data are assumed to fit a theoretical probability distribution before the standardization, which may induce errors in the outputs. The results depend on the distribution used (Sienz et al., 2012), but there is no agreement over the best one.

3. The SPI cannot differentiate the regions in relation with their proneness to drought. As a consequence of its normal distribution, the index values occur with similar frequencies at any location.

4. It can provide uncertain results in arid areas and dry times, with quasi-normal distribution of the precipitation. Wu et al., (2007) documented coherently this weakness, and recommended that the duration of the drought should receive more focus than its severity. Naresh Kunar et al. (2009) showed that the SPI under-estimates the intensity of dryness/wetness when the rainfall is very low/very high, respectively. This limitation could make arguable the SPI usage in climate change studies, since precipitations are expected to decrease dramatically in certain spots (i.e. Southern Europe) in the decades to come (Vasiliades et al., 2009).

5. It does not take into account pre-drought conditions and gives long-past and recent precipitation the same weight; therefore, abrupt peaks may occur within the series, although in reality the drought onset and recovery are gradual. Paulo and Pereira (2006) proposed a backtracking procedure for set up the initiation of a drought event, but its end remains sudden.

6. The initial drought categories were arbitrarily defined (McKee et al., 1993, 1995). Turgu (2008) proposed an operational cumulative probability correspondence between SPI thresholds and precipitation, and Quiring (2009) proposed an objective location-specific method for defining...
operational drought thresholds.

7. The use of SPI could be problematic in regions with less than 30 years of data or with a sparse meteorological network. Reconstruction of the SPI based on proxies could address this limitation, as shown by Touchan et al. (2005) on tree rings. Shahid (2008) applied a neural network analysis to fill in the gaps in data series, while Rhee and Carbone (2011) demonstrated that the spatial interpolation of the missing daily data would be done previous to SPI calculation.

4. TOPICS

A large number of publications approached various facets of the SPI, such as methodology, causes and applications, e.g. Bonsal et al. (2011, 2012) reviewed the drought research in Canada, with a lot of references to the SPI in relation with the causes, characteristics, prediction and monitoring, convincing on the utility of the index in complex applications. After considerations regarding the spatial coverage (a), the section overviews, generally in a thematic and chronological order, the SPI publications referring to methodology and concept (b), applications (c), variability and forecast (d), drought and wetness causes (e), comparison and combination with other indices (f).

Table 1 summarizes the topics from publications referring to the SPI extended to regional, continental or global scale, with the following remarks: the selection is not exhaustive; the term ‘variability’ may refer to either spatial, temporal or both; the topics mentioned for each publication are not necessarily exclusive, but dominant. Similar information for country and local scale may be found at [http://spi-support.blogspot.ro/p/topics.html](http://spi-support.blogspot.ro/p/topics.html).

4.1. Spatial coverage

The SPI has been used in applications across all the continents, in a large variety of geographical conditions and climates, from local focus to global exposure. Its performances do not depend on the size of the area, i.e. Pai et al. (2011) achieved realistic outputs by analyzing the drought both over India, and its 458 districts, respectively.

The majority of the publications are oriented to administrative, geographical or hydrological basins, i.e. Bonaccorso et al. (2003) – Sicily (Italy); Bordi et al. (2004) – Elbe Basin (Germany) and Sicily (Italy); Vicente-Serrano and López-Moreno (2005) – Ebro’s mountainous basin; Zsákovics et al. (2007) – Danube-Tisza interfluves; Khadr et al. (2009) – Ruhr river basin (Germany); Zhang et al. (2012b) – Xinjiang (China); Champagne et al. (2011) – Alberta (Canada).
Table 1. Regional and global journal articles using the SPI.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Geographical extension</th>
<th>Time scale (months)</th>
<th>Phenomena*</th>
<th>Key topics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ntale and Gan (2003)</td>
<td>Africa (E)</td>
<td>2, 6, 9, 12, 16, 24, 36</td>
<td>D</td>
<td>drought assessment; comparison with PDSI and BMI; improvement of SPI</td>
</tr>
<tr>
<td>Rouault and Richard (2005)</td>
<td>Africa (S)</td>
<td>3, 6, 12, 24</td>
<td>D</td>
<td>variability; assessment; correlation with ENSO</td>
</tr>
<tr>
<td>Manatsa et al (2008)</td>
<td>Africa (S)</td>
<td>6</td>
<td>D</td>
<td>relationship with ENSO and Darwin Sea level pressure anomalies</td>
</tr>
<tr>
<td>Kurnik et al (2011)</td>
<td>Africa (Horn)</td>
<td>3, 6, 9, 12</td>
<td>D</td>
<td>drought assessment; drought monitoring</td>
</tr>
<tr>
<td>Shahabfar et al (2012)</td>
<td>Asia (Central and SW)</td>
<td>8**</td>
<td>D</td>
<td>comparison with PDI</td>
</tr>
<tr>
<td>Zhang et al (2012a)</td>
<td>Asia (E)</td>
<td>1, 3</td>
<td>B</td>
<td>paleoclimate; variability; causes; correlation with ENSO and volcanic activity</td>
</tr>
<tr>
<td>Bothe et al (2012b)</td>
<td>Asia (Central)</td>
<td>1</td>
<td>B</td>
<td>patterns; relationship with circulation</td>
</tr>
<tr>
<td>Walker et al (2009)</td>
<td>South America (Amazon River)</td>
<td>13**</td>
<td>D</td>
<td>vegetation response to drought</td>
</tr>
<tr>
<td>Mo and Berbery (2011)</td>
<td>South America</td>
<td>6</td>
<td>B</td>
<td>variability; correlations with ENSO and NTA</td>
</tr>
<tr>
<td>Lloyd-Hughes and Saunders (2002)</td>
<td>Europe</td>
<td>3, 6, 9, 12, 24</td>
<td>D</td>
<td>variability; comparison with PDSI</td>
</tr>
<tr>
<td>Bordi and Sutera (2008)</td>
<td>Europe</td>
<td>3, 24</td>
<td>D</td>
<td>variability</td>
</tr>
<tr>
<td>Lopez-Moreno and Vicente-Serrano (2008)</td>
<td>Europe</td>
<td>1-12</td>
<td>D</td>
<td>variability; relationship with NAO</td>
</tr>
<tr>
<td>Bordi et al (2009)</td>
<td>Europe</td>
<td>3, 24</td>
<td>B</td>
<td>variability</td>
</tr>
<tr>
<td>Hannaford et al (2011)</td>
<td>Europe</td>
<td>1, 3, 6, 9, 12</td>
<td>D</td>
<td>hydrological response to meteorological drought; RSPI</td>
</tr>
<tr>
<td>Hirschi et al (2011)</td>
<td>Europe (SE)</td>
<td>3, 6</td>
<td>D</td>
<td>relationships between dryness and temperatures</td>
</tr>
<tr>
<td>Beniston (2012)</td>
<td>Europe</td>
<td>1, 3, 6</td>
<td>D</td>
<td>relationships between dryness and temperatures</td>
</tr>
<tr>
<td>Maule et al (2012)</td>
<td>Europe</td>
<td>1, 3, 6, 9, 12</td>
<td>D</td>
<td>validation of RCM</td>
</tr>
<tr>
<td>Singleton (2012)</td>
<td>Europe</td>
<td>1, 3</td>
<td>D</td>
<td>drought forecast</td>
</tr>
<tr>
<td>Heinrich and Gobiet (2012)</td>
<td>Europe</td>
<td>1, 3, 6, 9, 12, 18, 24</td>
<td>B</td>
<td>climate change</td>
</tr>
<tr>
<td>Bordi and Sutera (2001)</td>
<td>Europe, Northern Hemisphere</td>
<td>3, 6, 12, 24</td>
<td>B</td>
<td>patterns; teleconnections; comparison with PDSI</td>
</tr>
<tr>
<td>AghaKouchak and Nakhiiri (2012)</td>
<td>Global</td>
<td>6, 12</td>
<td>D</td>
<td>drought forecast; remote sensing application</td>
</tr>
<tr>
<td>Burke and Brown (2008)</td>
<td>Global</td>
<td>12</td>
<td>D</td>
<td>drought forecast</td>
</tr>
<tr>
<td>Lotsch et al (2003)</td>
<td>Global</td>
<td>1-12</td>
<td>B</td>
<td>remote sensing application; comparison with NDVI</td>
</tr>
<tr>
<td>Mueller and Seneviratne (2012)</td>
<td>Global</td>
<td>3, 6, 9</td>
<td>B</td>
<td>relationship surface moisture - temperature extremes</td>
</tr>
<tr>
<td>Orlowski and Seneviratne (2012)</td>
<td>Global</td>
<td>12</td>
<td>D</td>
<td>variability; climate change</td>
</tr>
</tbody>
</table>

*) D: drought; B: both drought and excedent.
**) Days.
Other studies refer to national scale, even if a large or complex territory, i.e. Domonkos (2003) – Hungary; Brázdil et al. (2009) – Czech Republic; Costa (2011) – Portugal; Păltineanu et al. (2009) – Romania; Dash et al. (2012) – Bangladesh.


4.2. Methodology and concept

McKee et al. (1993, 1995) published the original papers that introduced the SPI with limited methodological guidelines, so that in the following years many studies approached the topic. The methodological and conceptual developments have targeted mainly the PDFs, the time scales, and the areal relevance. Edwards and McKee (1997) provided a detailed methodology, clarifying the conceptual basis and the computation process. Hayes (2000) remarked that relatively few publications had explained the SPI, the term was occasionally misused in confusion with the Standardized Anomaly Index (Jones and Hulme, 1996), alternatives to gamma function-based normalization had been proposed, and different terminology for the SPI could be considered.

(a) PDFs

The gamma distribution was employed by most studies (Ji and Peters, 2003; Capra and Scicolone, 2012), but other PDFs have been equally applicable. Lloyd-Hughes and Saunders (2002) found that the gamma distribution provided the best representation of the precipitation data, excepting the arid regions of Europe for which the Cauchy distribution is mentioned as a possible solution. Zhang et al. (2009a) considered gamma and log-normal distributions performed similarly at 95% confidence level, and used the latter one because of its simplicity. Angelidis et al. (2012) suggest that the log-normal probability distribution can be more convenient to use for 12- and 24-months, while the gamma distribution is the best choice for time scales up to 6 months.

Guttman (1999) advocated the use of the Pearson type III distribution, and a few applications have supported his assumption. Thus, Vicente-Serrano (2006b) used Pearson Type III for analyzing the spatial patterns of drought on different time scales in the Iberian Peninsula, Naresh Kumar recommended it as an alternative to gamma, while Blain (2011) found out that it performs better than gamma in describing the long term rainfall series.
for the State of São Paulo (Brazil).

Ntale and Gan (2003) tried to improve the SPI by using an unbiased plotting-position formula that can estimate the non-exceeding probability of precipitation (applicable for long data sets) (a), and by addressing the distortions in the distribution tails for skewed precipitation with a different transformation procedure (b). Cebrián and Abaurrea (2012) tested eight distributions (exponential, Weibull, gamma, log-normal, generalized Pareto, geometric, negative binomial and Poisson), and found out that the geometric distribution fitted best the durations of the dry spells in Huesca (Spain). Sienz et al. (2012) claim for reconsider the adequacy of the gamma distribution, and pledge for using the Weibull type distribution.

While any transformation may provide reasonable results, the PDF should be selected cautiously, according to the climate background in the area of interest. It is recommended that several distributions are tested to fit the local precipitation series, before calculating the SPI.

(b) Time scales

There is no general recommendation regarding the appropriate scale, so that the selection depends mainly on the user’s expertise, and applications entailed (i.e. agriculture, surface or ground waters). Guttman (1999) limited the SPI’s reliability to 24 months. However, the performance remains remarkable even if accepting this appreciation, taking into account that drought events within temperate climate (Touchan et al., 2005), or severe and excessive droughts in arid climates (Al-Qinna et al., 2011) rarely exceed two years.

Mishra et al. (2009) used a probabilistic approach to characterize the SPI-based drought and emphasized the influence of the time scales on the results. Some other examples are provided below, grouped by their reference to meteorological, hydrological or agricultural drought.

For the southern Italy, Bordi et al. (2001a), and Piccarreta et al. (2004) show that the 6 month scale reveals intense rainfall with short periods of water deficit, the 12 month scale discloses an increase in dry conditions, whereas the 24 month scale is able to record moderate to severe droughts. Sönmez et al. (2005) revealed situations when shorter steps, i.e. 3-month, capture the moderate and severe drought, while longer steps, i.e. 12-month, fail. In a study combining remote sensing techniques and drought indices, Champagne et al. (2011) determined that most suitable time scale of precipitation extremes to capture the soil moisture anomalies is less than 9 months. On the other hand, Abarghouei et al. (2011) pledged for the relevance of 24-month rather than shorter scales in dry climates.

For groundwater concerns, Carbone and Dow (2005) emphasized the relevance of the 24-month SPI, and Mendicino and Versace (2007) confirmed the capability of the time scales longer than 12 months to monitor water resources, but shorter scales have been also tested. Shahib and
Hazarika (2010) used 6-, and 12-month SPI for groundwater drought in Bangladesh.

Tabrizi et al. (2010) investigated the relationships between time-based meteorological and streamflow droughts in the southwestern Iran, and Somorowska (2011) confirmed that the substantial drying of the Lasica river basin (Poland) was caused by an increase of the number of 3-, 6- and 12-month SPI droughts. Du et al. (2012a) explored the suitability of different SPI-temporal scales for hydrological applications, and found out that the 2 month-time scale was appropriate for detecting flood events.

Sub-monthly time scales were used in several agricultural drought studies. Anctil et al. (2002) studied the capability of the 5-day SPI to predict the end of an ongoing drought. For an application exploring the dryness impact in the Amazon Basin, Walker et al. (2009) used a 13-day moving average to smooth the SPI data, and marked the beginning of dry seasons as the falling of the moving averages below 1.0 standard deviation of the mean daily rainfall. Lu (2011) investigated the physical basis for developing a daily flood and drought index based on the conceptual methodology of the SPI. Zhang et al. (2012c) used a 10-day SPI (from 10 to 110 days) in China. Since many studies have demonstrated that the time step can bias the results, it is recommended to use multiple scales in SPI analysis. Time scales from 1- to 24-months are the most common (http://spi-support.blogspot.ro/p/topics.html), but longer and shorter intervals may be considered in some applications.

(c) Areal relevance
Some scholars aimed to adjust the SPI towards a better response to the local conditions in the area of interest. Thus, Quiring (2009) proposed an objective methodology to derive the drought thresholds according to the local conditions, conditioned by the length of the records and by an appropriate PDF, and tested the gamma, normal, log-normal, and exponential distributions. Türkeş and Tatlı (2009) computed the SPI values by considering the local-time means of the precipitation series by fitting an upper and a lower envelope to precipitation data, and claimed the proposed method guarantees better results mainly for dry and wet conditions.

4.3. Applications
This section presents the main assumptions and findings regarding the SPI use in different applications. The most common domains are agriculture (a), and hydrology (b). Besides, very many studies analyse the vulnerability of vegetation and water resources to precipitation deficit (c), mapping issues (d), or case studies (e). The SPI’s assessment and monitoring capabilities are likewise covered by journal publications, while the topics sometimes interfere with each other. Mishra and Singh (2011) reviewed the state-of-
the-art in drought modelling, and remarked the constant involvement of the SPI in such applications. The SPI was also used in non-conventional applications, i.e. atmospheric CO$_2$ seasonal cycle and ecosystem (Angert et al., 2005; Buermann et al., 2007; Wharton et al., 2012), drought social perception (Sinoga and Gross, 2012).

(a) Agriculture

Yamoah et al. (2000) published the first SPI application in agriculture, studying the combined repercussions of the wetness and nitrogen on the maize crop yields.

After about a decade of systematic investigations, it is common to merge the SPI values, other drought indices, and remote sensing products, mainly the Normalized Difference Vegetation Index (NDVI). Ji and Peters (2003) conducted a thorough analysis of the relationship between the NDVI-retrieved condition of the vegetation, and the SPI-based moisture availability in the U.S. Great Plains. They found that the correlation is significant in both grasslands and croplands, it varies over the growing season, and it has the highest values for the 3-month SPI. In 2003, Lotsch et al., (2003) performed a similar analysis for terrestrial ecosystems, and reported a high degree of correlation for 5-month time scale. Vicente-Serrano et al. (2006) and Vicente-Serrano (2007) combined the SPI and high temporal resolution remote sensing images for tackling the vegetation response to drought in the middle Ebro valley. Peled et al. (2010) compared the changes in vegetation over Europe as captured by NDVI and various drought indices, and found better correlations for the Normalized total depth Soil Moisture (NSM; Dutra et al., 2008), PDSI and PDSI-SC (PDSI-Self Calibrated; Wells et al., 2004) than for the 3-month SPI, because of the soil surface and temperature information included in the algorithms.

Derived from the NDVI, the Vegetation Condition Index (VCI; Kogan, 1995) is highly correlated with PDSI and with 6- and 9-month SPI, being less sensitive to short-term precipitation deficiencies (Quiring and Ganesh, 2010). While the SPI remains a useful tool, Gebrehiwot et al. (2011) pledged for the superiority of the VCI in vegetation drought applications. For sub-humid and humid areas of NW India, Jain et al. (2011) conclude that the 1 to 9-month SPI fits best the vegetation drought severity and duration retrieved by NDVI and VCI. Champagne et al. (2011) combined the passive microwave remote sensing with the SPI in analyzing the soil moisture in Canada.

Scientific efforts have been dedicated to determine the most appropriate time scale for various agricultural purposes, but there is no general agreement reached. Łabedzki (2007) showed that 1–3 month SPI reflects the agricultural drought development in Poland. The seasonal drought patterns in the arid and semi-arid regions of Gujarat (India) let Patel et al. (2007) conclude that the 3-month SPI of September is a good indicator
of anomalies for grain yields in drought-prone areas. Iglesias and Quiroga (2007) proposed a methodology for measuring the climatic risk to cereal production based on the 12-month SPI as climate indicator. Mkhabela et al. (2010) found poor correlation between SPI and wheat yields in the Canadian Prairies. Subash and Ram Mohan (2011) examined the performance of the SPI for detection and monitoring of drought, with reference to the rice-wheat crop in the monsoon India. Pasho et al. (2011) and Pasho et al. (2012) documented the SPI utility in quantifying the drought impacts on tree growth in NE Spain. Zhang et al. (2012c) used 10-day SPI timescale for predicting the maize drought disaster in China. Eventually, Sadat Noori et al. (2012) argue that the prediction of wheat production in Iran is possible with an anticipation of several months before harvest based on 1-, 3-, and 6 months SPI.

(b) Hydrology

Du et al. (2012a) reported that the SPI is a valuable tool for hydrological monitoring, both in respect of dryness and wetness. Despite most SPI applications in hydrology refer to water deficit, the earliest publication on the topic focused on floods. Thus, Seiler et al. (2002) claimed the utility of the SPI in assessing the flood risk, indicating that 3 to 6-month time scales should be used for quantifying the superficial water, while 12 to 24 months are suitable for the subsoil moisture. Further, the SPI’s potential to be used in hydrology has been validated by researches on streams, groundwater, and lakes.

Within different river basins, Cancelliere and Salas (2004), Vicente-Serrano and López-Moreno (2005), Edossa et al. (2010), and Ganguli and Janga Reddy (2012) analysed multiple facets of the river response to meteorological drought (i.e. duration, severity, return period) with 1 to 24-month time scales SPI. These studies have validated Seiler et al. (2002), revealing that the 3-6 months time scales are suitable for surface flows, the reservoirs respond better to 7-12 months, and longer time scales should be avoided in surface hydrology.

For hydrogeological applications, Bhuiyan et al. (2006) combined the SPI with the groundwater recharge deficit and NDVI information. Mendicino and Versace (2007) demonstrated its usefulness for monitoring the resources from Southern Italy, Khan et al. (2008) employed it to track the influence of the rainfall on groundwater and the impact on the irrigation needs in Australia, and Di Matteo et al. (2011) pledge for its utility in hydrogeology of the Mediterranean limestone areas.

Some studies compared the SPI and other indices in term of hydrological performances. Based on the results retrieved by SPI and SPEI (Standardized Precipitation Evapotranspiration Index; Vicente-Serrano, 2010) in the Tagus River Basin (Spain), Lorenzo-Lacruz et al. (2010) argue that the influence of temperature on hydrological drought is not negligible.
In a study extended over 1950-2099 across the Blue River Basin (Oklahoma), Liu L et al. (2012) acquired significant correlations between SPI and SRI (Standardized Runoff Index; Shukla and Wood 2008) with 2-month lag time.

Last, but not least, Myronidis et al. (2012) explored the long-term effect of drought on a Mediterranean shallow lake in Greece, and found that 3- and 24-month can be used for such correlations.

(c) Risk and vulnerability

In the recent decade, the SPI has become a common tool for assessing the drought risk and the vulnerability of certain areas and resources, and numerous publications report on the magnitude, intensity, frequency or spatial extension of drought hazards in agriculture and hydrology. Most of them describe the performances of multivariate techniques and models (Wu and Wilhite 2004), probabilistic approaches (González and Valdés, 2004; Liu L et al., 2011), and copulas (Ganguli and Janga Reddy, 2012; Shiau, 2006; Shiau et al., 2012; Zin et al., 2012).

Local and country scales prevail. Sönmez et al. (2005) investigated the drought vulnerability in Turkey, and Bordi et al. (2007) focused on the analysis of extreme wet and dry periods in Sicily. Pandey et al. (2010) scrutinized the temporal variability of the SPI-based drought severity within an effort to integrate hydro-meteorological and physiographic factors for assessing the vulnerability to drought in the Sonar basin (India). The SPI is useful for studying the country-wide vulnerability and risk to drought both under dry and wet climates, as demonstrated with the applications in Botswana (Batisani 2011), Greece (Karavitis et al., 2011), Iran (Mansouri Daneshvar et al., 2012), and Malaysia (Zin et al., 2012). Hirschi et al. (2011), Beniston (2012), and Mueller and Seneviratne (2012) approached the relationships between hot temperature extremes and dryness at regional (SE Europe), continental (Europe) and global scale, defining the surface moisture deficit with the SPI.

Hydrological risks have been widely approached. Roudier and Mahe (2010) evaluated the drought hazards within the Bani River Basin (Mali) using the Climatic Moisture Index (CMMI; Vörösmarty et al., 2005), demonstrated that the 10-day time scale SPI was inadequate for estimating the water deficit, and recommended the utilization of EDI (Effective Drought Index; Byun and Wilhite, 1996). Ganguli and Janga Reddy (2012) assessed the risk of hydrologic droughts in India.

The potential of the SPI to be used in forest fire and insurance is underexploited, despite some published reports. Caccamo et al. (2011) assessed the relationship between SPI and MODIS-based spectral indices at different time scales in Australia, as a tool for monitor the vegetation drought in the fire prone Sydney Basin Bioregion. Dimitrakopoulos et al. (2011) and Drobyshchev et al. (2012) reported on the SPI performance in
analyzing and detecting the forest fire in Greece and, respectively, in Sweden, while Hofer et al. (2012) selected the SPI to define the drought conditions in a multi-disciplinary forest fire risk assessment in the Iberian Peninsula.

Lyon et al. (2009) stressed the relationships between drought relief payments and meteorological indices like SPI and monthly rainfall anomalies, as a valuable tool for the insurance business.

Several studies have resulted in risk measures for drought analysis (Cebrián and Abaurrea, 2012), or Drought Hazard, Exposure, and Vulnerability Indices (DHIk, DEIk, DVIk) (Shiau and Hsiao, 2012). Sun et al. (2012) combined the SPI with two versions of PDSI to develop a multi-index drought (MID) model for improving the agricultural drought risk assessment and prediction.

(d) Mapping and drought regionalization

The standardization enclosed in the SPI sustains the spatial meaning, while its ultimate normal distribution leads to similar frequencies at any location, and complicates the interpretation. While very many publications just use spatial representations of the values, some applications have strived to bring more consistency to SPI interpolations, by approaching gridding methods, deriving indices more oriented to spatiality, or implementing GIS-based monitoring, and satellite imagery in regions with sparse meteorological networks (Bhuiyan et al., 2006; Gebrehiwot et al., 2011).

Lloyd-Hughes and Saunders (2002) developed a grid-based (0.5° resolution) drought climatology for Europe using the SPI and PDSI. Tonkaz (2006) mapped the SPI in southeastern Anatolia based on a GIS application. Rhee and Carbone (2008) used the SPI in a mapping exercise testing the influence of the spatial interpolation and data aggregation in drought assessment. Mishra and Nagarajan (2011) developed a GIS project to grid the SPI-derived drought in India, while Mishra and Nagarajan (2012) compared the SPI and irrigation demand maps, obtaining good correlations for 2-, and 3-month. Akhtari et al. (2008, 2009) suggest that the interpolation methods and SPI time-steps should be fitted to obtain the most relevant results. They found that krigging is the best method for one-month SPI, and the Thin Plate Smoothing Spline method is the best for 12-month scale.

The introduction of indices and methodologies to support the better spatial representation of the SPI has been developed in the recent years. Loukas and Vasiliades (2004), and Loukas et al. (2008) introduced and developed the Drought Severity-Areal Extent-Frequency (SAF), a method to assess the spatial characteristics and the frequency of the drought over an area, using GIS capabilities and SPI at various time scales.

Koutroulis et al. (2011) addressed the drought spatiality defining the Spatially Normalized–Standardized Precipitation Index (SN-SPI) in an
application over the Island of Crete. In their turn, Liu X et al. (2012) proposed the Areal Drought Magnitude (ADM), an aggregated index aimed to assess both temporal variation of drought magnitude and spatial extent of drought events. Recently, Mansouri Daneshvar et al. (2012) proposed a Drought Hazard Index (DHI) produced by summing up the spatial representation of the SPI values over a certain territory. In the same time, aiming to add relevancy to the SPI-based comparison of the drought in European regions, Hannaford et al. (2011) defined the Regional Standardized Precipitation Index (RSPI), further used by Maule et al. (2012).

Giddings et al. (2005) found the SPI analysis was relevant to justify distinct, self-content and homogenous precipitation zones in Mexico, with possible practical applications. Since then, other efforts to fundament the delineation of homogenous regions using the SPI have been done. Inspired by the SPI methodology, Reich et al. (2008) defined climatic zones in the states of Jalisco and Colima (Mexico) combining monthly temperature, precipitation and evaporation, and suggested the data transformation whenever they are highly skewed. Based on SPI12 and PCA, Raziei et al. (2009) were able to differentiate two climatic sub-regions in the western Iran.

Dubrovsky et al. (2009) introduced the relative SPI (rSPI) and the relative PDSI (rPDSI), obtained by using a reference series, either weather station or period data, in order to allow for a better comparison of spatial drought conditions. Further, Jung and Chang (2012) introduced the rSRI and used it in conjunction with rSPI for studying the hydrological drought risk under climate change perspectives in Oregon (USA).

Abolverdi and Khalili (2010) applied L-moments statistics to investigate the drought characteristics, and they distinguished between the different applicability of 3, 6, 12, and 24-month time steps SPI for extreme drought studies. Thus, they derived four homogenous sub-regions using SPI3, while longer intervals emphasized only one region in the southwestern Iran. Santos et al. (2011) and Moreira et al. (2012b) also used the SPI to differentiate homogenous regions relative to drought in Portugal.

(e) Case studies
4.4. Variability and forecast

The topics follow at least three directions, namely the past (a), and future (b) long-term variability and changes, and the operational drought forecast (c). Statistics and modelling approaches are abundant (Edwards and McKee, 1997; Komuscu 1999; Feng and Hu 2004; Chen et al., 2009; Logan et al., 2010; Nikolova et al., 2012), but tree-rings (Touchan et al., 2005; Linderholm and Molin, 2005; Bonsal et al., 2012; Levanič et al., 2012), and documentary archives (Min et al., 2003) were also utilized.

(a) Past variability

Investigating the past variability of the drought is probably the most common approach exploiting the SPI, and the publications started at the beginning of the 2000s. Thus, Lana et al. (2001) analyze the spatial and temporal variability of the precipitation in Catalonia (Spain) and discuss the SPI’s capacity to offer “the best picture of rainfall shortage and excess patterns”. The majority of the articles cover decadal time resolution (Sirdas and Şen, 2001; Bordi et al., 2009; Viste et al., 2012), but longer periods extend to centuries. The non-parametric Mann-Kendall test seems to be the most popular in decoding significant trends in precipitation and droughts. Zhai and Feng (2009) applied it in the Gansu Province (China), and Abarghouei et al. (2011) in Iran.

Min et al. (2003) compared the SPI-based drought temporal patterns from South Korea and East Asia, including a “preliminary study” over the pre-instrumental period. Touchan et al. (2005), Linderholm and Molin (2005), Levanič et al. (2012), and Seftigen et al. (2012) developed long-term SPI reconstructions (centennial) in Turkey, Romania, and respectively, Sweden using tree ring chronologies, and emphasized both the potential and the limitations of such approaches. Bonsal et al. (2012) assessed the variability of drought in the Canadian Prairie over pre-instrumental, instrumental and future period, combining the SPI and PDSI benefits. Tree-rings analysis extended to the year 1350, and future droughts were derived from statistically downscaled climate from several Atmosphere–Ocean Global models with multiple emission scenarios. Zhang et al. (2012a) selected the SPI as a precipitation deficit/surplus indicator in investigating the conjugated influence of El Niño and volcanic activity on the East Asia climate over the last 1,200 years.

The variations in precipitation may affect the duration-magnitude or the intensity-duration-frequency relationships, and SPI is suitable for such approaches (Sirdas and Şen, 2001; Hallack-Alegria and Watkins, 2007).

Kangas and Brown (2007) used thirteen SPI time steps from 1 to 120-month scales in order to examine the long term characteristics (1895-2003) of the precipitation regime in the U.S.A. with the help of the Parameter-
elevation Regression on Independent Slopes Model (PRISM) (Daly et al., 1994).

The studies tackle regions, i.e. NW Iberian Peninsula (Vicente-Serrano et al., 2011b), Gujarat (Patel et al., 2007), Huaihe River Basin (Li et al., 2012), countries, i.e Bangladesh (Shahib, 2010), Portugal (Paulo et al., 2012), or continents (Bordi and Sutera, 2008; Bordi et al., 2009).

(b) Operational forecast

As regards the short- and medium-term hydrological and meteorological drought and flood forecast, Hannaford et al. (2011), and Estrela and Vargas (2012) consider that the SPI exploitation is modest, in spite of the numerous outputs reported in international journals (Bacanli et al., 2009; Durdu, 2010; Al-Qinna et al., 2011; Belayneh and Adamowski, 2012; Blain, 2012), based on modelling, teleconnections, joint and statistics analysis.

The SPI and remote sensing products (NDVI) can be coupled for predicting agricultural drought and cereal productions with months in advance (Vicente-Serrano et al., 2006; Dutta et al., 2012).

Mishra and Desai (2006), Cancelliere et al. (2007), Paulo and Pereira (2007), Paulo and Pereira (2008), and Durduk (2010) used stochastic techniques, neural networks, and transition probabilities between drought classes and different time horizons for methodologies addressing the seasonal and non-seasonal forecast of the SPI with various periods ahead, successfully validated with measurements.

In Portugal, Moreira et al. (2008), and Moreira et al. (2012a) used the 12-month SPI in log-linear models and ANOVA-like inference approach aiming to predict drought categories, its initiating, development and termination, as well as the temporal changes in frequency and severity. In their turn, Santos et al. (2011) were concerned with the regional frequency analysis of the drought derived from 1, 3, 6, and 12-month SPI. Xu et al. (2011) noticed that the SPI of time scales larger than 9 months was effective in identifying most extreme summer and summer-autumn drought in the Han River Basin (China), so it may be used in the risk forecast.

Manatsa et al. (2008, 2010) documented the combination between El Niño-Southern Oscillation (ENSO) and the Indian Ocean dipole/zonal mode as a significant predictor of drought variability in the southern Africa, while Zhang et al. (2009b) proved that SPI is a useful index in modeling both dryness and wetness variations, and found similar periodicities between ENSO and SPI24 for Shanghai.

It is certain that joint inputs may improve the results significantly. Huang and Carbone (2009) developed a SPI-PDSI ensemble forecast for South Carolina, while Sohn et al. (2012) used the SPI3 in an experimental multi-model ensemble system designed to forecast drought and flood over South Korea. Keskin et al. (2009, 2011) found a good potential of the
Adaptive Neural-based Fuzzy Inference System, fuzzy logic and artificial neural networks methods to predict the regional meteorological drought using the 12-month SPI values. Hannaford et al. (2011) used the correlation between the Regional Deficiency Index (RgDI), a hydrological drought indicator, and Regional Standardized Precipitation Index (RSPI), designed as a meteorological drought indicator, for exploring the large-scale spatial coherence of droughts over Europe and prospect for forecasting. Rezaeian-Zadeh and Tabari (2012) applied a multilayer perceptrons (MLP) approach including the antecedent SPI, NAOI and SOI values to forecast the SPI in different climates of Iran, and reached the best results for 12 and 24-month time scales.

(c) Long-term predictions

The long-term predictions refer to the 21st century and many are based on IPCC gas emission scenarios (IPCC, 2007). One can remark the considerable spatial coverage, the diversity of scenarios and models, and the consistent use of the SPI, at different spatial and time-scales. The main topic is the meteorological drought, but hydrology, agriculture, and adaptation as well. The studies are published after 2007, and their main assumptions are briefly summarized here.

Sienz et al. (2007) used the monthly SPI and pointed out the relative stable trends in extreme dryness, and increasing wetness in winter and spring for Iceland along the 21st century in the A1B IPCC scenario. Mavromatis (2007) assessed the future wheat yields in Greece using the SPI and PDSI projections coupled to the Hadley Centre regional climate model (HadRM3) under the A2 IPCC scenario (IPCC, 2007). In their turn, Burke and Brown (2008) used SPI12 to explore the drought projections under single and double CO2 scenarios.

Standardized Precipitation Index; rSPI were jointly used to project drought conditions in the Czech Republic (Dubrovsky et al., 2009), or the hydrological drought risk (Jung and Chang, 2012) in Oregon (USA).

In their turn, Li et al. (2008), Loukas et al. (2008), Mishra et al. (2010), and Liu L et al. (2012) used various groups of models under different IPCC scenarios to scrutinize the SPI variability over 20th and 21st century in the Amazon region, Thessaly (Greece), Midwestern United States and Blue River Basin (Oklahoma). Tölle et al. (2012) highlighted regional differences in the future vulnerability to SPI-derived water surplus or deficit risks between locations in the central part of Germany. Based on 21st century runs of ARPEGE under three emission scenarios, Vidal et al. (2012) advance spatial theoretical adaptation scenarios for France, with the spatial consistency of the SPI and SSWI.

Apparently, the time scale can influence the outputs. For example, Vasilides et al. (2009) showed that the climate change is likely to affect the drought severity in the Lake Karla watershed (Greece), but the uncertainty
is quite large and increases with the SPI timescale. Strzepek et al. (2010) used 5- and 9-month SPI combined with the PDSI, to see how climate change affects the frequency of SPI meteorological droughts in the U.S.A. along the 21st century. Singleton (2012) analysed the performance of the ECWMF monthly forecast for predicting the meteorological drought, and found out that the reliability in forecasting SPI1 and SPI3 is weak, suggesting calibration as a possible improvement.

Heinrich and Gobiet (2012) combined the results of the ENSEMBLES project, the SPI and PDSI to analyse the dry and wet conditions in Europe in the next decades. Orlowsky and Seneviratne (2012) used the outputs of the Coupled Model Intercomparison Project (CMIP5) ensemble of GCM simulations (Taylor et al., 2012) to compare the drought past variations and future projections of the SPI and Soil Moisture Anomalies at planetary scale. Within the IPCC-A2 scenario, the SPI12, Percent of Normal (PN), and Erinç’s Aridity Index values show an increase in drought incidence over the Aegean, southeastern Anatolia, western and central parts of the Mediterranean region, and Sen et al. (2012) reflected the expected changes in the biomass, yield and growth duration for corn.

4.5. Drought/wetness causes

The SPI-based investigations on the drought/wetness causes have identified several triggering mechanisms: NAOI (Domonkos, 2003; Vicente-Serrano and Cuadrat, 2007; López-Moreno and Vicente-Serrano, 2008); ENSO/SOI (Scian et al., 2006; Liu et al., 2009; Blain, 2012); North Tropical Atlantic Index (NTA; Mo and Berbery, 2011); distance to water bodies that govern the origin and direction of air masses and flows (Vicente-Serrano and Cuadrat-Prats, 2007; Zhang et al., 2009a); Darwin Sea level pressure anomalies (Manatsa et al., 2008); monsoon cycles (Subash and Ram Mohan, 2011); El Niño and volcanic activity (Zhang et al., 2012a); SST (Wu and Kinter, 2009); Europe-Greenland Index (Sienz et al., 2007).

The teleconnections have been considered one of the main influencing factors. One of the earliest studies using the SPI linked the drought occurrence in Europe with the Tropical Pacific signal (Bordi and Sutera, 2001). NAOI has been tackled more often than other teleconnections (Vicente-Serrano and Cuadrat, 2007 for NE Spain; Di Mauro et al., 2008 for Sicily). According to the homogeneity of the NAO signal in respect to monthly precipitation, López-Moreno and Vicente-Serrano (2008) differentiated 17 European regions and described each of them in terms of SPI’s response at various time scales. They concluded that, generally, positive NAO phases determine negative SPI averages in southern Europe and positive average in northern areas, while the opposite situation occur during negative phases. However, regional variations or seasonal deviations must be carefully considered. Touchan et al. (2005) assumed that there are
similar spectral peaks in the SPI and NAO along 1251-1998, although without a clear statistical relationship.

ENSO may induce drought conditions in Americas, southern and western Asia, and southern Africa. Some studies combine the ENSO with NAO and/or other indices. Tadesse et al. (2004) observed strong relationships between the SPI and PDSI drought in Nebraska, and teleconnections like the Southern Oscillation Index (SOI), the Multivariate ENSO Index (MEI), and the Pacific Decadal Oscillation (PDO) Index. Shahid (2008) found significant relationships between SPI and MEI in Bangladesh. For the southern Africa, Rouault and Richard (2005) linked the drought to ENSO variability, but Manatsa et al. (2008) asserted that an earlier signal imposed by the Darwin Sea level pressure anomalies would be a superior drought predictor, and defined a country-wide aggregated value of the seasonal SPI, named Zimbabwe SPI, as a drought indicator, adjusting the Agnew scale (Agnew, 2000) to their needs. In the U.S.A., Mo et al. (2009) found that the Atlantic Multidecadal Oscillation (AMO) has a small direct influence on the 6-month SPI droughts, but it modulates significantly the ENSO signal. Keskin and Sorman (2010) found good correlations between a hydrometeorological index aggregating the SPI, SRI and SEI (a), NAO (b) and ENSO (c), for the vicinity of Ankara. ENSO and the Indian Ocean dipole were identified as possible mesoscale triggers for the agricultural drought in Zimbabwe (Manatsa et al. 2010), and Nepal (Sigdel and Ikeda, 2010). Mo and Berberi (2011) found that ENSO and NTA have a strong influence on the SPI-based drought and wet spells over South America, mainly when they act in unison or antagonistic, and pledge for using the findings in forecast. Lastly, Liu X et al. (2012) conducted a summative publication on the relationships between the 12-month SPI and several circulations relevant for China, including western Pacific Subtropical High (WPSH), East Asian Summer Monsoon (EASM) and ENSO.

Other approaches have focused on the atmospheric circulation, anthropogenic forcing, soil moisture, and cloud cover. Scian et al. (2006) referred to large scale atmospheric circulation to explain the extreme positive and negative rainfall anomalies in Argentina, using the monthly SPI in an EOF analysis. Brázdil et al. (2009) explored the synoptic climatology of the drought in Czech Republic, while Seftigen et al. (2012) linked the variability of the drought in Sweden to circulation patterns. Bothe et al. (2012a) correlated the summer precipitation in Tibet with circulation indices, and Bothe et al. (2012b) investigated the influence of the large-scale atmospheric circulation on the extreme precipitation in the Central Asia. In the Southern Amazon, Li et al. (2008) suggested that the anthropogenic and external forcing could be responsible for increasing dry conditions reflected by the 6-month SPI. Wu and Kinter (2009) correlated statistically the SST forcing with the droughts in the Great Plains,
considering the role of the soil moisture as well. They highlighted the importance of the time scale and, implicitly, the significant authority of the SPI to address such studies. Greene et al. (2011) investigated the relationships between drought derived from 1-month SPI and cloud cover retrieved from satellite imagery in an experiment over the Canadian Prairies.

4.6. Comparison and combination with other indices

The previous sections have already illustrated that the SPI has been critically compared and jointly used with several indices in a considerable number of publications, tackling mainly the PDSI, Reconnaissance Drought Index (RDI; Tsakiris and Vangelis 2004, 2005), SPEI, SRI, Percent of Normal (PN), and Rainfall Deciles (RD; Gibbs and Maher, 1965). A few syntheses referring to multiple indices have been also published. Moreover, the combination of more indices is a key issue for validating the results in specific applications. Within a condensed comparison of drought indices, Mishra and Singh (2010) concluded that their application should be defined according to the local conditions and utilization.

(a) Multi-indices approaches

Byun and Wilhite (1999) discussed the weaknesses of the major drought indices, including the SPI, and introduced the concept of effective precipitation as a basic tool for quantifying the drought duration and severity, and considered the daily scale as more appropriate than the monthly one. Keyantash and Dracup (2002) compared six indices (RD; SPI; Cumulative Precipitation Anomaly - CPA, Foley 1957; Rainfall Anomaly Index – RAI, van Rooy, 1965; Drought Area Index - DAI, Bhlame and Mooley, 1980; PDSI) in terms of their robustness, tractability, transparency, sophistication, extendibility and dimensionality. SPI ranked the second as weighted total, very close to RD, and scored maximum points as robustness, sophistication, and extendibility. Morid et al. (2006) included seven indices (RD; PN; SPI; China Z-Score Index – CZSI, Wu et al., 2001; Modified China Z-Score Index – MCZSI, Wu et al., 2001; Z-Score Index – ZSI, Wu et al., 2001; Effective Drought Index – EDI; Byun and Wilhite, 1996) in a comparison focused on their performances for drought monitoring in Iran. SPI and EDI were able to detect more accurately the onset of drought, its spatial and temporal variation. Quiring and Pradesh (2010) found low correlations between the VCI and PDSI, ZSI, SPI, RD, and PN. In a study aiming to evaluate the uncertainties in the projection of future drought, Burke and Brown (2008) reported that the SPI supplied much smaller global changes than indices considering the atmospheric demand for moisture (Potential Evapotranspiration Anomaly – PPEA, PDSI, and Soil Moisture Anomaly – SMA). The SPI seems to perform better than the Selianinov hydrothermic coefficient (CHT; Selianinov, 1928), Si and PN in identifying
mild and moderate drought, while CHT is more accurate in the spatial analysis of extreme drought events (Potop and Soukup, 2009).

(b) PDSI
Since the PDSI was considered the most powerful drought index at the time SPI was launched quite many studies refer to the two indices. McKee et al. (1993, 1995), and Edwards and McKee (1997) compared the SPI and the PDSI, and Guttman (1998) performed a spectral comparative analysis concluding that “the SPI may be a better indicator of dryness and wetness than the PDSI”. Hayes et al. (1999) emphasized how SPI addressed the PDSI’s drawbacks, and pledged for the combined use of the two indices. The performance and monitoring capabilities of SPI and PDSI were compared by Szalai and Szinell (2000) on the 1983 drought event in Hungary. Sims et al. (2002) suggested that the SPI is more representative of short-term precipitation and soil moisture variations than the PDSI, and propose a regression equation that uses SPI for soil moisture. Redmond (2002) asserted that the highest correlations occur between 6 to 12-month SPI, and other subsequent studies confirmed. Thus, Lloyd-Hughes and Saunders (2002) found a closer correspondence between SPI12 and PDSI, and Paulo and Pereira (2006) reached similar coherency in characterizing local and regional drought in Alentejo (Portugal) using SPI12, PDSI, and the Theory of Runs (TR) (Guerrero-Salazar and Yevjevich, 1975). Brázdil et al. (2009) used the same temporal scale for correlations over the droughts in the Czech Republic. Kangas and Brown (2007) used various time scales SPI and PDSI in analyzing the drought and pluvial characteristics over the U.S. and pledged for the comparison of the two indices to be performed in applications, with no a priori recommendation. In their turn, Ceglar et al. (2008) identified good correlations between SPI9 or SPI12 and PDSI for Ljubljana series (Slovenia).

Goodrich and Ellis (2006) commented on the conceptual and computational differences between SPI and PDSI, and recommended to use frequency distributions for comparative analysis. In analyzing the Canadian Prairies 2001/2002 drought, Bonsal and Regier (2007) found that SPI and PDSI retrieved comparable results, and emphasized the later index might be a better option for drought events associated with extreme temperatures. Vasiliades et al. (2011) demonstrated the utility of the 3- and 6-month SPI along with a PDSI-derived index for operational monitoring of the hydrological drought in Pinios river basin from Greece. Tunalioğlu and Durdu (2012) found that the PDSI-based drought indices performed better than the SPI in assessing the olive yield in western Turkey. Dash et al. (2012) found that the PDSI results for RegCM3 model and observed data are nearly the same to SPI calculations in Bangladesh.

Krysanova et al. (2008) introduced the DS, an index built from average daily temperature and precipitation, in a comparative study with
SPI and PDSI, and noticed that the former method was more sensitive to trends in drought frequency than the other two indices.

Sun et al. (2012) demonstrated that the prediction accuracy of the MID model, which exploits jointly the SPI and PDSI, is at least as accurate to using a single drought index.

Ntale and Gan (2003) analyzed the properties for BMI and modified versions of SPI and PDSI performances in East Africa, and found that the SPI was the most appropriate for drought monitoring due to characteristics already mentioned here (i.e. modest data requirements, temporal flexibility). As a result of a research developed over Sweden, Drobyshev et al. (2012) showed that the SPI’s performance in detecting the forest fire is comparable to other indices, like PDSI or the ratio between actual and potential evapotranspiration.

(c) RDI

Tsakiris and Vangelis (2004), and Tsakiris et al. (2005) introduced the RDI performing an extended comparison with the SPI. Tsakiris et al. (2007) presented the indices used for application in Mediterranean countries within the project Medroplan, including the SPI, PDSI, the method of deciles and RDI. Pashardis and Michaelides (2008) found a very good correlation between the two indices in Cyprus and pledged for the common implementation in drought assessment. Bazrafshan et al. (2010) compared the SPI with the RDI in coastal areas of Iran and indicated the SPI as better in detecting meteorological droughts. Asadi Zarch et al. (2011) performed a similar comparison for the whole Iran and found that the two indices provided comparable results, excepting the humid and sub-humid regions, and they were better correlated for 3, 6, and 9-month time scales than for the larger ones. In their turn, Khalili et al. (2011) concluded that for agricultural purposes the RDI can be more appropriate than the SPI, at least for 3, 6, and 12-month values.

(d) SPEI

There are many meteorological, hydrological, and agricultural drought studies that compare or combine the SPI and the recently developed SPEI, as the latter index supplies crucial information for drought analysis, namely the evapotranspiration. Lorenzo-Lacruz et al. (2010) considered that the hydrological drought response is eventually slightly higher for SPEI than for SPI-based analysis, because of the thermal influences. The SPI, SPEI and SC-PDSI reflect the meteorological drought to river discharge, but Joetzjer et al. (2012) found differences in their performances in two extreme large world basins (Amazon and Mississippi). Potop (2011) remarked that SPEI and an adjusted version of the Si provide better results than SPI in detecting agricultural drought, due to enclosure of specific information such as temperature or soil moisture. Combining the three indices was considered a
useful strategy for drought monitoring. Potop et al. (2012) remarked large differences between SPI and SPEI whenever the adversely trend in temperature and precipitation occurs, such as 1900-1920 or 2000-2010 in the lowlands of the Czech Republic. Besides, for short time-scales (1-2 months) the two indices provided comparable results for average drought durations, while for mid- and long-terms (3-24 months) the SPEI determined notably higher values than SPI. Paulo et al. (2012) demonstrated that 9 and 12-month SPI and SPEI identify the drought occurrence earlier than the PDSI and the PDSI modified for Mediterranean conditions. Besides, they found better correlation between SPI and SPEI for semiarid locations than for humid ones in Portugal. Recently, Vicente-Serrano et al. (2012) used data from 151 worldwide hydrological basins to evaluate comparatively the SPI, SPEI and PDSI for meteorological, agricultural or hydrological drought. They showed that the SPI and SPEI captured the droughts more accurately than the PDSI, and they argued that SPEI is superior to SPI for assessing summer drought. Telesca et al. (2012) found out structural similarities between SPI and SPEI in analyzing the drought in the Ebro river basin at 1, 3, 6, 9, and 12-month scale along 1950-2006.

(c) Other indices
Combinations of SPI with other indices were tackled occasionally and they are summarized in this section. It has to be mentioned that the term SPI has been sometimes misused for the Standardized Anomaly Index (SAI), and several new indices have been developed from the SPI concept.

Jones and Hulme (1996) defined the precipitation SAI as the difference between the amounts over a certain time scale and the precipitation average, divided by the standard deviation of the series, and Seiler et al. (2002) emphasized the differences between SAI and SPI. Nevertheless, a number of studies used the SAI and call it SPI, while in others it remains unclear if the precipitation series are fitted to a cumulative probability distribution prior to transformation into a standard normal distribution (Agniew, 2000; Ali and Lebel, 2008; Imanov et al., 2012; Kasei et al., 2010; Ali et al., 2011; Masoudi and Afrough, 2011; Mokhtari et al., 2011; Shamsipour et al., 2011). Mo (2008) addressed the meteorological, agricultural and hydrological droughts over the U.S. in a joint analysis based on model-derived SPI, SRI and Soil Moisture (SM). Keskin and Sorman (2010) applied a PCA procedure in order to aggregate the SPI, SRI, and SEI into a compacted hydrometeorological index capable to assess the water resources in the vicinity of Ankara (Turkey).

Byun and Kim (2010), and Kim et al. (2010) compared the SPI with the EDI, and expressed the superior performance of the latter in several aspects, such as better detection of long and short term droughts and better representation of the gradual development of droughts. In their turn, Akhtari
et al. (2009) evaluate the performance of several geostatistical methods in interpolating SPI and EDI.

Quiring (2010) developed an objective methodology for operational drought definition based on thresholds calculated for the SPI, PDSI and PN. Pai et al. (2011) showed that SPI and PN provided similarly results for identifying drought occurrences over India, whereas SPI performs better at district scale, at least during the southwest monsoon season.

Sušnik et al. (2012) compared the SPI with the Net Irrigation Requirements (NIR) in terms of detecting the agricultural drought. The CZSI and statistical ZSI are versatile indices that provide very similar results to SPI (Krepper and Zucarelli, 2010), but they could perform better for wet conditions, and they can be calculated on datasets with missing values (Wu et al., 2001).

Wu et al. (2004) combined the SPI and CSDI in assessing the drought risk of crops. Vergni and Todisco (2011) put the SPI in a comparative analysis with other climatic and agro-climatic indices (i.e. SDfI) in a drought variability study in Umbria (Italy).

Cancelliere and Salas (2004) comprise the 3-month SPI with other indices (i.e. PHDI) in analyzing the hydrologic drought length. Livada and Assimakopoulos (2007), and Zhang et al. (2009a) found exponential correlations between SPI and MAI (de Martonne, 1926), reflecting similarly well the dry conditions over Greece and over the Pearl River basin (China). Pâltineanu et al. (2009) consider that the combination of the climatic water deficit index and 12-month SPI may be useful for water management in agriculture. Somorowska (2011) jointly used the SPI and Standardized Cumulative Annual Deviation (SCAD) to assess the precipitation impact on the groundwater and stream flow in the central Poland. Further, in a study covering the continental U.S.A., Anderson et al. (2011) report good spatial and temporal correlations between the Evaporative Stress Index (ESI) retrieved from satellite imagery and the SPI at various timescales.

Barua et al. (2009) found out that the Aggregated Drought Index (ADI; Keyantash and Dracup, 2004) and the Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) perform better than SPI in identifying the historical droughts. Norouzi et al. (2012) argued that, for all types of droughts, ADI provided more reliable results comparing to SPI.

Ghasemi et al. (2011) pledged for monitoring the drought based on the method of the RD and on the SPI, considering that the later index could detect the onset and variations of the drought more adequately than the former.

The methodological concept behind the SPI computation inspired the development of analogous indices with applications in meteorology, climatology, soil science or hydrology: Standardized Water-Level Index (SWI; Bhuiyan, 2004); Standardized Streamflow Index (SSFI; Modarres, 2007); Standardized Runoff Index (SRI; Shukla and Wood, 2008);
Streamflow Drought Index (SDI; Nalbantis and Tsakiris, 2009); Relative Standardized Precipitation Index (rSPI; Dubrovsky et al., 2009); Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010); Standardized Flow Index (SFI) and Standardized Soil Wetness Index (SSWI; Vidal et al., 2010); Cumulation of Reduced Precipitation (CRP) and Weighted Average of Precipitation (WAP; Lu, 2011); Standardized Deficit Index (SDfI; Vergni and Todisco, 2011); Standardized Hydrological Index (SHI; Sharma and Panu, 2012).

The SPI was often used for comparing the performances and validating other indices, i.e. Dryness/Wetness Index (DWI; Shen et al., 2008); Evapotranspiration Deficit Index (ETDI) and Soil Moisture Deficit Index (SMDI; Narasimhan and Srinivasan, 2009); Scaled Drought Condition Index (SDCI; Rhee et al., 2010); Synthesized Drought Index (SynDI; Du et al., 2012b); Perpendicular Drought Index (PDI; Shahabfar et al., 2012), or the performance of regional climate model simulations to retrieve precipitation deficit (Maule et al., 2012).

5. STATUS OF THE OPERATIONAL USE

Several organizations have provided SPI-based interpolation products in near-real time, i.e. National Drought Mitigation Center (NDMC), Drought Management Centre for Southeastern Europe (DMCSEE), European Drought Observatory (EDO), many journal articles report on the SPI efficiency in monitoring activities, and one can expect an increasing usage in the years to come (Hayes et al. 2011; WMO 2012). NDMC was probably the first institution that implemented the SPI for operational use, creating national US maps since 1996 (Hayes et al., 1999). At ten years since its launch, the SPI was already one of the six key indicators combined within the Drought Monitor, a product designed to describe the drought conditions on a weekly basis (Svoboda et al., 2002). Goodrich and Ellis (2006) provided a comparative analysis between SPI and PDSI specifically to serve for a better implementation of a drought task force in Arizona. Carbone et al. (2008) described a drought monitoring system designed and implemented in the Carolinas (USA) that incorporates the PDSI, Palmer Hydrological Drought Index (PHDI;), Moisture Anomaly Index (Z-index; Palmer, 1965; Quiring and Ganesh, 2010), PMDI, Keetch-Byram Drought Index (KBDI), CMI and SPI, while McRoberts and Nielsen-Gammon (2012) spur for using the SPI as a high-resolution monitoring tool to assess drought on multiple time scales for the areas where precipitation is the most important triggering factor. However, Quiring (2009) reported that only 6 of the 33 state drought plans used the SPI for monitoring, in favour of other indices like reservoir levels, PDSI or precipitation amounts.

In Europe, Tsakiris and Vangelis (2004) proposed a procedure to
interpolate the SPI values over a complex terrain that could support a Drought Watch System for an area at mesoscale extent. Mendicino and Versace (2007) coupled SPI-based drought, satellite products and water balance modeling into a GIS designed to serve the implementation of an Integrated Drought Watch System in the Southern Italy. Further, Mendicino et al. (2008) provided an example of water resources management in agriculture, in which SPI thresholds indicate the pre-alert and alert state about the drought. Caparrini and Manzella (2009) present the concept of an integrated system for drought monitoring and water resources assessment in Tuscany (Italy), based on the cross-evaluation of the SPI, vegetation indices and hydrological model outputs.

Ceglar et al. (2012) describe the interoperability between DMCSEE and EDO and observe that even low resolution precipitation datasets could reproduce quite well the general drought temporal variability at shorter scale in Slovenia, with a possible application in estimating the impact of the meteorological drought on maize yield. Further, Medved-Cvikl et al. (2012) evaluated the utility of the integrated monitoring system developed within the DMCSEE.

Rouault and Richard (2005), and Kurnik et al. (2011) observed some spatial characteristics of the drought in the southern Africa, demonstrated the SPI’s superiority for drought monitoring at regional scales, and pointed out the necessity to identify and build suitable data sets. Morid et al. (2006) recommended SPI and EDI for operational drought monitoring in the Tehran province of Iran, after comparing seven indices. Based on a case study in South Asia, Smakhtin and Hughes (2007) promoted the operational use of the SPI with a software package capable to estimate, display and analyze multiple drought indices automatically. AghaKouchak and Nakhjiri (2012) demonstrated that the characteristics of the SPI, the present technological development and data availability favour the near real-time drought monitoring even in ungauged areas. They promote a drought monitoring tool that incorporates three large datasets of ground-based and satellite retrieved information, namely Global Precipitation Climatology Project (GPCP), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) and Tropical Rainfall Measuring Mission (TRMM).

A summary list of the institutions providing operational SPI information at different scales may be found in the at http://spi-support.blogspot.ro/p/operational-use.html/

6. CONCLUSIONS AND PERSPECTIVES

The SPI is characterized by technical credibility, policy relevance, and technical adequacy (Karavitis et al., 2011), it brings important benefits to
the drought investigators, like simplicity and flexibility, and its drawbacks can be overcome with reasonable efforts. Therefore, at two decades after the first publication, the SPI has become one of the most known and used drought indices in the world, getting to be a “universal meteorological drought index” (Hayes et al., 2011).

The scientific literature referring to the SPI is abundant, and it tackles aspects like methodology, suitability for different purposes and geographical circumstances, performance, comparison with other indices, and monitoring. In the first decade, the publications were fewer and addressed mainly methodological and conceptual matters, but the number of published articles and the diversity of applications have increased significantly in the last years (2010-2012). The geographical coverage is remarkable, reaching all the continents. While at least 70 countries have already implemented the SPI in drought monitoring and assessment, the operational applications can still be extended.

The debates have revealed that the SPI calculation should carefully consider the PDF and time scale appropriate for the application and area envisaged, as they can influence the results. There is no general agreement on the use of thresholds and categories, and many studies have addressed the SPI’s limitations, such as the performances in low precipitation areas (Zhai and Feng, 2009), the focus on a single variable to characterize complex phenomena (Gebrehiwot et al., 2011), or the deficiencies in considering the conditions previous to the period of interest (Paulo and Pereira, 2006). Therefore, one can assume that methodological adjustments in the SPI computation and application should be still tackled in future studies.

The original concept (McKee et al., 1993) has inspired the computation of new indices (i.e. SRI, SDI, SPEI), while some methodological developments refer to better spatial representativeness (Dubrovsky et al., 2009), or introduce other variables (Vicente-Serrano et al., 2010). Despite the numerous reports published in the recent years, the combination of the SPI with other indices and the use of remote sensing information are constantly encouraged as a way likely to improve the results (Szalai and Szinell, 2000; Wu and Wilhite, 2004; Gebrehiwot et al., 2011; Potop, 2011; WMO, 2012).

At present, the applications are oriented mainly to agriculture and hydrology, but the potential is considerable higher (i.e. ecosystem research, forest fire and insurance business). The SPI has clearly proved its utility in assessing the drought variability, or for short- and long-term predictions. Estrela and Vargas (2012) suggest that the SPI has still an unused potential for drought forecasting, and Singleton (2012) considers that better calibration, superior models, and right adjustment of the SPI calculation to the purpose could add more accuracy to the drought forecasting. At the same time, the wetness usage in wetness analysis should be reinforced.
While simplicity doubled with accuracy of the results sustain the SPI’s authority over other drought indicators, the overview of the studies and applications have revealed that the combined use of more indices is the best strategy for securing the relevance of the outputs.

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References


Di Matteo L, Valigi D, Cambi C. 2011. Climatic characterization and response of water resources to climate change in limestone areas: some considerations on the importance of geological setting. Symposium on Data-Driven Approaches to Droughts. Paper 41.


Dutra E, Viterbo P, Miranda PMA. 2008. ERA-40 reanalysis hydrological applications in


Krysanova V, Vetter T, Hattermann F. 2008. Detection of change in drought frequency in


Moreira EE, Mexia JT, Pereira LS. 2012b. Assessing homogeneous regions relative to


Rezaeian-Zadeh M, Tabari H. 2012. MLP-based drought forecasting in different climatic

59


Vergni L, Todisco F. 2011. Spatio-temporal variability of precipitation, temperature and


