An Integration of Statistics Temporal Methods to Track the Effect of Drought in a Shallow Mediterranean Lake

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Abstract During the last decades, a progressive decrease of water level in shallow Mediterranean lakes was recorded. This contribution tried to identify whether the rapid decrease of the Lake Doiran (N. Greece) water level was associated with drought phenomena. Drought characteristics over the study area were revealed by employing the Standardized Precipitation Index (SPI) in different time scales. Negative trends of the SPI drought index were recognized by using the Mann-Kendall non parametric test, which suggested that drought conditions were intensified through time. The impact of the intense drought phenomena to the lake's water level became evident by employing the Pearson correlation coefficient. A year ahead forecast of future drought conditions was achieved by training a hybrid ARIMA/ANN model. The predicted results indicated that mild drought conditions should be anticipated in the future and the water level would further drop as well.

Keywords Water level fluctuations · Drought · SPI index · Mann-Kendall test · Hybrid ARIMA/ANN · Lake Doiran

1 Introduction

Drought is considered to be not only the most complex and least understood of all natural hazards but it can also affect more people than any other hazard (Hagman 1984). It is a natural phenomenon characterised by a significant decrease of water availability during a significant period of time and over a large area (Nalbantis and Tsakiris 2009). The occurrence of drought events depends on their duration, intensity and frequency and could lead to severe consequences in various sectors of human life such as economy, water resources, agricultural production and energy as well.

In many studies, a common trend of water level gradual lowering in shallow Mediterranean lakes was documented (Mitrak et al. 2004; Beklioglu et al. 2007). Lake

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Doiran is a freshwater lake, which is situated in the Balkan Peninsula in South Eastern Europe with a surface area of 40.1 km^2. During the last decades, the lake suffered from large scale hydrological changes, which led the lake to an advanced state of degradation. These changes were climaxed in year 2000, when the water surface was shrunk by 11 km^2, the water volume was decreased from 262 million m^3 to only 80 million m^3 and a simultaneous deterioration of the water quality was observed (Popovska and Bonacci 2008).

Primarily, the purpose of this study was to investigate whether the water level fluctuations of Lake Doiran were associated with drought episodes in the region. In particular, the standardized precipitation drought index (SPI) (McKee et al. 1993) was used to quantify drought conditions over the study area. Furthermore, the drought trends over the study area were analysed by means of nonparametric Mann-Kendall (MK) test (Mann 1945; Kendall 1975). Finally, the relationship between the drought episodes and the water level variations was evaluated by utilizing statistic methods. A secondary objective was to develop a stochastic model capable in forecasting drought. In this study, a hybrid ARIMA/ANN model based on SPI values was proposed so as to predict drought episodes.

In the literature, there are many studies which employed different tools and techniques in order to interpret a lake's water level fluctuation. A very common method was the use of water budget models so as to explicate the lake level oscillation changes (Troin et al. 2010). Other studies were focused on energy budget models in order to estimate the evaporation from the lake surfaces that led to changes in water level (Lenters et al. 2005; Gianniou and Antonopoulos 2007). Remote sensing techniques had been used successfully to investigate the impact of the drought on lakes inundation area and volume (Tweed et al. 2009). Finally, statistic procedures were used in order to illustrate the strong relationship between the drought years, whose determination was based on the percentage of normal precipitation, and the lake levels fluctuations (Awange et al. 2008).

Several drought indices were derived in past decades (Mishra and Singh 2010). Regarding the recent developments in drought indices, we distinguished the Streamflow Drought Index (SDI), which was based on cumulative streamflow volumes for overlapping periods of 3, 6, 9 and 12 months within each hydrological year (Nalbantis and Tsakiris 2009), and the Reconnaissance Drought Index (RDI), which utilized the ratios of precipitation over reference crop evapotranspiration for different time scales (Tsakiris et al. 2007). The latter produced better assessment of drought severity compared to the SPI, if the drought analyses were applied for agricultural purposes (Khalili et al. 2011). On the other hand, SPI was widely used for defining and monitoring droughts (Tsakiris and Vangelis 2004; Shahid and Behrawan 2008) because it is simple since its calculation is based only on the long-term precipitation records. Additionally, it can be computed for different time scales according to end user interests and it can be employed to compare the precipitation abnormalities between different geographical regions due to the fact that it is irrespective of geographical location. In our case, the SPI index was selected in order to track drought since it had been successfully linked with other parameters affected by drought such as the normalized difference vegetation index (NDVI) and the water supply vegetation index (WSVI) (Jain et al. 2010), the fluctuation of crop yields (Potop et al. 2010), the groundwater level data (Khan et al. 2008; Shahid and Hazarika 2010), the vegetation condition index (Vicente-Serrano 2007), the Karst Spring Discharges (Fiorillo and Guadagno 2010) and the streamflow (Zhai et al. 2010). Thus, it was considered to be ideal for correlation with the lake level fluctuations.

The trends of drought over the basin of Lake Doiran must firstly be identified so as to prepare a rational water resources management plan. The tendency in hydro-meteorological time series, such as annual and seasonal streamflow, precipitation and evapotranspiration series (Zhao et al. 2010) and drought (Moradi et al. 2011; Sousa et al. 2011), was usually

detected by using the non-parametric MK test (Goosens and Berger 1986). The main reason which made this non-parametric statistic test so popular and widespread was due to its nature since it only required the data to be independent. Thus, it was more suitable for non-normally distributed and censored data, which are frequently encountered in hydro-meteorological time series (Yue et al. 2002). In this study, the MK test was applied in the time series of SPI index in order to identify the trends of drought for different timescales and periods.

Seasonal forecasting of SPI can be generated by using stochastic methodologies that are able to compute drought transition probabilities and to forecast future SPI values and which are based on the past SPI index values (Cancelliere et al. 2007). Durdu (2010) illustrated that drought prediction up to two months ahead could be realized with acceptable results by using autoregressive integrated moving average (ARIMA) results on an SPI series in order to predict SPI time series. Bacanli et al. (2009) showed that both the values of SPI and precipitation in the previous months could be used for generating a drought estimation model by constructing an Adaptive Neuro-Fuzzy Inference System (ANFIS) forecasting model. In this paper, an ARIMA model was initially proposed, which calculated the future lake's water level fluctuations. The latter were utilized by an ANN model in forecasting the SPI drought index magnitude for a year ahead. The combination of the ARIMA with the ANN model in the form of a hybrid model provided significantly better predictions compared to the ones derived by a separately implemented ANN or ARIMA model (Koutroumanidis et al. 2009).

2 Study Area and Data Used

Lake Doiran is a trans-boundary natural tectonic lake of the Balkan Peninsula, which lies between (41′10°–41′15° N and 22′12°–22′47° E) and it is shared by both Greece and FYROM (Fig. 1). It has a surface area of about 40.1 km^2, out of which 36.8 % belongs to Greece. It is a shallow lake with a rounded shape and it has an average altitude of 148 m above sea level. It has a maximum depth of 10 m, a north-to-south length of 8.9 km and a maximum width of 7.1 km.
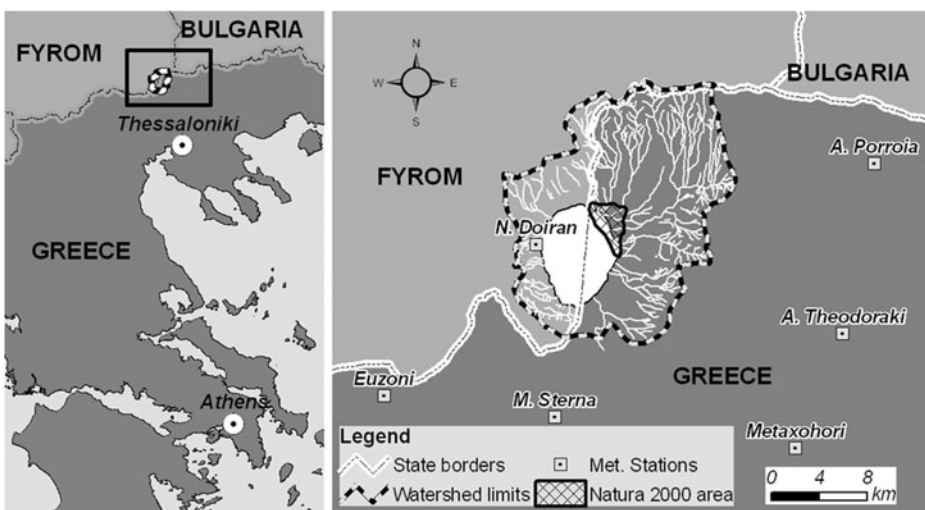

Fig. 1 Location map of the study area

The basin of Lake Doiran covers a total area of about 276 km^2, out of which 30 % is within FYROM and 70 % is within Greek territory. It is characterized by low relief plains that are mostly surrounded by hilly mountains. The lake system has no surface outlet, since the bottom of the artificial channel that has been built to carry away the overflow from the lake is nowadays considerably higher than the level of the lake's water surface (Katsavouni and Petkovski 2004).

The climate of Lake Doiran is typical thermo-Mediterranean with sunny, dry and hot summer periods and mild winters. Monthly rainfall data records were collected from five meteorological stations in Greece and from one in FYROM, which are located within or around of Lake's Doiran basin (Fig. 1). These rain gauges incorporate the statistical sequence of rainfall measurements, which cover the period 1973–2008. Minimum temperatures are rarely under 3.7 °C, while average annual air temperature is 14.3 °C and the hottest months of the year are July and August with a mean temperature of 24.9 °C and 26.1 °C respectively. The basin's mean annual precipitation is 629.5 mm, while the 58 % of the rainfall occurs from October to April. During the period 1984–2001, a deficit is observed in the mean annual rainfall by 138.6 mm for the 13 of the total 18 years period compared to the long term mean rainfall (1973–2008). Meanwhile, in what regards the period 2002–2007, the mean annual rainfall presents a consecutive surplus by an average of 155.9 mm compared to the long term mean rainfall.

Monthly measurements of water lake levels concerning the period 1973–2008 were obtained by the Ministry of National Works and Environment of Greece and they are displayed in Fig. 2. During the period 1984–2002, the lake has experienced a dramatic drop of the water level starting from 146.3 m and reaching the lowest level of 141.1 m in 2002 (Myronidis 2010). These large hydrologic changes led to a reduction of the lake's water surface from 39.9 km^2 to 31.1 km^2 (Katsavouni and Petkovski 2004). However, between November 2002 and May 2008, there was a raise in the lake level by 2.1 m, whereas a simultaneous significant increase in the lake's surface and volume was recorded. Those changes were the results of the increased precipitation and the transfer of groundwater from Gjavato wells, which are located in the Vardar/Axios River basin, to the lake.
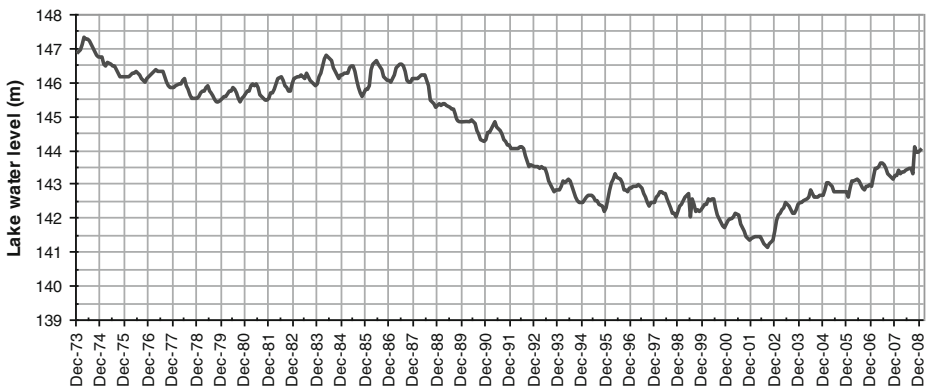

Fig. 2 Time series of water level from in-situ measurements

3 Methodology

Initially, in section 3.1, past drought phenomena were monitored by means of SPI index. In section 3.2, the Mann-Kendall test was performed in order to evaluate the drought trends over the basin of Lake Doiran, while in section 3.3, the association between the drought episodes and the water level fluctuations was revealed by utilizing statistic techniques. Finally, in section 3.4, a projection of future drought conditions over the study area was demonstrated by using sophisticated methods.

3.1 Identification of Past Drought Phenomena

Meteorological data concerning the monthly precipitation for a 35 years period (1973–2008) were used from all six rain gauges of the study area. The missing rainfall records at some stations were estimated by employing the normal ratio method. The minimum percentage of missing data per Meteorological Station (M.S.) was found to be 0.5 % (N. Doiran), while the maximum one was 4.6 % (M. Sterna). Moreover, the percentages of incomplete precipitation data records for the M.S. of Euzonoi, A. Porroia, A. Theodoraki and Metaxohori were 3.9 %, 3.8 %, 2.8 % and 2.5 % respectively. The estimated amounts of missing data were considered small to create any problems in the analysis (Feidas et al. 2007). Double mass method and two parametric statistical tests (Student's t and Chi-Square test) were applied so as to adjust any heterogeneity of the precipitation data, while the details of these methods can be obtained from WMO (1986). The precipitation data were found homogeneous by demonstrating the previous tests of randomness. Afterwards, the monthly areal weighted average precipitation of Lake's Doiran basin was estimated by using the Thiessen polygon and the mean monthly rainfalls magnitude of the rain gauges (Vasiliades et al. 2010). Finally, the corresponding time series of areal weighted average precipitation in the basin was used in order to evaluate any drought or excess events by calculating SPI values for different time scales, namely 1, 3, 6, 9, 12, 24, 48 months (Loukas et al. 2007).

The Standardized Precipitation Index (SPI) is a tool, which was primarily developed to identify meteorological drought and wet events by using only series of monthly rainfall (McKee et al. 1993). Mathematically, the standardized precipitation index is simply the difference of precipitation from the mean for a specified time period divided by the standard deviation, where the mean and standard deviation are determined by past records.

The computation of SPI becomes complicated, when the SPI is normalized so as to reflect the variable behavior of precipitation for time steps shorter than 12 months (Shahid and Hazarika 2010). To overcome this problem, the long-term precipitation records of the station are fitted to a gamma distribution, as the gamma distribution has been found to adjust to the precipitation distribution quite well. This is done through a process of maximum likelihood estimation of the gamma distribution parameters, α and β. Then, the cumulative probability of an observed precipitation event for each time scale of interest is deduced. The cumulative distribution is transformed to a normal distribution with a mean of zero and standard deviation of one since the probability distribution is determined by fitting an incomplete gamma distribution to the data, which is the value of the SPI (Xingcai et al. 2009).

Positive SPI values indicate higher than median precipitation, while negative values indicate lower than median precipitation. The duration of drought (DD) is usually more valuable for investigating or assessing the drought conditions in the past (Xingcai et al. 2009). A drought event is considered to occur at a time when the value of SPI is continuously negative and ends when SPI becomes positive (Mishra et al. 2008). The SPI based drought classification is illustrated in the following table (Table 1).

Table 1 Drought classification based on SPI values

SPI	Value Category
> 0	Non-drought
0.0 to −0.99	Mild drought
−1.0 to-1.49	Moderate drought
−1.5 to −1.99	Severe drought
≤ −2.00	Extreme drought

A measure of the accumulated magnitude of the drought (DM) can be defined as follows according to McKee et al. (1993).

$$DM = \sum_{j=1}^{x} SPI_{ij} \tag{1}$$

where j starts with the first month of a drought and continues to increase until the end of the drought (x) for any of the i time scales. The DM has units of months and will be numerically equivalent to drought duration if each month of the drought has SPI=−1.0 (McKee et al. 1993). The Average drought magnitude (ADM) is computed by dividing total DM by the count of drought events in order to estimate average drought intensity for each drought category (Xingcai et al. 2009).

3.2 Drought Trends over the Lake Doiran Basin

The Mann-Kendall test was applied in order to analyze the drought tendency over the basin of Lake Doiran. The MK test was conducted, as it had been proposed by Sneyers (1990), in order to examine both annual and seasonal drought trends and to detect the turning point by using the data series of SPI index on different timescales. In the Mann-Kendall test, for each x_i (i=1, . . ., n) of the time series, the number n_i of lower elements x_j ($x_j < x_i$) preceding it (j<i) was calculated and the test statistics t was given by:

$$t = \sum_{i} n_i \tag{2}$$

In the absence of any trend (null hypothesis), *t* was asymptotically normal, independent from the distribution function of the data and:

$$u(t) = \frac{(t - \bar{t})}{\sqrt{\text{var}(t)}} \tag{3}$$

had a standard normal distribution, with t and var(t) given by:

$$t = \frac{n(n-1)}{4} \tag{4}$$

$$\text{var}(t) = \frac{n(n-1) \cdot (2n+5)}{72} \tag{5}$$

Therefore, the null hypothesis could be rejected for high values of |u(t)|, being the probability α_1 of rejecting the null hypothesis when it was derived by a standard normal distribution table:

$$a_1 = P(|u| > |u(t)|) \tag{6}$$

The sequential form of the Mann–Kendall test, consisting of the application of the test to all the series starting with the first term and ending with the i_{th} term (and the reverse), was also used for a progressive analysis of the series. In the absence of any trend, the obtained graphical representation of the direct (u_t) and the backward (u_t') series with this method produced curves that overlap several times. However, in the case of a significant trend (5 % level $|u_t|>1.96$), the intersection of the curves enabled one to detect approximately its time of occurrence (Sneyers 1990).

3.3 Influence of Drought on the Lake Water Level

The Pearson correlation coefficient (Gerber and Voelkl Finn 2010) was employed in order to trace the association between the annual cumulated magnitudes of drought at different time scales and the annual water level fluctuations. Additionally, the same coefficient was utilized so as to evaluate the relation between the different time scales of the SPI indices and the monthly lake level fluctuations. The Pearson correlation coefficient was selected among others due to the fact that it is better for measuring the strength of the linear relationship between normally distributed datasets such as SPI, which is well known to be closer to normal distribution (Anagnostopoulou 2003; Livada and Assimakopoulos 2007).

Furthermore, in order to investigate potential differences in the association between the monthly water level variations and the different monthly SPI indices, for seasonal and for wet/dry time periods of the hydrological year, a database was initially created, which included the water level fluctuations time series and the calculated SPI indices at a monthly time step for all time scales. In that database, a variety of filters was applied according to the season—the wet (Oct-Mar) and dry (Apr-Sep) periods of the hydrologic year—so as to isolate only both the corresponding monthly records of SPI indices and the water level fluctuations. The filtered records were then imported in SPSS, where the Pearson correlation coefficient was calculated for the affected variables so as to depict the linkage between the SPI indices and the water level fluctuations for the different year instances.

Finally, as it was indicated in the last paragraph of section 2, since 2003, the water level of the lake was further affected by the transfer of additional quantities of water coming from wells located in Vardar/Axios basin into the lake. Thus, the overall influence of drought on the lake water level was probably greater during the period 1973–2003 compared to the total period of our data (1973–2008), since no transfer of groundwater to the lake took place. Therefore, all the aforementioned correlation methods, which had been employed so as to track the linkage between the drought episodes and the lake water level, were repeated for both the total reference period (1973–2008) and the shorter period (1973–2003), so as to illustrate the effect of the recharge of the lake with additional amounts of water.

3.4 Future Drought Prognosis

A hybrid ARIMA/ANN model was developed in order to forecast the future three month SPI values for twelve-month lead time. The hybrid model was implemented in four steps with a parallel creation of the ARIMA and ANN models. In the first step, we provided the inputs, which were the water fluctuation in the case of the ARIMA model and the water fluctuation and the SPI3 index in the case of the ANN model. It should be marked that the selection of SPI3 index as input series in the ANN model was not made arbitrarily but due to the fact that the SPI3 index registered the higher correlation values with the water level fluctuations compared to all other SPI indices, as it is demonstrated in section 4.3.

The second step regarded the internal calculations, which were made by the models. In the case of the ARIMA model, the simple non–seasonal ARIMA model has a general form

of (p,d,q), where p is the order of the non–seasonal autoregressive term (AR), q is the order of the non–seasonal moving average term (MA) and d is the order of the non–seasonal differencing (Koutroumanidis 2005). In general, an ARIMA (p,d,q) model can be presented as follows:

$$\phi(B)\nabla x^{d}z_t = \theta(B)\alpha_t \text{ or } z_t = \sum_{i=1}^{p} \phi_t z_{t-1} + a_t - \sum_{k=1}^{q} \theta_\kappa \alpha_{t-k} \tag{7}$$

where ∇ is a backward shift operator that is defined as $\nabla z_t = z_t - - z_{t-1}$ and d is the order of the non-seasonal differencing. Readers could find more information regarding ARIMA models in the paper of Koutroumanidis et al. (2009). The ARIMA model was created by using SPSS v. 19, where the input time series was the water level fluctuation and the model parameters (p,d,q) were defined according to those parameters that produced the lower RMSE and sMAPE errors compared to the other tested models (Koutroumanidis 2005). The RMSE is a quadratic scoring rule that measures the average magnitude of the error and sMAPE is an accuracy measure based on percentage (or relative) errors.

In the case of the ANN model, this was trained by employing two time series, the water level fluctuations and the SPI3 index. The ANN model that was applied in this paper was a Nonlinear Autoregressive with External Input model (NARX model). This model relates the current value of a time series to current and past values of the driving (exogenous) series. In our case, the driving series were the monthly water level fluctuations, while the current values, which are related to the driving series, were the SPI3 index values. Additionally, the model contains an error term, which relates to the fact that knowledge of the other terms will not enable the current value of the time series to be exactly predicted. An algebraic determination of the NARX model is the following:

$$y_t = F(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, u_t, u_{t-1}, u_{t-2}, u_{t-3}, \ldots) + \varepsilon_t \tag{8}$$

where y is the variable which we want to predict (SPI3) and u is the externally determined variable (water level fluctuation). In this scheme, information about u helps to predict y, just like previous values of y itself do. The ε represents the error term, which sometimes is also referred as noise. The function F is some non linear function, which is a neural network in this study (Leontaritis and Billings 1985).

The ANN model, which was trained in this research, was created by using MATLAB 2011a and it consisted from 40 hidden neurons and two numbers of delays, while the sigmoid function was used as the transfer function. The input data were randomly divided as follows: 70 % for the network training, 15 % for the network validation and 15 % for the network testing purposes. This was mainly done because one of the most common problems that occur during neural network training is data over fitting, where the network tends to memorize the training examples without learning how to generalize to new situations. The abovementioned percentages can be changed by the user according to the sample size studied in each case. The default method for improving generalization is called early stopping and regards the dividing of the available training data set into three subsets: (i) the training set, which is used for computing the gradient and updating the network weights and biases; (ii) the validation set, whose error is monitored during the training process because it tends to increase when data is over fitted; and (iii) the test set, whose error can be used to assess the quality of the division of the data set. Moreover, the flowchart of the ANN model is illustrated in the following diagram (Fig. 3).
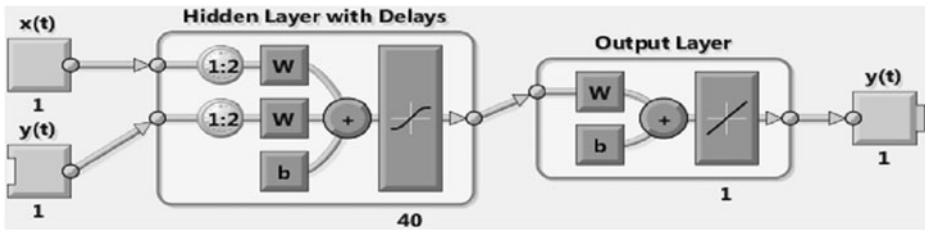
Fig. 3 Flowchart of the ANN model

The two input parameters used for training and testing of the network x(t) and y(t), which represent the water level fluctuation and the SPI3 index respectively, the 40 hidden neurons and the 2 layers used in order to train the NARX network, along with the one output parameter (the predicted SPI3 index) after the Output Layer, are shown in Fig. 3. In the flowchart, the letter w represents the internal weight coefficients, which are determined during the network training stage. The letter b denotes the bias on each neuron. The ANN performance is measured by using the Pearson correlation coefficient R, the RMSE and the sMAPE.

The third step is the outputs. These outputs were a) the water fluctuation prediction for a year ahead created by the ARIMA model and b) the trained ANN model that is capable to estimate SPI3 values according to water level fluctuations. The output from the ARIMA model was then feed backed to the ANN model, creating the fourth and last step, which was the SPI3 prediction for twelve month ahead starting from 3/2009. The prediction quality of the hybrid ARIMA/ANN model was then estimated by calculating the RMSE and the sMAPE statistics.

4 Results-Discussion

4.1 Identification of Past Drought Phenomena

In this study, the SPI program, which had been obtained from the U.S. National Drought Mitigation Center (NDMC) and is readily available in the internet (Hayes 2003), was used to calculate aggregated SPI values for each month of the year at seven time scales (1, 3, 6, 9, 12, 24 and 48 months) by using the monthly areal weighted average precipitation time series of Lake Doiran (Loukas et al. 2007). In the following figure, the output of SPI 12 values time series for the basin of Lake Doiran is shown, which was produced by using the aforementioned software (Fig. 4).

The results from the elaboration of the SPI12 denoted that drought conditions were prevailing for approximately 205 of the 423 months of the timeline in the basin of Lake Doiran. Furthermore, mild drought conditions were recorded in 30.7 % of this period, moderate drought conditions were observed in about 10 % of this timescale, severe dry conditions were recorded in 5.9 % of this period, while extreme drought conditions were observed in 1.9 % of this timescale. The most extreme drought months of the entire reference period were registered on March, February and April in 1989 and the SPI12 values were -2.3, -2.2, and -2.2 respectively. An outstanding situation of water excess conditions occurred in 2003 and the average SPI12 value was 2.5, while its highest peak was recorded on June (3.2). The drought magnitude for the period 1973–2008 is shown in Fig. 5 and it was computed through the accumulation of the absolute values (SPI values less than -1) of the 12 month SPI index for all months of the year.

During the periods 1973–1984 and 2003–2008, normal dry and wet spells were observed in the Doiran basin, while in the intermediate period (1985–2002), the basin had experienced
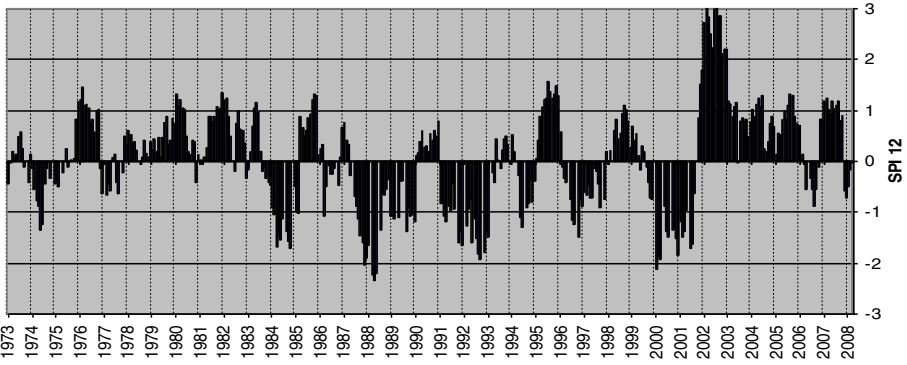
Fig. 4 Regional SPI12 series for the basin of Lake Doiran

intense drought phenomena with heavy drought magnitude due to reduced rainfalls. Similar results, which had confirmed that Greece had experienced the driest conditions during the period 1988–2000, were also reported by Livada and Assimakopoulos (2007), when they studied the spatial and temporal analysis of drought in Greece by using the SPI index. Finally, all the aforementioned procedures were repeated for the timescales of 3, 6 and 24 months in order to identify and characterize the drought episodes that had been registered in the study area and the results were summarized in the following table (Table 2).

The above table illustrated not only the large number of occurring drought episodes in the basin of Lake Doiran but also their allocation in the different time steps and drought severity categories. Additionally, recent studies in Greece had also documented that moderate and severe droughts were common in other parts of the country too (Anagnostopoulou 2003; Loukas and Vasiliadis 2004). As the time scale increased, the average duration of the drought event was also increasing significantly. The simultaneous increase of both the drought duration and the time scale had also been documented by Xingcai et al. (2009). However, by increasing the time scale, the number of drought episodes decreased, while their severity, which was expressed by the average drought magnitude, increased. The same results had been reported in the recent researches by Moradi et al. (2011) and Xingcai et al. (2009). Thus, the timescale played an important role in the identification and characterization of
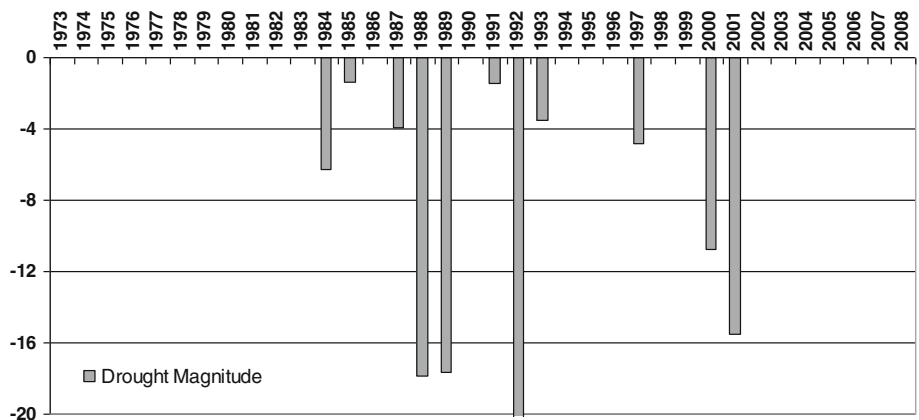

Fig. 5 The accumulated drought magnitude of SPI24 index

Table 2 Drought episodes and their main characteristics in Doiran basin (in months)

Drought index	Drought Characteristics	Moderate drought	Severe Drought	Extreme drought	Total
SPI-3	Number of Episodes	29	16	8	53
	Mean Duration	1.3	1.3	1.5	1.4
	Max Duration	2	2	3	3
	Average drought Magnitude	−1.6	−2.2	−3.1	−2.1
SPI-6	Number of Episodes	29	20	8	57
	Mean Duration	1.3	1.2	1.6	1.4
	Max Duration	2	3	4	4
	Average drought Magnitude	−1.6	−2	−3.3	−2
SPI-12	Number of Episodes	27	16	5	48
	Mean Duration	1.5	1.6	1.6	1.6
	Max Duration	3	3	4	4
	Average drought Magnitude	−1.9	−2.6	−3.4	−2.3
SPI-24	Number of Episodes	15	11	4	30
	Mean Duration	2.2	2.0	2.8	2.3
	Max Duration	4	4	4	4
	Average drought Magnitude	−2.8	−3.5	−6.2	−3.5

drought episodes. In other words, a small change in monthly rain could have a crucial effect on the short term time scale, whereas in large scales, a higher content of precipitation would be necessary so as to change the condition of drought (Moradi et al. 2011).

4.2 Drought Trends over the Lake Doiran Basin

The MK trend test was applied to the SPI drought index for different timescales in order to understand the trends of drought over the basin during the period 1973–2008. The trend analysis results indicated that there were no significant positive trends of the SPI index time series during the autumn, winter and annual periods in all time scales. Furthermore, no significant but negative trends of the SPI index time series were presented during the spring and summer periods in all time scales. However, the method was also applied in the SPI series during the period 1973–2002, due to the fact that these recognized trends were not caused by a linear increase in precipitation data but by an abrupt change in precipitation in 2002, when the watershed received heavy precipitation from extreme rainfall events.

MK test was performed for the different seasons and timescales and the test results were summarized in Table 3. The gray cells of Table 3 indicated the statistical significant trends, while the exact time of the occurred specific change was reported inside the parenthesis. The 1 month SPI and the 3 month SPI indices showed a non significant ($ut<−1.96$) negative trend on a seasonal and annual basis. However, statistically significant negative trends (at the 95 % level) were revealed in almost all data series from SPI6 to SPI48, where the trend's magnitude was increasing as the time scale raised. The latter suggested that drought was intensified as the time scale increased. The above were in a good agreement with the results of Sousa et al. (2011), which had illustrated a clear trend towards drier conditions during the 2nd half of the century in the Greek territory. Moreover, several studies had also documented the negative trends of precipitation in Greece (Feidas et al. 2007; Mavromatis and Stathis 2010). The observed negative trends in annual precipitation in Greece had been attributed to

Table 3 Results of MK test (statistic ut) on annual and seasonal basis during the period 1973–2002

	Annual	Autumn	Winter	Spring	Summer
SPI1	−1.4	−0.7	0.0	−0.7	−0.8
SPI3	−1.7	−0.9	0.2	−1.1	−2.3 (Jun 78)
SPI6	−3.3(Sep 84)	−2.8 (Noe 81)	−1.5	−1.1	−3.5 (Jun 79)
SPI9	−4.2(Aug 85)	−2.5(Sep 83)	−1.7	−2.1(May 87)	−2.5(Jun 87)
SPI12	−4.7 (Feb 87)	−2.4 (Noe 84)	−2.6 (Jan 86)	−2.7 (May 87)	−3.1 (Aug 87)
SPI24	−6.4 (Noe 86)	−3.3 (Sep 85)	−3.6 (Jan 87)	−2.7 (Apr 86)	−3.5 (Aug 86)
SPI48	−8.6 (Aug 87)	−4.5 (Aug 85)	−4.6 (Dec 86)	−4.3 (Mar 87)	−4.6 (Jun 86)

the hemispheric circulation modes of the North Atlantic Oscillation Index, which had been connected with the Mediterranean Oscillation Index (Feidas et al. 2007).

In Table 3, the ut values for the summer season were considerably higher compared to any other season, which denoted that the summer drought trend had been much more intense. This drought pattern came in line with the IPCC (2007) projections of increased probability for summer droughts in the South Eastern Mediterranean. Finally, trend analysis in all time series showed that the statistical significant drought change happened during the period 1985–1986. This result came in reasonable agreement with the study of drought in the Mediterranean by Sousa et al. (2011), which had spotted the turning point of drought tendency in Greece (around 1983).

4.3 Influence of Drought on the Lake Water Level

A database having the two variables was formed by tying together the information concerning the annual accumulate DM of SPI24 for the basin of Lake Doiran from Fig. 5, as well as that regarding the yearly oscillations of water level from in-situ measurements from Fig. 2. The Pearson correlation coefficient regarding these two variables was computed to be equal to 0.5 at a confidence level of 99 % for the whole reference period by using SPSS. Thus, a moderate relationship (Gerber and Voelkl Finn 2010) was statistically illustrated between the accumulate drought magnitude of SPI24 and the annual oscillations of water level, implying that as the drought magnitude became more and more negative the water level was dropping. Additionally, the accumulate drought magnitude was estimated for all the different SPI indices, while the same correlation techniques were also repeated. However, only the SPI48 showed similar results with the Pearson value (0.49) for the whole reference period at a 95 % level of significance. The residual indices showed that as the timescale of the SPI indices was decreasing, the value of Pearson correlation coefficient was also reduced from 0.37 for SPI12 at 95 % level of confidence to the statistically insignificant 0.19 for SPI3. Finally, the correlation results for the shorter period were found slightly greater for all the aforementioned associations.

Positive correlations were revealed between the different time scales of the SPI index and the monthly lake level fluctuations by using the Pearson coefficient for the period 1973–2003. These correlations illustrated similar shape curves, which started from the moderate correlation on the SPI3 and they decreased as the timescale of the SPI index was raising (Fig. 6).

All correlation results regarding the indices of SPI3–SPI24 for the various time instances of the year were found significant at a level of 99 %, with the exception of summer, where only SPI3 continued to depict the same level of significance, while all other indices had a confidence level of 95 %. The maximum correlation (0.36) was recorded in the SPI3
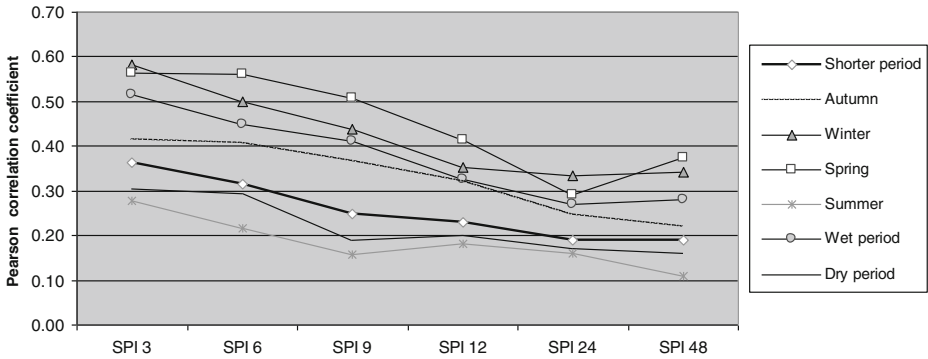
Fig. 6 Pearson R correlation values between the water level fluctuation and the multi-scale SPI for the different time periods of the hydrologic year

timescale for the shorter reference period, while strong correlations were also recorded in spring and winter for the 3 months timescale (0.60 and 0.56 respectively). The correlation level between the SPI48 and the monthly water level fluctuations for the different time periods of the year evidenced weak but significant correlation at a level of 99 % for both the short period and the wet period. Weak correlation in a confidence interval of 95 % was observed between the SPI48 and the water level for autumn, winter and dry semester, while no statistical significant correlations were recorded between the two variables during spring and summer. It should be noted that a weak and positive correlation, which however was not statistically significant, was recorded between the SPI1 and the monthly lake water level for all periods of the year.

Low values of Pearson R coefficient ranging from 0.38 to 0.61 in different timescales had also been reported by Fiorillo and Guadagno (2010), when they tried to correlate the karst spring discharge series and the SPI index in Serino spring. Moreover, even smaller correlation coefficient values between the groundwater fluctuation data and the SPI drought index, which ranged from 0.15 to 0.23, had been reported by Shahid and Behrawan (2008). Finally, weak correlation between the SPI index and the groundwater fluctuations had been reported in the Murray Irrigation Area (Khan et al. 2008). The weak correlations in those studies was attributed to either the complex nature of the groundwater recharge and discharge processes in this area (Khan et al. 2008) or due to over exploitation of groundwater resources for irrigation purposes (Shahid and Behrawan 2008).

In our study, the moderate correlation values between the lake's water level and the SPI index was explained by the similarity with the above causes. More specifically, in the Greek side of the watershed, the need for supplemental irrigation regarding the 76 km^2 of agricultural land so as to meet crop water demand was satisfied from the excessive pumping of the groundwater table by more than 450 groundwater wells (Myronidis 2010). Furthermore, there were no detailed regional hydro-geological investigations so as to define the interaction between the lake waters and the groundwater (Katsavouni and Petkovski 2004). Finally, since 2003, unknown volumes of water had been transported from another watershed and were recharged in the lake. Thus, drought was not the only key driver that affected the water level of the lake and this was the reason why moderate correlation values were depicted in our study.

Furthermore, the Pearson coefficient showed that higher correlations were registered during the wet period of the hydrologic year compared to the ones during the dry period for all time scales at a confidence level of 99 %. Compared to the shorter period, when the

total reference period for the aforementioned SPI timescales, seasons and semesters of the year was considered, the Pearson correlation coefficient depicted similar results but with reduced values at the same levels of significance.

Pearson coefficient indicated that there were weak, positive but not statistically significant correlations between the water level variations and the one month SPI for each individual month for both the total and the shorter reference period. On the other hand, as it is depicted in Fig. 7, SPI3 and SPI6 illustrated a strong correlation with the monthly water level oscillations for most months of the year during the shorter reference period at a 99 % level of confidence. The only exceptions in the former correlations were recorded on June and July, where the correlations were weak and statistically insignificant. The same results concerning June and July were demonstrated for the residual SPI indices, which suggested that the correlations were probably affected by an additional variable, the excessive pumping. The correlation results between the monthly water level fluctuations and the SPI12 to SPI48 indices revealed that as the time scale of the SPI became larger, the level of correlation was reduced. Finally, the fact that the correlation results during the total reference period (1973–2008) were found considerably smaller compared to the ones during the shorter period for all the aforementioned associations, led to the conclusion that, since 2003, the correlations between the affected variables were influenced by an additional parameter, which was probably the recharge of the lake with additional amounts of water.

4.4 Drought Prediction Results

The simple non–seasonal ARIMA model, where the parameters (p,d,q) were found equal to (3,2,3) respectively, was selected among the other tested models that were generated from the different combinations of p,d,q parameters. The reason of this choice was due to the fact that this model produced the lowest RMSE and sMAPE errors equal to 0.13 and 9.5 % respectively, which are considered to be much better, compared to the other tested models. The ARIMA (3,2,3) model created a prognosis for the future water fluctuations of the lake for the period starting from 2/1974 until 2/2010. The results that were produced from the implementation of this model are shown in the following diagram (Fig. 8):

The performance of the ANN model—which was trained in order to estimate SPI3 values by utilizing the two time series of actual water level fluctuations and SPI3 index, regarding the training set, the validation set, the test set and the overall network—is displayed in the following figure (Fig. 9).

Training set was part of the data series that was presented during training and the network was adjusted according to its error. Validation set was used to measure network
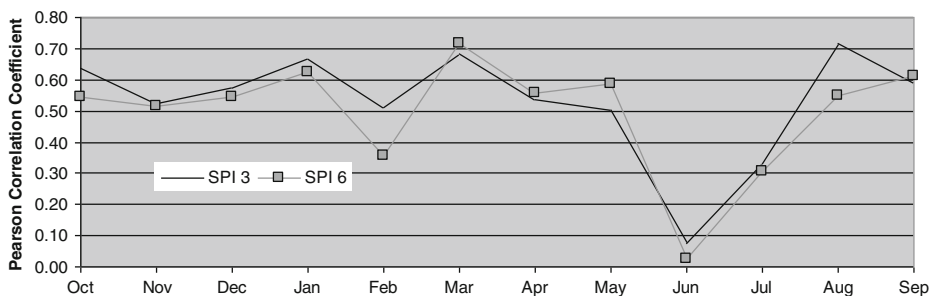

Fig. 7 Pearson R correlation values between the water level fluctuation and the multi-scale SPI for each individual month of the hydrologic year
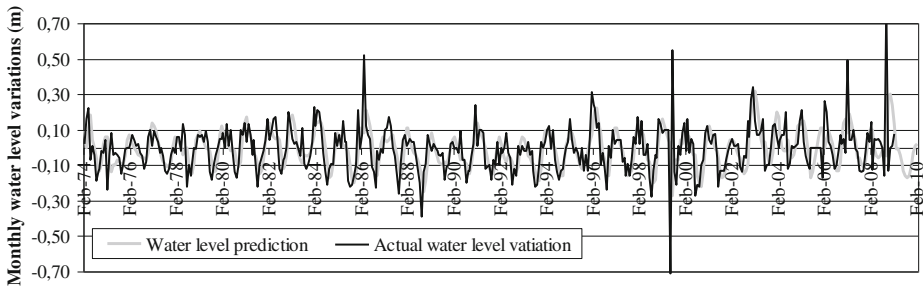
Fig. 8 Actual water level variation and water level prediction using the ARIMA (3,2,3) model

generalization and to halt training when generalization stopped improving. Testing set had no effect on training and thus, it provided an independent measure of network performance
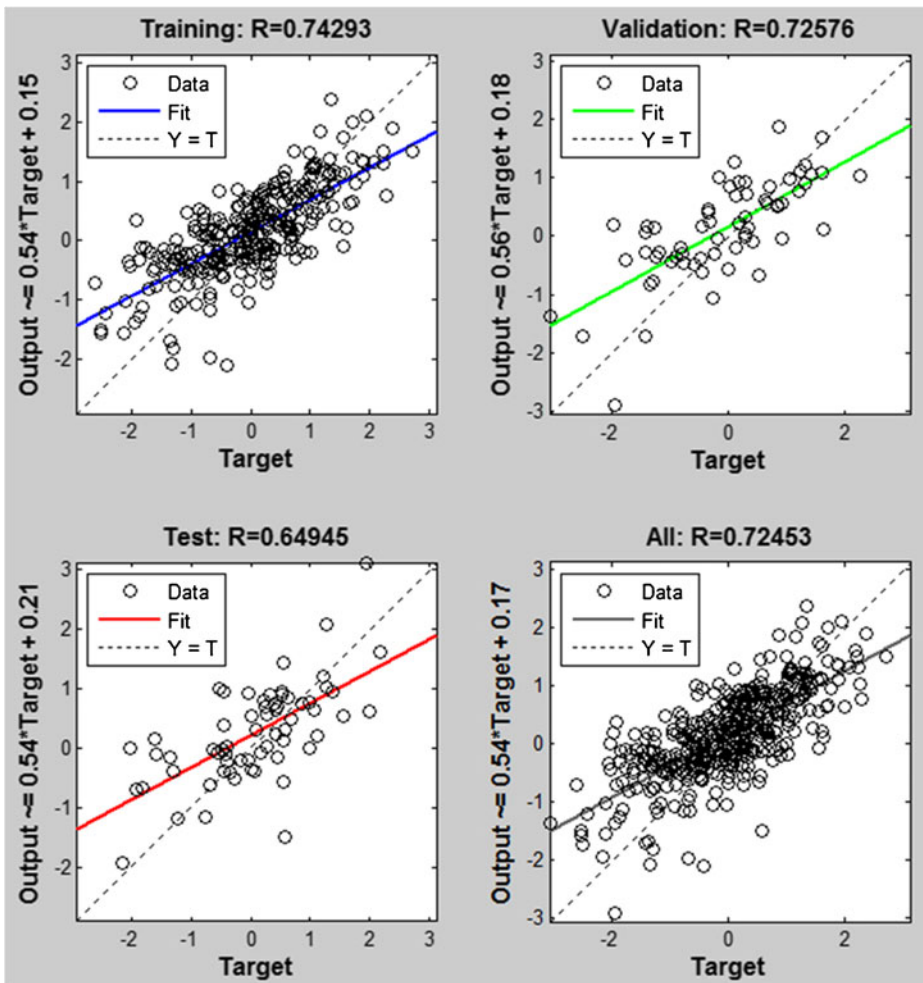

Fig. 9 ANN model performance regarding the training set, the validation set, the test set and the overall network
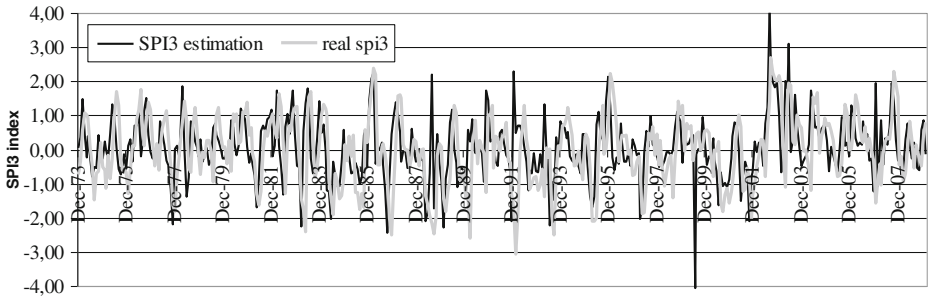
Fig. 10 Actual SPI3 values and SPI3 prediction by using the ANN model

during and after training. Finally, "all" set was the implementation of the ANN model to the entire data. The dashed line in each diagram represents the perfect result (outputs=targets), while the solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets, which varies from 0 to 1, where greater R values represent a stronger linear relationship between outputs and targets. In our case, the R coefficient was found to be approximately 0.72 for the overall network, whereas RMSE and sMAPE were computed equal to 0.1 and 8 % respectively. These performance criteria denote that the ANN model managed to estimate SPI3 with a good precision. The results that were produced from the implementation of the ANN model are shown in the following diagram (Fig. 10).

In the next stage of the hybrid methodology, the water level fluctuations, which have been calculated by using the ARIMA model during the period 1974–2010, were feed backed to the already trained neural network as entry variables so as to predict the SPI3 index for a year ahead starting from 03/2009. The acquired results from this projection, which was realized by the utilization of the ANN model, as well as the results regarding the water level fluctuation prediction, which was made by the ARIMA model, are presented in the following table (Table 4).

These results indicated that mild drought conditions should be expected in most months of the time spam from March 2009 to February 2010 and the lake's water level would further drop by 0.88 m at the end of the aforementioned period. The quality control of the hybrid ARIMA/ANN model predictions assessed the RMSE and sMAPE values to be approximately 0.11 and 5 % respectively. Thus, it can be stated that the hybrid model performance can satisfactorily predict the future values of SPI3 index. The model performance would be more precise if the water level of the lake was not influenced from the recharge of the lake with additional amounts of water and/or the excessive pumping from the groundwater table. Moreover, the forecast of lake level fluctuations using stochastic models was not considered to be able to produce highly accurate results (Talebizadeh and Moridnejad 2011). Finally, it should be mentioned that when the hybrid ARIMA/ANN model was originally formulated, although the monthly temperature variable was included in the predictors, the obtained model performance was considerably smaller.

Table 4 SPI3 and water level fluctuation predictions by using the hybrid ARIMA/ANN model

Prediction	M-09	A-09	M-09	J-09	J-09	A-09	S-09	O-09	N-09	D-09	J-10	F-10
SPI3 Index	−0.14	−0.02	−0.02	−0.03	−0.02	−0.06	−0.14	−0.13	0.01	0.15	0.03	0.04
Water Flux	−0.01	−0.01	−0.04	−0.09	−0.13	−0.16	−0.17	−0.16	−0.11	−0.03	0.01	0.02

5 Conclusions

The aim of this paper was to provide an integrated assessment of the impact of drought on the lake's water level. The SPI index on different timescales was employed in order to track drought and it was found that drought conditions occurred in 48 % of the total reference period. Moreover, intense drought magnitude was denoted from 1985 to 2002 and the average duration of the drought events was increasing as the time scale increased. A trend analysis was carried out to the SPI drought index on various timescales in order to identify series presenting significant tendency by using the non-parametric Mann-Kendall test. Results of the application of MK test showed that there was a statistically significant downward tendency, which suggested that drought was intensified on annual and seasonal basis. Summer had the strongest decreasing trend compared to winter that had the weakest, while the turning point in the drought tendency occurred sometime between 1985 and 1986.

A moderate relationship between the DM of SPI24 and the water level fluctuations became evident by means of the Pearson correlation coefficient. Moderate correlation values between the lake's water level and the 3 month SPI index were also recorded by using the Pearson R correlation coefficient. A sophisticated hybrid ARIMA/ANN model was practiced in order to provide prediction of the SPI3 index values a year ahead. The analysis concluded that wild drought conditions as well as a simultaneous decrease of the Lake's water level should be expected. In summary, by using scientific tools and advanced techniques, it became evident that the water level of Lake Doiran was strongly affected by the intense drought phenomena, which were recorded in the past. However, the exact percentage of the drought's influence could not be quantified precisely, since it was not the only driver responsible for the lowering of lake's water level. In the future, an integrated analysis of the Lake's water balance should be scheduled.

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