



Drought distribution using the standardized precipitation index: case of Gabes Basin, South Tunisia

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Abstract

The current research examines the temporal and spatial distribution of drought in Gabes Basin (South-Eastern Tunisia), observed over the last four decades. Monthly data of precipitation, registered in nine synoptic stations spread over the watershed for the period extending from 1977 to 2015, were used to determine the standardized precipitation index to characterize drought. The SPIs displayed results, as computed at 3, 6, 12, 24, 48, and 72 months, helped define the periods of rainfall excess and deficit, corresponding to wet and dry periods, respectively. The relevant results proved to highlight a significant variability in the SPI-associated values. On the short-term scale, the reached results proved to display a frequent fluctuation exceeding the standards, while the long-term scale relating results appeared to indicate that the dry and wet periods turned out to be rather pronounced. Furthermore, by the increasing of time scales, the extension of drought conditions will increase. On the medium and long terms, however, dry spells characterized with long periods become less frequent. Thus, the most remarkable periods in drought intensities, durations, and extensions were detected during the end of 1980 and the beginning of 2000 for different rainfall stations studied. The major drought sequence was detected to take place over the period extending from 2001 to 2005 relevant to the SPI-72 months, affecting the whole watershed. It was also found that drought occurrence in the region was mainly influenced by medium- and long-term climatic factors. Furthermore, the spatial map distribution of extreme drought events for the long term was developed displaying the variation of drought severity across the study basin.

Keywords Drought distribution · Standardized precipitation index · Gabes Basin · Spatio-temporal variability

Introduction

Drought is a complex hydrologic extreme, which has a considerable impact on various fields such as agriculture, water resources (water scarcity), and ecosystems. It is one of the most disastrous climatic hazards affecting several areas worldwide (Wilhite 2000). It is considered as one of the most costly natural disasters in the world, engendering a

total economic damage estimated at USD 135 billion (Masih et al. 2014). In general, the insufficiency of precipitation for long periods causes droughts. In its latest reports, the Expert Group of Intergovernmental Conference on Climate Change reveals that there will be an occurrence of drought events in the future year (IPCC 2007). For these reasons, climate analysis is one of the important studies for the life of mankind (Gentilucci et al. 2018a, b). Several studies were interested in examining and assessing drought in various areas of the world (Dai 2011; Ellouze et al. 2009; Ionita et al. 2016; Wang et al. 2016).

Several definitions of drought have been suggested so far from conceptual and/or operational perspectives (Wilhite 2000). The conceptual definition helps to describe the extension of the phenomenon and its effects. It depicts drought as deficient rainfall extended over a long period that causes severe damages and yield loss (Ionita et al. 2016). The operational definition helps to precise and identify the drought events in a time frame and in terms of thresholds and severity (Ionita et al. 2016; Wilhite 2000). It is sought by the

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analysis and comparison of the actual situation with the past multi-year average. For example, in agriculture, daily precipitation is compared to evapotranspiration in order to estimate the rate of soil moisture depletion and identify.

The drought has also been addressed in terms of frequency, threshold/severity, and timespan. It is studied from three different perspectives depending on influential parameters such as rainfall, evaporation, the moisture of soils, vegetation, and streamflow (Ionita et al. 2016; Rajasekaran et al. 2018). For the first type, based on precipitation and evaporation, it refers to the meteorological drought. The second group, based on soil moisture and vegetation, represents agricultural drought. The third, based on stream flow, represents hydrological drought. On the other hand, the variability of droughts has been examined in several researches mostly focusing on local and regional study cases, particularly in areas exposed to severe drought such as the Euro-Mediterranean area (Livada and Assimakopoulos 2006; Touchan et al. 2008; Vicente-Serrano 2006), Southeastern Europe (Cheval et al. 2014; Koleva and Alexandrov 2008), and China (Chang et al. 2016; Zhao et al. 2015, 2017).

Drought sequences could be locally affecting one/several areas or even more extended context. They could last over various periods (months, seasons, or years). This natural phenomenon is so complex that there is not yet a uniform method developed to study droughts even though several drought indicators are commonly deployed (Dai et al. 2004; Ionita et al. 2016; Palmer 1965; Wells et al. 2004).

In fact, different indices have been developed for drought monitoring and quantifying such as Palmer drought severity index (PDSI), rainfall anomaly index (RAI), crop moisture index (CMI), surface water supply index (SWSI), standardized precipitation index (SPI), temperature vegetation drought index (TVDI), among others (Dai 2011; McKee et al. 1993; Palmer 1965, 1968; Sandholt et al. 2002; Shafer and Dezman 1982; Van Rooy 1965; Wells et al. 2004; Zhao et al. 2017). Zhao et al. (2017) used the modified temperature vegetation drought index (mTVDI) for analyzing temporal and spatial patterns of drought phenomenon in China (1982–2010). Results showed generally that drought frequency was increasing. Although, the severe drought frequency raised significantly (4.86%) while the slight drought frequency raised slowly during the study period. Wells et al. (2004) studied the self-calibrating Palmer drought severity index (SC-PDSI) at 761 sites in America such as Colorado, North Dakota, Nebraska, etc. The findings showed an evaluation of SC-PDSI. It was more spatially than PDSI index. It also reported the extreme dry and wet conditions including frequencies expected to rare conditions. McKee et al. (1993) have proposed a new characterization of drought. It explicitly specifies different time scales and uses the standardized precipitation index. This new

definition admits a consistent set of data which will be computed with drought begin, end, magnitude, and intensity. The SPI is also used as a drought monitoring tool at the beginning of 1992 in Colorado.

As far as statistical analysis of precipitation distribution is concerned, SPI is the most commonly used index. The SPI introduced by McKee et al. (1993) is based on long-term precipitation records that are fitted to a probability distribution which is then transformed to a normal distribution, ensuring zero mean and unit standard deviation (Bordi et al. 2001; Giddings et al. 2005; Guttman 1999; Van Loon 2015). In recent decades, there has been an increasing use of SPI as a powerful tool to assess the characteristics of droughts variability and drivers and to represent precipitation anomalies. The SPI allows accurately evincing and expressing drought severity and duration. Besides, SPI has the advantage to calculate the rainfall deficit over several time scales (3, 6, 12, 24 months or more) reflecting the effects of droughts on water usable sources. Each time scale is suitable to a specific impact: studying short scale SPI is better to understand the soil water storage (Edwards and McKee 1997); SPI-6 months are performant in analyzing the seasonal variation of rainfall; SPI-12 months and long-term precipitation anomalies/trends are well correlated to the variation of groundwater, streamflow, and reservoir storage (Boudad et al. 2018). It is worth noting that SPI is commonly used in more than 70 countries worldwide since experts have recommended it to all National Meteorological and Hydrological Services for studying droughts (Hayes et al. 2011; Svoboda et al. 2012).

In Tunisia, many studies showed that the occurrence of 1-year drought is highly frequent countrywide, while 2 years or more consecutive droughts are less frequent in the North, moderate in the center, and highly frequent in the south (Mouelhi and Laatiri 2014). Ellouze and Abida (2008) demonstrated a high variability of SPI values in the short term when drought events were characterized by high frequency and short duration. However, for the long term, the values stabilize and reveal less frequent but more prolonged sequences.

Considering SPI as an efficient tool for the computing and evaluation of drought evolution and distribution, this index was used in the present study to address the issue of drought identification and characterization in Gabes Basin, southeast of Tunisia. Various time scales (3, 6, 12, 24, 48, and 72 months) over the period extending from 1977 to 2015 were assessed by means of SPI for nine rainfall stations, evenly distributed over the study area, and extreme drought events were thus determined. In addition, SPI temporal variability in Gabes Basin for the nine rainfall stations was analyzed to identify the severity of the drought episodes that hit the watershed over the study period.

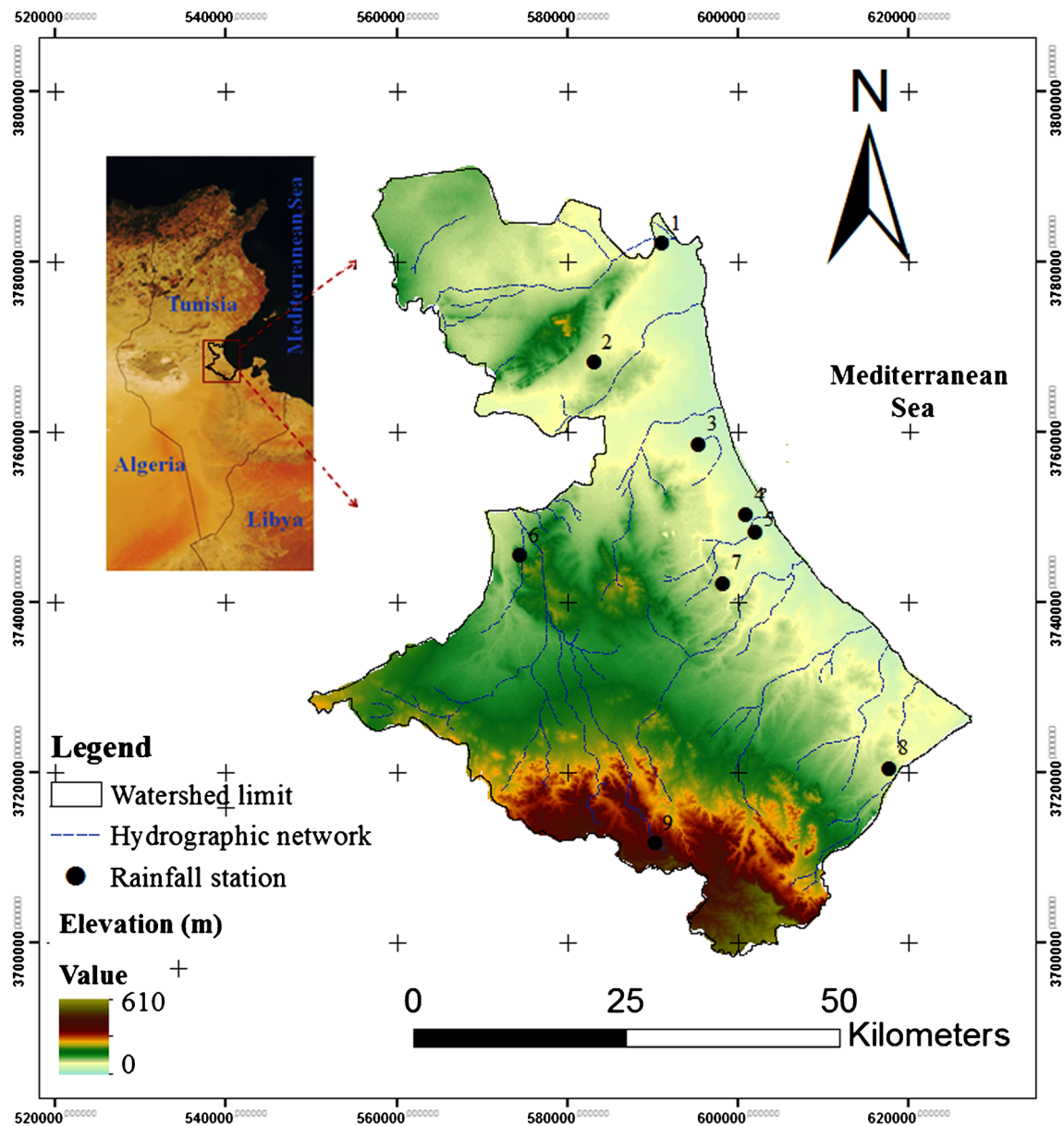


Fig. 1 Geographical situation and distribution of rainfall stations in Gabes Watershed

Materials and methods

Study area and data acquisition

The study area in this work concerns Gabes Basin, in the south-east of Tunisia (Fig. 1). The study basin has a Mediterranean climate, with an arid bioclimatic stage, characterized by mild and wet winters and hot and dry summers. Due to its position, it undergoes the influence of two climatic factors: the Sahara in the South and the Mediterranean Sea in the East. Annual temperatures range from 18 to 20 °C. Average annual evaporation varies between 1500 and 2000 mm. Most of the year, winds are of Eastern and North-eastern directions. Winds from the South and South-West, with average velocities exceeding 5 m/s, are

usually dry and are accompanied with sand storms. Gabes Basin is marked by its rainfall scarcity and erratic distribution, with intense events, resulting in flash floods. The mean annual precipitation over the study zone is about 158 mm where the highest records of more than 200 mm are registered in the East (coastal line) and the lowest records of less than 90 mm in the northwestern part (Ellouze et al. 2009).

Nine rainfall stations from Gabes Basin (Fig. 1) were used to collect a series of monthly precipitation data during the period 1977–2015. The precipitation data sets were obtained from the Tunisian official relevant authorities (DGRE 1977–2015). Most of the stations were coastal with altitudes not exceeding 100 m except for station 9, where the altitude is 441 m. At a first stage, the test of Man Kendall (Gilbert 1988;

Kendall 1957; Mann 1945) was applied to all datasets of rainfall in order to check their randomness, homogeneity, and absence of trends. All stations passed the test with a confidence interval of 95%. We note that the first step of the analysis consists of counting and verifying the precipitations series by using statistical criteria as stationarity, independence, and homogeneity tests. In the same context, Gentilucci et al. (2018a, b) confirmed that for having an important result, essentially reliable data is influenced by the quality controls and test of homogeneity. On the study of Climatic Variations in Central of Italy, data were validated with five control procedure. There were logical and gross error check, tolerance test, internal consistency check, spatial and temporal consistency (Gentilucci et al. 2018a, b).

Methodology

The standardized precipitation index (SPI) was calculated according to McKee et al. (1993) based on monthly data. In this work, SPI was computed for short- (3 months), medium- (6 and 12 months), and long-term scales (24, 48, and 72 months). The gamma probability density function was used to fit precipitation time series and then transformed/normalized to a normal distribution for which the mean is null and its standard deviation is unit. Accordingly, the SPI is the standard deviations indicating the values greater or less than the long-term precipitation median (Edwards and McKee 1997; Ionita et al. 2016).

This drought index is computed as mentioned for different time scales (short, medium, and long scales). It is determined by the following equation:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} X^{\alpha-1} e^{-\frac{x}{\beta}}$$

with α and β , the shape and the scale parameters of the distribution which are obtained by the method of least squares; $\Gamma(\alpha)$, the probabilistic gamma distribution function; X , the height of the rainfall at monthly scale.

The estimation of the SPI is done by adjusting the frequency distribution of precipitation in each station to the Gamma distribution. The values of the parameters α and β of the gamma function are estimated for each station and for each time scale (3, 12, 6, 24, 48, 72 months).

The drought intensities are classified into several categories (moderate, severe, and extreme) based on SPI values as per McKee et al. (1993). The present investigation concerns mainly the extreme drought conditions. In this context, to assess the spatial variability of droughts, the kriging technique was applied to characterize the Gabes area watershed in conformity with the SPIs drawn values. The methodology adopted of drought characterization and identification is presented in Fig. 2.

Results and discussion

Annual rainfall distribution

The annual variability of rainfall in the nine selected stations of the study area is shown in Fig. 3. The variability of annual rainfall in the selected stations over the period 1977–2015 is presented in the box plot of Fig. 3B to describe the global behavior of annual rainfall. Each box includes 50% of the data with the median value of the variable displayed as a line. Top and bottom of the box represent the inter-quartile ranges (25–50% and 50–75%). The lines extending from the top and bottom of each box mark the minimum and maximum values that fall within an acceptable range. Mean annual rainfall ranged between 101 mm in station 2, situated in the West, and 195 mm in station 8 in the South particularly in the coastal part. Figure 3 displays a rainfall distribution characterized by a high and irregular variability, from 1 year to the next, over the entire basin. It also identifies alternating wet and dry periods. Excess years were recurrent and intense especially in the East due to the proximity of this zone to the Mediterranean coastline, and the South due to the high topography of this area, which includes the mountains of Matmata. However, the rest of the basin (the North and the West), which represents plane continental areas was rather characterized by more frequent deficit years.

The results also show that a remarkable amount of precipitation falls in mountainous and coastal areas. Previous results have shown that precipitation generally increases with the topographical elevation and generally decreases away from coastal areas in Gabes Basin. In this context, Ellouze et al. (2009) observed that annual rainfall variability in southern Tunisia was influenced by topography. Accordingly, results obtained show that rainfall variability in Gabes Basin is influenced by the effects of altitude and the Mediterranean Sea. Therefore, it was also important to note the influence of the Mediterranean Sea conditions on annual rainfall distribution in the study zone.

Analysis of SPI 3, 6, 12, 24, 48, and 72 months

SPI was used to characterize hydrological extremes in Gabes basin for the study period. We computed the SPI for each month, then for August based on the annual rainfall of the previous 12 months from September, considering a whole hydrological year. Figures 4 and 5 display the temporal distribution of the monthly values on various scales: short (SPI-3 months), medium (SPI-6 and 12 months), and long terms (SPI-24, 48, and 72 months) starting from 1977 to 2015 for the nine selected stations. The obtained results show a heterogeneous distribution in the short and medium terms over the whole. It can be seen that different drought indices demonstrate almost similar variation patterns in the long term, but

Fig. 2 Flowchart of methodology for drought characterization

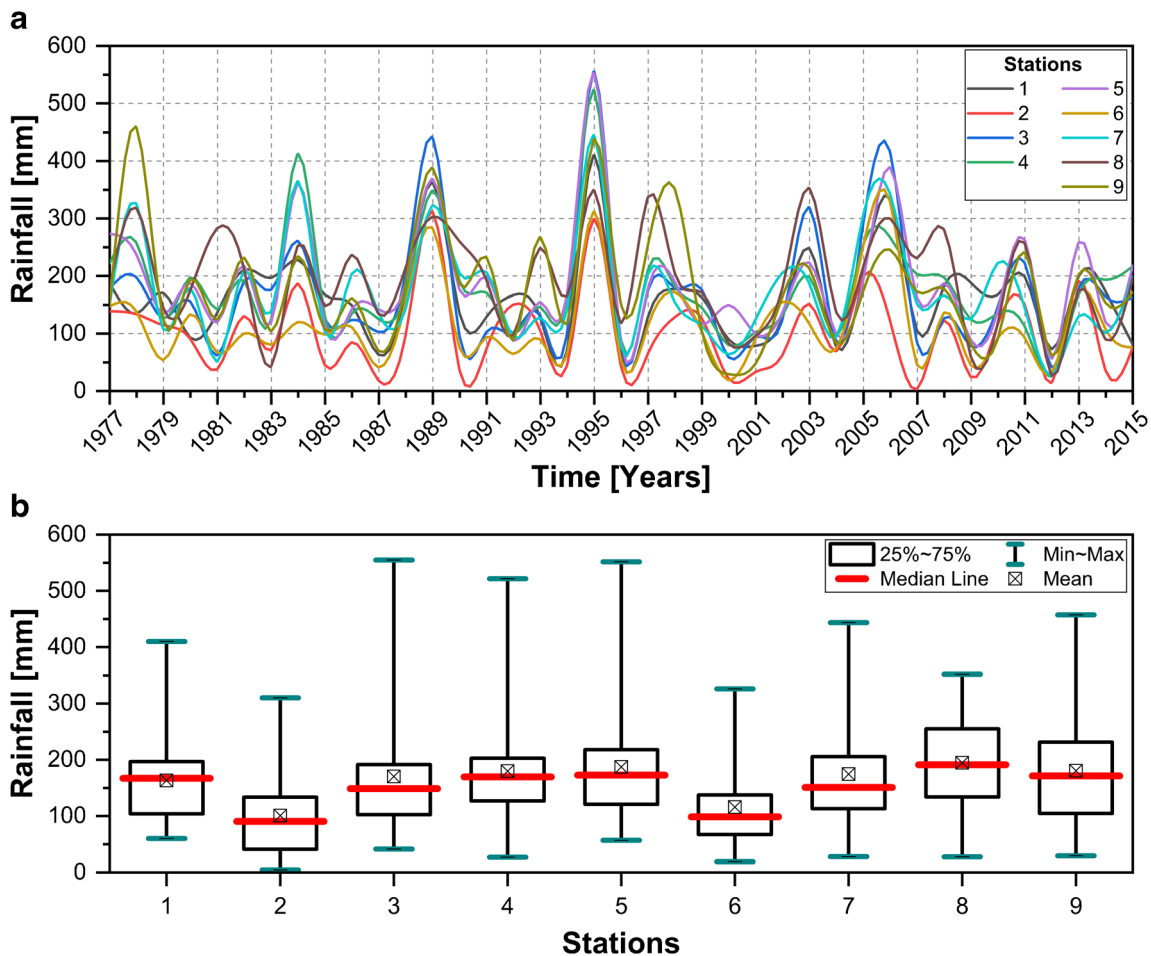
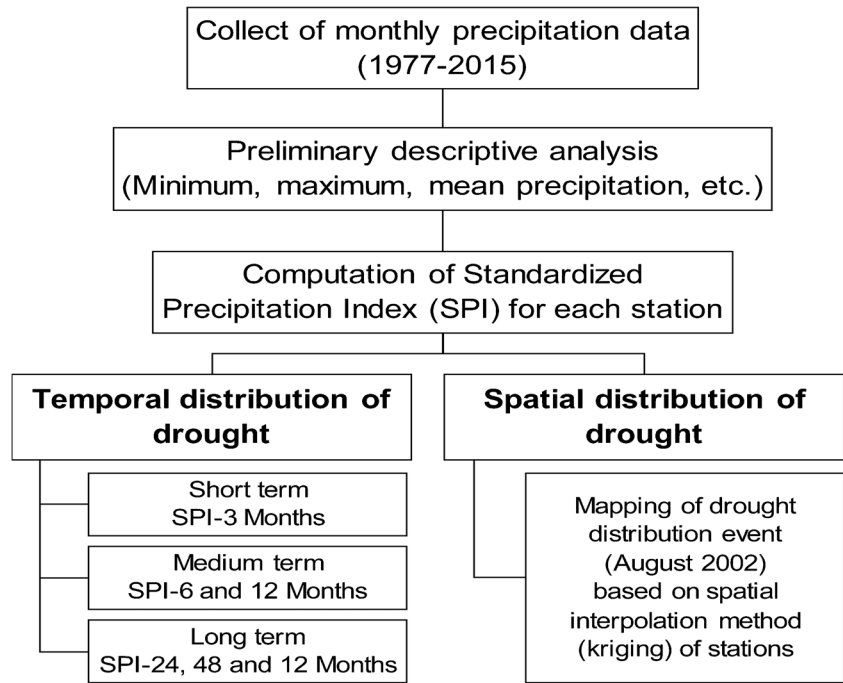
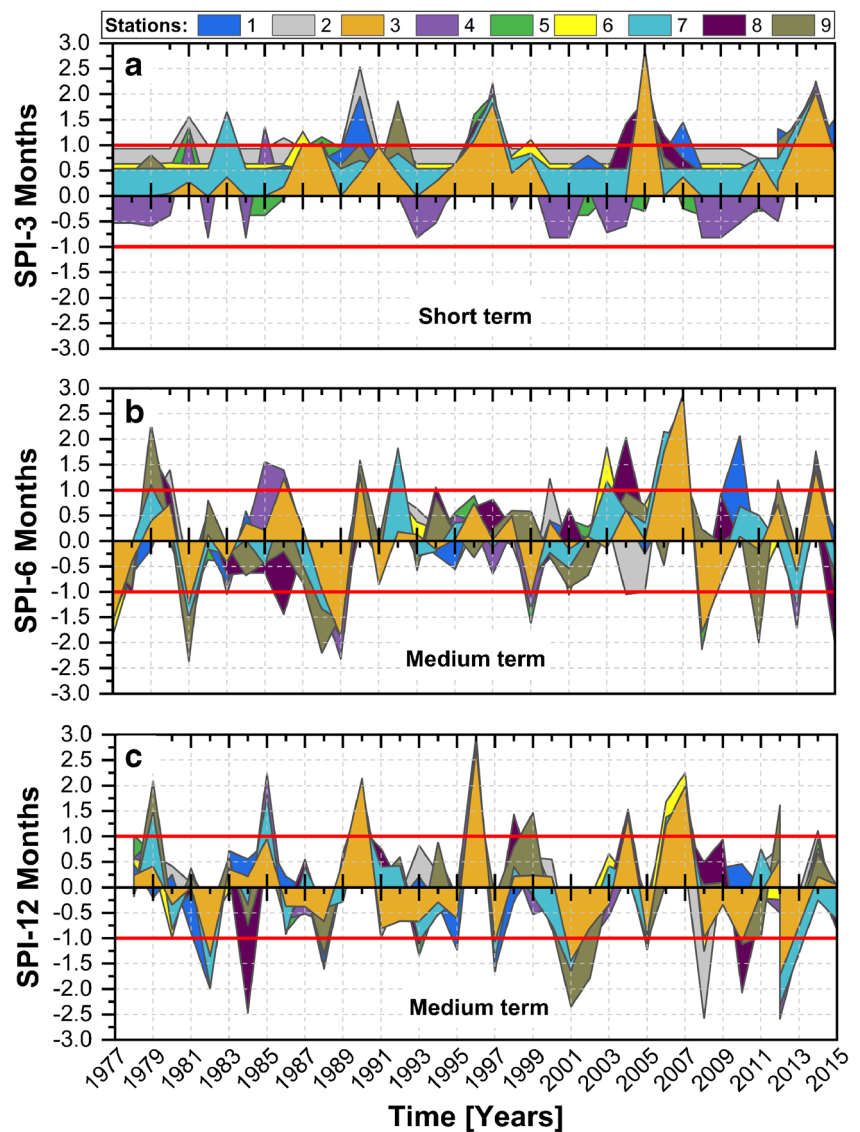


Fig. 3 **A** Annual rainfall variability at nine selected representative stations (1977–2015); **B** Box plot of annual rainfall variability for each station

Fig. 4 Temporal variation of SPI at short and medium term for the nine examined stations (1977–2015). (a) SPI-3 months, (b) SPI-6 months, (c) SPI-12 months

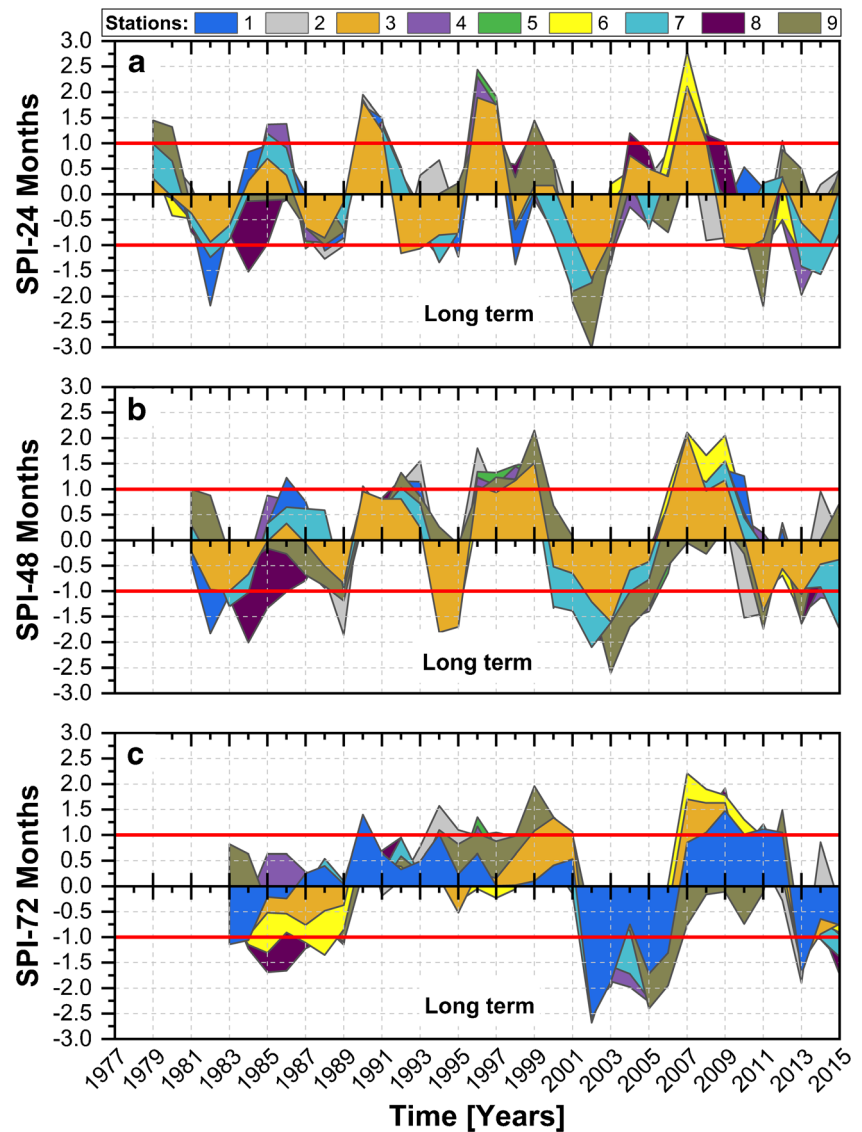


display some differences in particular drought events with regard to their intensity/severity and duration. As could be inferred from Figs. 4 and 5, dry sequences alternated wet sequences, although there was not any evident trend at different time scales.

As seen in Figs. 4 and 5, this prolonged dry period is clear and pronounced at medium-term (SPI-6 and 12 months) as well as at long-term (SPI-24, 48 and 72 months) scales. SPI-3 months presents a high occurrence of alternated dry/wet episodes (Fig. 4a). SPI-3 months fluctuates frequently above the standard at the short-term scale. With an increased scale, the frequency of variation dry/wet episodes is lower and displays a longer duration. At SPI-12 months, results displayed a heterogeneous distribution over the entire Gabes Watershed. Each station was found to have its dry periods; however, some years seem exceptionally dry or wet in the whole study area. In general, an annual analysis of rainfall reveals the same trend

(increasing and decreasing) between the different stations but with different magnitudes over the study period. Alternating periods of excess and deficit of precipitation are well defined in all studied stations. In the long term (SPI-24, 48, and 72), the alternating excess and deficit precipitation periods are also well defined and individualized. In effect, the longer the selected time scale is, the less likely it is for the historical data and the statistical index to vary. This would help us accurately define the dry episodes, which necessitates using long-term time scales for effective characterization of the drought sequences to take place. At the SPI-72 month-scale level, the 4-year frequency of successive dryness sequences turns out to be easy to detect. On synthesizing the above-cited analysis, the following dry years could be historically identified: 1997, 2001, 2002, 2003, 2004, 2005 (Fig. 5). According to Fig. 5, the deficit episodes proved to be more frequent than the wet episodes concerning the years 1980 and 2000, with regard to

Fig. 5 Temporal variation of SPI at long term for the nine examined stations (1977–2015). (a) SPI-24 months, (b) SPI-48 months, (c) SPI-72 months



the nine stations. Such finding has already been supported by a number of previously conducted studies. Indeed, the latter proved to indicate that the semi-arid parts of Africa stand as some of the most drought-prone regions, and that the risk for these drought events to increase even more is more likely (Bank 2010; Masih et al. 2014; Rojas et al. 2011; Schilling et al. 2012). North Africa would be particularly affected with considerable droughts, featured with a noticeably reduced intensity of precipitation, higher frequency and longer duration of drought periods (Beniston et al. 2007; El Rafei 2009). It was also discovered that the droughts characterizing the decades 1980s and 2000s were intense and widespread (Masih et al. 2014). Arid areas in Africa are extremely sensitive to droughts due to the high heterogeneity of climatic patterns as well as to other reasons, including, poverty, high dependency on rainfed agriculture, and poor infrastructure, in addition to the lack of effective resources management and disaster

recovery strategies (Masih et al. 2014; WBGU 2008). The frequent predominance of hydrological extremes, mainly floods and droughts, can be closely related to the potential impacts of climatic changes on the hydrological cycle (IPCC 2007). Generally, precipitations tend to reflect the persistence of local climatic characteristics. The findings reached by the present study appear to suggest that determining the precise influence of the precipitation regime on the Gabes watershed specificities can be informative of the local and global climatic changes.

Spatial variability of the drought events

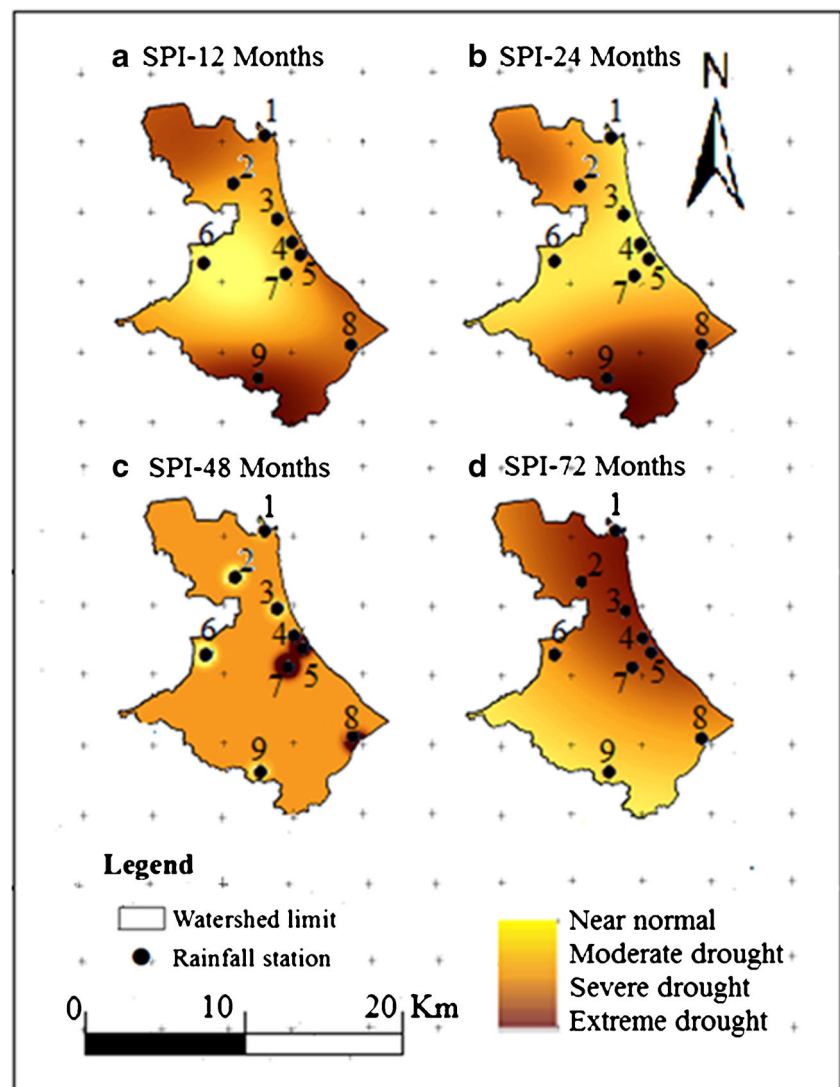
Four of the most severe drought events were selected to investigate and compare their spatial distribution through variographic analysis and ordinary kriging technique. These drought sequences took place in August 2002. In the first

place, the experimental variograms were calculated. Then, various variographic models are tested to select the best-fit model. Adjustment of the variogram model was performed via ArcGIS 10.1. The best values fit for application with the variogram model were selected through testing the three following models: spherical, Gaussian, exponential. The model displaying the least error should be selected. The Gaussian model proved to yield the lowest error rate. Therefore, it was selected as being the most suitable model. It was implemented to map SPI in the medium- and long-term (SPI-12, 24, 48, and 72 months) scales, with expectations to the Gabes catchment. It ended up by opting for in the choice of the Gaussian distribution model, whereby rainfall variability could be more effectively represented.

SPI maps were elaborated to represent the four most severe identified drought events, in a bid to represent the spatial variability of precipitation (Fig. 6a–d). They were performed to characterize the long-term drought variability relevant to the Gabes Basin. The SPI Mean monthly values proved to range

from -3.01 to -0.23 throughout the study period. It helped display the spatial heterogeneity of the hydrological extreme drought in the Gabes Basin. This remarkable fluctuation noticeable in SPI appeared to be higher, indicating the extreme intensity of drought phenomena over the period ranging from 1977 to 2015. Figure 6a (August 2002) depicts similar drought conditions throughout the entire study area, except for the Southern region, where a rather severe drought condition was observed (station 9). This status illustrates relatively normal to moderate drought conditions, as identified throughout almost the entire basin. Figure 6b (August 2002) exhibits different severe and extreme drought conditions. Moderate conditions are exceptionally observed throughout the eastern region (station 5). Concerning the August 2002 event (Fig. 6c), moderate drought conditions were observed to persist across the different parts of the basin. Still, a severe and extreme drought appeared to characterize both of the Southern and coastal regions (stations 4, 8, and 7). Figure 6d (August 2002) highlights the predominance of extreme drought patterns, with relatively normal

Fig. 6 Spatial evolution of SPI in Gabes Watershed for dry episode: August 2002. (a) SPI-12 months, (b) SPI-24 months, (c) SPI-48 months, (d) SPI-72 months



to moderate drought conditions prevailing in the North and South (stations 6, 8, and 9).

Figure 6 illustrates the spatial evolutions of drought phenomena, as detected using medium- and long-term scales (SPI-12, 24, 48, and 72 months), highlighting a wide range of drought conditions. Indeed, it indicates that the spatial extension of drought conditions would tend to increase with the increase in time scale. Noteworthy, however, is that the drought condition, as revealed by the SPI-72 months, proves to be more pronounced, highlighting extreme drought categories. The long-term analysis (24 and SPI-72 months) proved to indicate that severe and extreme droughts appear to be characterized with higher probabilities, compared to moderate events persistent in most of the Gabes Watershed. Extreme dry conditions are more prominently observed by SPI-72 months concerning almost the entirety of the studied basin, except for stations 6, 8, and 9. Based on the reached records, the SPI-72 months turns out to perform far better than the SPI-12, 24, and 48 months in detecting the spatial evolution of the drought event. Concerning the present study, the SPI-72 month time scale proved to stand as a rather effective tool useful for identifying the recurrence of dry periods in the arid region. In another conducted research, the SPI at a 12-month time scale was selected because it proved to stand as the most suitable fit for water-resource management purposes and more appropriate for identifying the persistence of dry periods (Milanovic et al. 2014). On increasing the time span, a slower response of SPI to the rainfall changes was perceived. The 12-month time scale related results appeared to indicate the persistence of dry periods of long duration, closely connected with the drought global impact on the region's hydrologic regimes and water resources (Moreira et al. 2008).

Conclusion

Tunisia, and particularly the South-East, stands as one of the highly arid regions lying in the Mediterranean Basin. It is faced with a great problem of water scarcity. Drought is an extreme hydrological phenomenon, which proves to damage the water-scarcity situation and to have significant negative socio-economic impacts. This study is conducted to investigate the spatio-temporal variability of natural drought hazards occurring over the period 1977–2015, across the Gabes Basin, South-East Tunisia. The analysis was focused on computing the standardized precipitation index (SPI), as observed at different time scales (3, 6, 12, 24, 48, and 72 months scales). The SPI was applied to identify the dry and wet episodes, along with the spatial distribution of drought in the Gabes Basin, during the period 1977–2015, using monthly precipitation means. Actually, the period extending from 2001 to 2005 was identified through SPI-72 months. It was detected as

major drought sequence in terms of duration and spatial extent. Drought intensive periods present a cyclic behavior with a several years in Gabes region as indicated by the long-term observation data. It was found the frequency of successive sequences of dry 4 years at the SPI-72 months. The most notable drought intervals were mostly discovered to prevail during the end of the year 1980 and the beginning of the year 2000, with respect to the nine rainfall stations. The comparison established between them has displayed similar climatic conditions and common dry spells with the same frequency, duration, and severity ranges. The attained results displayed a large spatial extent of affected area which was influenced with the severe and extreme drought conditions persistent across the different parts of the Gabes Watershed, except for the SPI-12 months. Generally, dry conditions proved to be more prominent, as observed on the basis of SPI-72 months.

This finding suggests clearly that various water-resource management strategies should be revised and modified in terms of accordance with temporal variability of precipitation and spatial extent of drought. The study should provide us with great help in distinguishing drought circumstances relating mainly to the water resources and agricultural conditions relevant to the study basin. It also helped to evaluate the potential drought risks in the region and assess the possible outcomes of such a natural risk on the environment, society, and economy. It serves to provide some effective solutions likely to be adopted, in a bid to mitigate the drought related impacts.

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