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Assessment of Hydrological Drought Revisited

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Abstract A variety of indices for characterising hydrological drought have been devised which, in general, are data demanding and computationally intensive. On the contrary, for meteorological droughts very simple and effective indices such as the Standardised Precipitation Index (SPI) have been used. A methodology for characterising the severity of hydrological droughts is proposed which uses an index analogous to SPI, the Streamflow Drought Index (SDI). Cumulative streamflow is used for overlapping periods of 3, 6, 9 and 12 months within each hydrological year. Drought states are defined which form a non-stationary Markov chain. Prediction of hydrological drought based on precipitation is also investigated. The methodology is validated using reliable data from the Evinos river basin (Greece). It can be easily applied within a Drought Watch System in river basins with significant storage works and can cope with the lack of streamflow data.

Keywords Hydrological drought · Drought prediction · SPI · Markov chain · Evinos basin

1 Introduction

Drought is a natural phenomenon characterised by a significant decrease of water availability during a significant period of time and over a large area. It occurs in parts of the Earth virtually every year thus affecting economic activities, human lives and various elements of the environment. Due to complexities of the global hydrological cycle it is practically impossible to identify the origin of drought. As a convention,

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decrease of precipitation is considered as the origin of drought. This results in delayed reduction of runoff and storage either as soil moisture or as free water while a more delayed reduction of groundwater flows and reserves is observed. Depending on the choice of the form of water and its related variable of interest, drought is conventionally characterised as meteorological, hydrological or agricultural (Beran and Rodier 1985).

Hydrological drought is defined as a significant decrease in the availability of water in all its forms appearing in the land phase of the hydrological cycle. These forms are reflected in various hydrological variables such as streamflow (including snowmelt and springflow), lake and reservoir level, and groundwater level. Among these variables, streamflow is, by far, the most significant variable from the viewpoint of quantity of water. It is the key variable for expressing surface water resources. Hence, a hydrological drought event is related to streamflow deficit with respect to normal conditions. Each drought event is characterised through four attributes: (a) its severity expressed by a drought index, (b) its time of onset and its duration, (c) its areal extent, and (d) its frequency of occurrence.

Research results, although useful for understanding drought phenomena, are very often inappropriate for operational use in drought monitoring and forecasting systems. Specifically, in regard to the above attributes of hydrological drought, several operational requirements should be fulfilled. First, the assessment of drought severity requires an index or indices which (a) are easily understood, (b) are carrying physical meaning, (c) are sensitive to a wide range of drought conditions, (d) are independent of the area of application, (e) reveal drought with short lag after its occurrence, and (f) are based on data which are readily available. Second, the practical identification of a drought event in the course of time is difficult and, to a large degree, dependent on the methodology used. Third, the frequency of drought occurrence remains a significant parameter. Last, the areal extent of a drought event, although very useful for meteorological droughts, is not of interest for hydrological droughts since water managers are interested on streamflow only at a small number of points in space (basin outlets, reservoir inlets and outlets etc.); evidently, streamflow at these points provides an integrated measure of spatially distributed runoff; furthermore, the river basin is proposed by the Water Framework Directive as the only scale for applying measures for water resources protection and management. In view of the above requirements, the four-dimensional relationship of drought severity–duration–frequency–area can well be reduced into a much simpler two-dimensional relationship of severity versus frequency.

Existing indices for characterising a hydrological drought such as Palmer Hydrological Drought Index (PHDI), or Surface Water Supply Index (SWSI) are, in general, data demanding and computationally intensive. On the contrary, for meteorological droughts, very simple and effective indices such as the Standardised Precipitation Index (SPI) have been proposed and extensively tested. Much in the direction of simplicity, the Reconnaissance Drought Index (RDI) has been proposed recently incorporating apart from cumulative precipitation the cumulative evapotranspiration (Tsakiris and Vangelis 2005; Tsakiris et al. 2006). Hence, a simple index for hydrological droughts is always welcome.

Another critical operational constraint is related to the availability of hydrological information. Very often streamflow data are lacking in real-time due to: (a) delays in processing river stage recordings, (b) changes in the stage–discharge curve which are not well monitored. To remedy this problem, use of other data is needed which are readily available (e.g., precipitation depths).

The aim of this study is two-fold: (1) to propose a methodology for assessing hydrological droughts based on streamflow deficit while fulfilling the above operational requirements, and (2) to investigate the possibility of predicting hydrological drought based on precipitation when streamflow information is lacking. To achieve these goals, a testing framework is set up. The study area is the Evinos river basin, in central Greece.

2 The Methodology Proposed

2.1 General

As mentioned in the Section 1, drought is characterised by a complex relationship of drought severity, time of onset and duration, areal extent and frequency of occurrence. This is reduced to a simpler relationship of severity versus frequency. In Section 4 we discuss how the proposed methodology bypasses the variables "time of onset" and "duration". As mentioned also in the Section 1, the areal extent of a hydrological drought can be easily omitted.

In the introduction a variety of hydrological variables were mentioned which are used to characterise a hydrological drought. In this study we will exclusively make use of streamflow which commonly represents surface water resources. The use of streamflow as the key variable for assessing hydrological droughts is not new since many authors have used it in their studies (e.g., Ben-Zvi 1987).

2.2 The Treatment of Time

Drought is a natural phenomenon which is gradually developing and is identified only after it has been well established. This is the reason why a coarse time step for hydrological variables is sufficient in the vast majority of cases. The typical time step used is monthly which is also employed in this study.

The onset of a drought event is defined as the time when a drought index falls below a certain truncation level. Similarly, the termination of drought is the time when the drought index rises above the truncation level. Forecasting of the onset and of the termination of a drought event remains an extremely difficult task (Cordery and McCall 2000) although promising research efforts relate droughts to the El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) (Vogt and Somma 2000).

The truncation level has been defined in various ways. For stationary processes a fixed value has been used while for periodic processes a set of seasonally varying values is more appropriate. In all cases, the mean (or the median) over a long period of time has been the typical choice. This is used in this work also. Other choices involve a fixed probability percentile (Zelenhasic and Salvai 1987; Correia et al. 1987), or a fraction of the mean (Clausen and Pearson 1995).

In the classical approach in treating time, successive non-overlapping time intervals are used. In the proposed methodology, time is treated in a somewhat different way: (1) October the first is considered the beginning of the hydrological year which is typical in the Mediterranean region; (2) every three months (31st December, 31st March, 30th June, 30th September) a drought assessment is made regarding the time interval from the start of the hydrological year up to that time; (3) at the same dates, predictions are issued regarding future drought conditions. The above treatment of time corresponds perfectly to situations with water resource systems possessing considerable total storage capacity whereby inflows are integrated in time.

To fulfil the above operational requirements four overlapping time periods are utilised within each hydrological year: October–December, October–March, October–June, and October–September (one complete hydrological year). In this paper, these are referred to as reference periods. They will be used in the definition of drought indices discussed below. A similar treatment of time is used for calculating the meteorological drought index RDI (Tsakiris and Vangelis 2005).

The choice of 3-month intervals in performing drought assessments is dictated by the need to balance the following conflicting objectives: (1) track drought as closely as possible which necessitates small time intervals; (2) respect operational constraints of monitoring organisations which precludes very frequent assessments; (3) minimise carry-over effects between successive time intervals which are much more significant for small time scales.

2.3 The Streamflow Drought Index (SDI)

It is assumed that a time series of monthly streamflow volumes $Q_{i,j}$ is available where i denotes the hydrological year and j the month within that hydrological year ($j = 1$ for October and $j = 12$ for September). Based on this series we obtain

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \quad i = 1, 2, \ldots \quad j = 1, 2, \ldots, 12 \quad k = 1,\ 2,\ 3,\ 4 \tag{1}$$

where $V_{i,k}$ is the cumulative streamflow volume for the i-th hydrological year and the k-th reference period, $k = 1$ for October–December, $k = 2$ for October–March, $k = 3$ for October–June, and $k = 4$ for October–September.

Based on cumulative streamflow volumes $V_{i,k}$ the Streamflow Drought Index (SDI) is defined for each reference period k of the i-th hydrological year as follows

$$\mathrm{SDI}_{i,k} = \frac{V_{i,k} - \overline{V}_k}{s_k} \quad i = 1, 2, \ldots, \quad k = 1,\ 2,\ 3,\ 4 \tag{2}$$

where $\overline{V}_k$ and s_k are respectively the mean and the standard deviation of cumulative streamflow volumes of reference period k as these are estimated over a long period of time. In this definition the truncation level is set to $\overline{V}_k$ although other values could be used.

The hydrological drought index of Eq. 2 is identical to the standardised streamflow volume. This is not entirely new since Ben-Zvi (1987) made use of the standardised annual streamflow volumes. More precisely, he had noted "we define here a deep shortage as the occurrence of an annual volume of streamflow which is lower than the mean by at least one standard deviation". However, he had not tackled the problem of non-stationarity since he had worked on annual data.

Generally, for small basins, streamflow may possess a skewed probability distribution which can well be approximated by the family of the Gamma distribution functions. The distribution is then transformed into normal. In this work we use the two-parameter log-normal distribution for which the normalisation is simple: it suffices taking natural logarithms of streamflow. The SDI index is defined as

$$\mathrm{SDI}_{i,k} = \frac{y_{i,k} - \overline{y}_k}{s_{y,k}} \qquad i = 1, 2, \ldots, \qquad k = 1,\ 2,\ 3,\ 4 \tag{3}$$

where

$$y_{i,k} = \ln\left(V_{i,k}\right), i = 1, 2, \ldots, \qquad k = 1,\ 2,\ 3,\ 4 \tag{4}$$

are the natural logarithms of cumulative streamflow with mean $\overline{y}_k$ and standard deviation $s_{y,k}$ as these statistics are estimated over a long period of time.

Based on SDI, states of hydrological drought are defined which are identical to those used in the meteorological drought indices SPI and RDI. Five states are considered which are denoted by an integer number ranging from 0 (non-drought) to 4 (extreme drought) and are defined through the criteria of Table 1.

The problem of treating intermittent or ephemeral flows is of importance when dealing with hydrological droughts. Three cases can be distinguished: (1) watercourse with perennial flow, (2) watercourse with ephemeral flow and without complete dryness throughout a whole hydrological year, (3) watercourse with no flow in some hydrological years. According to our definition of SDI, case 2 becomes irrelevant since cumulative streamflow will always possess some positive value. Only the case of completely dry hydrological years (case 3) remains which is arbitrarily classified as extreme drought (state equal to 4).

General requirements *a* to *e* given in the introduction for all indices are fulfilled by the proposed index since this is analogous to the well-known index SPI which fulfils these requirements. Requirement *f* is also fulfilled in many cases where streamflow data are available through modern monitoring systems. The case of lack of streamflow data is also covered through the methodology explained in Subsection 2.5.

2.4 The Standardised Precipitation Index (SPI)

The Standardised Precipitation Index (SPI) is widely used for defining and monitoring meteorological droughts. Since its appearance (McKee et al. 1993), it has been extensively used in America (Hayes et al. 1999), Asia (Min et al. 2003), Africa (Rouault and Richard 2003; Ntale and Gan 2003) and Europe (Lloyd-Hughes and Saunders 2002; Domonkos 2003; Bonaccorso et al. 2003; Paulo et al. 2003; Tsakiris and Vangelis 2004; Paulo and Pereira 2007).

Table 1 Definition of states of hydrological drought with the aid of SDI

State	Description	Criterion	Probability (%)
0	Non-drought	$\mathrm{SDI} \geq 0.0$	50.0
1	Mild drought	$-1.0 \leq \mathrm{SDI} < 0.0$	34.1
2	Moderate drought	$-1.5 \leq \mathrm{SDI} < -1.0$	9.2
3	Severe drought	$-2.0 \leq \mathrm{SDI} < -1.5$	4.4
4	Extreme drought	$\mathrm{SDI} < -2.0$	2.3

To track a meteorological drought at multiple time-scales, the U.S. National Drought Mitigation Centre (NDMC) computes the SPI for five time steps (1, 3, 6, 9, and 12 months). The Gamma probability distribution has been used for precipitation with provision for treating precipitation intermittency through using composite distributions. Normalisation of the final distribution is required (Edwards and McKee 1997). Positive SPI values reflect wet conditions while negative values indicate a meteorological drought. State definition is given in Table 2 (Wilhite et al. 2000).

In this work, SPI is modified in a way completely analogous to that of SDI which is described in Subsection 2.3. It is assumed that a time series of monthly depths of areal precipitation $P_{i,j}$ is available where i denotes again the hydrological year and j the month within that hydrological year. Based on this series the following sequences are derived

$$R_{i,k} = \sum_{j=1}^{3k} P_{i,j} \quad i = 1, 2, \ldots, \quad j = 1, 2, \ldots, 12, \quad k = 1,\ 2,\ 3,\ 4 \tag{5}$$

where $R_{i,k}$ is the cumulative precipitation depth for the k-th reference period of the i-th hydrological year and reference periods k have been defined in Subsection 2.2.

The modified SPI index is calculated as

$$\mathrm{SPI}_{i,k} = \frac{R_{i,k} - \overline{R}_k}{s_{R,k}} \quad i = 1, 2, \ldots, \quad k = 1,\ 2,\ 3,\ 4 \tag{6}$$

where $\overline{R}_k$ and $s_{R,k}$ are respectively the mean and the standard deviation of the cumulative precipitation depths for the k-th reference period as these statistics are estimated over a long period of time.

To remove skewness from cumulative precipitation, the modified SPI can alternatively be defined as

$$\mathrm{SPI}_{i,k} = \frac{w_{i,k} - \bar{w}_k}{s_{w,k}}\ i = 1, 2, \ldots, \quad k = 1, 2, 3, 4 \tag{7}$$

where

$$w_{i,k} = \ln\left(R_{i,k}\right)\ i = 1, 2, \ldots, \quad k = 1, 2, 3, 4 \tag{8}$$

are the natural logarithms of cumulative precipitation and $\bar{w}_k$ and $s_{w,k}$ are respectively the mean and the standard deviation of these logarithms as estimated over a long period of time.

Table 2 Definition of states of meteorological drought with the aid of SPI

Description of state	Criterion
Extremely wet	$\mathrm{SPI} \geq 2.0$
Very wet	$1.5 \leq \mathrm{SPI} < 2.0$
Moderately wet	$1.0 \leq \mathrm{SPI} < 1.5$
Near normal	$-1.0 \leq \mathrm{SPI} < 1.0$
Moderately dry	$-1.5 \leq \mathrm{SPI} < -1.0$
Severely dry	$-2.0 \leq \mathrm{SPI} < -1.5$
Extremely dry	$\mathrm{SPI} < -2.0$

The reasons for using SPI are the following: (1) it has minimum data requirements, and (2) it requires minimum computational effort. However, if RDI could be easily obtained the same procedure could be followed.

2.5 The Methodological Steps

In the introduction we have set the goals of this work: (1) to propose an index based on streamflow deficit for assessing hydrological droughts within an operational context, and (2) to investigate the possibility for assessing hydrological droughts in the absence of streamflow data.

To achieve the first goal the SDI index is used. Starting from historical streamflow series, an SDI series is taken which yields a series of drought states. The underlying process is assumed to possess the structure of a non-stationary Markov chain. Markov chains have been widely applied to predicting droughts (mainly meteorological ones) within the frame of early warning systems (Lohani and Loganathan 1997; Lohani et al. 1998; Ochola and Kerkides 2003). Recently, Paulo and Pereira (2007) have used Markov chains for predicting drought via the SPI index.

Let $Q_{i,j}$ ($i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, 12$) be the observed time series of monthly streamflow volumes for the river basin under study, where N is the number of hydrological years.

First, the cumulative streamflow volumes $V_{i,k}$ ($i = 1, 2, \ldots, N$; $k = 1, 2, 3, 4$) are calculated via Eq. 1. Second, the series $\mathrm{SDI}_{i,k}$ of the SDI index is calculated based on Eq. 2 or 3. Third, the series of states $x_{i,k}$ ($i = 1, 2, \ldots, N$; $k = 1, 2, 3, 4$) is obtained according to the criteria of Table 1. For each k, the related state process $X_{i,k}$ takes discrete values $m \in [0, 1, 2, 3, 4]$. Fourth, the frequency of appearance of each state m in each reference period k, $F_{m,k}$, is estimated as

$$F_{m,k} = \frac{n_{m,k}}{N} \tag{9}$$

where $n_{m,k}$ is the number of occurrences of state m in reference period k within the available sample of N years. This is an estimate of the marginal probability $p_{m,k}$ of appearance of state m in reference period k, i.e.

$$p_{m,k} = P\left(X_{i,k} = m\right) m \in [0, 1, 2, 3, 4]\ \forall i \tag{10}$$

where $P(.)$ denotes probability. For each k, probabilities $p_{m,k}(m = 0, 1, 2, 3, 4)$ form a 5×1 column vector $\mathbf{p}_k$.

Fifth, the frequency of state transition $F_{m,m',k}$ from state m in reference period k to state m' in reference period $k + 1$ is

$$F_{m,m',k} = \frac{n_{m,m',k}}{\sum\limits_{m'} n_{m,m',k}} \tag{11}$$

where $n_{m,m',k}$ is the number of occurrences of state m in reference period k and state m' in reference period $k + 1$. This is an estimate of the transition probability $p_{m,m',k}$ which is defined as

$$p_{m,m',k} = P\left(X_{i,k+1} = m' \,\middle|\, X_{i,k} = m\right) \quad m \in [0, 1, 2, 3, 4] \quad m' \in [0, 1, 2, 3, 4]\ \forall i \tag{12}$$

where $P(.|.)$ denotes conditional probability. For each k, transition probabilities form a 5×5 matrix denoted as $\mathbf{P}_k$.

Assume now that the current time interval is (i,k). Before characterising current drought state, one can predict the marginal probabilities for the next reference period $k+1$ as

$$\mathbf{p}_{k+1} = \mathbf{P}_k \, \mathbf{p}_k \tag{13}$$

Within an operational context, at the end of time interval (i,k), all historical data up to that time are assumed to become available. This allows classifying the current interval. Thus, vector $\mathbf{p}_k$ of Eq. 13 has now one element equal to one and all other elements zero. It follows from Eq. 13 that the only information needed for drought prediction is the matrix $\mathbf{P}_k$ as this is approximated by its estimate, the matrix of state transition frequency. This is the main output of our methodology when working off-line on historical series. In real-time situations, the output is (a) a single value of current state and (b) the probabilities of future states as obtained from a stored matrix of state transition probability.

The second goal of the paper, i.e. predicting hydrological drought based on precipitation, is achieved through replacing the first two steps of the above methodology with: (a) calculating SPI on historical data of areal precipitation; (b) regressing SDI on concurrent SPI based on a common period of data for each reference period separately; (c) predicting SDI through SPI via the regression equations of item b. Thereafter, methodological steps are identical to those given above for the first goal of the paper.

To test the applicability of the above variant of the proposed methodology, the matrix of state transition frequency obtained via precipitation is compared to that obtained through streamflow. Comparisons are made on the same data used for the SDI–SPI regression and are, therefore, not completely fair. Data from another period should be used according to the common practice in hydrological modelling: clearly distinguish between calibration and verification data sets.

A rigorous testing framework was set up which includes the following: (1) the matrix of state transition frequency is calculated through the SDI index as obtained based on streamflow data from a real-world basin; (2) the same matrix is calculated through SDI predicted from SDI–SPI regression equations; (3) the two matrices of state transition frequency are compared on the common period used in their estimation; (4) comparison is extended to another time period for verification purposes.

3 Case Study

3.1 The Study Area

The methodology proposed was applied to a river basin located in the West Sterea Hellas Water District in central Greece (Fig. 1). This is the Evinos river basin at the site of the Agios Demetrios dam with upstream basin area of 352 km^2, mean elevation of 990 m above the mean sea level, and steep slopes. Its average annual streamflow is 297×10^6 m^3 (Efstratiadis et al. 2000). Water from the Agios Demetrios reservoir is diverted eastwards to the adjacent Mornos reservoir for the water supply

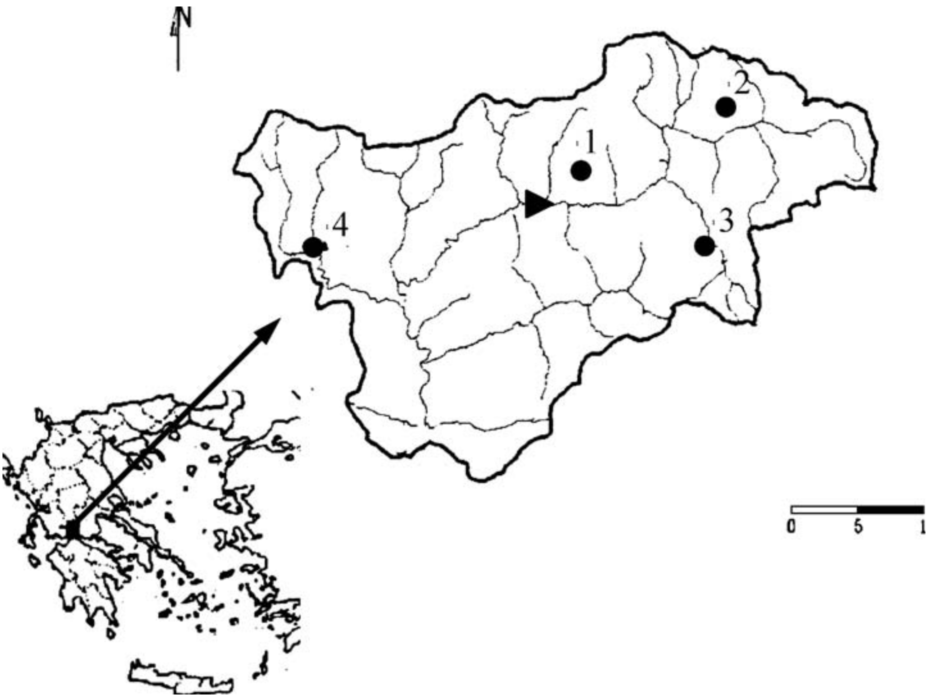

Fig. 1 The Evinos basin upstream Poros Reganiou hydrometric station; the Agios Demetrios Reservoir is shown in *triangle* while precipitation gauges are in *circles*; station numbers correspond to the following names: 1 Arachova, 2 Grammeni Oxia, 3 Gregorio and 4 Drymonas

of the Greater Athens area. The reservoir possesses a surface area of 3.6 km^2 (at the elevation of the spillway crest) and an active storage capacity of 112.1×10^6 m^3. The Agios Demetrios reservoir and the adjacent Mornos reservoir form the main storage facilities of the water supply system of Athens.

Monthly streamflow data at the Agios Demetrios dam have been obtained through processing raw data of concurrent velocity and stage measurements combined with stage recordings at the daily or the hourly time step, mainly at the Poros Reganiou hydrometric station, downstream of the dam site. Data cover the period from 1970–71 to 1999–2000.

Precipitation gauging stations used in this study are shown in Fig. 1. Monthly precipitation depths obtained from daily observations in three stations were available in the report mentioned above. These allowed for calculating a series of areal precipitation for the period from 1963–64 to 1991–92. This series was then extended up to 1999–2000 based on data from Drymonas station which lies outside the basin but within the greater Evinos basin.

4 Results

First, skewness coefficients of cumulative streamflow volumes for all reference periods were calculated based on initial (original) data series. These are shown in

Table 3 Skewness coefficient of streamflow, areal precipitation and their natural logarithms

Variable	Calculation basis	Oct–Dec	Oct–Mar	Oct–Jun	Year
Streamflow	Initial data	*0.863*	−0.324	−0.324	−0.365
	Logarithms	−0.279	*−1.455*	*−1.222*	*−1.259*
	Final data	−0.279	−0.324	−0.324	−0.365
Areal precipitation	Initial data	0.605	−0.273	−0.293	−0.276
	Logarithms	−0.032	*−1.321*	*−1.040*	*−0.793*
	Final data	−0.032	−0.273	−0.293	−0.276

Statistically significant values (at the 0.10 probability) are in italics

Table 3. The test of Snedecor and Cochran (1967) was applied which gave critical upper limits of the absolute value of the skewness coefficient equal to 0.986 and 0.662 respectively at 0.02 and 0.10 significance level. Hence, only the 3-month streamflows exhibit skewness which is statistically significant at the 0.10 significance level. Taking natural logarithms for all reference periods removed skewness from the October–December data series but introduced significant negative skewness to all other series at both 0.02 and 0.10 significance levels. This led to using the definition of Eq. 3 for SDI of October–December while keeping Eq. 2 for the other reference periods. Data from the period 1970–71 to 1999–2000 were used. All calculated skewness coefficients are given in Table 3. None of them is statistically significant at the 0.02 significance level for the final data which was used to define SDI.

Precipitation has shown behaviour which is analogous to that of streamflow: only the skewness of the October–December period is close to being significant at the 0.10 significance level (see Table 3). As a consequence, to calculate SPI, precipitation series were processed exactly as streamflow series.

The evolution of SDI from one hydrological year to another and each reference period separately is depicted in Figs. 2, 3, and 4 where the SDI series were grouped by two. As expected, significant discrepancies are observed only when passing from the

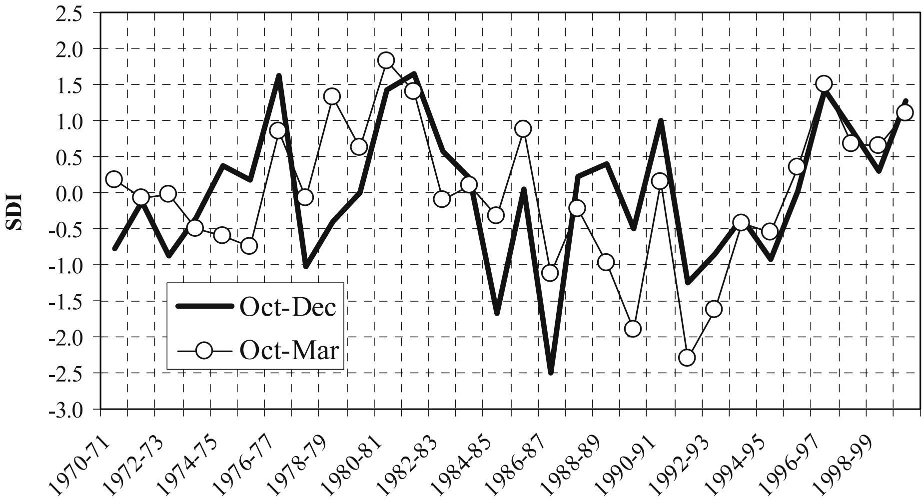

Fig. 2 SDI series for reference periods October–December and October–March

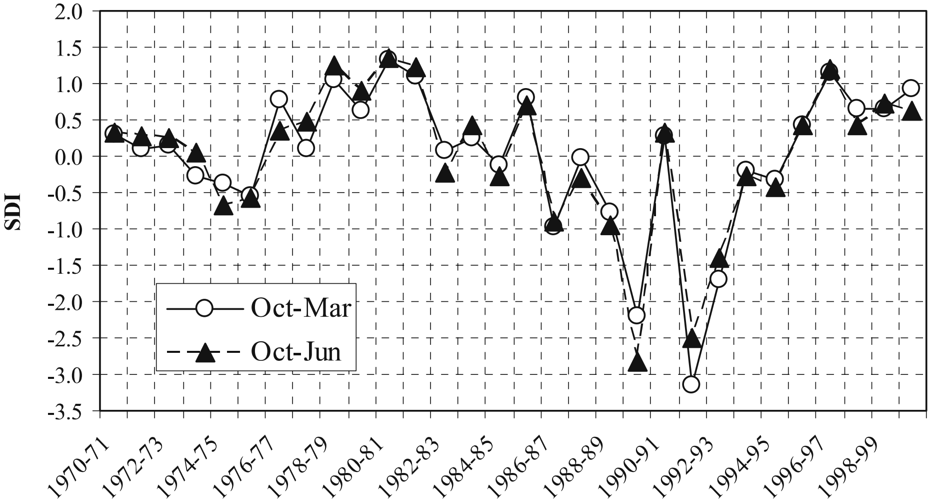

Fig. 3 SDI series for reference periods October–March and October–June

first 3-month period (October–December) to the first semester (October–March). This is due to the typical Mediterranean hydrological regime which is manifested as a wet period of 6 months of the hydrological year and a mostly dry period thereafter. As a result, high predictive capacity of drought state is expected when, in the end of March the following question is raised: will the 9-month period of the running year be considered as drought period? The same holds for the assessment in the end of June.

Regarding the frequency of state transition, preliminary tests showed very small observed number of occurrences of states, 3 (severe drought) and 4 (extreme

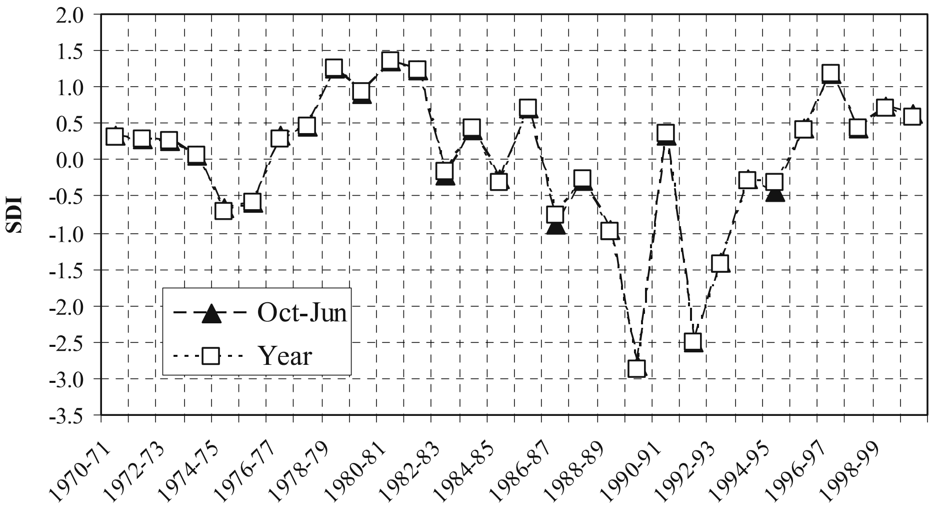

Fig. 4 SDI series for reference periods October–June and the hydrological year (October–September)

Table 4 Frequency of state transition as estimated from: (a) SDI based on streamflow data, (b) SDI predicted from areal precipitation through SPI

(a) From streamflow				(b) From precipitation		
State for Oct–Dec	State for Oct–Mar			State for Oct–Mar		
	0	1	2	0	1	2
0	0.706	0.294	0.000	0.625	0.375	0.000
1	0.222	0.556	0.222	0.500	0.500	0.000
2	0.000	0.500	0.500	0.000	0.500	0.500
State for Oct–Mar	State for Oct–Jun			State for Oct–Jun		
	0	1	2	0	1	2
0	1.000	0.000	0.000	0.600	0.400	0.000
1	0.250	0.667	0.083	0.200	0.800	0.000
2	0.000	0.000	1.000	0.000	0.000	1.000
State for Oct–Jun	State for Oct–Sep			State for Oct–Sep		
	0	1	2	0	1	2
0	1.000	0.000	0.000	0.800	0.200	0.000
1	0.250	0.667	0.083	0.200	0.700	0.100
2	0.000	0.250	0.750	0.000	0.000	1.000

drought). To remedy this problem, the above three states were grouped into one state to which we assigned number 2. In Table 4 (left part) we present the matrices of state transition frequency for all pairs of reference periods when passing from one period to the next lengthier period (three pairs in all). These matrices are the main tools for predicting drought state in real-time in the case of availability of streamflow data (see Subsection 2.5).

The SDI values were regressed on the concurrent SPI values for the period from 1970–71 to 1991–92. Statistics for defining SPI were calculated on a 29-year period (1963–64 to 1991–92). Preliminary tests with non-linear regression gave no improvement over linear regression which is our final model. The constant regression coefficient (the intercept) was found to be insignificant at the 0.01 significance level. Thus, only regression lines passing through the point (0,0) were kept. The regression coefficient (slope) and the determination coefficient (R^2) of the linear regression equations are significant and are given in Table 5 (case without delay) while in Fig. 5 the regression lines and the data points are shown for each reference period separately.

For all reference periods the determination coefficient is high and comparable to values which are very often obtained when calibrating rainfall-runoff models.

Table 5 Regression coefficient (a) and determination coefficient (R^2) of linear regression equations of SDI on SPI (with zero intercept)

k	Without delay			With delay		
	Reference period for streamflow	a	R^2	Reference period for streamflow	a	R^2
1	October–December	0.8944	0.7913	November–January	0.8127	0.6019
2	October–March	0.8654	0.7993	November–April	0.8514	0.8101
3	October–June	0.8873	0.8461	November–July	0.8701	0.8416
4	October–September	0.8788	0.8446	November–October	0.8835	0.8435

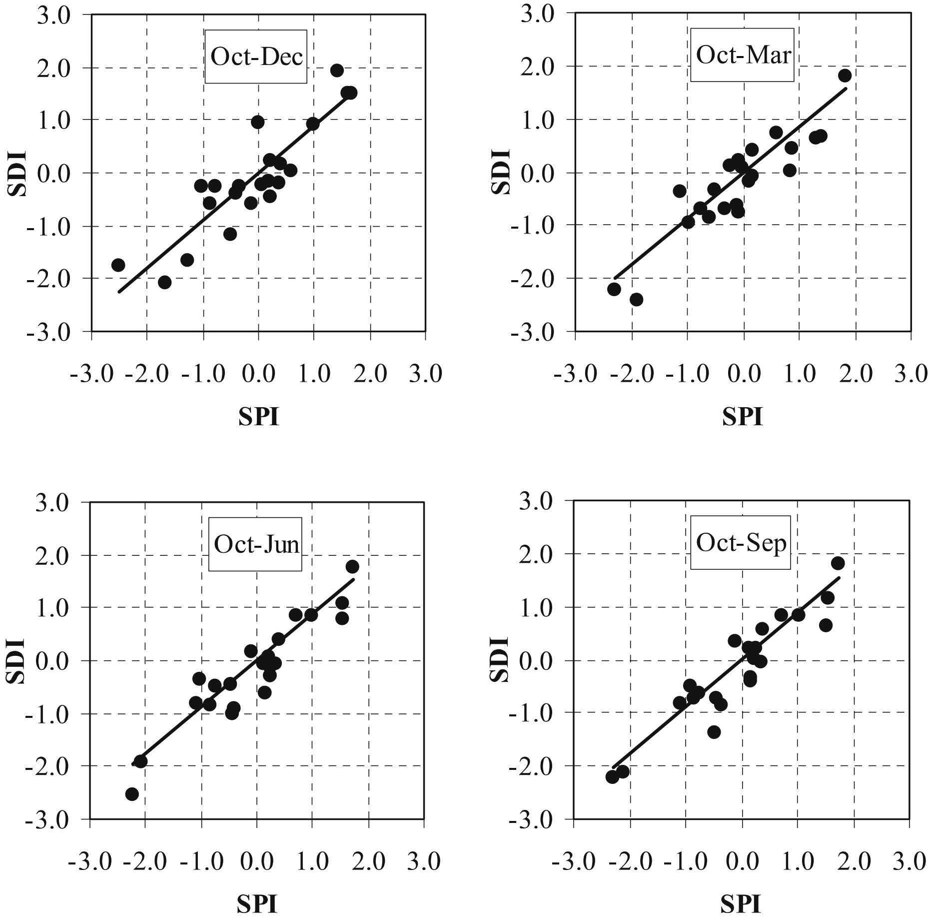

Fig. 5 Linear regression of SDI on SPI for each reference period separately

The regression coefficient is statistically significant and varies from 0.86 to 0.90. The latter observation implies that a meteorological drought of certain severity produces a hydrological drought of lower severity. This is explained by the delays in the rainfall-runoff processes as well as other kinds of error (model errors, data errors, sampling errors). The effect of the delay between precipitation and streamflow was also investigated. For this, a delay of 1 month was assumed by defining SDI on the following reference periods; $k = 1$ for November–January, $k = 2$ for November–April, $k = 3$ for November–July, and $k = 4$ for November–October (of the next hydrological year). SPI definition was not modified. Again R^2 and the slope (but not the intercept) were found significant at the 0.01 significance level. Numerical values are given in Table 5 (case with delay). For $k = 1$, R^2 was clearly inferior to that of the case without delay. This is expected for our test basin which responds to precipitation within a few hours with direct flow as the dominant process (Nalbantis 1995). Consequently, one month is a too large delay for our test basin. For other periods, R^2 was essentially unaffected. This is due, at least in part, to the greater delay of streamflow in regard to precipitation for the 9- and 12-month periods. For the October–March period the result is numerical to a large extent and reflects all kinds of uncertainty. The above results led us to keep data without delay.

The regression equations were used to predict SDI and then calculate the matrices of state transition frequency for all reference periods (Table 4, right part) as explained in previous sections. These matrices are compared with those obtained through direct use of streamflow data. A fair agreement is shown for all combinations of states while the larger discrepancies are observed when the starting state is 0 (non-drought).

To verify the proposed methodology, predictions of SDI through SPI were obtained for the period from 1992–93 to 1999–2000. Data from this period were not previously used in the regression of SDI on SPI. The predicted SDI series allowed calculating states of hydrological drought for the same period which are called predicted states. These are then compared to states obtained directly through the streamflow-based SDI. No statistical measures could be derived due to the small length of the verification period. Numerical values are given in Table 6. A high degree of successful prediction is observed for the wet period of October to March while predictions for other reference periods are less good. Closer examination of Table 6 allows for making the following remarks: (a) the October–December period may be too small to allow accurate prediction of drought state since it is affected by a carry-over effect from previous year; (b) for the whole wet period of October–March predictions are clearly successful which means that, for this period, precipitation deficit can well predict hydrological drought; (c) for the next two periods, successful predictions of the October–March period are deteriorated and are found to be limited to two extreme cases: (1) when starting from state 0 and remaining in state 0, and (2) when starting from state 2 and remaining in state 2; this means that, for these periods, precipitation may not suffice for good prediction of streamflow and other variables such as evapotranspiration may be necessary. It must be noted, however, that the above degree of success is a lower limit since, for the verification period, areal precipitation is calculated based on data from one station outside the test basin which certainly lowers data quality in respect to the calibration period. For this reason, we believe that verification enhances the conviction about the validity of the methodology proposed which was initially founded on good results from the calibration period.

Table 6 Comparison of states based on streamflow data (called observed) with those based on precipitation via the SDI–SPI relationship (called predicted); successful prediction is denoted as 'Y'

Year	Oct–Dec			Oct–Mar			Oct–Jun			Oct–Sep		
	Obs.	Pred.	Success	Obs.	Pred.	Success	Obs.	Pred.	Success	Obs.	Pred.	Success
1992–93	1	2		2	2	Y	2	2	Y	2	2	Y
1993–94	1	0		1	1	Y	1	0		1	0	
1994–95	1	0		1	0		1	0		1	0	
1995–96	0	1		0	0	Y	0	0	Y	0	0	Y
1996–97	0	0	Y	0	0	Y	0	0	Y	0	0	Y
1997–98	0	0	Y	0	0	Y	0	1		0	1	
1998–99	0	0	Y	0	0	Y	0	0	Y	0	0	Y
1999–00	0	0	Y	0	0	Y	0	0	Y	0	0	Y

5 Concluding Remarks

This paper aims at proposing a methodology for forecasting hydrological droughts within an operational context regarding river basins with works of large total storage capacity.

The main features of the methodology are: (1) a simple index called Streamflow Drought Index or SDI is used to characterise severity of the hydrological drought; (2) the problem of predicting drought onset and duration is bypassed through using cumulative streamflow volumes for overlapping periods of 3, 6, 9 and 12 months within each hydrological year; these time periods are referred to as reference periods; (3) predicting the areal extent of drought is also automatically bypassed through using streamflow at a basin outlet which is already a spatially integrated variable; (4) five drought classes (states) are considered: 0 for non-drought, 1 for mild drought, 2 for moderate drought, 3 for severe drought and 4 for extreme drought; (5) when the appropriate historical data are available, the main output of the methodology is the matrix of state transition frequency for a selected pair of reference periods under the hypothesis of a Markov chain for the underlying state process; (6) within an operational real-time context, the output is a single value of drought state while the probabilities of remaining in the same state or passing to other states in the next reference period are withdrawn from tables which have been obtained off-line (as in the previous item).

Since, in general, streamflow data are difficult to obtain in real-time, the possibility of using a meteorological drought index was investigated. More specifically, a linear function of SPI was found to predict SDI to an accuracy level which is sufficient for characterising drought severity. This involves prior calibration of a simple regression equation with modified SPI as the explanatory variable and SDI as the explained variable.

A rigorous testing framework was set up which allowed for illustrating and validating the methodology in two ways. First, the matrices of frequency of state transition were compared which have been obtained from streamflow and precipitation separately. Second, drought state comparisons are made for a data record different from that used in the calibration of the SDI–SPI relationship. This calibration is an essential part of our methodology. It creates the link to hydrological processes of the basin tested which may involve delays in the precipitation–streamflow relationship. Of course, results of initiatives for ungauged basins such as PUB (Predictions in Ungauged Basins) will hopefully help avoiding calibration entirely.

The methodology proposed was validated on data from a Greek basin in the West Sterea Hellas Water District. We believe that the proposed methodology can be easily applied and can be very useful within a Drought Watch System. However, further validation is certainly required. This is part of ongoing research in our laboratory. Specifically, longer data records and a variety of streamflow regimes are being tested.

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