Nat. Hazards Earth Syst. Sci., 12, 1561–1572, 2012
www.nat-hazards-earth-syst-sci.net/12/1561/2012/
doi:10.5194/nhess-12-1561-2012

Natural Hazards and Earth System Sciences

Drought analysis and short-term forecast in the Aison River Basin (Greece)

S. Kavalieratou, D. K. Karpouzos, and C. Babajimopoulos

Dept. of Hydraulics, Soil Science and Agricultural Engineering, Faculty of Agriculture,
Aristotle University of Thessaloniki, Greece

Correspondence to: C. Babajimopoulos (babajim@agro.auth.gr)

Received: 29 March 2011 – Revised: 28 January 2012 – Accepted: 7 February 2012 – Published: 21 May 2012

Abstract. A combined regional drought analysis and forecast is elaborated and applied to the Aison River Basin (Greece). The historical frequency, duration and severity were estimated using the standardized precipitation index (SPI) computed on variable time scales, while short-term drought forecast was investigated by means of 3-D loglinear models. A quasi-association model with homogenous diagonal effect was proposed to fit the observed frequencies of class transitions of the SPI values computed on the 12-month time scale. Then, an adapted submodel was selected for each data set through the backward elimination method. The analysis and forecast of the drought class transition probabilities were based on the odds of the expected frequencies, estimated by these submodels, and the respective confidence intervals of these odds. The parsimonious forecast models fitted adequately the observed data. Results gave a comprehensive insight on drought behavior, highlighting a dominant drought period (1988–1991) with extreme drought events and revealing, in most cases, smooth drought class transitions. The proposed approach can be an efficient tool in regional water resources management and short-term drought warning, especially in irrigated districts.

1 Introduction

Drought is an extreme recurrent climatic event characterized by lower than normal precipitation. Although it occurs in all climatic zones, its characteristics vary significantly from one region to another. Drought conditions can have critical environmental and economical impacts, especially in high water demanding areas with intensive agricultural activity. Various definitions of drought have been used, reflecting differences in regions, needs, and disciplinary approaches. Dracup et al. (1980) associate drought with precipitation (meteorological), streamflow (hydrological), soil moisture (agricultural) or any combination of these parameters. A more extended classification is provided by Wilhite and Glantz (1985), where four approaches are proposed: meteorological, hydrological, agricultural and socio-economic. The first three approaches deal with techniques to measure drought as a physical phenomenon, while the last one relates drought and socio-economic impacts that occured when demand for economic goods exceeds supply, as a result of a weather-related shortfall in water (Mishra and Singh, 2010).

In order to monitor and quantify drought, several indices have been proposed. Drought indices are composite numerical figures incorporating mainly values of hydrometeorological indicators. A drought index usually measures the departure from the local normal condition in a moisture variable based on its historical distribution (Dai, 2011). Precipitation based drought indices are the first indicators of droughts, since hydrological drought emerges a considerable time after a meteorological drought has been established (Wilhite and Buchanan-Smith, 2005), due to the effect of storage. Paulo and Pereira (2006), in their comparative work on meteorological drought indices, note that drought characterization by means of Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) produce more coherent information than theory of runs, but SPI is easier to apply in real cases since it requires less data (namely only precipitation data) than PDSI. The SPI has the advantage of statistical consistency and the ability to reflect both short-term and long-term drought impacts (Guttman, 1998; Hayes et al., 1999). Another advantage of the SPI is that it is independent of time period, location and climate. Therefore, SPI values are more suited to be used as drought triggers in risk management and decision analysis (i.e. thresholds that determine when drought management actions should begin and end) and can be tailored to time periods of users' interest (Edossa et al., 2010).

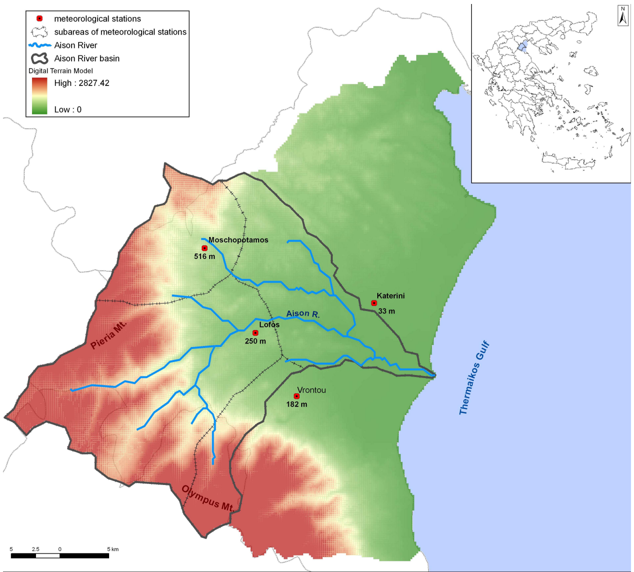

Fig. 1. Aison River Basin – Pieria (Greece).

Table 1. Location of the stations considered for drought analysis.

	Katerini	Lofos	Moschopotamos	Vrondou
Latitude	22°30′	22°23′	22°19′	22°26′
Longitude	40°16′	40°13′	40°20′	40°12′
Elevation (m)	31	250	516	182

Table 2. Summary statistics of the annual precipitation time series (mm).

	Katerini	Lofos	Moschopotamos	Vrondou
Count	34	34	34	34
Average	629.81	831.08	770.89	844.88
Median	624.65	803.4	714.85	815.1
Std. deviation	198.95	218.59	198.42	254.23
Minimum	321.4	411.6	387.8	404.1
Maximum	1341.67	1219.61	1339.0	1389.8
Range	1020.27	808.01	951.2	985.7
Areal prec. coef.	0.24	0.48	0.18	0.10

As drought management is increasingly adopting a risk-based approach (Sene, 2010), many countries are implementing drought monitoring, forecasting and early warning systems. Towards this direction, general guidelines to develop a drought management plan in compliance with the European Water Framework Directive 2000/60 objectives are also proposed by the European Group on drought and water scarcity (Rossi, 2009). In this context, the stochastic properties of the SPI time series can be used for predicting the likelihood and potential severity of future droughts, thus assisting in drought management. Forecasting techniques based on SPI include Markov chains, loglinear models (Paulo et al., 2005), neural networks (Mishra et al., 2007), renewal processes (Mishra et al., 2008), ensemble forecasting (Hwang and Carbone, 2009) and other stochastic techniques (Cancelliere et al., 2007).

Aiming to uncover drought behaviour in an agricultural region, namely the Aison River Basin in Northern Greece, a combined regional drought analysis and forecast is elaborated and applied. The historical frequency, duration and severity of meteorological drought were estimated using the SPI computed on variable time scales, while short-term drought forecast was investigated by means of loglinear models. The adopted methodology is applied at distinct sites (locations of meteorological stations) as well as for the whole study area, in order to support drought management decisions at both farm and basin scale.

2 Study area and data

Aison River Basin is located in Northern Greece and covers an extent of approximately 730 km^2 (Fig. 1). The Aison River drains the water of the central part of the prefecture of Pieria and constitutes the greatest receiver of surface water. The primary economic activity in this area is agriculture, resulting in high irrigation needs. As drought affects the farmers' choice of irrigation systems (Schuck et al., 2005), an investigation of the regional drought conditions is considered as a prerequisite for adopting more technically efficient irrigation systems, especially during low precipitation periods. In this study, precipitation measurements from four existing stations have been used: Katerini, Lofos, Moschopotamos and Vrondou. Their coordinates and elevations are presented in Table 1, while their locations are displayed in Fig. 1.

The stations have a common period of monthly data lasting 34 yr, from 1974 to 2007. Basic summary statistics for the annual time series are presented in Table 2. The areal precipitation is calculated in a GIS environment through a modified Thiessen method where polygons are created according to both distance and elevation minimization. These polygons provide weight coefficients (Table 2) that show the influence of every individual station on the Aison Basin related to distance and elevation criteria.

The data required for drought assessment by general indices are usually monthly data. The length of the time interval is region- and case-specific. Different timescales are designed to reflect the impacts of precipitation deficits on different water resources. Regions like the Mediterranean are likely to experience multi-year as well as seasonal droughts (Hisdal and Tallaksen, 2000). Thus, SPI values computed from 3-, 6-, 9-, 12-, and 24-months aggregated rainfall observations are used for drought assessment in the study area.

Table 3. Drought classification by SPI value.

SPI value	Category	SPI value	Category
2.00 or more	Extremely wet	0 to −0.99	Near normal (Mild drought)
1.50 to 1.99	Severely wet	−1.00 to −1.49	Moderate drought
1.00 to 1.49	Moderately wet	−1.50 to −1.99	Severe drought
0 to 0.99	Near normal (Mildly wet)	−2 or less	Extreme drought

3 Methods

The Standardized Precipitation Index (SPI), developed by McKee et al. (1993), quantifies precipitation deficit for multiple timescales. The SPI relies on a long-term precipitation record for a desired region, "ideally a continuous period of at least 30 yr" (McKee et al., 1993). Moreover, a 30-yr period is practically considered an adequately large data sample for which reliable estimates can be determined (Arguez and Vose, 2011). Monthly precipitation values accumulated for the time scale of interest are fitted to a probability distribution, which is then transformed to the standard normal random variable z with mean as zero and variance as one. The z score is the value of the SPI. Positive SPI values indicate greater than mean precipitation, while negative values indicate less than mean precipitation. Because the SPI is standardized, wetter and drier climates can be represented in the same way. Wet periods can also be monitored using SPI.

The classification system shown in Table 3 (McKee et al., 1993) is used to define the strength of the precipitation anomaly. The SPI value of −1 is commonly used as threshold for drought event definition (Cancelliere et al., 2005). The duration of the drought event is defined by its beginning and end, while its severity is the accumulated SPI values for the duration of the event and its intensity is measured as the drought severity divided by the drought duration.

Computation of the SPI involves fitting a gamma probability distribution to a given frequency distribution of precipitation totals for a station. The gamma distribution is considered to fit well to monthly precipitation time series and was originally used in the development of the SPI method. However, other distributions can also be used if they better fit a particular time series (Guttman, 1999). An extended description of the method used for the SPI computation can be found in Edwards and McKee (1997).

Two-dimensional (2-D) and three-dimensional (3-D) loglinear models have been successfully used to model the expected frequencies of class transitions of SPI values and served as a tool for short-term forecasting of drought. Paulo et al. (2005) used 2-D loglinear models to fit drought class transitions matrices constructed for several sites in southern Portugal. Based on SPI values, four drought classes were considered: non drought ($\mathrm{SPI} \geq 0$), mild drought ($-1 < \mathrm{SPI} < 0$), moderate drought ($-1.5 < \mathrm{SPI} \leq -1$) and severe or extreme drought ($\mathrm{SPI} \leq -1.5$). The computed odds and respective confidence intervals were used to predict drought class transitions one month ahead, given the drought class of a certain month. The 2-D quasi-association model sufficiently fitted five of the data series used, while the 2-D quasi-symmetry model was selected for two series.

Moreira et al. (2008) extended the work of Paulo et al. (2005) using the same drought classification and 3-D loglinear models to predict drought class transitions one month ahead, given the drought class for the last two months, which also allows for extending the prediction to two months ahead. The quasi-association model adequately fitted their data (14 sites in southern Portugal).

In the present work, a 3-D loglinear models approach was used to investigate drought class transitions in the Aison River Basin, based on the SPI values computed on a 12-month time scale. Since in our study the SPI value of −1 was the threshold for the definition of drought, the four drought classes used were non drought ($\mathrm{SPI} > -1$), moderate drought ($-1.5 < \mathrm{SPI} \leq -1.0$), severe drought ($-2 < \mathrm{SPI} \leq -1.5$) and extreme drought ($\mathrm{SPI} \leq -2$).

The aim of this analysis is knowing the drought class of two consecutive months to predict the drought class for the following month. For this purpose a 3-dimension contingency table is constructed for each station and for the areal time series. A 3-D contingency table has three categories (A, B, C) representing the three consecutive months ($t-2$, $t-1$ and t, respectively). Each category has a level (i, j, k for A, B, C, respectively). The level of a category (month) represents its drought class (1 = non drought, 2 = moderate drought, 3 = severe drought and 4 = extreme drought). Each cell of the contingency table shows the observed counts of the transitions between the levels of the three categories, as displayed in Table 4. For example, O_{421} is the number of the occurrences of the three consecutive months with drought classes 4, 2 and 1, respectively.

The construction of the contingency table is based on the assumption that the monthly SPI series are homogeneous and disregards which months the 3-month sequence involves. Loglinear models with Poisson sampling (Agresti, 2002) are used to fit the observed frequencies O_{ijk} and estimate the corresponding expected frequencies Eijk.

Several models were tested, among them the quasi – association model , which was found to be adequate for most of the cases studied by Paulo et al. (2005) and Moreira et

Table 4. Three-dimensional contingency table of observed drought class transitions O_{ijk}.

	i															
	1				2				3				4			
	j				j				j				j			
k	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	O_{111}	O_{121}	O_{131}	O_{141}	O_{211}	O_{221}	O_{231}	O_{241}	O_{311}	O_{123}	O_{331}	O_{341}	O_{411}	O_{421}	O_{431}	O_{441}
2	O_{112}	O_{122}	O_{132}	O_{142}	O_{212}	O_{222}	O_{232}	O_{242}	O_{312}	O_{223}	O_{332}	O_{342}	O_{412}	O_{422}	O_{432}	O_{442}
3	O_{113}	O_{123}	O_{133}	O_{143}	O_{213}	O_{223}	O_{233}	O_{243}	O_{313}	O_{323}	O_{333}	O_{343}	O_{413}	O_{423}	O_{433}	O_{443}
4	O_{114}	O_{124}	O_{134}	O_{144}	O_{214}	O_{224}	O_{234}	O_{244}	O_{314}	O_{423}	O_{334}	O_{344}	O_{414}	O_{424}	O_{434}	O_{444}

Table 5. Selected loglinear quasi-association submodels for all sites.

Site	Selected submodel	RD	df	p-value
Katerini	$\log E_{ijk} = \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \eta v_j w_k + \delta_4 I(i=j=k)$	35.774	51	0.948
Lofos	$\log E_{ijk} = \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \alpha u_i w_k + \eta v_j w_k + \tau u_i v_j w_k + \delta_4 I(i=j=k)$	44.262	49	0.665
Moschopotamos	$\log E_{ijk} = \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \eta v_j w_k + \tau u_i v_j w_k + \delta_2 I(i=k)$	31.204	50	0.983
Vrondou	$\log E_{ijk} = \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \alpha u_i w_k + \eta v_j w_k + \tau u_i v_j w_k + \delta_1 I(i=j) + \delta_3 I(j=k)$	38.994	49	0.846
Aison basin	$\log E_{ijk} = \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \alpha u_i w_k + \eta v_j w_k + \tau u_i v_j w_k + \delta_4 I(i=j=k)$	42.231	49	0.742

al. (2006, 2008). The general form of this model is given by the following equation:

$$\begin{aligned} \log E_{ijk} &= \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \alpha u_i w_k \\ &+ \eta v_j w_k + \tau u_i v_j w_k + \ + \delta_{1i} I(i=j) + \delta_{2i} I(i=k) \\ &+ \delta_{3j} I(j=k) + \delta_{4i} I(i=j=k) \end{aligned} \quad (1)$$

where E_{ijk} is the expected frequency; A, B and C are the categories corresponding to three consecutive months $t-2$, $t-1$ and t, i, j and $k \epsilon \{1,2,3,4\}$: 1 $\rightarrow$ non drought, 2 $\rightarrow$ moderate drought, 3 $\rightarrow$ severe drought, 4 $\rightarrow$ extreme drought. λ is the constant term of the model; $\lambda_i^A, \lambda_j^B, \lambda_k^C$ represent the i-th, j-th, k-th levels for categories A, B, C, respectively; u_i, v_j, w_k are the i-th, j-th, k-th level scores of categories A, B, C, respectively, usually taken as $u_i = i, v_j = j, w_k = k$, β, α, η, τ are linear association parameters; δ_{1i} , δ_{2i} , δ_{4i} are parameters associated to the i-th diagonal element of category A; δ_{3j} is a parameter associated with the j-th diagonal element of category B, and I is an indicator function defined as:

$$I(\text{condition}) = \begin{cases} 1 \text{ if condition is true} \\ 0 \text{ if condition is false} \end{cases} \quad (2)$$

This model comprises two components: (a) the linear-by-linear association model consisting of the first eight terms and (b) the rest four terms describing the effect of the diagonal elements of the 3-D contingency table. These four terms reflect the persistency of drought in the same class for consecutive months. The persistency of each drought class is associated with a different parameter value. For example having the first two months in drought class 1 ($i = j = 1$) is associated with the parameter δ_{11}, while having the first two months in drought class 2 ($i = j = 2$) is associated with the parameter δ_{12}. As a result, a maximum of 16 parameters are needed to account for drought class persistency.

Since the homogenous form of the second component of the model is more suitable for ordered variables (Lawal, 2003), which is our case, the following simplified form of the equation of the model (Eq. 1) is proposed:

$$\begin{aligned} \log E_{ijk} &= \lambda + \lambda_i^A + \lambda_j^B + \lambda_k^C + \beta u_i v_j + \alpha u_i w_k \\ &+ \eta v_j w_k + \tau u_i v_j w_k + \ + \delta_1 I(i=j) + \delta_2 I(i=k) \\ &+ \delta_3 I(j=k) + \delta_4 I(i=j=k) \end{aligned} \quad (3)$$

This model is the extension of the 2-D parsimonious quasi-symmetry model in three dimensions (Agresti, 2002; Lawal, 2003). Drought classes are ordered variables and the model (3) exploits this characteristic, resulting in a reduced number of estimated parameters. In this model drought class persistency is homogenized, i.e. having the first two months in the same drought class is associated with parameter δ_1, regardless of the actual drought class. Thus, in the proposed model, a maximum of only 4 parameters is required to account for drought class persistency.

Table 6. Estimated parameter values.

Parameters		Estimates				
		Katerini	Lofos	Moschopotamos	Vrondou	Aison R. Basin
λ		−40.505	−72.850	74.572	−72.271	−59.503
λ_i^A	$[i=1]$	11.372	19.456	−16.278	21.357	16.427
	$[i=2]$	7.958	14.038	−12.512	15.318	11.821
	$[i=3]$	4.537	7.434	−6.894	8.055	5.781
	$[i=4]$	0	0	0	0	0
λ_j^B	$[j=1]$	19.781	32.935	−37.042	27.646	26.553
	$[j=2]$	14.694	24.852	−29.659	20.687	19.956
	$[j=3]$	8.618	13.489	−16.446	11.101	10.426
	$[j=4]$	0	0	0	0	0
λ_k^C	$[k=1]$	11.372	19.456	−16.278	21.357	16.427
	$[k=2]$	7.958	14.038	−12.512	15.318	11.821
	$[k=3]$	4.537	7.434	−6.894	8.055	5.781
	$[k=4]$	0	0	0	0	0
β		1.294	2.726	−3.055	2.504	2.174
α			0.811		1.620	0.727
η		1.294	2.726	−3.055	2.504	2.174
τ			−0.419	0.358	−0.536	−0.327
δ_1					0.764	
δ_2				0.728		
δ_3					0.764	
δ_4		1.142	0.868			1.051

By default, due to the definition of the SPI and the relevant classification system, moderate, severe and extreme droughts (classes 2, 3, 4) comprise a relatively small portion of the SPI time series (McKee et al., 1993). Although they exhibit a similar trend for persistency with class 1, as it was observed in our data series, the numbers of the relevant observed frequencies are small. Hence, homogenizing drought class persistency and reducing the number of estimated parameters resulted in models that fitted the data better than model (1) in all our cases. Thus, in this work, a quasi-association model with homogenous diagonal effect was considered more appropriate to describe the observed drought class transitions.

The goodness of fit of a loglinear model is tested by a chi-square test performed on the value of the residual deviance (RD) of the model:

$$\mathrm{RD}=2\sum_i\sum_j\sum_k O_{ijk}\log\left(\frac{O_{ijk}}{E_{ijk}}\right) \tag{4}$$

The residual deviance has an approximate chi-square distribution with degrees of freedom equal to the number of the cells of the contingency table minus the number of linearly independent estimated model parameters. If the p-value of a model exceeds a chosen level of significance α (in our case $\alpha=0.05$), then the null hypothesis that the model fits well to the data is not rejected.

Model (3) fitted adequately all data series studied in the present work. For each station, an alternative submodel was selected, including only the most significant parameters through the backward elimination method. The selected submodels and the respective residual deviance, degrees of freedom (df) and p-value of the submodel are presented in Table 5. The parameters of the selected submodels were estimated by the maximum likelihood method. Their values are presented in Table 6. The software used for model fitting was SPSS 17.

The analysis and forecast of the drought class transition probabilities are based on the odds of the estimated expected frequencies. Odds are ratios of expected frequencies, as defined by the following equation:

$$\Omega_{kl|ij}=\frac{E_{ijk}}{E_{ijl}},\ \mathrm{k}\neq \mathrm{l} \tag{5}$$

Odds represent how more probable an event is to occur instead of another. Equation (5) means that, given that a site was in drought class i at month $t-2$ and in class j at month $t-1$, it is $\Omega_{kl|ij}$ times more probable that at month t, it will be in class k than in class l.

The odds have asymptotic normal distribution; thus the log transform of the odds, which equals $\log E_{ijk}$–$\log E_{ijl}$, converges to a normal distribution more rapidly. For the

Table 7. Areal precipitation – drought analysis results for all time scales.

	SPI	Drought Periods (SPI < −1)				Number and duration of periods				
		Duration (months)	min	mean		Wet (SPI > 1.0)	Near Normal (−1.0 < SPI < 1.0)	Moderate dr. (SPI < −1.0)	Severe dr. (SPI < −1.5)	Extreme dr. (SPI < −2.0)
SPI1										
number		51				51	86	51	21	5
min	−2.742	1	−2.74	−2.74		1	1	1	1	1
mean	−0.001	1.27	−1.53	−1.50		1.27	3.23	1.27	1.29	1.00
max	3.283	3	−1.02	−1.02	3		13	3	3	1
total		65			65		278	65	27	5
total %						15.93	68.14	15.93	6.62	1.23
SPI3										
number		31				28	41	31	15	5
min	−2.695	1	−2.70	−2.14	1		1	1	1	1
mean	−0.010	2.03	−1.55	−1.42		2.32	1.00	2.03	1.60	1
max	2.999	7	−1.00	−1.04		4	1	7	4	1
total		63			65		278	63	24	5
total %						16.01	68.47	15.52	5.91	1.23
SPI6										
number		22				24	45	22	11	5
min	−2.529	1	−2.53	−1.90		1	1	1	1	1
mean	−0.004	2.77	−1.53	−1.31		3.17	1.00	2.77	2.00	1.60
max	2.975	9	−1.00	−1.02		7	1	9	7	4
total		61				76	266	61	22	8
total %						18.86	66.00	15.14	5.46	1.99
SPI9										
number		15			21		41	15	8	3
min	−2.568	1	−2.57	−1.93		1	1	1	1	1
mean	−0.003	4.00	−1.54	−1.33		3.33	1.00	4.00	2.50	2.33
max	2.825	13	−1.00	−1.02		11	1	13	8	5
total		60				70	270	60	20	7
total %						17.50	67.50	15.00	5.00	1.75
SPI12										
number		15				12	33	15	6	3
min	−2.458	1	−2.46	−2.03		1	0	1	1	1
mean	−0.001	4.27	−1.46	−1.28		5.00	0.97	4.27	3.17	3.67
max	2.824	13	−1.00	−1.00		12	1	13	11	8
total		64			60		273	64	19	11
total %						15.11	68.77	16.12	4.79	2.77
SPI24										
number		8				7	39	8	6	4
min	−2.369	1	−2.37	−1.80		1	0	1	1	1
mean	0.001	8.00	−1.67	−1.34		10.43	0.97	8.00	4.83	2.50
max	1.985	24	−1.00	−1.03		24	1	24	17	7
total		64				73	248	64	29	10
total %						18.96	64.42	16.62	7.53	2.60

Table 8. Maximum values of drought characteristics for all stations and time scales.

		max severity		max intensity		max duration	
		value	month	value	period	value	period
SPI1	Katerini	−2.41	Aug 1992	−2.11	Oct 1989	3	Nov 2006–Jan 2007
	Lofos	−2.30	May 2002	−2.17	May 2006	4	Jun 2000–Sep 2000
	Moschopotamos	−2.51	Sep 2001	−2.51	Sep 2001	3	Feb 1989–Apr 1989
	Vrondou	−2.61	Apr 1986	−2.61	Apr 1986	3	Jun 2000–Aug 2000
	Aison Basin	−2.74	Sep 2001	−2.74	Sep 2001	3	Jun 2000–Aug 2000
SPI3	Katerini	−2.45	Jan 2007	−2.01	May 2000–Aug 2000	8	Oct 1989–May 1990
	Lofos	−2.93	Sep 2000	−2.87	Aug 2000–Sep 2000	7	Oct 1989–Apr 1990
	Moschopotamos	−3.05	Apr 1989	−2.54	Mar 1989–May 1989	6	Jan 1977–Jun 1977
	Vrondou	−2.51	Jan 2007	−1.85	Jun 1988–Sep 1988	8	Oct 1989–May 1990
	Aison Basin	−2.70	Jan 2007	−2.14	Jun 2005	7	Oct 1989–Apr 1990
SPI6	Katerini	−2.78	Aug 2000	−2.13	Jun 2000–Sep 2000	9	Nov 1989–Jul 1990
	Lofos	−2.60	Jan 1990	−1.88	Nov 1989–Jul 1990	9	Nov 1989–Jul 1990
	Moschopotamos	−2.30	Oct 1984	−1.60	Feb 1977–Aug 1977	8	Dec 1989–Jul 1990
	Vrondou	−2.40	Sep 1988	−1.82	Nov 1989–Jul 1990	9	Nov 1989–Jul 1990
	Aison Basin	−2.53	Mar 1990	−1.90	Nov 1989–Jul 1990	9	Nov 1989–Jul 1990
SPI9	Katerini	−2.73	Aug 1977	−1.88	Oct 1989–Sep 1990	12	Oct 1989–Sep 1990
	Lofos	−2.51	Apr 1990	−1.92	Aug 2000–Sep 2000	13	Sep 1989–Sep 1990
	Moschopotamos	−2.10	Jun 1990	−1.81	Apr 1977–Dec 1977	13	Sep 1989–Sep 1990
	Vrondou	−2.48	Apr 1990	−1.70	Aug 1989–Sep 1990	14	Aug 1989–Sep 1990
	Aison Basin	−2.57	Apr 1990	−1.93	Aug 2000–Sep 2000	13	Sep 1989–Sep 1990
SPI12	Katerini	−2.47	Jul 1990	−2.07	Dec 1989–Nov 1990	12	Dec 1989–Nov 1990
	Lofos	−2.44	Mar 1990	−1.96	Nov 1989–Nov 1990	13	Nov 1989–Nov 1990
	Moschopotamos	−2.61	Nov 1977	−1.78	Nov 1989–Oct 1990	12	Nov 1989–Oct 1990
	Vrondou	−2.37	Mar 1990	−1.81	Oct 1989–Dec 1990	15	Oct 1989–Dec 1990
	Aison Basin	−2.46	Mar 1990	−2.03	Nov 1989–Nov 1990	13	Nov 1989–Nov 1990
SPI24	Katerini	−2.47	Apr 1990	−1.58	Apr 1989–Dec 1991	33	Apr 1989–Dec 1991
	Lofos	−2.50	Nov 2001	−1.67	Sep 1989–Mar 1991	19	Sep 1989–Mar 1991
	Moschopotamos	−2.18	Aug 1978	−1.67	Jan 1998–Oct 1998	24	Mar 1989–Feb 1991
	Vrondou	−2.52	Apr 1990	−1.71	Oct 1988–Oct 1991	37	Oct 1988–Oct 1991
	Aison Basin	−2.37	Apr 1990	−1.80	Apr 1989–Mar 1991	24	Apr 1989–Mar 1991

Poisson sampling an estimator of the standard error is $\sqrt{\mathrm{Var}(\log\Omega_{kl|ij})}$. For the general form of the model applied in this work (Eq. 3):

$$\begin{aligned}
&\log\Omega_{kl|ij} = \log E_{ijk} - \log E_{ijl} = \\
&= \lambda_k^C - \lambda_l^C + \alpha u_i (w_k - w_l) + \eta v_j (w_k - w_l) \\
&+ \tau u_i v_j (w_k - w_l) \\
&+ \delta_2 I(i=k) - \delta_2 I(i=l) + \delta_3 I(j=k) - \delta_3 I(j=l) \\
&+ \delta_4 I(i=j=k) - \delta_4 I(i=j=l)
\end{aligned} \tag{6}$$

Equation (6) was used for the calculation of the variance of the logarithm of odds, since all the terms in the right hand side of this equation are known and the variances and covariances of the estimated parameters were computed as part of the model fitting process.

The upper and lower bounds of the log-odds asymptotic confidence interval with probability 1-a can be estimated as:

$$\log\Omega_{kl|ij} \pm z_{1-\alpha/2}\sqrt{\mathrm{Var}(\log\Omega_{\mathrm{kl|ij}})} \tag{7}$$

where $z_{1-\alpha/2}$ is the 1-α/2 quantile of a standard normal variable.

The asymptotic confidence intervals for the odds are obtained by exponentiating the corresponding asymptotic confidence intervals of the logarithm of the odds. If a confidence interval includes the unit, then the two events are considered equally probable.

Table 9. Observed and expected drought class transitions for the Aison River Basin.

observed	*i*															
	1				2				3				4			
	j				*j*				*j*				*j*			
k	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	302	4	0	0	13	8	1	0	1	2	0	0	0	0	0	0
2	13	9	0	0	1	16	2	0	0	1	1	0	0	0	2	0
3	1	0	1	0	0	2	0	0	0	1	0	1	0	0	0	2
4	0	1	0	0	0	0	0	2	0	1	0	0	0	0	1	6
expected	*i*															
	1				2				3				4			
	j				*j*				*j*				*j*			
k	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	299.71	7.96	0.03	0.00	13.72	6.61	0.17	0.00	0.43	1.31	0.21	0.01	0.02	0.33	0.34	0.14
2	13.72	6.61	0.17	0.00	2.68	16.87	0.69	0.03	0.12	1.25	0.67	0.15	0.01	0.35	0.84	0.84
3	0.43	1.31	0.21	0.01	0.12	1.25	0.67	0.15	0.01	0.29	1.44	0.36	0.00	0.08	0.49	1.16
4	0.02	0.33	0.34	0.14	0.01	0.35	0.84	0.84	0.00	0.08	0.49	1.16	0.00	0.03	0.37	5.98

4 Results and discussion

SPI values, based on the monthly precipitation time series, for 1-, 3-, 6-, 9-, 12- and 24-month aggregation time scales were used for drought analysis in the study area of Pieria. The SPI value of -1 was selected as the critical value for the definition of drought events. For the computation of the SPI values, all precipitation time series were assumed to be gamma distributed. The results of the drought analysis for the Aison River Basin (areal precipitation) are presented in Table 7.

Different aggregation time scales were used, as they reflect drought impacts on different types of water resources. For all time scales, it can be seen in Table 7 that 30–45 % of the total number of months with SPI < -1 belong to severe or extreme drought classes. In most of the cases and especially for small time scales, SPI values remained negative after the termination of a drought event, sometimes for the whole period until the initiation of the next drought event. Usually, on larger time scales the two events and the period in between were considered as a continuous drought episode. Consequently, longer aggregation time scales led to less but more persisting drought events, as it is evident in the following graphs of SPI3, SPI6, SPI12 and SPI24 for the Aison River Basin in Fig. 2 (SPI9 graph is omitted due to space limitations). This should be taken into account when SPI is used as a drought indicator in the context of a drought monitoring and early warning system, where certain SPI values are selected as triggers for drought management. Although the value of -1 is frequently used as the threshold defining the initiation and termination of a drought event, it should not be considered as the trigger for ending an issued warning or a drought management action.

According to the applied drought event definition, the SPI value can become negative without a drought necessarily occurring. In Fig. 2, it can be noted that as the time scale increases, the percent of the times that a negative SPI results in drought (SPI < -1) decreases. For example, 53 % of the times the SPI3 goes below zero result in drought. This percentage is 44 %, 41 % and 34 % for the SPI6, SPI12 and SPI24, respectively.

Table 8 summarises for each drought characteristic its maximum value and the period this value was recorded, for all stations and aggregation time scales.

Among the identified drought periods at the local and regional level, the period from October 1988 to July 1991 is pointed out as it includes almost all the drought events with maximum duration (for all stations and all aggregation time scales), and also most of the drought events with maximum intensity, especially in aggregation time scales equal or greater than six months. During this period, almost the whole Greek territory suffered from severe or extreme droughts (Livada and Assimakopoulos, 2007). Similar drought conditions were also observed in Italy (Rossi and Somma, 1995). Other significant drought periods that were also identified have an impact degree depending on the time scale and site location. The drought period around the middle of the 1970s was also reported by Loukas and Vasiliades (2004) in their work concerning the region of Thessaly in Greece, which is located southwest of the present study area.

The quasi-association model with homogenous diagonal effects fitted properly the observed drought class transitions. For each site, expected frequencies resulted from the application of the submodel selected through the backward elimination method. As an example, the 3-D contingency tables of the observed and expected frequencies of drought class transitions for the Aison River Basin are presented in Table 9.

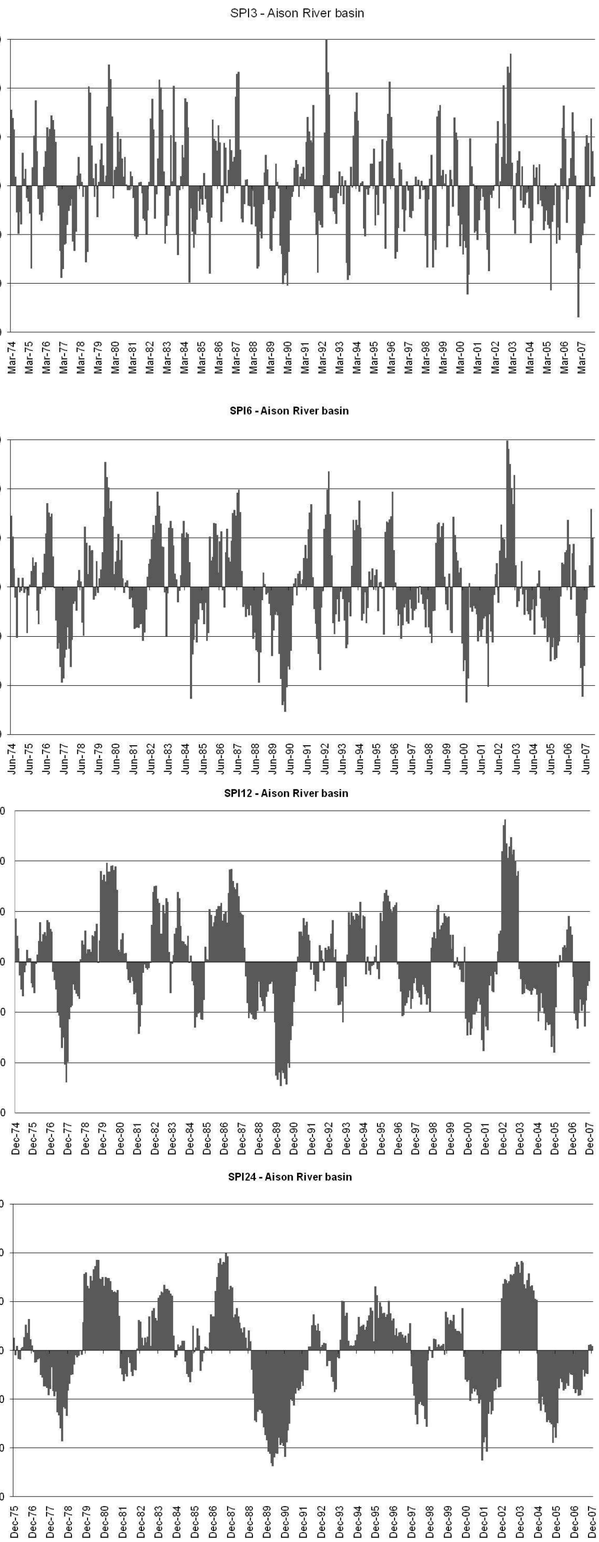

Fig. 2. SPI values of variable time scales for the Aison River Basin.

The odds of the expected frequencies and the respective confidence intervals of these odds, which serve as a tool for short-term drought forecasting, were computed for all sites. In Table 10 odds and confidence intervals for the Aison River basin data set are presented.

From a total of 96 odds for each site (all possible combinations), the number of confidence intervals, not including the unit, was 71 for Katerini, 70 for Lofos, 78 for Moschopotamos, 60 for Vrondou and 59 for the areal precipitation data series. The results were quite satisfying, considering the fact that due to the small number of the defined drought events, many of the three month drought class combinations had an observed frequency equal to zero. For the Aison River Basin data set, for instance, zero observed frequencies were 38 out of 64 (see Table 9).

Based on the computed odds and respective confidence intervals, all possible combinations of drought classes for two consecutive months ($t-1$, t) and the most probable drought class for the following month ($t+1$), for each data series, are presented in Table 11.

According to Table 11, smooth drought class transitions appear to be more probable than transitions to classes two or three levels more (or less) severe. Also, in most of the cases the second month's drought class is preserved in the third month. These conclusions are in accordance with the results of former studies (Paulo et al., 2005; Mishra et al., 2007; Moreira et al., 2008) and with the fact that droughts usually do not initiate or come to an end suddenly.

5 Concluding remarks

In the present work, the frequency, duration and severity of meteorological drought in the Aison River Basin were analysed using the SPI computed on variable time scales. Monthly precipitation time series from four meteorological stations operating in the study area and the areal precipitation resulting from them composed the data sets for this analysis.

A number of drought events of different classes were defined for all the time scales at the local (sites) and basin scale. Most of them belonged to the moderate drought class, but "extreme drought" events were also identified. Especially, during the period from October 1988 to July 1991, the study area suffered the longest-lasting and most severe drought. Also, most of the months with maximum drought intensity were observed in this time period.

Since SPI is a drought indicator independent of time and space, the detected drought conditions for various sites and time scales are comparable. Although in drought analysis the SPI value of (-1) is frequently considered the critical value for the termination of a drought event, drought management actions should not end before SPI becomes positive, especially when the time scale of the SPI is small (i.e. SPI3 or SPI6, which are often preferred when monitoring agricultural and hydrological droughts).

Table 10. Odds and respective confidence intervals for the Aison River Basin.

i	j	k	l	odds	conf. interval bounds		i	j	k	l	odds	conf. interval bounds	
				E_{ijk}/E_{ijl}	lower	upper					E_{ijk}/E_{ijl}	lower	upper
1	1	1	2	21.843	13.6082	35.0608	3	1	1	2	3.431	1.1074	10.6296
1	1	1	3	699.6305	162.5601	3011.0883	3	1	1	3	49.3921	4.8073	507.4746
1	1	1	4	17 295.3904	1007.7466	296 831.1036	3	1	1	4	548.7847	11.1006	27 130.3808
1	1	2	3	32.03	8.0463	127.5025	3	1	2	3	14.396	3.3576	61.7245
1	1	2	4	791.8061	49.8936	12 565.8703	3	1	2	4	159.9504	7.693	3325.6207
1	1	3	4	24.7208	3.9314	155.4448	3	1	3	4	11.1108	1.5215	81.1389
1	2	1	2	1.2048	0.66	2.1993	3	2	1	2	1.0421	0.4456	2.4375
1	2	1	3	6.0908	1.9585	18.9421	3	2	1	3	4.5569	1.0456	19.8602
1	2	1	4	23.7647	4.2363	133.3152	3	2	1	4	15.3789	1.6115	146.7635
1	2	2	3	5.0553	1.8922	13.5061	3	2	2	3	4.3727	1.5727	12.1577
1	2	2	4	19.7245	3.6134	107.669	3	2	2	4	14.7571	2.2302	97.6461
1	2	3	4	3.9017	0.9682	15.724	3	2	3	4	3.3748	0.7638	14.9122
1	3	1	2	0.1902	0.0532	0.6798	3	3	1	2	0.3165	0.1163	0.8617
1	3	1	3	0.1517	0.018	1.2813	3	3	1	3	0.1469	0.0394	0.5476
1	3	1	4	0.0934	0.006	1.4449	3	3	1	4	0.431	0.0887	2.0942
1	3	2	3	0.7979	0.251	2.536	3	3	2	3	0.4642	0.177	1.2174
1	3	2	4	0.4914	0.0782	3.0858	3	3	2	4	1.3615	0.4387	4.2256
1	3	3	4	0.6158	0.1599	2.3723	3	3	3	4	2.9332	0.7771	11.0706
1	4	1	2	0.03	0.0039	0.2329	3	4	1	2	0.0961	0.0224	0.4125
1	4	1	3	0.0038	0.0001	0.1405	3	4	1	3	0.0388	0.0036	0.4219
1	4	1	4	0.0004	0	0.0486	3	4	1	4	0.0121	0.0008	0.185
1	4	2	3	0.1259	0.0221	0.7165	3	4	2	3	0.4034	0.123	1.3233
1	4	2	4	0.0122	0.0006	0.2512	3	4	2	4	0.1256	0.0272	0.5808
1	4	3	4	0.0972	0.0171	0.5509	3	4	3	4	0.3114	0.1027	0.9436
2	1	1	2	5.1177	2.7017	9.6941	4	1	1	2	2.3002	0.4037	13.1047
2	1	1	3	109.894	21.9326	550.6281	4	1	1	3	22.1994	0.7184	686.0095
2	1	1	4	1821.2821	93.8622	35 339.754	4	1	1	4	165.3586	0.721	37 922.9151
2	1	2	3	21.4733	6.1224	75.3142	4	1	2	3	9.6512	1.4697	63.3758
2	1	2	4	355.8787	26.902	4707.8143	4	1	2	4	71.89	1.4457	3574.9489
2	1	3	4	16.5731	2.7489	99.9202	4	1	3	4	7.4488	0.7052	78.6756
2	2	1	2	0.3916	0.2079	0.7376	4	2	1	2	0.9692	0.2797	3.3587
2	2	1	3	5.2683	2.0726	13.3915	4	2	1	3	3.9416	0.405	38.358
2	2	1	4	19.1174	4.4829	81.5261	4	2	1	4	12.3714	0.3912	391.2549
2	2	2	3	13.4532	5.0469	35.8616	4	2	2	3	4.0667	1.0922	15.1424
2	2	2	4	48.8181	10.7707	221.2675	4	2	2	4	12.7643	0.9998	162.9563
2	2	3	4	3.6287	0.9275	14.1972	4	2	3	4	3.1387	0.5581	17.6532
2	3	1	2	0.2453	0.084	0.7165	4	3	1	2	0.4084	0.1375	1.2135
2	3	1	3	0.2526	0.0482	1.3248	4	3	1	3	0.6998	0.121	4.049
2	3	1	4	0.2007	0.0307	1.3101	4	3	1	4	0.9256	0.1126	7.6075
2	3	2	3	1.0294	0.3968	2.671	4	3	2	3	1.7136	0.6183	4.749
2	3	2	4	0.8179	0.2245	2.9803	4	3	2	4	2.2663	0.5127	10.0173
2	3	3	4	0.7945	0.2439	2.5884	4	3	3	4	1.3226	0.3834	4.5624
2	4	1	2	0.0537	0.0099	0.2923	4	4	1	2	0.1721	0.0426	0.6957
2	4	1	3	0.0121	0.0007	0.2132	4	4	1	3	0.1243	0.012	1.2919
2	4	1	4	0.0021	0.0001	0.078	4	4	1	4	0.0242	0.0019	0.309
2	4	2	3	0.2254	0.0562	0.9034	4	4	2	3	0.7221	0.2144	2.4314
2	4	2	4	0.0392	0.0046	0.3332	4	4	2	4	0.1406	0.0292	0.6775
2	4	3	4	0.174	0.045	0.6728	4	4	3	4	0.1948	0.0586	0.6473

Table 11. Most probable drought class for month $t+1$, given the drought classes of the two previous months ($t-1$, t).

		Katerini	Lofos	Moschopotamos	Vrondou	Aison R. Basin
t-1	t	t+1	t+1	t+1	t+1	t+1
1	1	1	1	1	1	1
1	2	1	2, 1	2, 1	2, 1	2, 1
1	3	1, 2, 3, 4	2, 3, 4	3, 4	2, 3, 4	2, 3, 4
1	4	4, 3	4	4	4	4
2	1	1	1	1	1	1
2	2	2, 1	2	2, 1	2	2
2	3	1, 2, 3, 4	2, 3, 4	2, 3, 4	3	2, 3, 4
2	4	4, 3	4	4	4	4
3	1	1	1	1	1, 2	1
3	2	1	1, 2	1	2	1, 2
3	3	3	3	3	3	2, 3, 4
3	4	4, 3	4, 3	4, 3	4	4
4	1	1	1, 2	1	1, 2, 3, 4	1, 2
4	2	1	2, 3, 1	1	2, 3, 4	1, 2, 3, 4
4	3	1, 2, 3, 4	1, 2, 3, 4	1, 2, 3, 4	3, 2	1, 2, 3, 4
4	4	4	4, 3	4, 3	1, 2, 3, 4	4

Short-term forecasting of droughts was based on the odds of the expected frequencies of drought class transitions and the respective confidence intervals. The 3-D loglinear quasi-association model with homogenous diagonal effect proposed in this study fitted adequately to the observed data sets. The expected class transition frequencies for each data set were successfully estimated by an adapted submodel selected through the backward elimination model. The odds of the expected frequencies and their confidence intervals could reliably predict the drought class transitions one or two months ahead, given the drought classes of the last two months, in most of the cases. The results of short-term forecasting approach showed that smooth drought severity class transitions appear to be more probable than abrupt ones.

Based on the quality of the results, the proposed approach, with a continuous update of precipitation records, could be regarded as a useful tool for regional water resources managers and irrigators for drought analysis and short-term warning at the farm and basin scale. Towards this direction, an upgraded network of on-line meteorological stations has been recently established in the Aison River Basin, supporting the viability and any future extension of the proposed models as well, as the reliability of results.

Acknowledgements. This research was supported by the Program Interreg III B- MEDOCC through the project MEDDMAN – "Integrated water resources management, development and confrontation of common and transnational methodologies for combating drought within the MEDOCC region".

Edited by: N. R. Dalezios
Reviewed by: G. Karantounias and G. Rossi

References

Agresti, A.: Categorical Data Analysis, Second Edition, Wiley Series in Probability and Statistics, John Wiley & Sons Inc., Hoboken, New Jersey, 710 pp., 2002.

Arguez, A. and Vose, R. S: The Definition of the Standard WMO Climate Normal: The Key to Deriving Alternative Climate Normals, B. Amer. Meteorol. Soc., 92, 699–704, 2011.

Cancelliere, A., Bonaccorso, B., Cavallaro, L., and Rossi G.: Regional Drought Identification Module REDIM, Department of Civil and Environmental Engineering, University of Catania, Catania, Italy, 43 pp., 2005.

Cancelliere, A., Di Mauro, G., Bonaccorso, B., and Rossi, G.: Drought forecasting using the Standardized Precipitation Index, Water Resour. Manage., 21, 801–819, 2007.

Dai, A.: Drought under global warming: a review, WIREs, Climate Change, 2, 45–65, 2011.

Dracup, J. A., Lee, K. S., and Paulson Jr., E. G.: On the Definition of Droughts, Water Resour. Res., 16, 297–302, 1980.

Edossa, D. C., Babel, M. S., and Gupta, A. D.: Drought in the Awash River Basin, Ethiopia, Water Resour. Manag., 24, 1441–1460, 2010.

Edwards, D. C. and McKee, T. B.: Characteristics of 20th Century Drought in the United States at Multiple Time Scales, Atmospheric Science Paper No. 634, Climatology Report No. 97-2, Colorado State University, Fort Collins, Colorado, 155 pp., 1997.

Guttman, N. B.: Comparing the Palmer Drought Severity Index and the Standardized Precipitation Index, J. Am. Water Resour. Assoc., 34, 113–121, 1998.

Guttman, N. B.: Accepting the Standardized Precipitation Index, A calculation algorithm, J. Am. Water Resour. Assoc., 35, 311–322, 1999.

Hayes, M. J., Svoboda, M., Wilhite, D. A., and Vanyarkho, O.: Monitoring the 1996 drought using the Standardized Precipitation Index, B. Am. Meteorol. Soc., 80, 429–438, 1999.

Hisdal, H. and Tallaksen, L. M.: Drought Event Definition, ARIDE Technical Report No. 6, Department of Geophysics, University of Oslo, Oslo, 41 pp., 2000.

Hwang, Y. and Carbone, G.: Ensemble Forecasts of Drought Indices Using a Conditional Residual Resampling Technique, J. Appl. Meteorol., 48, 1289–1301, 2009.

Lawal, H. B.: Categorical data analysis with SAS and SPSS applications, Lawrence Erlbaum Associates, New Jersey, 561 pp., 2003.

Livada, I. and Assimakopoulos, V. D.: Spatial and temporal analysis of drought in Greece using the Standardized Precipitation Index (SPI), Theor. Appl. Climatol., 89, 143–153, 2007.

Loukas, A. and Vasiliades, L.: Probabilistic analysis of drought spatiotemporal characteristics in Thessaly region, Greece, Nat. Hazards Earth Syst. Sci., 4, 719–731, doi:10.5194/nhess-4-719-2004, 2004.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scale, Eighth Conference on Applied Climatology, Anaheim, CA, 179–186, 1993.

Mishra, A. K. and Singh, V. P.: A review of drought concepts, J. Hydrol., 391, 202–216, 2010.

Mishra, A. K., Desai, V. R., and Singh, V. P.: Drought Forecasting Using a Hybrid Stochastic and Neural Network Model, J. Hydrol. Eng., 12, 626–638, 2007.

Mishra, A. K., Singh, V. P., and Desai, V. R.: Drought characterization: a probabilistic approach, Stoch. Environ. Res. Risk Assess., 23, 41–55, 2008.

Moreira, E. E., Paulo, A. A., Pereira, L. S., and Mexia, J. T.: Analysis of SPI drought class transitions using loglinear models, J. Hydrol., 331, 349–359, 2006.

Moreira, E. E., Coelho, C. A., Paulo, A. A., Pereira, L. S., and Mexia, J. T.: SPI-based drought category prediction using loglinear models, J. Hydrol., 354, 116–130, 2008.

Paulo, A. A. and Pereira, L. S.: Drought concepts and Characterization, Water Int., 31, 37–49, 2006.

Paulo, A. A., Ferreira, E., Coelho, C. A., and Pereira, L. S.: Drought class transition analysis through Markov and Loglinear models, an approach to early warning, Agr. Water Manage., 77, 59–81, 2005.

Rossi, G.: European Union policy for improving drought preparedness and mitigation, Water Int., 34, 441–450, 2009.

Rossi, G. and Somma, F.: Severe drought in Italy: characteristics, impact and mitigation strategies. Drought Network News: October 1995, available at: http://drought.unl.edu/archive/dnn-archive/arch6.pdf, last access: January 2012.

Sene, K.: Hydrometeorology, Forecasting and Applications, Springer, Dordrecht Heidelberg London New York, 355 pp., 2010.

Schuck, E. C., Frasier, W. M., Webb, R. S, Ellingson, L. J., and Umberger, W. J.: Adoption of more technically efficient irrigation systems as a drought response, Int. J. Water Resour. Dev., 21, 651–662, 2005.

Wilhite, D. A. and Buchanan-Smith, M.: Drought as Hazard: Understanding the Natural and Social Context, in: Drought and Water Crises, edited by: Wilhite, D. A., Taylor and Francis Group, New York, 3–32, 2005.

Wilhite, D. A. and Glantz, M. H.: Understanding the drought phenomenon: The role of definitions, Water Int., 10, 111–120, 1985.