

AN EARLY WARNING SYSTEM FOR SPATIOTEMPORAL FORECASTING AND MODELLING OF DROUGHT

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ABSTRACT

Drought identification, forecasting and monitoring are fundamental stages in the planning and management of natural resources and water resource systems in a river basin. Early and timelines forecasting of a drought event can help to take proactive measures and set out drought mitigation strategies to alleviate the impacts of drought. In this study an early warning system is developed for spatiotemporal forecasting and monitoring of drought. The methodology is based on the integration of artificial intelligence techniques with geostatistical interpolation methods. The raster-based integrated drought monitoring and forecasting system is demonstrated for operational drought management using a meteorological drought index, the Standardized Precipitation Index (SPI). The basic elements of the system are determined, and important issues and processes are analytically discussed, such as the representation of the spatial and temporal simulation error, extraction of optimal design solution in machine learning methods for reliable and accurate spatiotemporal drought forecasting. The early warning system uses previous SPI values calculated at various timescales and analyzes the drought level based on the lead time of SPI for operational use via a hybrid spatiotemporal drought forecast model. To identify more clearly the hazard, advanced spatial interpolation methods are incorporated in the early warning system to produce raster drought forecast maps. Comparison of the forecasted drought maps with selected historical drought maps show that reliable and accurate predictions of drought characteristics (severity, duration and area) are estimated for medium term prediction intervals at larger timescales of SPI and for short term prediction intervals at smaller SPI timescales in Pinios river basin, Thessaly, Greece. The above findings could be useful in developing a drought preparedness plan in the region.

1 INTRODUCTION

Drought is a complex phenomenon that is difficult to accurately describe because its definition is both spatially variant and context dependent. Therefore a uniform method for defining and monitoring drought conditions and quantifying the severity of drought does not exist. There are two main types of drought definitions: conceptual and operational (*Mishra and Singh, 2010*). Conceptual definitions are formulated in general terms and they are used to help explain what a drought is. Operational definitions are very specific and they are used to identify the onset, end, and degree of severity of a drought. These definitions are classified into four categories: meteorological,

agricultural, hydrological, and socioeconomic drought (Mishra and Singh, 2010). The large number of conceptual drought definitions that exist illustrates the challenge of accurately describing drought and the lack of agreement in regard to drought definitions. Similar challenges exist when considering operational definitions of drought. Developing appropriate operational drought definitions is extremely difficult since drought, unlike other natural hazards, has no definitive onset/end, is slow to evolve, and is regionally relative. However, the science behind defining and monitoring drought is at the center of the communication between stakeholders and policymakers. Failure to adequately define and monitor drought can have a significant negative impact, particularly if it fails to trigger a response (e.g., limiting water use) when one is sorely needed, or if it triggers a response when one is not required. There is very little discussion in the scientific literature regarding how drought indices should be used from an application standpoint to monitor drought and to trigger drought response. Because drought indices will be used by policymakers with little understanding of the mechanisms and flaws of each index, a certain level of standardization must be applied to limit the misleading or confusing message they may communicate to novice stakeholders.

Local, state, and federal agencies commonly use drought indices to monitor drought conditions and to communicate information about drought conditions to the private sector and public stakeholders. However, most drought indices were not specifically designed with this purpose in mind and they are commonly utilized in a variety of applications. For example, drought indices have been used in drought warning systems, probability based modelling, spatiotemporal analysis, use of GCMs for drought scenarios, and crop yield forecasting (Mishra and Singh, 2011). However, one of the most important uses of drought indices is for operational drought applications, since these applications are used to trigger water conservation measures and determine whether (and how much) drought assistance will be provided to affected regions.

In this study an integrated methodological and systematic approach is developed for spatiotemporal forecasting and monitoring of drought. The methodology is based on the integration of artificial intelligence techniques with geostatistical interpolation methods. The raster-based early warning and monitoring system is demonstrated for operational drought management using a meteorological drought index the Standardized Precipitation Index (SPI). The basic elements of the system are determined, and important issues and processes are analytically discussed, such as the representation of the spatial and temporal simulation error, extraction of optimal design solution in machine learning methods for reliable and accurate spatiotemporal drought forecasting. Each one of the aforementioned elements is considered as cores, where integrated algorithms are applied that combine various computational intelligence techniques such as artificial neural networks, genetic algorithms and geostatistical methods.

2 STUDY AREA AND DATABASE

Pinios river basin is located in central Greece and is a plain region surrounded by high mountains. The plain region with an area of about 4,000 km² is one of the most productive agricultural regions of Greece. The main crops cultivated are cotton, wheat and maize, whereas, apple, apricot, cherry, olive trees and grapes are cultivated at the foothills of the eastern mountains. Pinios River and its tributaries traverse the plain area,

and the basin total drainage area is about 9,500 km² (Fig. 1). The climate is continental at the western and central side of Pinios river basin and Mediterranean at the eastern side. Winters are cold and wet and summers are hot and dry with large temperature difference between the two seasons. Mean annual precipitation over Thessaly region is about 700 mm and it is distributed unevenly in space and time. The mean annual precipitation varies from about 400 mm at the central plain area to more than 1850 mm at the western mountain peaks. Generally, rainfall is rare from June to August. The mountain areas receive significant amounts of snow during the winter months and transient snowpacks develop. The water of Pinios River is used primarily for irrigation and for use in hydroelectric power plant located at Smokovo. The intense and extensive cultivation of water demanding crops has lead to a remarkable water demand increase, which is usually fulfilled by the over-exploitation of groundwater resources. For example, nearly 65,000 ha are irrigated with surface water and more than 210,000 ha of agricultural area are supplied by groundwater. The overexploitation of the groundwater, especially during extended dry periods, has led to the deterioration of the already disturbed water balance and the degradation of water resources. Thessaly experienced severe, extreme and persistent droughts during the periods from mid to late 1970s, from late 1980s to early 1990s and the first years of 2000s (Loukas and Vasiliades 2004; Vasiliades et al. 2011). These three drought periods were quite remarkable and affected large areas. During these three periods, the monthly and annual precipitation was significantly below normal in Thessaly. The prolonged and significant decrease of monthly and annual precipitation has a dramatic impact on natural vegetation, agricultural production and the water resources of the region.

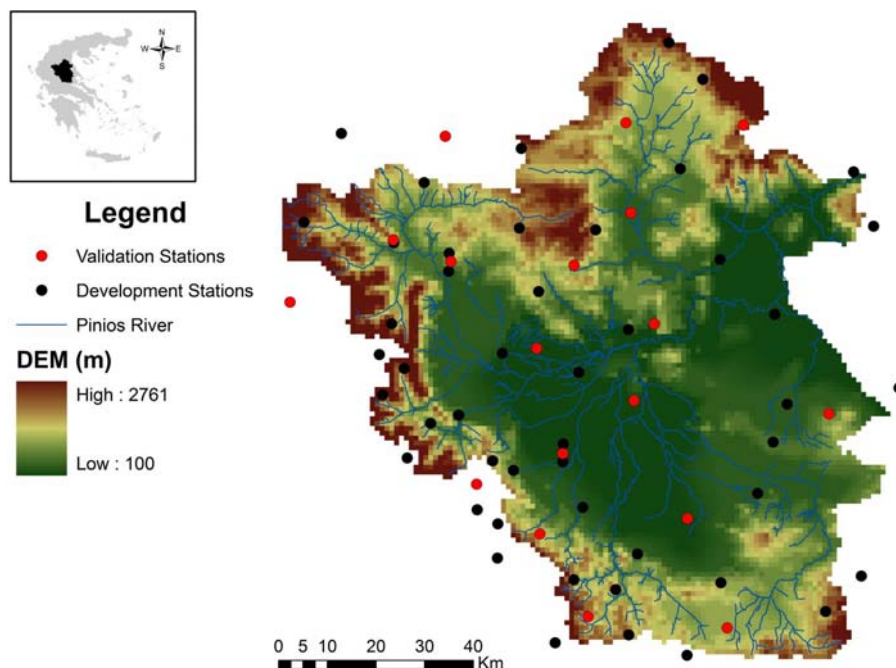


Figure 1. Pinios river basin, digital elevation model with 1-km pixel size and available precipitation stations.

Processed monthly precipitation data from a large network of precipitation stations (Fig. 1) for the period October 1960 to September 2002 were used to estimate temporal and spatial patterns of drought using a meteorological drought index the Standardised Precipitation Index, SPI. The supervised split sample test has been employed in order to separate the station sample into development and validation stations and to ensure that the study area is evenly covered by precipitation stations. Applying this method 73% of the available stations (48 stations) were held for the methods development and 27% of the available precipitation stations (18 stations) withheld for independent validation of the methodologies. In the development stations the elevation ranges from 31 m to 1183 m with a mean elevation of 559 m and the mean annual precipitation is 878 mm and is ranging from 409 mm to 1850 mm. Similar elevation and precipitation distribution is observed in validation stations. Pinios river basin elevation was estimated from a digital elevation model with pixel size of 1-km. This pixel resolution was selected as a compromise of computation time and spatial resolution suitable for identifying spatiotemporal patterns of drought. Hence, the total area of the basin was divided into approximately 9400 grids and their elevation is ranging from 100 m to 2760 m (Fig. 1).

3 EARLY WARNING DROUGHT SYSTEM

This paper proposes and develops an Early Warning System (EWS) for spatiotemporal forecasting and monitoring of drought at Pinios river basin, which is a 4-tier system framework composed of a) calculation of SPI at multiple time scales using precipitation data from meteorological stations, b) a GIS tool for spatiotemporal monitoring which uses advanced geostatistical methods that incorporate auxiliary information to create raster SPI observed maps at pixel size of 1-km c) a hybrid spatiotemporal scheme for integrated spatial and temporal forecasting of SPI at the meteorological stations, d) a GIS tool for creating raster forecast maps of drought and aggregated the results (forecast and observed maps) at watershed or sub-watershed level for operational drought management. The elements of the system are described in the following subsections.

3.1 Calculation of SPI at multiple time scales

The EWS is developed primarily for operational use and applications. For this reason the SPI calculated at multiple time scales is employed for drought identification. The main advantage of the SPI is that can be calculated for multiple time-scales. This is very important because the timescale over which precipitation deficits accumulate functionally separates different types of drought and, therefore, allows to quantify the natural lags between precipitation and other water usable sources such as river discharge, soil moisture and reservoir storage. Computation of the SPI involves fitting a Gamma probability density function to a given frequency distribution of precipitation totals for a station, area or a watershed. The cumulative probability is subsequently transformed to the standard normal random variable Z with mean equal to zero and variance of one, which is the value of the SPI (McKee *et al.* 1993). The capability of SPI in detecting different types of drought was demonstrated at Pinios river basin for hydrological and water resources drought identification (Vasiliades, 2010; Vasiliades *et al.*, 2011). In these studies, robust relationships were found analysing the role of the

time scales of SPI on soil moisture, river discharges and reservoir storages. Hence, the SPI at 3-month, 6- month, 9- month, 12- month και 24- month timescales using monthly precipitation data for all the available raingauges (Fig. 1) were selected for spatiotemporal drought analysis, modelling and forecasting in Pinios river basin.

3.2 Spatiotemporal monitoring tool

Spatial continuous data (or spatial continuous surfaces) play a significant role in planning, risk assessment, and decision making in drought management. They are, however, usually not always readily available and often difficult and expensive to acquire, especially for mountainous regions. Thus, the values of an attribute at unsampled points need to be estimated, meaning that spatial interpolation from point data to spatial continuous data is necessary. In such instances, spatial interpolation methods provide tools to fulfil such task by estimating the values of a meteorological variable at unsampled sites using data from point observations within the same region. *Zhang and Srinivasan (2009)*, in a comparative study of spatial interpolation methods for daily precipitation, suggested to implement multiple spatial interpolation methods and to select the one with better evaluation statistics in order to provide accurate spatiotemporal interpolations. *Vasiliades (2010)* applied eight (8) spatial interpolation methods (Thiessen Polygons, Inverse Distance Weighted, Simple Kriging, Ordinary Kriging, Simple Kriging with Varying Local Means, and combinational methods based on ordinary regression with auxiliary information using spatial coordinates and elevation and geostatistical methods for the regression residuals), for spatiotemporal drought modelling at Pinios river basin using the same raingauge database as in the present study. In the latter study, the combinational method of a regression model with spatial coordinates and elevation with residual simple kriging with local varying means (SKlm_R) outperformed the other interpolation methods for about 60% of the period of analysis, while the other methods provided more accurate SPI than SKlm_R for the remaining 40% for all timescales at the study area (*Vasiliades, 2010*). Thus, the interpolation method SKlm_R is selected for spatiotemporal application and for creation of raster maps of SPI using pixel size of 1-km.

The SK with varying local means (SKlm) is an extension of SK by replacing the stationary mean with known varying means at each point that depend on the secondary information. If the secondary variable is categorical, the primary local mean is the mean of the primary variable within a specific category of the secondary variable. If it is continuous, the primary local mean is a function of the secondary variable or can be acquired by discretising it into classes. SK is then used to produce the weights and estimates. Further details on SKlm and on the mathematical equations could be found in *Goovaerts (1997)* and applications of the method in several studies (i.e. *Zhang and Srinivasan, 2009*).

A Geographic Information System tool, which incorporates the SKlm_R interpolation method, was developed to facilitate automatic spatial SPI estimation. The basic input data include a point shapefile that contains the geographic location of the raingauges, and SPI records for each raingauge in text format, and a Digital Elevation Model (DEM) to provide elevation information. The GIS program automatically reads in each month's SPI value for each raingauge, and then SKlm_R is implemented to estimate the spatial distribution of SPI. The interpolated spatial SPI data are output in raster format, which can be used for further analysis. Finally, several statistics that

evaluate the characteristics and accuracy of the estimated spatial SPI are calculated. The SKlm_R was applied for spatiotemporal monthly SPI interpolation between October 1960 and September 2002 using the 48 development precipitation stations (Fig. 1).

3.3 Hybrid spatiotemporal forecasting scheme

Drought forecasting is a critical component of drought hydrology which plays a major role in risk management, drought preparedness and mitigation. Several studies were developed recently for forecasting droughts using meteorological drought indices (Mishra and Singh, 2011). The spatiotemporal forecasting in this study is focused on short (1-2 months ahead) and medium (3-6 months ahead) term prediction intervals. A hybrid spatiotemporal scheme for integrated spatial and temporal forecasting at point station has been recently developed by the authors (Vasiliades and Loukas, 2010). Temporal forecasting is achieved using feed-forward neural networks and the temporal forecasts are extended to the spatial dimension using a spatial recurrent neural network model of Elman type. The methodology is demonstrated for an operational meteorological drought index the Standardized Precipitation Index (SPI) calculated at calculated at 3-month, 6- month, 9- month, 12- month και 24- month timescales. 48 precipitation stations and 18 independent precipitation stations, located at Pinios river basin in Thessaly region, Greece, were used for the development and spatiotemporal validation of the hybrid spatiotemporal scheme. Several quantitative temporal and spatial statistical indices (Eff, R, RMSE, MAE) were considered for the performance evaluation of the models. Furthermore, qualitative statistical criteria based on contingency tables between observed and forecasted drought episodes were calculated. Drought episodes were identified when SPI values ≤ -1 (McKee et al. 1993).

The hybrid spatiotemporal forecasting scheme is developed with the integration of 1) a generalised neural network time series model to capture the temporal characteristics of each spatially separated location and 2) a spatial artificial neural network to discover the hidden spatial and temporal correlation among all locations using the temporal forecasts. The Gamma Test (GT) was used to select the input variables and the training data length, so that the trial and error workload to be greatly reduced [Stefansson et al., 1997; Evans and Jones, 2002]. The use of the GT in input variable preprocessing enables to quickly evaluate and estimate the best mean squared error that can be achieved by a smooth model on any unseen data for a given selection of inputs, prior to model construction.

Neural networks are a class of flexible nonlinear models that can adaptively discover patterns from the data. Theoretically, it has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and estimates any complex functional relationship with high accuracy. For a detailed review of artificial neural network (ANN) models and their application in hydrology the reader can refer to Govindaraju and Rao (2000). Several generalised neural networks models have been developed efficiently, with the aid of the GT, for 1-month up to 6-month ahead forecasting for the examined timescales of SPI. The values of SPI in the previous months are used for generating a drought temporal forecasting model. In the construction of forecasting models, again, different models were generated for each of the SPI output for 3, 6, 9, 12 and 24 months. The data sets for all stations were divided into two subsets, training and validation data set. The training data set includes monthly SPI records between 1960 and 1992 years for the 48 development precipitation stations.

In order to get more reliable evaluation and comparison, forecasting models are tested by evaluating a data set which was not used during the training process. Testing data set consists of SPI records observed between 1992 and 2002 years for the 48 development precipitation stations and SPI data for the years 1960-2002 for the 18 independent validation rainfall stations. Generalised feed forward artificial neural network models were employed for temporal forecasting of SPI. The input nodes are the identified previously lagged observations, while the output provides the forecast of a future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. In this study, recursive or iterative multistep generalised neural networks (RANN) for forecasting several time steps ahead were employed. A recursive multistep approach is based on one output node, forecasting a single step ahead, and the network is applied recursively, using previous predictions as inputs for subsequent forecasts. The topology of the generalised MLPs is exploited in conjunction with the BFGS backpropagation algorithm, a second-order nonlinear optimization technique, which is usually faster and more reliable than other backpropagation variants. Moreover, Bayesian regularization (Mackay, 1992) is applied in order to insure that the MLPs provide accurate forecasts for input values unknown to the network. Finally, the technique bagging with ensembles was followed to ensure generalization (Breiman, 1996). The ensembles were generated using bootstrap resampling with replacement of the available training data set and used in the MLPs training. Further details could be found in Vasiliades and Loukas (2010).

In order to achieve spatiotemporal forecasting the temporal forecasts of the generalised RANN method are extended to the spatial dimension using dynamic neural networks. Among other dynamic neural networks, the Elman type of the dynamic recurrent neural network (RNN) was employed to discover the hidden and deeply entangled spatial relationships (Elman, 1990). A dynamic RNN has its own internal potential or internal state that is used to describe the dynamic characteristic of the network. Moreover, Elman neural network has a backward connection between the hidden and context layer. This feedback path allows it to learn temporal and spatial patterns of input data, which is essentially useful in geographic spatial-temporal relationship forecasting. RNNs of SPI temporal forecasts with the spatial coordinates of the rainfall stations were created for short and medium term SPI prediction intervals and trained using the adaptive BFGS algorithm, which uses a self-adaptive scaling factor for the Hessian matrix and is equipped with non-monotone strategy (Peng and Magoulas, 2007). This algorithm is a modified version of BFGS, which combines the usage of adaptive non-monotone learning with the self-scaling utility; where the former takes the benefits of Lipschitz constant taking into account the local shape of a given function, while the latter has been proved to have the ability of solving unconstrained nonconvex optimisation problems.

3.4 Raster-based early warning system

Finally, the hybrid spatiotemporal forecasting models are incorporated in the automated spatial interpolation system for the creation of raster forecasting drought maps with pixel size of 1-km. The automated spatial interpolation system could be used either as a drought monitoring system or as a drought forecasting system. The method incorporated in the system is again the method SKIm_R which was the best interpolation method for the production of observed SPI drought maps (Vasiliades,

2010). The early warning system is used for raster-based drought monitoring and forecasting at pixel level and for the estimation of the areal values (average SPI values of the 9400 grids with pixel size 1-km) of the study area for operational applications and drought management. The SKlm_R requires semivariogram models to be fitted to the experimental semivariogram values. In this study, the spherical theoretical semivariogram model was applied to monthly values of SPI forecasts and observations for all study timescales and fitted using weighted least squares regression (Goovaerts, 1997). Figure 2 presents the flow diagram of the proposed early warning system for Pinios river basin.

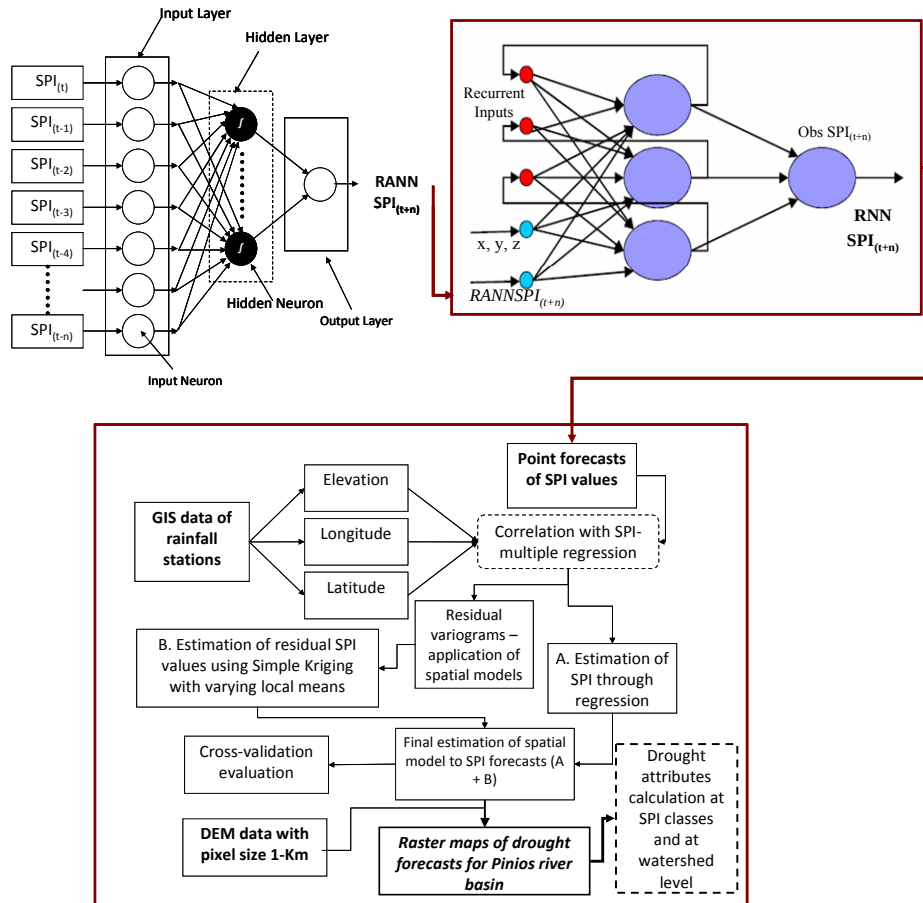


Figure 2. Flow diagram of the proposed early warning system.

4 APPLICATION AND RESULTS

Calculation of the SPI in all raingauges showed that the Gamma distribution is suitable for simulating monthly accumulated precipitation at timescales of 3-, 6-, 9-, 12-

and 24-months, since the Kolmogorov-Smirnov test is not rejected at 5% significance level in all stations. Application of the hybrid spatiotemporal forecasting scheme identified the operational lead time for drought forecasting and drought monitoring. Conceptually there should be a ‘deterministic limit’ for predicting a pre-defined drought event ($SPI_{obs} \leq -1$). Simply defined this could be the point in lead time beyond which forecasts ($SPI_{forecasts} \leq -1$) concerning that event are more likely, on average, to be wrong than right. Defined in this way, this provides some guidance on when to shift the emphasis, in forecasts for particular events, towards the probabilistic. For rare events at least, correct null forecasts – i.e. the majority - can be ignored as not relevant ($SPI > -1$). The ‘deterministic limit’ for the event in question is then simply the lead time at which, over a suitably large forecast sample, hits equals the sum of misses and false alarms or Critical Success Index or Threat Score, CSI, is 0.5 (Hewson, 2007). Based on this criterion when the CSI of the forecasts is larger than 0.5 then the methodology could be applied for operational drought management for the study lead time. This is demonstrated in Figure 3, which, shows that the model efficiency for SPI-9 is quite high at the lead time $t+4$ (four months ahead) whereas the CSI suggests that drought forecasting is feasible until 3-months ahead. As an example, Figure 4 shows the forecasting results for the hybrid spatiotemporal forecasting scheme for SPI-9_{t+3} at one independent spatiotemporal validation station. The spatial recurrent neural network (RNN) is able to reproduce the observed SPI timeseries and improves the temporal generalised recursive neural network RANN forecasts. Furthermore, all the evaluation statistics are improved and the CSI value shows that the RNN model is appropriate for forecasting 3-months ahead (Fig. 4). Generally, the lead time of forecasting for operational use depends on the SPI timescale. Hence, the hybrid spatiotemporal drought forecasting model could be operationally used for short term prediction intervals at shorter timescales of SPI (i.e. SPI-3_{t+1}, SPI-6_{t+2}) and for medium term prediction intervals at larger SPI timescales (i.e. SPI-9_{t+3}, SPI-12_{t+4}, SPI-24_{t+6}). A promising outcome of the results is that reliable and unbiased forecasts up to six months ahead were achieved for large SPI timescales (e.g. 24 months) which are used for water resources management at the study area.

To identify more clearly the hazard, the interpolation method SKIm_R is incorporated in the early warning system to produce raster drought forecast maps (Fig. 2). Figure 5 shows the forecast drought maps of SPI-12 at selected lead times for the extreme drought episode in November 1977. Raster forecast maps show that the proposed early warning system is able to reproduce drought attributes (area and severity) and the forecasting accuracy is decreased as the lead time is increasing (Fig. 5). For example at 4-months ahead forecasting (SPI-12_{t+4}) the forecasted area under drought conditions with $SPI \leq -1$ is slightly underestimated by -2.4% with subsequent decrease in average drought severity by -17.8%. The forecasted maps show that this drought episode is extreme at lead times $t+1$ and $t+2$ and severe for 3 and 4 months ahead prediction. In general, the comparison of the forecasted drought maps with selected historical drought maps for the study SPI timescales show that reliable and accurate predictions of drought characteristics (severity, duration and area) are estimated for medium term prediction intervals at larger timescales of SPI and for short term prediction intervals at smaller SPI timescales in Pinios river basin.

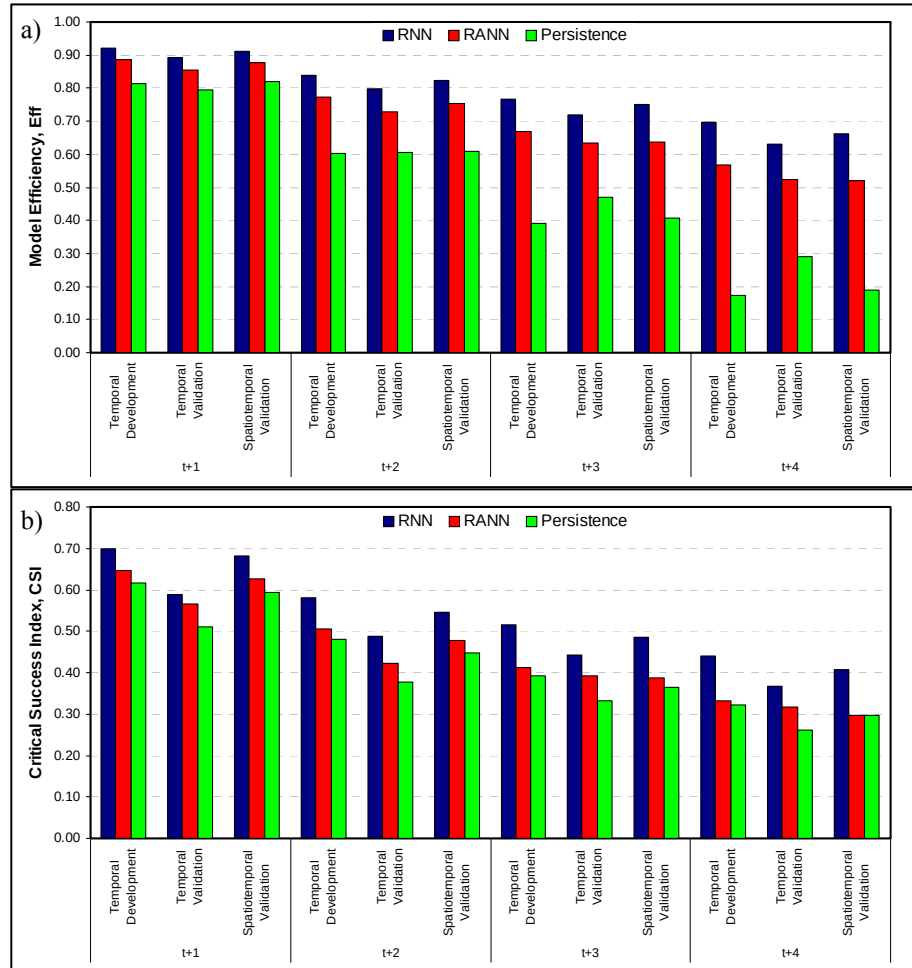


Figure 3. Evaluation statistics of the hybrid spatiotemporal scheme for SPI-9month a) model efficiency and b) critical success index.

5 CONCLUSIONS

Application of the early warning system for operational applications show that reliable and accurate predictions of drought characteristics (severity, duration and area) are estimated for medium term prediction intervals at larger timescales of SPI and for short term prediction intervals at smaller SPI timescales in Pinios river basin, Thessaly, Greece. The GIS program developed in this study can serve as an effective and efficient tool to implement advanced geostatistics methods that incorporate auxiliary information to improve spatiotemporal estimation. The drought monitoring and forecasting decision system uses previous SPI values calculated at different timescales of the available rainfall stations as the forecast inference factors, and then analyzes the drought level

based on the lead time of SPI for operational use via the proposed hybrid spatiotemporal drought forecast model.

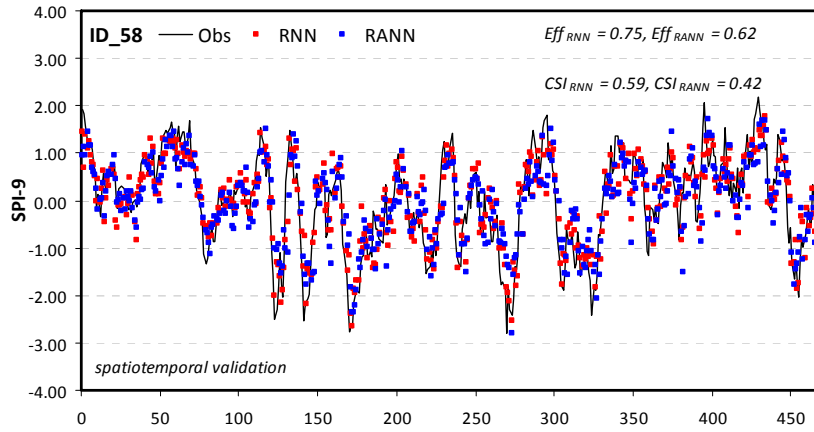


Figure 4. Spatiotemporal validation forecasting results for SPI-9_{t+3} at precipitation station ID_58.

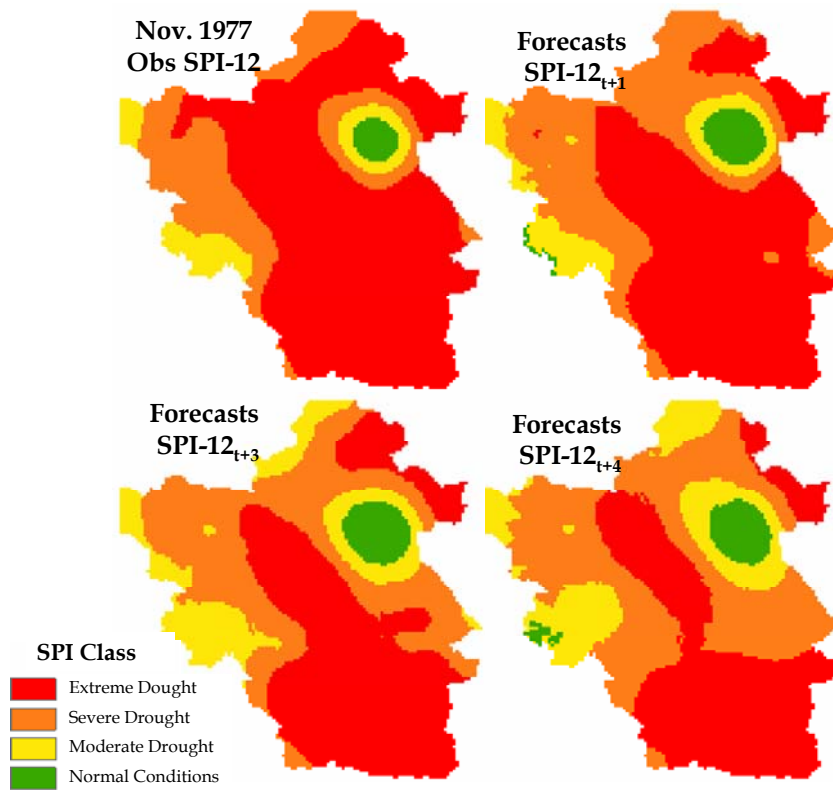


Figure 5. Drought forecast maps for SPI-12 month in November 1977.

To identify more clearly the hazard, advanced spatial interpolation methods are incorporated in the forecasting system to produce raster drought forecast maps. Comparison of the forecasted drought maps with selected historical drought maps show that that reliable and accurate predictions of drought characteristics (severity, duration and area) are estimated for medium term prediction intervals at larger timescales of SPI and for short term prediction intervals at smaller SPI timescales in Pinios river basin. It is believed that implementation of the early warning drought system with real-time rainfall data will help to judge if this region is a potential drought prone area. If the danger indicator is reached, the water managers and relevant civil protection agencies shall be properly informed to take preventive measures and minimize the possible loss according to the drought severity level.

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