AN OPERATIONAL DROUGHT MONITORING SYSTEM USING SPATIAL INTERPOLATION METHODS FOR PINIOS RIVER BASIN, GREECE

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EXTENDED ABSTRACT

In this study an integrated methodological and systematic approach is developed for drought monitoring. A Drought Monitoring System (DMS) is developed based on the integration of Geographical Information Systems with geostatistical interpolation methods and a meteorological drought index the Standardized Precipitation Index (SPI). The DMS is demonstrated for operational drought management in Pinios river basin, Greece, calculates SPI at multiple timescales for each available precipitation station and then applies eight (8) spatial interpolation methods to the SPI values for drought mapping. The DMS incorporates simple interpolation methods (Thiessen Polygons, Inverse Distance Weighted) geostatistical (Simple Kriging, Ordinary Kriging, Simple Kriging with Local Means), and combinational methods based on ordinary regression with auxiliary information (spatial coordinates and elevation) and geostatistical methods for the regression residuals. These methods were applied at monthly time step for drought mapping using 48 precipitation stations, located in the wider Thessaly region, and monthly rainfall data for 42 hydrologic years (October 1960 - September 2002) to identify the spatial and temporal interpolation error. The DMS automatically calculates the SPI, reads in each month the SPI value for each precipitation station, and then the selected interpolation methods are 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 evaluation metrics that assess the characteristics and accuracy of the applied spatial interpolation methods are calculated using the cross-validation technique. The results show that different interpolation methods can obtain similar areal mean SPI values, but with significantly different areal distribution. The results show that use of elevation and spatial coordinates as secondary variables improves the accuracy of spatial SPI estimation. The combinational method of a regression model with spatial coordinates and elevation and regression-residuals simple kriging with local varying means outperformed the other methods for about 55% of the period of analysis, for all SPI timescales at the study area. Identified historical drought events were used for drought mapping and comparison of the raster maps created with the interpolation methods. The maps have similar areal values but different areal distribution of drought is observed. The major conclusion is that the spatial interpolation methods could be applied for spatiotemporal drought mapping but caution should be given in the selection of the method, since the spatial and temporal error is varying with the application time step. In order to provide accurate drought mapping, it is suggested to implement multiple spatial interpolation methods and select the one with better evaluation metrics. The DMS could serve as an effective and efficient operational tool to implement drought mapping and monitoring useful for water resources management in the study area.

Keywords: drought monitoring, standardized precipitation index, spatiotemporal interpolation, spatial interpolation methods, geostatistics, Pinios river basin
1. INTRODUCTION

Drought monitoring is a fundamental component of drought risk management. Meteorological drought indices, which are mainly functions of precipitation showing the severity of dryness during a particular time period, are often used for monitoring purposes and they are essential elements in drought monitoring systems (Smakhtin and Hughes, 2007). These systems are capable to identify drought onset, progress, severity, areal extent and termination of a drought event and are mainly used to trigger drought contingency plans. Most of these indices are calculated using climate data from the meteorological stations, which are point measurements. For monitoring purposes, it is necessary to operationally produce the maps of drought severity from point measurements to trace drought development in the entire region or country. Spatial interpolation could be used to estimate meteorological variables at other locations. A number of methods have been proposed for surface interpolation of climate variables like rainfall and temperature. Although there are several methods to perform this, it can be difficult to determine which one best reproduces actual conditions. Each method’s advantages and disadvantages depend strongly on the characteristics of the data set: a method that fits well with some data can be unsuitable for a different set of data. Thus, criteria must be found to decide whether the method chosen is suited for the point data set. It is also important to specify the aims of the interpolation, because different aims can require different criteria for evaluation of the interpolation (Borrough and McDonnell, 1998). The correct determination of the spatial distribution of meteorological variables is as important as their measurement. Depending on the spatial attributes of the data, the accuracy of the results may vary widely among spatial interpolation methods. The choice of spatial interpolator is especially important in mountainous regions with fewer data, where the values of variables may change over short spatial scales.

The comparison of spatial interpolation methods has been the subject of many meteorological studies (Dobesch et al., 2007). These studies show the superiority of the geostatistical methods over the conventional methods for estimation of meteorological variables at ungauged locations. However, for spatial drought monitoring because of the estimation procedure of the meteorological drought index, a spatial interpolation technique is selected a-priori (e.g. Loukas and Vasilides, 2004; Tsakiris and Vangelis, 2004; Smakhtin and Hughes, 2007). Up to now limited studies assess the effect of different approaches for spatial interpolation of drought indices (Akhtari et al., 2008). This study intends to partially fill this gap and evaluate the performance of eight (8) spatial interpolation methods for mapping of drought indices in Pinios river basin, Greece. Furthermore, a Drought Monitoring System (DMS) is developed for spatiotemporal visualization and mapping of drought. The DMS is demonstrated for operational drought management using a meteorological drought index the Standardized Precipitation Index (SPI) (McKee et al., 1993) which was shown to perform satisfactorily at the study area in the context of drought monitoring (Vasiliades and Loukas, 2011). The DMS incorporates simple interpolation methods (Thiessen Polygons, Inverse Distance Weighted) geostatistical (Simple Kriging, Ordinary Kriging, Simple Kriging with Local Means), and combinational methods based on ordinary regression with auxiliary information (spatial coordinates and elevation) with geostatistical methods for the regression residuals. The design and application of the DMS is described analytically in the next paragraphs.

2. STUDY AREA AND DATABASE

Thessaly is a plain region surrounded by high mountains. Thessaly plain is one of the most productive agricultural regions of Greece. Climate is continental at the western and central side of Thessaly 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. 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. Mean annual precipitation over the Thessaly region is about 700 mm, varies from about 450 mm at the central plain area to more than 1850 mm at the western mountain peaks and it is distributed unevenly in space and time. Pinios River and its tributaries traverse the plain area, and the basin total drainage area is about 9,500 km² (Fig. 1). The waters of Pinios River are used primarily for irrigation. 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). Processed monthly precipitation data from 48 precipitation stations for the period October 1960 to September 2002 were used for the estimation of SPI (Fig. 1). Raingauge elevation is ranging from 31 m to 1183 m with a mean elevation of 559 m and the mean annual precipitation is 878 mm and ranges from 409 mm to 1850 mm.

![Figure 1](image-url): Pinios river basin, digital elevation model with 1-km pixel size and available precipitation stations.

3. DROUGHT MONITORING SYSTEM
This study develops a Drought Monitoring System (DMS) for spatiotemporal monitoring of drought at Pinios river basin, which is a 3-tier system framework composed of a) calculation of SPI at multiple time scales using precipitation data from meteorological stations, b) a module for spatiotemporal drought monitoring using eight (8) spatial interpolation methods that incorporates advanced geostatistical methods that incorporate auxiliary information to create raster SPI observed maps at pixel size of 1-km, and c) production of raster SPI maps for monitoring drought and aggregation of the results at watershed level for operational drought management. The methods incorporated are simple interpolation methods (Thiessen Polygons, Inverse Distance Weighted).
geostatistical (Simple Kriging, Ordinary Kriging, Simple Kriging with Local Means), and combinational methods based on ordinary regression with auxiliary information (spatial coordinates and elevation) with geostatistical methods for the regression residuals. The flowchart of this DMS is shown in Figure 2. The basic input data include a point shapefile that contains the geographic location of the precipitation station, and monthly precipitation data for each rainfall station in text format, and a Digital Elevation Model to provide elevation information. The DMS automatically calculates the SPI at 3-month, 6-month, 9-month, 12-month, and 24-month timescales, and then reads in each month the SPI value for each precipitation station, and the interpolation method selected by the user 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 at watershed level. Finally, several statistics that evaluate the characteristics and accuracy of the applied spatial interpolation method are calculated (Fig. 2). The calculation elements of the system are described in the following subsections.

![Flowchart of the Drought Monitoring System](image)

**Figure 2**: Flowchart of the Drought Monitoring System.

### 3.1. Calculation of Standardized Precipitation Index
The DMS is developed primarily for operational use and drought management. For this reason, the Standardized Precipitation Index (SPI) calculated at multiple time scales is employed for drought identification. The SPI has been developed by McKee et al. (1993) to quantify the precipitation deficit for multiple time scales in order to define and monitor droughts. The main advantage of the SPI is that can be calculated for multiple time-scales (e.g. 6-months, 12-months). This is very important because the timescale over which precipitation deficits accumulate functionally separates different types of drought and, therefore, allows quantifying the natural lags between precipitation and other water usable sources such as river discharge, groundwater, 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 meteorological station. 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 et al., 2011). Hence, the SPI at 3-month, 6- month, 9- month, 12- month και 24- month timescales using monthly precipitation data for all the available precipitation stations (Fig. 1) are selected for spatiotemporal drought analysis and monitoring at the study area.

3.2. Spatial Interpolation Methods

Eight (8) interpolation methods are selected and incorporated in the DMS, which include Thiessen polygons (TP), Inverse Distance Weighted (IDW), Ordinary Kriging, Simple Kriging (SK), Kriging with External Drift (KED), Simple Kriging with varying Local Means (SKlm), and Regression Kriging (RK) which is a combination method based on ordinary regression with auxiliary information (spatial coordinates and elevation) and OK for the regression residuals and Regression Simple Kriging with Local Means (SKlm R) which is a combination of regression with secondary information and SKlm for the regression residuals. The aim of spatial interpolation methods is to estimate the value of a random variable, Z, at one or more unsampled points from a set of sample data (Z(x1), Z(x2), …, Z(xN)) at points (x1, x2, …, xN) within a spatial domain, where N is the number of sample data. TP assigns the SPI value of each unsampled point to the value observed by the closest precipitation station. The IDW method explicitly implements the assumption that observations closer to one another are more alike than those farther apart. Thus, IDW assumes that each measured point has a local influence that diminishes with distance. Kriging is a category of advanced geostatistical techniques that provides the best linear unbiased estimation of the variable of interest at an unobserved location from observations of the random field at nearby locations. In Kriging methods, the random variable Z is decomposed into a trend (m) and a residual (e), where Z(x) = m(x) + e(x). The Kriging estimator is given by a linear combination of the surrounding observations. The weights of the points that surround the predicted points are calculated based on the spatial dependence (i.e., semivariogram or covariance) of the random field. In the OK, the trend is considered as unknown and constant whereas in SK known and constant and in KED method the trend is considered as a linear function of the spatial coordinates and the elevation. The SKlm is an extension of SK by replacing the stationary mean with known varying means at each point that depend on the secondary information. 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 the study geostatistical methods and on the mathematical equations could be found in Goovaerts, 1997. The two combinational methods (RK and SKlm R) as explained previously are linear functions of the spatial coordinates and elevation and the residuals of the regression are analysed using the OK and SKlm, respectively.

In this study, for every month, geostatistical method and timescale of SPI, spherical theoretical semivariograms were fitted to the omnidirectional experimental semivariograms. The spherical semivariograms were combined with a nugget-effect model for the fitting of the experimental semivariogram of monthly SPI values. The parameters were calculated using weighted least squares for minimization of the weighted sum of squares of differences between experimental and model semivariogram values. Drought maps must be assessed by statistics that indicate the degree of concordance between models and reality. Cross-validation is a popular method that has been used to compare the prediction performances of spatial interpolation methods. In cross-validation, each of the precipitation station SPI data is temporarily removed at a time and the remaining data are used to estimate the value of the deleted datum. The difference between the observed and estimated values is used to evaluate the accuracy of interpolation methods. In this study the correlation coefficient (R) between observed and simulated data is used as a first indication of the reliability of the model, and the

CEST2013_0644
Nash-Sutcliffe efficiency (Eff) to assess the overall performance of the spatial methods. Furthermore, other two evaluation metrics are used to determine the performance of each model, the mean absolute error (MAE) and the root mean square error (RMSE). MAE and RMSE account in real units the level of overall agreement between the observed and modelled datasets and for a perfect model the result would be zero. MAE is unbiased where RMSE consists of a weighted measure of the error in which the largest deviations between the observed and modelled values contribute the most and subsequently is more sensitive than MAE (Dawson et al., 2007).

4. RESULTS
The Drought Monitoring System has been applied to Pinios River basin for operational drought monitoring. The Standardized Precipitation Index was used as an index drought calculated at 3-month, 6-month, 9-month, 12-month and 24-month timescales. The results are presented only for SPI-6 month timescale due to paper length limitations. The overall performance of the different interpolation methods in the DMS is shown in Figure 3. In this figure the box plot is used to plot the evaluation metrics for the whole period of analysis (Mar 1961-Sep 2002 = 499 months) obtained by the different interpolation methods using the cross-validation technique. Fig. 3 shows that TP and KED failed to represent the spatial distribution of the SPI-6 values for the 48 precipitation stations whereas the other methods show similar patterns for the Eff and the RMSE evaluation metrics. A detailed inspection of these metrics show that the method SKlm_R is slightly better that the other methods since the values have the smallest range and their median or mean values are the best of the examined methods. For example the Eff is ranging from -0.40 to 0.64 with a mean value of 0.15. Similar patterns are observed and for the other two metrics the correlation coefficient and the mean absolute error. The overall accuracy assessment of the eight interpolation methods shows that SKlm_R performed better than the other methods, while the Thiessen polygon method performed the worst. But it is also worth noting that no one method can consistently outperform other methods for all the months. Table 1 lists the number of months that different interpolation methods performed the best among all methods for the evaluation metrics. The method SKlm_R outperformed all the other methods for at least 56% of the time followed by SK, RK and SKlm (Table 1). Similar findings are also found and with the other timescales of SPI.

![Figure 3](image_url)

**Figure 3:** Box plots of the cross-validation evaluation metrics of the monthly application of the different interpolation methods for SPI-6 month.

**Table 1:** Number of months that different interpolation methods outperform the other methods for cross-validation evaluation metrics.

<table>
<thead>
<tr>
<th>Metric</th>
<th>IDW</th>
<th>KED</th>
<th>OK</th>
<th>RK</th>
<th>SK</th>
<th>SKlm_R</th>
<th>SKlm</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eff</td>
<td>16</td>
<td>4</td>
<td>14</td>
<td>44</td>
<td>49</td>
<td>344</td>
<td>34</td>
<td>0</td>
</tr>
</tbody>
</table>
 Monthly interpolations were performed for all the period of analysis (Mar 1961-Sep 2002 = 499 months), the visual inspection of figures showing the difference between SPI-6 drought distribution maps estimated by different interpolation methods is only shown for March 1990. This month was selected was selected to show that different methods can produce similar maps with different distribution patterns and could have very different accuracy evaluation metrics even if their distribution patterns are similar. It should be mentioned that the method SKlm_R outperformed the other methods in all evaluation metrics for this particular month. Figure 4 presents the interpolated drought spatial pattern estimated by different interpolation methods and Table 2 shows the percentage of area which is under drought conditions based on the SPI drought classes. Table 2 is produced from the estimated SPI-6 values of the DMS application at the study area. Although the drought maps in Fig. 4 show substantially different spatial variation, the areal mean SPI-6 values obtained by all the eight methods are very close to each other, which range between -1.81 and -1.87 and classify the month as severe dry (-1.5≤SPI<-2). However, the percentages of area which are under drought conditions are quite different especially in the classes severe and moderate (-1.0≤SPI<-1.5) drought conditions. The extreme (SPI≤-2) drought class shows the smallest variability from 31-40% and five out of the eight methods show that Pinios river basin is completely affected by drought conditions (Table 2).

<table>
<thead>
<tr>
<th>Area (%)</th>
<th>IDW</th>
<th>KED</th>
<th>OK</th>
<th>RK</th>
<th>SK</th>
<th>SKlm_R</th>
<th>SKlm</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme dry</td>
<td>36.8</td>
<td>39.8</td>
<td>36.9</td>
<td>34.2</td>
<td>35.0</td>
<td>38.9</td>
<td>31.6</td>
<td>36.3</td>
</tr>
<tr>
<td>Severe dry</td>
<td>43.1</td>
<td>39.3</td>
<td>43.9</td>
<td>45.7</td>
<td>61.6</td>
<td>43.9</td>
<td>63.0</td>
<td>32.3</td>
</tr>
<tr>
<td>Moderate dry</td>
<td>19.0</td>
<td>18.9</td>
<td>19.2</td>
<td>20.1</td>
<td>3.4</td>
<td>17.1</td>
<td>5.4</td>
<td>22.5</td>
</tr>
<tr>
<td>Total dry</td>
<td>98.9</td>
<td>97.9</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>91.1</td>
</tr>
</tbody>
</table>

5. CONCLUDING REMARKS

A drought monitoring system (DMS) is developed to monitor droughts using the Standardized Precipitation Index calculated in multiple timescales for Pinios river basin, Greece. The DMS includes several spatial interpolation methods for automatic spatial SPI-based drought estimation. These methods were applied monthly for 42 hydrologic years (Oct 1960 - Sep 2002) to identify the spatial and temporal interpolation error and subsequent drought mapping. The results show that different interpolation methods can obtain similar areal SPI values, but their distribution is quite different. The accuracy of the spatial precipitation estimated by the evaluation metrics show that the combinational methods which incorporate auxiliary information (spatial coordinates and elevation) improve the spatial SPI estimation. It is also worth noting that no one interpolation method can consistently perform better than the other methods. However, the combinational method of a regression model with spatial coordinates and elevation and regression-residual simple kriging with local varying means (SKlm_R) outperformed the other methods for about 55% of the period of analysis, while the other methods provided more accurate SPI than SKlm_R for the remaining 45% for all timescales at the study area. In order to provide accurate drought mapping, it is suggested to implement multiple spatial interpolation methods and select the one with better evaluation metrics. The DMS could serve as an effective and efficient operational tool to implement drought mapping and monitoring useful for water resources management in the study area.
Figure 4: Drought spatial distribution by different interpolation methods March 1990 using 6-month SPI.

REFERENCES