This study reports an analysis of the spatial drought patterns for a region of southern Italy (Calabria) based on a homogenous monthly precipitation data set of 129 rain gauges for the period 1916–2006. Drought was expressed using the Standardized Precipitation Index (SPI), and drought events were analyzed using both the short-time (3 and 6 months) and the long-time (12 and 24 months) SPI. In particular, in order to characterize the SPI spatial pattern, index data of the three most severe drought events were interpolated and mapped using a geostatistical approach. Results show that these heavy drought episodes have widely affected the Calabria region and the drought that occurred in 2002 was the worst in terms of spatial extent both at short- and long-time scales.

Keywords: precipitation; SPI; geostatistics; Calabria

1. Introduction

Given the prolonged lack of precipitation events over a large part of Europe during the last few decades, research has recently focused on drought, (Fink et al., 2004; Hannaford, Lloyd-Hughes, Keef, Parry, & Prudhomme, 2011; Lloyd-Huhes & Saunders, 2002), and numerous drought indices have been developed. Drought indices are useful for monitoring and assessing this phenomenon since they simplify complex interrelationships between many climate and climate-related properties. Indices facilitate communication of climate anomalies to diverse user audiences and allow scientists to assess quantitatively climate anomalies in terms of their intensity, duration, frequency, recurrence probability and spatial extent (Tsakiris, Pangalou, & Vangelis, 2007; Wilhite, Hayes, & Svodoba, 2000). Such information is extremely useful for planning and designing water resources management schemes. Moreover, these indicators serve to identify, locate or delimit regions that suffer from a deficit of available water, a condition that can severely affect the effective use of cropland and farmland (Tsakiris et al., 2007). Most drought indices are based on meteorological or hydrological variables. These include the Palmer Drought Severity Index (PDSI; Palmer, 1965), the Rainfall Anomaly Index (RAI; Van Rooy, 1965), the Rainfall deciles (Gibbs & Maher, 1967), the Crop Moisture Index (CMI; Palmer, 1968), the Bhalme and Mooley Drought Index (BMDI; Bhalme & Mooley, 1980), the Surface Water Supply Index (SWSI; Shafer & Dezman, 1982), the National Rainfall Index #
The SPI has been widely used in different countries of the world (Khan, Gabriel, & Rana, 2008; Logan, Brunsell, Jones, & Feddema, 2010; Manatsa, Mukwada, Siziba, & Chinyanganya, 2010; Raziei, Saghafian, Paulo, Pereira, & Bordi, 2009; Xingcai, Zongxue, & Bo, 2009; Chai & Feng, 2009), in the Mediterranean basin (Livada & Assimakopoulos, 2007; So¨nmez, Ko¨mu¨scu¨, Erkan, & Turgu, 2005; Vicente-Serrano, 2006) and also in central (Vergni & Todisco, 2011) and southern Italy (Bonaccorso, Bordi, Cancelliere, Rossi, & Sutera, 2003; Capra & Scicolone, 2012).

In this study, drought was expressed using the Standardized Precipitation Index (SPI), which has been evaluated both on short- and long-time scales. A homogenized and gap-filled database for 129 monthly rainfall series in the 1916–2006 period has been used. From this analysis of the SPI values, three of the most severe drought events have been selected. The aim of this study was to analyze the spatial patterns, at different timescales, of the selected drought events using a geostatistical approach.

2. Methods

The study area was the Calabria region in southern Italy, with a surface of 15,080 km² and a coastline of 738 km on the Ionian and Tyrrenian coasts of the Mediterranean Basin. The region has an oblong shape with a length of 248 km and a width ranging between 31 and 111 km. The regional orography highlights mountainous features: 42% of the land is mountainous, 49% hilly and only 9% is completely flat with an average elevation of 597 m a.s.l. For its geographic position and for its mountainous nature, Calabria is a region with a high spatial variability of its climatic features and of hydrological phenomena such as flood and drought (Caloiero, Coscarelli, Ferrari, & Mancini, 2011).

The database used was the one presented in Brunetti et al. (2012), who performed multiple applications of the Craddock test (Craddock, 1979) for removing inhomogeneities and a two-step procedure proposed by Simolo, Brunetti, Maugeri, and Nanni (2010) for solving problems due to missing data. The original data were the monthly precipitation series relative to the period 1916–2006, registered in Calabria and collected by the former Italian Hydrographic Service. At the end of the homogeneity and gap-filling procedures, a total of 129 daily rain gauge measurements for the period 1916–2006 were made available for this analysis.

In the present paper, among the different drought indices, only the SPI has been adopted to assess drought occurrence in Calabria because the SPI allows climatic conditions to be monitored over a wide spectrum of time scales, and comparisons of dry and wet periods in different locations; moreover, it is based on precipitation alone, so that an assessment of meteorological drought is possible even when other agricultural and hydro-meteorological measurements are not available (Bonaccorso et al., 2003). The SPI can be considered the most robust and effective drought index and its main advantage is that it can be calculated for different time-scales; on short-time scales (e.g. 3 or 6 months) it describes drought affecting vegetation and agricultural crops, while on long–time scales (e.g. 12 or 24 months) it is more suitable for water resource management (Bonaccorso et al., 2003; Edwards & McKee, 1997). The computation of the SPI requires the knowledge of a frequency distribution from historical precipitation data (at least 30 years of data) at a location for a given time period. Lloyd-Huhes and Saunders (2002) provided a detailed description of the calculation of the SPI. In particular, they tested the standardization procedure (probability transformation) assuming normal, log-normal, and gamma statistics for precipitation, and concluded that the gamma distribution provides the best model for describing
monthly precipitation over most of Europe. The probability density function, $g(x)$, is defined as:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for} \quad x > 0$$  \hspace{1cm} (1)

where $\alpha > 0$ and $\beta > 0$ are the shape and scale parameters, respectively, $x$ is the amount of precipitation, and $\Gamma$ is the gamma function. The $\alpha$ and $\beta$ parameters of the gamma probability density function are estimated for each rain gauge, for each time scale of interest (3, 6, 12 and 24 months), and for each month of the year. The resulting parameters are then used to find the cumulative probability, denoted $G(x)$, of an observed precipitation event for the given month and time scale for the rain gauge considered. Since the gamma distribution is undefined at $x = 0$, and the precipitation distribution may contain zeros within the time scale considered, the cumulative probability becomes:

$$H(x) = 1 + (1 - q)G(x)$$  \hspace{1cm} (2)

where $q$ is the probability of zero precipitation. The cumulative probability distribution $H(x)$ is then transformed into the standard normal distribution to generate the SPI values. Table 1 shows the climatic classification according to the SPI suggested by the National Drought Mitigation Center. In this paper, results concerning both the short-time and long-time scales are discussed. The SPI on 3, 6, 12, and 24-month time scales has been calculated and then, with respect to the 129 rain gauges, dry events identified.

Among several drought events, the severest ones were selected and SPI data were spatially predicted and mapped using Ordinary Kriging (OK) (Webster & Oliver, 2007). SPI data were modelled as an intrinsic stationary process and each SPI datum $z(x_a)$ at different location $x_a$ ($x$ is the location coordinates vector and $a$ the sampling points $= 1, \ldots, N$) was interpreted as a particular realization of a random variable $Z(x_a)$. Interested readers should refer to textbooks such as Goovaerts (1997), Chilès and Delfiner (1999), Wackernagel (2003), Webster and Oliver (2007), among others, for a detailed presentation of the theory of random functions. The quantitative measure of spatial correlation of the regionalized variable $z(x_a)$ is the experimental variogram $\gamma(h)$ which is a function of the distance vector ($h$) of data pairs $[z(x_a), z(x_{a+h})]$. A theoretical function, called the variogram model, is fitted to the experimental variogram and allows estimation of the variogram analytically for any distance $h$. Experimental variograms can be modeled using only functions that are conditionally negative definite, in order to ensure the non-negativity of the variances. The objective is to build a permissible model that captures the main spatial features of the attribute under study. The variogram model generally requires two parameters: range and sill. The range is the distance over which pairs of SPI values are spatially correlated, while the sill is the variogram value corresponding to the range. The optimal fitting will be chosen on the basis of cross-validation, which checks the compatibility between the data and the structural model.

| SPI value                | Class            |
|-------------------------|------------------|
| SPI $\geq$ 2.00         | Extremely wet    |
| 1.5 $\leq$ SPI $<$ 2.00 | Very wet         |
| 1.00 $\leq$ SPI $<$ 1.50| Moderately wet   |
| $-1.00 \leq$ SPI $<$ $1.00$ | Near normal |
| $-1.50 \leq$ SPI $<$ $-1.00$ | Moderate drought |
| $-2.00 \leq$ PI $<$ $-1.50$ | Severe drought   |
| SPI $<$ $-2.00$         | Extreme drought  |
considering each data point in turn, removing it temporarily from the data set and using its neighboring information to predict the value of the variable at its location. The estimate is compared with the measured value by calculating the experimental error, i.e. the difference between estimate and measurement, which can also be standardized by estimating the standard deviation. The goodness-of-fit was evaluated using the Mean Error (ME) and Mean Squared Deviation Ratio (MSDR). The ME proves the unbiasedness of estimate if its value is close to 0, while the MSDR is the ratio between the squared errors and the kriging variance (Webster & Oliver, 2007). If the model for the variogram is accurate, the mean squared error should equal the kriging variance and the MSDR value should be 1. The fitted variograms were used to estimate SPI values at ungauged locations using Ordinary Kriging at the nodes of a 250 m × 250 m interpolation grid.

3. Results

Several dry periods have occurred during the last century with reference to short-term scales. In particular, one of the most important drought events occurred in the spring-summer of 1945. Dry conditions, which spread across the study area, have also been observed in the period 1990–1992. From 1950 to 1975 the worst dry conditions seemed to affect smaller areas and for a shorter time than previous ones. Most recently, in this century, the most severe and prolonged drought event has been detected in the autumn-winter 2001–2002 (Figure 1). The long-time scale SPI shows a different behavior than the short-time scale SPI. In particular, the most important drought events occurred from the 1980s onwards such as in the winters 1989, 1990 and 1992; in particular, the 1990 drought seems to be particularly important. Also for the long-time scale SPI, the most severe and prolonged drought event this century has been detected in the autumn-winter 2001–2002 (Figure 2).

Among all these drought events, those of March 1990, March 1992 and February 2002 have been selected and spatially analyzed to show examples of a short-term drought (1992), a long-term drought (1990) and both a short- and long-term dry period (2002; see Main Map).

With the aim of quantifying the spatial pattern of the SPI data for the selected events, a variographic analysis was carried out. A variogram map (not shown) was calculated revealing no relevant difference as a function of direction (anisotropy); the experimental variograms looked upper bounded. A bounded isotropic nested variogram model was fitted to each drought event (Table 2). With the exception of the 3-month, 6-month and 24-month SPI data of March 1990, the fitted models included a nugget effect and two spherical models (Webster & Oliver, 2007): one at short range and the other at long range (Table 2). This means that a spatial dependence of SPI data occurred at two distinct spatial scales. The nugget effect (Webster & Oliver, 2007) implies a positive intercept of the variogram. It arises from errors of measurement and spatial variation within the shortest sampling interval (Webster & Oliver, 2007). For March 1990, the fitted models for the 3-month and 24-month SPI data (Table 2) included a nugget effect and a spherical model, while the fitted model for the 6-month included two spherical models. The goodness-of-fit for the variogram models was verified by cross-validation and the statistics used, i.e. the mean of the estimation error and variance of the mean squared deviation ratio, showed satisfactory results (quite close to 0 and 1, respectively). The above variogram models were used with OK to produce the maps of predicted SPI data for the selected events.

From the spatial analysis of the three selected drought events it has emerged that the drought in 1990 was very important, from the perspective of water resources management. In fact with regard to the 24-month SPI calculated for March 1990, the drought event affected almost the entire region which falls within the severe or extreme drought classes. Similar results, but with
lower values, have been obtained for the 6-month SPI, in particular on the northern side of the region, affecting vegetation and agricultural practices. The 3-month and 12-month SPI showed higher negative values in the northeastern side of the region and near normal conditions in the south and, in particular, on the Ionian side. A different behavior emerged from the spatial analysis of the SPI data concerning the 1992 drought event. In fact, while for the previous event higher SPI negative values have been detected for both, the short-time and the long-time scales, this event is strictly related to vegetation and agricultural practices. With respect to the 3-month and the
6-month SPI, severe or extreme SPI values have been detected on the northern side of the region, in particular in the Ionian side and in the lower areas of this part of the region, while the extreme southern part of the region showed near normal conditions. The 12-month SPI presents high spatial variability, with severe or extreme SPI values on the Ionian side, moderate values in inland areas and in particular near areas of relief and near normal condition on the Tyrrhenian side. The last event analyzed was the 2002 one which affected the whole region in terms of vegetation, agricultural practices and water resource management.
Table 2. Variogram model parameters for SPI data.

| Variable Year   | Model       | Sill (–)    | Range (m)   |
|-----------------|-------------|-------------|-------------|
| March 1990      | Nugget effect | 0.0505      | –           |
| 3-month         | Spherical   | 0.4461      | 56,556.20   |
| 6-month         | Spherical   | 0.1322      | 8309.90     |
| 12-month        | Spherical   | 0.1693      | 36,882.20   |
| 24-month        | Nugget effect | 0.1391      | –           |
|                 | Spherical   | 0.0604      | 10,439.40   |
|                 | Spherical   | 0.1428      | 29,095.30   |
| March 1992      | Nugget effect | 0.0101      | –           |
| 3-month         | Spherical   | 0.032       | 14,602.90   |
| 6-month         | Spherical   | 0.4274      | 45,325.30   |
| 12-month        | Nugget effect | 0.033       | –           |
|                 | Spherical   | 0.1376      | 19,769.60   |
|                 | Spherical   | 0.1442      | 46,740.20   |
| 24-month        | Nugget effect | 0.0182      | –           |
|                 | Spherical   | 0.2599      | 8050.60     |
|                 | Spherical   | 0.216       | 51,782.00   |
| February 2002   | Nugget effect | 0.1125      | –           |
| 3-month         | Spherical   | 0.0933      | 15,699.00   |
| 6-month         | Spherical   | 0.1211      | 41,137.80   |
| 12-month        | Nugget effect | 0.0287      | –           |
|                 | Spherical   | 0.1882      | 11,172.40   |
|                 | Spherical   | 0.2335      | 42,512.90   |
| 24-month        | Nugget effect | 0.0657      | –           |
|                 | Spherical   | 0.1955      | 10,139.60   |
|                 | Spherical   | 0.2019      | 75,226.10   |
|                 | Nugget effect | 0.3089      | –           |
|                 | Spherical   | 0.1557      | 8735.50     |
|                 | Spherical   | 0.2441      | 77,800.50   |

4. Conclusion

The proposed approach allowed to analyze the spatial behavior of drought in the study area. First, the most severe dry periods, as well as the corresponding duration and areas affected, have been detected. The analysis on short-time scale SPI showed that the most important drought event occurred in the summer of 1945. Moreover, a general increase in drought events can be observed since the 1980s. The long-time scale SPI showed different behavior. Only few drought events can be observed before the 1980s, which affected small regional areas and relating to short time interval. Three events were selected and spatially analyzed. The geostatistical approach allowed to quantify their models of spatial variability, to predict their values at ungauged locations and to map them. From the spatial analysis of the three selected drought events it emerged that the event in 1990 was very important for its impact on water resources management. A different behavior emerged from the spatial analysis of the SPI data concerning the 1992 drought event which is strictly related to vegetation and agricultural practices. The last event analyzed was from 2002. It affected the entire region with impacts on vegetation, agricultural practices and water resource management.
Software

In order to collect monthly data at each rain gauge and to extract the SPI values, Microsoft Excel software was used. All statistical and geostatistical analyses were performed by using the ISATIS 2013.03. The spatial layout were created using Esri ArcGIS 9.3.1.

Acknowledgements

The authors thank the reviewers for their critical comments and suggestions, which greatly improved the quality of our manuscript and map.

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