A novel soil moisture-based drought severity index (DSI) combining water deficit magnitude and frequency

Carmelo Cammalleri,* Fabio Micale and Jürgen Vogt
Joint Research Centre, European Commission, Ispra, Italy

Abstract:
A correct identification of drought events over vegetated lands can be achieved by detecting those soil moisture conditions that are both unusually dry compared with the ‘normal’ state and causing severe water stress to the vegetation. In this paper, we propose a novel drought index that accounts for the mutual occurrence of these two conditions by means of a multiplicative approach of a water deficit factor and a dryness probability factor. The former quantifies the actual level of plant water stress, whereas the latter verifies that the current water deficit condition is unusual for the specific site and period. The methodology was tested over Europe between 1995 and 2012 using soil moisture maps simulated by LisFlood, a distributed hydrological precipitation–runoff model. The proposed drought severity index (DSI) demonstrates to be able to detect the main drought events observed over Europe in the last two decades, as well as to provide a reasonable estimation of both extension and magnitude of these events. It also displays an improved adaptability to the range of possible conditions encountered in the experiment as compared with currently available indices based on the sole magnitude or frequency. The results show that, for the analyzed period, the most extended drought events observed over Europe were the ones in Central Europe in 2003 and in southern Europe in 2011/2012, while the events affecting the Iberian Peninsula in 1995 and 2005 and Eastern Europe in 2000 were among the most severe ones. © 2015 European Commission - Joint Research Centre. Hydrological Processes published by John Wiley & Sons Ltd.

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INTRODUCTION
Over the past decades, an intensification in drought-related disasters was observed worldwide (e.g. Allen et al., 2010). This suggests the need of increasingly accurate methods to monitor and quantify drought events. Over continental Europe, the European Drought Observatory (http://edo.jrc.ec.europa.eu) focuses on integrating drought information at different scales (e.g. continental, Member States and river basins) by comprising a range of indicators including precipitation maps, satellite data and modelled soil moisture, as well as a combined drought indicator (Sepulcre-Cantó et al., 2012).

The need for a variety of indicators is dictated by the complexity of drought events and the wide range of possible impacts, as well as by the large range of spatio-temporal scales involved; in fact, drought is a natural phenomenon substantially driven by a precipitation deficit, and it may be commonly classified into the following: (i) meteorological drought, based on precipitation anomalies compared with climatology, (ii) agricultural drought, describing the impacts on soil moisture and yields, and (iii) hydrological drought, quantifying streamflow deficits, groundwater depletion and reduction in the water level of reservoirs.

Focusing our attention on the effect of drought on vegetated lands, the so-called ‘flash drought’ events (Svoboda et al., 2002) (rapidly occurring events of dryness that last less than 1 year) are of great interest due to their impacts on plant productivity. A formal definition of such events is that they are the result of a water supply shortage that reduces plant water availability to unusually low levels and negatively affects ecosystem productivity (e.g. Panu and Sharma, 2002). This definition relies on the capability to identify a usual state of the system, on the basis of the most recent historical observations and on the assumption that this usual state represents an equilibrium condition for the system. Because the analysis is focused on ‘flash droughts’, the assumption that a time series of about 20 years allows an estimation of the usual state of the system is reasonable.

Starting from the previously reported definition of drought, two main traits of such events can be identified: (1) drought is an unusual dry state compared with the ‘normal’ state of the system and (2) the soil water deficit...
should reach a level causing severe stress conditions for the vegetation canopy. Those two characteristics must manifest at the same time in order to identify a drought event, because an unusually low level of water availability that is however well above the plant stress level is not affecting the ecosystem, whereas a high level of water stress that is rather common for a specific site and period cannot be considered an exceptional event such as a drought.

Soil moisture is seen as one of the most suitable variables to monitor and quantify the impact of water shortage on vegetated lands due to its effects on the terrestrial biosphere and the feedback into the atmospheric system; similarly, also, evapotranspiration-derived indices (e.g. evaporative fraction, ratio actual to reference evapotranspiration) are considered key parameters for water stress assessment and quantification. Such considerations justify the large literature focused on the use of these quantities for a spatially distributed monitoring of drought events at regional to continental scales (e.g. McVicar and Jupp, 1998; Sheffield and Wood, 2007; Wang et al., 2011; Anderson et al., 2013). Nevertheless, the majority of the studies are focused on either one of the previously outlined characteristics.

One notable attempt on quantifying the discrepancy between moisture demand and supply based on local mean conditions is the Palmer Drought Severity Index (PDSI, Palmer, 1965). This index is currently largely used in the USA for drought detection (Heim, 2002), even if several limitations of PDSI were detected. Dai et al. (2004) pointed out how PDSI is oversimplified in treating some key hydrological processes (i.e. no snow accumulation and simplified evapotranspiration schematization) and how this index is indeed more a measure of meteorological drought rather than agricultural drought.

On the one hand, the increasingly sophisticated land-surface process models allow for the direct use of their hydrological outputs to derive drought indicators; this is an appealing alternative for a detailed spatially distributed monitoring of drought phenomena, replacing the simplified water budget methodologies adopted in the past. On the other hand, the growing amount of detailed information on soil moisture dynamics requires a straightforward procedure to extract only the most useful information for drought detection in an effective way.

Indicators based on the soil water deficit and related plant water stress on the one hand (e.g. Sridhar et al., 2008; Hogg et al., 2013) quantify the status of the soil moisture at a certain time compared with the possible range of variability for that specific site (on the basis of soil and plant properties) but without accounting for the previous history and natural climatology of the site. As a consequence, water deficit indices are able to capture the degree of water stress, but they do not provide information on the frequency on which that level of water stress is reached in the specific site and period. This may lead to an unusually high number of drought events for areas that are arid or semi-arid, because the low soil moisture values that occur yearly during the dry season would be misinterpreted as droughts.

Indicators based on anomaly detection of soil moisture or evapotranspiration-derived quantities on the other hand (e.g. Anderson et al., 2007; Sepulcre-Cantó et al., 2012; Anderson et al., 2013; Choi et al., 2013) focus on the ‘rarity’ of an event only, without considering the actual water deficit conditions at which those anomalies occur. Such approaches, which are generally robust for environments with a strong inter-annual variability, may lead to an overestimation of drought events in generally wet systems characterized by a small inter-annual variability, where even very infrequent events may be far from causing actual water stress to the plants.

Similar limitations can be observed in approaches based on the detection of a certain percentile of a probability distribution of soil moisture data (e.g. Sheffield et al., 2004); in fact, over areas with a limited variability in soil moisture small variations can lead to extreme percentiles that are indeed rather close to the normal status. Hence, even if percentiles and anomalies are widely seen as good methodologies for drought detection, they can be misleading when applied over large areas characterized by a variety of conditions in soil moisture dynamics.

With the aim of developing a methodology that is flexible enough to be applicable on a wide range of soil moisture dynamics, the major goal of this study is to develop a drought index capable of removing the limitations related to the use of the sole water deficit or anomaly information by combining those data into a unique synthetic descriptor of the severity of a drought event. The development of this index is based on the consideration that only the events that are at the same time ‘rare’ and ‘stressful’ for the vegetation should be regarded as drought.

**METHOD**

*Soil moisture as water deficit indicator*

Soil moisture in the plant root zone is the primary source of water for vegetated lands; hence, it is obviously seen as one of the best indicators to quantify the stress of vegetation due to a precipitation shortage. In the real world, soil moisture, $\theta$ (m$^3$m$^{-3}$), ranges between the residual content, $\theta_r$, and saturation, $\theta_s$; however, $\theta$ becomes a limiting factor only in a narrow range of soil water content, usually between the plant wilting point ($\theta_{wp}$; as the minimal point of soil moisture the plant requires not to wilt) and a critical content ($\theta_{cr}$; soil
moisture below which a significant decrease of water extraction by plants as well as the decrease of yield can be observed), which values are a function of the soil–plant system. Various formulations are available in the literature to obtain water availability/deficit from soil moisture data (Seneviratne et al., 2010); a common feature of these formulations is to use a transformation of \( \theta \) able to account for the fact that there is a soil moisture regime under which soil moisture is not a limiting factor (wet regime, \( \theta_c < \theta < \theta_f \)) and another regime under which the plant is no more able to recover from wilt (dry regime, \( \theta_f < \theta < \theta_{wp} \)).

One of the formulations available is the s-shaped curve proposed by van Genuchten (1987), which allows rescaling \( \theta \) into a water deficit index, \( d \), ranging between 0 (no deficit) and 1 (full deficit):

\[
d = \frac{1}{1 + \left( \frac{\theta}{\theta_{50}} \right)^n}
\]

where \( \theta_{50} \) is the average between \( \theta_c \) and \( \theta_{wp} \) and \( n \) is an empirical shape factor. One of the advantages of Equation (1) is to have a smooth transition between the dry/wet regimes and the central range of variability of \( \theta \); this partially reduces the problems related to an imperfect parameterization of \( \theta_c \) and \( \theta_{wp} \).

In agro-hydrological applications, \( \theta_c \) and \( \theta_{wp} \) are usually derived from the soil water retention curve as a function of the water potential values corresponding to fully open and fully closed stomata, respectively. Those water potential values vary with plant species, being generally slightly lower (in absolute value) for trees than for crops. At the current state, in the absence of detailed information on these parameters at European scale, two fixed average values of water potential were used for all the plant types: \( \theta_{wp} \) was derived from the retention curve at soil water potential of \(-30\,000\) mm, and \( \theta_c \) was computed as 50% of the field capacity (soil moisture at a water potential of \(-3300\) mm), as suggested in the work of Allen et al. (1998). This simple parameterization allows deriving both \( \theta_c \) and \( \theta_{wp} \) as a sole function of soil type.

Similarly, the empirical exponent \( n \) assumes different values as a function of the plant type and its resistance to stress; empirical fittings on \textit{in situ} data report exponent values between 1 and 2 when Equation (1) is expressed as a function of water potential values rather than \( \theta \) (Feddes et al., 2004; Yang et al., 2013). Accounting for the relationship between \( \theta \) and water potential (retention curve) in the specific sites, this range roughly corresponds to \( n \) values between 4 and 8. In this study, an intermediate value of 6 was used for all the cases.

A schematic representation of the relationship \( \theta-d \) is depicted in Figure 1, showing how \( d \) accounts for the fact that the effect of soil moisture variability is negligible when \( \theta \) is greater than well-watered condition (wet regime) and, analogously, that no differences in plant water stress can be observed if \( \theta \) goes below the wilting point (down to the residual soil water content). It should be pointed out that the exact shape of the curve in Figure 1 varies (under the aforementioned assumption on plant critical water potentials) as a function of soil type. In summary, the \( d \) index represents a measure of the degree of water stress suffered by the plant in a given site and period, making the values obtained in different sites comparable; however, it does not provide any information on the actual frequency of those values in the history of the site for the specific period.

\section*{Probability of drier than normal conditions}

Information on the inter-annual variability of time-aggregated (i.e. monthly) soil moisture and water deficit can be used to analyze the occurring frequency of a given event and to characterize the usual state of the system. It is a common practice to quantify how ‘unusual’ a dry event is, compared with the ‘normal’ state for a specific site, by means of standard (\( z \)) scores. The \( z \)-score for a given month–year is computed by standardizing the variable via the population (multiple-year data for a specific month) mean and standard deviation, implicitly assuming that the data follow a normal distribution. However, double-bounded variables (as both \( \theta \) and \( d \)) are generally characterized by a skewed distribution. Sheffield et al. (2004) pointed out that a better statistical representation of soil moisture data can be obtained by means of the beta distribution (Gupta and Nadarajah, 2004); here, we assume that this distribution is also able to reproduce the statistical structure of \( d \), given that the
logistic transformation made by Equation (1) further increases the constraints of the two boundaries. The reliability of this hypothesis is discussed in detail in the next sections.

The probability density function (pdf, $f$) and cumulative density function (cdf, $F$) of the beta distribution can be expressed as respectively

$$f(d; a, b) = \frac{1}{B(a, b)} d^{(a-1)} (1 - d)^{(b-1)} \quad (2a)$$

$$F(d; a, b) = \frac{B(d; a, b)}{B(a, b)} \quad (2b)$$

where $a, b \geq 0$ are the shape parameters, $B(a, b)$ is the beta function and $B(d; a, b)$ is the incomplete beta function (Olver et al., 2010); in this form, the beta distribution supports $d \in [0, 1]$.

Sheffield et al. (2004) suggested to use $F(\theta)$ to detect drought by means of a defined threshold (e.g. $F(\theta) > 0.9$). This method implicitly assumes that the reference ‘usual’ state for a given month is the median of the distribution, analogously to how the z-score uses the mean. It is well known that for symmetric distributions, the three main measures of central tendency (mean, median and mode) coincide, whereas for skewed distributions, they markedly differ. For asymmetric distributions, statisticians suggest to use either the median or the mode as measure of central tendency (Huber and Ronchetti, 2009), mainly because the mean is not robust due to the very low breakdown point (Maronna et al., 2006). In practical applications, the median is generally preferred because it is easy to estimate compared with the mode (Hampel et al., 1986); on the other hand, the mode is closer to the intuitive understanding of ‘usual’ than the mean or the median, because it is the most frequent/typical value (Bickel, 2002). This description fits well the definition of ‘usual’ state as the most likely status for a given site and period. However, under certain conditions, mode estimates have suffered from high bias and low efficiency (high variance), and these issues have contributed to the limited use of the mode in the past as measure of central tendency (Bickel and Frühwirth, 2006). The use of a theoretical fitting on the sample can overcome the limitations related to such numerical estimations of the mode.

Once the mode, $m$, is selected as the reference ‘usual’ status of water deficit, the simplest way to define how probabilistically close an event $d$ is to the mode is to use the probability that a generic event lies between $d$ and $m$, computed as $|F(d) - F(d=m)|$. Focusing only on $d \geq m$, which are the values of interest for drought detection, it is clear how $|F(d) - F(d=m)|$ ranges between 0 and $[1 - F(d=m)]$; hence, in order to have a standardized index, it is necessary to feature-scaling this quantity through the possible range of variability, as

$$F^*(d) = \begin{cases} 
\frac{F(d) - F(d=m)}{1 - F(d=m)} & d \geq m \\
0 & d < m 
\end{cases} \quad (3)$$

The standardized percentile [$F^*(d)$] in Equation (3) represents the probability of occurrence of an event with respect to the subsample of the values $d \geq m$; it varies between 0 (for the mode or lower values) and 1 [for the maximum difference $1 - F(d=m)$]. The feature-scaling standardization performed through Equation (3) considers that the full distribution is split by $m$ into two subsets that likely have very different tails (due to the skewness).

In this study, the mode computed from the theoretical beta distribution, $m = (a - 1)/(a + b - 2)$ for $a, b > 1$, is adopted as reference status in Equation (3). However, the quantity $F^*$ introduced by Equation (3) can be analogously defined with respect to the median (rather than the mode), by assuming a constant value $F(d=m)=0.5$ by definition; this shows how the approach adopted by Sheffield et al. (2004) can be simply re-defined in terms of $F^*$ values. Similar considerations can be made for normally distributed data, for which mode, median and mean coincide. In all those cases, $F^*$ represents the percentile relative to the subsample constituted by $d \geq \text{usual}$ status.

Starting from these considerations, the largely used z-score classification introduced by McKee et al. (1993) can be re-defined in terms of $F^*$ as reported in Table I. The meteorological drought classes identified by McKee et al. (1993) as a function of the precipitation z-score (usually named standardized precipitation index (SPI)) can be analogously re-defined as dryness frequency classes in the case of soil water deficit (accounting for the opposite sign in precipitation and water deficit anomalies due to their antithetical relationship with drought); $F^*$ values can be computed for each $z$ in Table I assuming $F(d=m)=0.5$ because $z$ is by definition a standard normal random variable (hence mode, median and mean coincide). It should be noted that the two classes normal and mildly rare as originally defined by McKee et al. (1993) are here modified accordingly to Agnew (2000).

The classes reported in Table I show how the range of $F^*$ values associated to normal, intermediate and extreme conditions are rather different in amplitude; for example, normal or wetter than usual events have $F^*$ values between 0 and 0.6 ($\Delta F^* = 0.6$), mildly rare events have $0.6 < F^* \leq 0.68$ ($\Delta F^* = 0.08$) and extremely rare events have $F^* > 0.95$ ($\Delta F^* = 0.05$). The successive step is to derive from $F^*$ a dryness probability index, $p$, that converts the probability that a certain soil water deficit status is dryer than usual into an equal-interval quantity between 0 and 1. As reported in Table I, this $p$ index should be equal to 0 for all the normal and wetter than normal conditions ($F^* < 0.6$); it should start to be $>0$ (i.e. 0.05) only for
$F^* > 0.68$, and it should become equal to 1 for all those cases that have extremely rare dry conditions for the specific site and time step ($F^* > 0.95$).

Following these qualitative considerations, an empirical fitting was performed between $F^*$ and $p$ based on the values reported in Table I:

$$p = \exp \left[ -\frac{(F^*(d) - 1)^2}{0.03} \right] \tag{4}$$

The plot in Figure 2 represents the fitted relationship between $F^*$ and $p$, clearly showing how Equation (4) fairly respects the desired values reported in Table I (represented by the open circles in the plot). The $p$ index quantifies how drier is the specific case compared with the frequency distribution of the cases observed in the past history. However, it does not account for the actual magnitude of the water stress (since $F^*$ is standardized on the observed data); the latter trait is instead accounted by the $d$ index.

Drought severity index

From the previous sections, it is clear that the factors $d$ and $p$ capture separately the two main aspects influencing a drought event as defined in the introduction: (i) intensity of the observed water deficit ($d$) and (ii) rarity of the event compared with that of the site history ($p$). The proposed drought severity index (DSI) aims at combining the two indices in order to obtain a single measure of the severity of a specific soil water status in terms of drought.

In order to evaluate the best computational approach to be adopted to combine the two indices, some qualitative considerations on the desired characteristics of the DSI index have to be carried out. Conceptually, the mutual relationships among $p$, $d$ and DSI should allow DSI to be the same as $p$ and $d$ when the two indices are in agreement, whereas DSI should have low values if $p$ is close to zero (independently from $d$) or if $d$ is close to zero (independently from $p$). These last considerations aim at avoiding medium/high DSI values when one of the two conditions deficit/rarity is not met. In all the other cases, DSI should assume a somewhat intermediate value between the two indices.

A possible solution to obtain a DSI that behaves as described is to use a simple multiplicative-based relationship, as

$$DSI = \sqrt{pd} \tag{5}$$

where the square root allows at returning $DSI = p$ (or $d$) when $p = d$. It is simple to verify that Equation (5) respects the imposed constrains: $DSI \to 0$ if $p \to 0$, and $DSI \to 0$ if $d \to 0$.

Drought severity index values range between 0 and 1, where 0 corresponds to no drought and 1 is the most extreme drought event. In order to simplify the readability of DSI maps, we classified the index into four equal-interval drought classes: (1) no/mild, DSI < 0.25, (2) moderate, 0.25 < DSI < 0.5, (3) severe, 0.5 < DSI < 0.75, and (4) extreme, DSI > 0.75. Additionally, as a synthetic descriptor of the total severity of all drought in a given year accordingly to DSI, a yearly-cumulated DSI metric

### Table I. Values of $z$-score and $F^*$ corresponding to McKee et al. (1993) and Agnew (2000) standardized precipitation index, SPI, classes and related dryness probability index, $p$ values

| Class   | SPI range  | Return period (yrs) | $z^*$ | $F^*$ | $p$ |
|---------|------------|---------------------|-------|-------|-----|
| Normal  | $> -0.84$  | $<5$                | 0.84  | 0.60  | 0.00|
| Mild    | $-0.84$ to $-1.00$ | 5–7      | 1.00  | 0.68  | 0.05|
| Moderate| $-1.01$ to $-1.50$ | 7–15      | 1.50  | 0.87  | 0.50|
| Severe  | $-1.51$ to $-2.00$ | 15–40    | 2.00  | 0.95  | 0.90|
| Extreme | $< -2.00$  | $>40$              | ~4.00 | ~1.00 | ~1.00|

*Each $z$ value is the end of the corresponding SPI class. The sign is changed to account for the opposite meaning of precipitation and water deficit anomalies.
(YDSI) is obtained by summing up all the $\text{DSI} > 0.25$ (moderate, severe and extreme droughts) observed for a specific year:

$$\text{YDSI} = \sum_{i=1}^{12} \text{DSI}_i | \text{DSI}_i > 0.25$$

Because the YDSI summarizes the year-scale severity of all drought events that occurred in a specific year, it is not able to distinguish between short but highly severe and long but moderately severe events because of its synthetic nature, but it provides a proxy of the total severity of all droughts during 1 year. The YDSI ranges ideally between 0 and 12, and YDSI $\geq 0.6$ (i.e. at least 2 months with moderate drought) can be observed in drought-affected years.

**MATERIALS**

*Soil moisture simulation*

Long records of root zone soil moisture data can be obtained through land-surface modelling. In this study, the Lisflood distributed hydrological rainfall–runoff model (de Roo et al., 2000) is used to obtain an 18-year (1995-2012) data set of 5-km daily soil moisture maps over Europe. Lisflood is a model developed by the flood research group of the Joint Research Centre (JRC) of the European Commission to reproduce the hydrology of large and transnational European river catchments. Lisflood runs operationally at a daily time step within the European Flood Awareness System (Thielen et al., 2009), and it provides near-real-time daily output maps of different variables, including soil moisture.

Lisflood simulates the main hydrological processes occurring in the land–atmosphere system, including infiltration of effective precipitation, soil evaporation and plant transpiration, slow runoff (i.e. deep percolation) and groundwater recharge. Soil moisture status is reproduced in two vertical layers, namely topsoil (corresponding to the plant root zone) and subsoil. Soil water is redistributed between the two sub-layers and to the groundwater following a 1-D vertical flow mechanism accordingly to the Darcy’s law and the van Genuchten retention curve (van Genuchten, 1987). Detailed information on model implementation can be found at http://floods.jrc.ec.europa.eu/lisflood-model.html, whereas an analysis of the performance of Lisflood in terms of soil moisture anomalies (SMAs) over Europe can be found in the work of Cammalleri et al. (2015).

For the goal of this study, daily topsoil moisture maps are aggregated to a monthly timescale as simple averages and converted into $\text{delta}$ maps following Equation (1). Soil hydraulic properties on the modelling domain were derived from the soil classes in the European Soil Database (http://eusoils.jrc.ec.europa.eu/ESDB_Archive/ESDBv2/index.htm) accordingly to the HYPRES data set (Wösten et al., 1999). Meteorological forcing was produced daily on a 5 x 5-km$^2$ grid within the European Flood Awareness System development (Ntegeka et al., 2013); those maps are derived from raw data collected by two primary sources: the EU-FLOOD-GIS database, constituted by about 4000 meteorological stations; and the JRC-MARS database, which integrates both national meteorological services and data acquired via the Global Telecommunication System (Ntegeka et al., 2013). As described in van der Knijff et al. (2008), land-surface coverage and vegetation classes were derived from the CORINE land-use database, whereas climatological leaf area index monthly maps were derived from the Moderate-Resolution Imaging Spectroradiometer (MODIS) standard product (Myneni et al., 2003).

The beta distribution was fitted at pixel scale (about 200000 land grid cells) for each month following the maximum likelihood method described by Hahn and Shapiro (1994). The goodness of fit was tested following the one-sample Kolmogorov–Smirnov test at 0.05 significance level; the null hypothesis cannot be rejected in almost all the cases (96.08% of the fittings), suggesting that the probabilistic structure of the modelled water deficit index data can be reliably reproduced with a beta distribution.

**Recent drought events in Europe**

The European domain is one of the most extensively monitored areas in the world, and a large data set of past drought events is available, especially in the last decades. Numerous events are widely documented in the EM-DAT International Disaster Database (http://www.emdat.be), in the European Drought Reference database (http://www.geo.uio.no/edc/droughtdb), and in the work of Spinoni et al. (2015). Among the most significant events affecting the natural vegetation and agricultural compartments during our simulation period (1995–2012), there are the ones in Iberian Peninsula in 1995 and 2005, the summer drought and heat wave in Central Europe in 2003 and the persistent drought event over Eastern Europe in 2000. These events, which have documented effects on both natural and managed vegetated lands, can be used to qualitatively evaluate the ability of the proposed index to capture both the occurrence and magnitude of actual droughts.

The Iberian drought in 1995 was part of a long-lasting drought occurring over that area between 1991 and 1995, costing to the Spanish Government about €0.6 billion in emergency measures (Llamas, 2000). Similarly, the event in the year 2005 caused a serious reduction of Spanish cereal production (of about 40%, Garcia-Herrera
et al., 2007) and a declaration of natural disaster in Portugal with an estimated economic cost for farmers of ~€1 billion (1.5% of gross domestic product).

In 2003, Central Europe experienced one of the warmest and driest summers in the last century, resulting in about €12 billion in economic losses (Demuth, 2009), observing crop failure and extensive forest fires. A substantial drop in cereal yields was recorded, as well as a 30% reduction in gross primary productivity (Ciais et al., 2005). In 2000, Eastern Europe, including Romania, former Yugoslavia, Hungary and Bulgaria, experienced a spring–summer drought that negatively affected crop production (Croitoru et al., 2011); with less extent, the same countries were damaged also in 2003 and 2007.

During the hydrological year 2011/2012, most of European Union countries were hit by warm and dry conditions, which contributed to a global decline of grain production jointly with the devastating drought in the American heartland.

RESULTS

As an example of the DSI operating principles, time series of $p$, $d$ and DSI are reported in Figure 3 for two sites with rather different characteristics in soil moisture dynamics: a site in Spain ($-3.98^\circ$ E, $37.57^\circ$ N – Figure 3, left panel) and one in Sweden ($15.45^\circ$ E, $59.65^\circ$ N – Figure 3, right panel). The values of $d$ in the Spanish site show the typical behaviour of a dry environment, with high values during the hot/dry summer and low deficits in winter. Those values clearly exemplify the role of $d$ as a descriptor of the occurrence of water deficit only, because it is obvious that not all the high $d$ values observed during summer can be considered droughts. Consequently, DSI detects among these values only the ones that are also characterized by high $p$ values (rare events); for example, focusing on the summer peaks in $d$ (one per year), only few of them have a corresponding high $p$. This example represents a case where the sole anomalies (as well as percentiles) can be successfully used to detect drought, as demonstrated by the strong analogy between $p$ and DSI time series. On the opposite, the $d$ values in the Swedish site are almost always close to 0 (no water stress) even for some high $p$ events; as a consequence, the DSI does not detect as drought those rare events that are characterized by low $d$ values. In this case, it is obvious that all the few high $d$ values are also rare events (high $p$), while the opposite is not necessarily true (rare events may have very low $d$ values). It is possible to summarize that in a dry environment (i.e. Spain), the drought occurrence is regulated by the rarity of the events ($p$), whereas in wet environments (i.e. Sweden), it is the water deficit magnitude ($d$) that controls the actual occurrence of a drought.

The behaviour of DSI can be investigated over the whole domain by representing the spatial distribution of the occurring frequency (over the 18-year simulation

![Figure 3. Examples of time series of monthly $d$, $p$ and (drought severity index) DSI in Spain ($-3.98^\circ$ E, $37.57^\circ$ N – on the left) and Sweden ($15.45^\circ$ E, $59.65^\circ$ N – on the right)](image-url)
period) of each of the four drought classes described in Section Drought severity index. The goal of this analysis is to spatially compare the probability of occurrence of an event of a specific drought class for any given area during the analyzed period (1995–2012). The maps in Figure 4 depict the spatial distribution of the occurring frequency of each class; these maps highlight how, as expected, the largest part of the months is under no/mild droughts and how over some areas in north and north-east Europe, all the occurred drought events have DSI < 0.25. Moderate and severe events occurred mainly in Mediterranean countries, but some events were observed also for Central Europe, Southern England and the costal zones of Sweden. Finally, extreme events substantially occurred only for Mediterranean areas, but some events were observed also for Central Europe, Southern England and the costal zones of Sweden. It should be noticed that, even if the colour bars of the four maps in Figure 4 look the same, the extreme values were rescaled specifically for each map, thus allowing to better highlight the spatial features of each map.

A synthetic description of the cumulative severity of all droughts for a specific year according to DSI was obtained by representing the YDSI maps for each year over the full European domain, as reported in Figure 5. A first analysis of these YDSI maps highlights the ability of the index to capture the main drought events identified in Section Recent drought events in Europe. Focusing on the area mapped from orange to red, it easy to notice that large and consistent patterns are observable over the Iberian Peninsula in both 1995 and 2005, as well as in Eastern Europe in the map of 2000; the large event in 2003 and the event between 2011 and 2012 all over the southern part of the domain are also quite well highlighted by larger clusters of YDSI > 1.5 in the corresponding maps. The areas mapped in Figure 5 represent all the pixels with at least 1 month with DSI > 0.25, even if a threshold of YDSI ≥ 0.6 was considered as the minimum to assume an area interested by drought to some extent.

In order to quantify the added value of the DSI compared with the indices currently proposed in the

![Figure 4. Occurrence frequency of drought severity index (DSI) values subdivided into four drought classes: no/mild (upper-left panel), moderate (upper-right panel), severe (lower-left panel) and extreme (lower-right panel). The colour bar is rescaled for each map on the extreme values (L = lowest, H = highest) observed for the specific class.](image)
literature, two indicators were selected for a further intercomparison: (i) the soil moisture anomalies (SMAs) (Spenneman et al., 2015), which focus on the ‘rarity’ of an event, and (ii) the soil moisture index (SMI, Sridhar et al., 2008), evaluating the actual plant water availability. Monthly SMA and SMI maps were computed using the same source data of DSI (i.e. Lisflood simulation and soil parameters); hence, yearly maps were computed by summing up the values $< -1.5$ for SMA and $< -1$ for SMI (moderate or worse events); the adopted threshold for SMA was chosen on the basis of the $z$-values reported in Table I ($z = 1.5$ corresponds to moderate drought accordingly to the work of McKee et al., 1993), whereas for SMI on the basis of the values reported in Table II of the work of Sridhar et al. (2008). Both values correspond to the lower limit of the moderate-drought class for each index, analogously to the value 0.25 for DSI.

The plots in Figure 6 represent the spatial-averaged time series of these three indices over two contrasting regions: Andalucía in Spain (Figure 6, left column) and Dalarna in Sweden (Figure 6, right column). The time series show how SMA detects as drought (SMI $< -1$) all the dry seasons in the arid ecosystems of Southern Spain, whereas DSI and SMA agree in highlighting three main events during 1995, 1999 and 2005. On the contrary, SMA detects five drought events in central Sweden (SMI $<-1.5$), even if both DSI and SMA suggest the practical absence of relevant water stress. As a result, DSI seems the only index capable to return reasonable estimates over these two contrasting environments.

Further differences between DSI and both SMA and SMI can be noticed on the spatial distribution of the yearly-cumulated indices, as depicted in Figure 7. The maps, focusing on the 4 years where notable drought events occurred, highlight that even if both SMI and SMA return high values in the areas recognized as affected by drought (Iberia Peninsula in 1995 and 2005, Central Europe in 2003 and East Europe in 2000), the magnitude of these two indices is similarly high also over other areas not recognized as drought affected; as an example, SMA in Poland shows values comparable with that in Spain in both 1995 and 2003, whereas Spain and Eastern Europe show similar results in 2000 according to SMI. Generally, it is clear that DSI returns a stronger contrast between the areas recognized as drought and the remaining domain compared with the other two indices. It is worth noticing that the range of variability of the three colour bars was specifically tuned for each index in order to account for the different range of variability of the three indices and to allow for the direct intercomparison of the maps.

The overall impact of the events observed in Figure 5 can be further quantified by computing the extensions of the areas affected by drought and the average severity of those events. With this aim, we defined a YDSI threshold value that discriminates between affected and unaffected
Figure 6. Time series of monthly drought severity index (DSI, upper line), soil moisture index (SMI, middle line) and soil moisture anomalies (SMA, lower line) for two regions: Andalucía in Spain (left column) and Dalarna in Sweden (right column). Data surpassing the moderate drought kick-off threshold (0.25, 0.25 and 1.5 for DSI, SMI and SMA, respectively) are depicted in grey, whereas moderate or worse drought conditions are depicted in red.

Figure 7. Spatial distribution of the yearly-cumulated drought severity index (DSI, upper line), soil moisture anomalies (SMA, middle line) and soil moisture index (SMI, lower line) for 4 years characterized by drought events over different areas. The extreme values (L = lowest, H = highest) of the colour bars were adapted to the specific range of variability of each index in order to simplify the visualization. The DSI maps, which are the same of Figure 7, are here reported again only for the sake of a direct intercomparison.
areas; assuming that a significant drought event has at least 2 months with DSI > 0.25 (moderate drought), we choose a threshold on YDSI of 0.6 to discriminate the ‘minimum’ drought. With this threshold, the fraction of the domain with YDSI ≥ 0.6 was computed for each year, as well as the average value of YDSI within those areas. These data are represented in Figure 8 through barplots.

The grey bars in the plot in Figure 8 show that the largest events in the last two decades were the ones in 2003 and 2011/2012, with 14–15% of the European domain interested by a relevant drought. The events interesting Eastern Europe in 2000 and the Iberian Peninsula in 1995 and 2005 have also notable extensions, ranging between 10% and 12%. It is worth mentioning that, among those events, the most severe were the two occurring in the Iberian Peninsula, with a spatial-average YDSI of 1.7 and 1.5 in 1995 and 2005, respectively. From this point of view, the event of 2003, even if very large, was not among the most intense ones, likely because it occurred mainly in Central Europe where water deficits are generally not so high; on the contrary, the event during the hydrological year 2011/2012 was among the largest and most severe ones. Those average YDSI values may seem low, but they can be seen as associated to events ranging between a very long moderate drought (i.e. 6 months with DSI > 0.25) and a flash severe one (i.e. 2 months with DSI > 0.8). Also, given that this values are spatial averages, it is clear that more extreme conditions can be found over smaller sub-areas.

Finally, focusing only on the areas affected by the events in 1995, 2000, 2003 and 2005, we plotted the yearly-total DSI averaged on the countries likely interested by these events (Figure 9): Spain and Portugal for 1995 and 2005 (upper panel); Romania, former Yugoslavia, East Hungary (Central, Great Plain and North regions), Bulgaria, Greece and Albania for 2000 (central panel); and Germany, France, Belgium, Netherlands, North Italy, Austria, Switzerland, Czech Republic, Slovakia and West Hungary (Transdanubia region) for 2003 (lower panel).

The barplots in Figure 9 clearly show how the aforementioned events are immediately recognizable in the time series, with yearly DSI totals for the years of these events about three times greater than the average of the remaining years.

SUMMARY AND CONCLUSIONS

In this paper, a novel index aiming at capturing the severity of drought in vegetated land is presented; this DSI is based on monthly root zone soil moisture data and accounts for both the magnitude of the associated water deficit, d factor, and the probability that the observed value is actually dryer than a reference ‘usual’ condition for the specific site and period, p factor. DSI is based on the square root of the product of these two factors (both...
varying between 0 and 1) in order to jointly quantify the
global effect of the two main features of drought events;
the proposed multiplicative approach is able to account
for qualitative considerations on the desirable properties
of the DSI for specific combinations of \( d \) and \( p \).

The methodology was tested over Europe between
1995 and 2012 by means of modelled monthly soil
moisture data derived from Lisflood daily simulations.
DSI showed the capability to perform as expected over
both commonly dry and wet environments. Yearly-
cumulated maps of the index (YDSI) highlighted the
ability to detect the main drought events that occurred in
Europe in the last two decades (as recorded by past-
drought databases), also providing a reasonable estima-
tion of both extension and magnitude of these events,
even if no quantitative validation was feasible because of
the lack of independent ‘measurements’ of drought
severity. The new index shows observable improvements
over two other indices already available in the literature,
SMA and SMI; those two indices, based only on the
‘rarity’ or on the ‘severity’ of the water deficit,
respectively, are commonly reliable only for some cases,
whereas the DSI seems to adapt its behaviour to a larger
range of conditions.

It is clear that the reliability of the obtained results is
strongly related to the actual capability of the modelled
soil moisture to capture the real dynamic of soil moisture;
however, even if Lisflood outputs have demonstrated a good
reliability over Europe (Cammalleri et al., 2015), further
investigations may be required in order to fully quantify
the reliability of those drought estimates. However, these
considerations do not invalidate both the consistency of
the DSI theoretical background and the validity of the
qualitative comparison made with other indices.

The proposed modelling framework is of general
validity, and improvements and/or modifications to the
procedure can be easily implemented by maintaining the
main structure of the procedure. Indeed, some of the
relationships adopted in the development of the index
may require refinements or adjustments. The parameter-
ization of the water stress function can be refined by
accounting for plant specific settings of critical water
potential values or replaced with other methodologies
to derive plant water deficit, as far as the range of variability
of \( d \) remains from 0 (no deficit) to 1 (full deficit). These
refinements require a detailed analysis of the literature
available on the relationship between soil water content
and plant water stress, which at the current status do not
provide clear insight for large scale applications. The
probability distribution used for fitting \( d \) values can be
replaced with another one that better fits the available data
set; the adopted classification of \( F^T \) values can be
modified with more detailed information becoming available.
The simple multiplicative approach may be
refined according to a different conceptualization of the
expected values of DSI. All those possible minor
modifications of the proposed procedure can be easily
implemented because it is based on a combination of two
factors both varying in the range 0–1.

To the extent of our knowledge, this is the first attempt
on combining the effects of water deficit magnitude and
the probability that such deficit is an extreme case for the
specific site and time into a unique indicator, even if the
concepts adopted for its development (i.e. water deficit
index and anomaly detection) are already consolidated in
the literature of vegetation drought detection using
hydrological variables. The proposed methodology seems
also suitable for an extended use with other hydrological
quantities that display connections with vegetation water
stress similar to soil moisture (e.g. evapotranspiration-
derived indices).

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REFERENCES

Agnew CT. 2000. Using the SPI to identify drought. Drought Network
News (1994-2001) 12(1): 1–12 http://digitalcommons.unl.edu/
droughtnetnews/1.

Allen RG, Pereira LS, Raes D, Smith M. 1998. Crop evapotranspiration:
guidelines for computing crop water requirements. FAO Irrigation and
Drainage Paper no. 56, Rome, Italy.

Allen CD, Macalady AK, Chenchouni H, Bachelet D, McDowell N,
Vennetier M, Kitzberger T, Rigling A, Breshears DD, Hogg EH,
Gonzalez P, Fenshram R, Zhang Z, Lim J-H, Castro J, Demidova N,
Allard G, Running SW, Semerci A, Cobb N. 2010. A global overview
of drought and heat-induced tree mortality reveals emerging climate
change risks for forests. Forest Ecology and Management 259:
666–684.

Anderson MC, Norman JM, Mecikalski JR, Otkin JP, Kustas WP. 2007.
A climatological study of evapotranspiration and moisture stress
across the continental U.S. based on thermal remote sensing: II.
Surface moisture climatology. Journal of Geophysical Research 112:
D11112.

Anderson MC, Hain CR, Otkin JP, Zhang X, Mo K, Svoboda M, Warlow
B, Pimstein A. 2013. An intercomparison of drought indicators based
on thermal remote sensing and NLDAS-2 simulations with U.S.
drought monitoring classifications. Journal of Hydrometeorology 14:
1035–1056.

Bickel DR. 2002. Robust estimators of the mode and skewness of
continuous data. Computational Statistics and Data Analysis 39(2):
153–163.

Bickel DR, Frühwirth R. 2006. On a fast, robust estimator of the mode:
comparisons to other robust estimators with applications. Computa-
tional Statistics and Data Analysis 50(12): 3500–3530.

Cammalleri C, Micale F, Vogt J. 2015. On the value of combining
different modelled soil moisture products for European drought
monitoring. Journal of Hydrology 525: 547–558.

Choi M, Jacobs JM, Anderson MC, Bosh DD. 2013. Evaluation of drought
indices via remotely sensed data with hydrological variables. Journal of Hydrology 476: 265–273.
Ciais P, Reichstein M, Viovy N, Granier A, Oge J, Allard V, Aubinet M, Buchmann N, Bernhofer C, Carrafa A, Chevallier F, de Noblet N, Friend AD, Friedlingstein P, Grunwald T, Heinesch B, Keronen P, Knoblauch K, Krinner G, Loustau D, Manca G, Matteucci G, Miglietta F, O'Neill, J, Papale D, Pilegaard K, Rambal S, Seufert G, Soussana JF, Sanz MJ, Schulze ED, Vesala T, Valentini R. 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature* 437: 529–533.

Dai A, Trenberth KE, Qian T. 2004. A global dataset of Palmer drought severity index for 1870–2002: relationship with soil moisture and effects of surface warming. *Journal of Hydrometeorology* 5: 1117–1130.

Demuth S. 2009. Learning to live with drought in Europe. *A World of Science* 7(3): 18–20.

de Roo APJ, Wesselings C, van Deusen W. 2000. Physically based river basin modelling within a GIS: The LISFLOOD model. *Hydrological Processes* 14: 1981–1992.

Feddes RA, de Rooij GH, van Dam JC. 2004. *Unsaturated-Zone Basin Modelling: Progress, Challenges and Applications*. Kluwer Academic Publishers: Dordrecht, The Netherlands; 364.

Garcia-Herrera R, Paredes D, Trigo RM, Trigo IF, Hernández H, Feddes RA, de Rooij GH, van Dam JC. 2004. *Physical Models for River Basins*. Dordrecht, the Netherlands; 253.

Hampel FR, Ronchetti EM, Rousseeuw PJ, Stahel WA. 1986. *Robust Statistics: The Approach Based on Influence Functions*. John Wiley and Sons: Hoboken, NJ, USA; 376.

Heim RR Jr. 2002. A review of twentieth-century drought indices used in the United States. *Bulletin of the American Meteorological Society* 83: 1149–1165.

Hogg EH, Barr AG, Black TA. 2013. A simple soil moisture index for representing multi-year drought impacts on aspen productivity in the western Canadian interior. *Agricultural and Forest Meteorology* 178-179: 173–182.

Huber PJ, Ronchetti EM. 2009. *Robust Statistics, Second Edition*. John Wiley and Sons: Hoboken, NJ, USA; 380.

Llamas MR. 2000. Some lessons learnt during the drought of 1991–1995 in Spain. In *Drought and Drought Mitigation in Europe* Vol. 14, Vogt J, Somma F (eds). *Adv. Natural Tech. Hazard Res.* Kluwer Academic Publishers: Dordrecht, the Netherlands; 253–264.

Maronna RA, Martin DR, Yohai VJ. 2006. *Robust Statistics: Theory and Methods*. John Wiley and Sons: Hoboken, NJ, USA; 436.

McKee TB, Doesken NJ, Kleist J. 1993. The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference of Applied Climatology: Anaheim, CA, Am. Meteorol. Soc.; 179–184.

McVicar TR, Jupp DLB. 1998. The current and potential operational uses of remote sensing to aid decisions on drought exceptional circumstances in Australia: a review. *Agricultural Systems* 57: 399–468.

Myneni R, Knyazikhin Y, Glassy J, Votava P, Shabanov N. 2003. FPAR LAI (ESDIS MOD15A2) 8-day composite NASA MODIS land algorithm. User’s Guide, 17 pp.

Niegeka V, Salamon P, Gomes G, Sint H, Lorini V, Zambrano-Bigiarini M, Thielen J. 2013. EFAS-Meteo: A European Daily High-resolution Gridded Meteorological Data Set for 1990–2011. EUR - Scientific and Technical Research series. Publications Office of the European Union: Luxembourg; 46 DOI: 10.2788/51262.

Oliver FWJ, Lozier DW, Boisvert RF, Clark CW. 2010. *NIST Handbook of Mathematical Functions*. Cambridge University press: Cambridge, UK; mixed media.

Palmer WC. 1965. Meteorological drought. Research Paper 45: U.S. Dept. of Commerce; 58.

Panu US, Sharma TC. 2002. Challenge in drought research: some perspectives and future directions. *Hydrological Sciences Journal* 47: S19–S30.

Sepulcre-Cantó G, Horion S, Singleton A, Carrao H, Vogt J. 2012. Development of a combined drought indicator to detect agricultural drought in Europe. *Natural Hazards and Earth System Sciences* 12: 3519–3531.

Seneviratne SI, Corti T, Davin EL, Hirschi M, Jaeger EB, Lehner I, Orlowsky B, Teuling AJ. 2010. Investigating soil moisture–climate interactions in a changing climate: a review. *Earth-Science Reviews* 99: 125–161.

Sheffield J, Wood EF. 2007. Characteristics of global and regional drought, 1950–2000: analysis of soil moisture data from off-line simulation of the terrestrial hydrologic cycle. *Journal of Geophysical Research* 112: D17115.

Sheffield J, Goteti G, Wen F, Wood EF. 2004. A simulated soil moisture based drought analysis for the United States. *Journal of Geophysical Research* 109: D24108.

Spennemann PC, Rivera JA, Celeste Saulo A, Penalba OC. 2015. A comparison of GLDAS soil moisture anomalies against standardized precipitation index and multisatellite estimations over South America. *Journal of Hydrometeorology* 16: 158–171.

Spinoni J, Naumann G, Vogt J, Barbosa P. 2015. The biggest drought events in Europe from 1950 to 2012. *Journal of Hydrology: Regional Studies* 3: 509–524. DOI: 10.1016/j.ejrh.2015.01.001.

Sridhar V, Hubbard KG, You J, Hunt ED. 2008. Development of the soil moisture drought index to quantify agricultural drought and its “user friendliness” in severity-area-duration assessment. *Journal of Hydro meteorology* 9: 660–676.

Svoboda M, LeComte D, Hayes M, Heim R, Gleason K, Angel J, Rippey B, Tinker R, Palecki M, Stooksbury D, Miskus D, Stephens S. 2002. The drought monitoring. *Bulletin of the American Meteorological Society* 83(8): 1181–1190.

Thielen J, Bartholmes J, Ramos M-H, de Roo A. 2009. The European flood alert system – part 1: concept and development. *Hydrology and Earth System Sciences* 13: 125–140.

van der Knijff JM, Younis J, de Roo APJ. 2008. LISFLOOD: A GIS-based distributed model for river basin scale water balance and flood simulation. *International Journal of Geographical Information Science* 24(2): 189–212.

van Genuchten MT. 1987. A numerical model for water and solute movement in and below the root zone. Research Report No 121. U.S. Salinity laboratory, USDA, ARS: Riverside, California.

Wang A, Lettenmaier DP, Shef J. 2011. Soil moisture drought in china, 1950–2006. *Journal of Climate* 24: 3257–3271.

Wösten JHM, Lilly A, Nemes A, Le Bas C. 1999. Development and use of a database of hydraulic properties of European soils. *Geoderma* 90: 169–185.

Yang Y, Gruen H, Hutson JL, Wang H, Ewenz C, Shang S, Simmons CT. 2013. Examination and parameterization of the root water uptake model from stem water potential and sap flow measurements. *Hydrological Processes* 27: 2857–2863.