



Revisiting Major Dry Periods by Rolling Time Series Analysis for Human-Water Relevance in Drought

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Received: 2 February 2022 / Accepted: 30 April 2022 / Published online: 20 May 2022
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Abstract

Drought is increasingly gaining importance for society, humans, and the environment. It is analyzed commonly by the use of available hydroclimatic or hydrologic data with little in-depth consideration of specific major dry periods experienced over a region. Also, it is not a common practice to assess the probability of drought categories with a rolling time series and hence the changing knowledge for operational drought monitoring. A combination of such quantitative analysis with a comprehensive qualitative assessment of drought as a human-water relation aimed to fill this gap performing a case study in the Seyhan River Basin, Turkey. Six major dry periods were identified from the precipitation time series of 19 meteorological stations. Major dry periods were analyzed by rolling time series and full time series, and they were also analyzed individually. A major dry period could be important in terms of its duration while another in terms of its severity or intensity, and each with its own impact on the human-water relations that can be influential on the drought mitigation, management and governance. Significantly higher probabilities were calculated for extreme droughts with the use of individual major dry periods. An important outcome from the study is that drought is underestimated in practice with the sole use of the whole data record.

Keywords Meteorological drought · Rolling time series · Seyhan River Basin · Spatiotemporal analysis · Standardized precipitation index

1 Introduction

Drought can broadly be defined as a prolonged deficit in hydrological/meteorological drivers without being confused with water shortage, where water demand is greater than water supply (van Loon et al. 2016). It is a natural hazard (Tsakiris et al. 2013; Khanmohammadi

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et al. 2022) unless it is caused or intensified by human activities, which may then be called anthropogenic drought. It is a threat to water and food security, and consequently to all water-dependent sectors. It can make even wealthy societies vulnerable by causing conflicts between water users, affecting the human-water relationship, disturbing the environment, and reducing the resilience of the ecosystem conditions.

A drought impact is an observable loss or change that occurred at a specific place and time. It has a widespread impact on various elements of hydrological cycle; a prolonged drought reduces soil moisture (Williams et al. 2009; Singh et al. 2019), and with excessive withdrawal it might cause groundwater level to deplete which may then permit salt water intrusion into the freshwater aquifer in a coastal river basin (Basack et al. 2013, 2022). There is little consensus on which type of drought analysis is most meaningful for the measurement of drought impacts on society and environment (Bachmair et al. 2016). Society needs information about when and where drought conditions transform into impacts. Such information can help people to prepare and react proactively by developing management and response strategies to mitigate drought impacts. Despite numerous drought studies in the literature, what knowledge is missing is an integration that bridges the gap between scientific developments and current operational practices including drought impacts.

In drought analysis, physically measurable indicators such as precipitation, streamflow and groundwater are conventionally used (Bonaccorso et al. 2012) together with indices; Standardized Precipitation Index (SPI; McKee et al. 1993), Normalized Difference Vegetation Index (NDVI; Kogan 1995), Streamflow Drought Index (SDI; Nalbantis 2008), Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010), Effective Reconnaissance Drought Index (Tigkas et al. 2017), Discrepancy Precipitation Index (DPI; Tayfur 2021) and Standardized Supply and Demand Water Index (SSDWI; Zhou et al. 2022) among many others. There exists a comprehensive body of literature using drought indices (Yacoub and Tayfur 2017; Roushangar et al. 2022). They are useful in the determination of the onset, development, recovery, termination of drought (Nemati et al. 2019), and in the quantification of its severity, intensity and frequency (van Loon 2015; Sattar et al. 2019; Aksoy et al. 2021; Kim et al. 2022). The collection of these characteristics provides a good basis to monitor drought effectively, to take proper measures against drought, and to keep drought exposure at an affordable level (Heim 2002).

In this study, we focus on the Seyhan River Basin in the Eastern Mediterranean. It is the breadbasket of the country because of the richness of the agriculture and advantageous climate. The river basin experienced extended periods of below-normal precipitation and major dry periods. Recent droughts in 2008 and 2014 raised concerns to preparing the Drought Management Plan at the governmental level (GDWM 2019). It could be considered representative for other regions with a similar climate in this wider area. Due to its geographical proximity, a comprehensive drought analysis will be particularly helpful in getting knowledge applicable to the Eastern Mediterranean region and Middle East because of some general problems such as poor data, inadequate models or misspecification of variables controlling drought and also the political instability (Barlow et al. 2016; Ide 2018).

Previous studies only considered the full records of meteorological data in the drought analysis. In this study, we revisited the drought by focusing on major dry periods that the river basin exposed to in the past. As a new approach, we introduced a non-stationary rolling time series analysis, which is composed of data recorded until each dry period first to which the length of the dry period itself is added. The non-stationary analysis proposed in this study is more complex than the common practice of the stationary time series analysis. Besides this technical context, we discuss the results through the relation of humans to

water as emerged from the amplified potential for sociopolitical and economic disruption of drought in the Eastern Mediterranean (Cook et al. 2016). The aim of this study therefore focuses at identifying individual major dry periods from the precipitation records of the river basin to respond following research questions:

- Which additional insight can be gained from revisiting major dry periods?
- How can a time series analysis be made more useful for not underestimating the drought?
- How can the quantitative outcomes be converted into qualitative knowledge through human-water relation?

Our research questions are addressed using two complementary approaches; firstly, through revisiting each major dry period and implementing the rolling time series analysis of SPI, and secondly, through a qualitative analysis of drought as the relation of humans to water. We close the analysis with a quantitative and qualitative discussion of the results regarding the major dry periods and their use in practice, to identify the knowledge gaps, conclusions and ways forward.

2 Material and Methods

2.1 Study Area and Dataset

Turkey is divided into 25 hydrological basins among which Seyhan River Basin is in the southern part of the country (Fig. 1). The river basin's headwaters rise to 3700 m a.s.l. in the

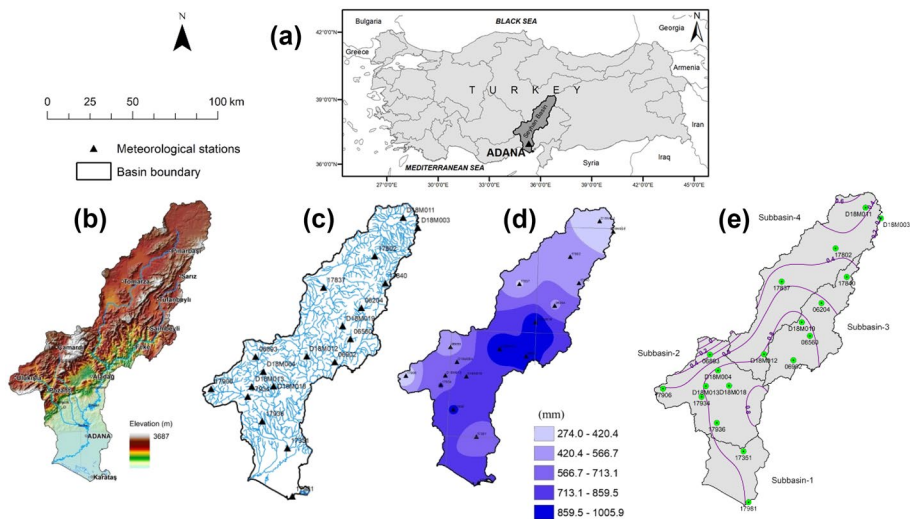


Fig. 1 (a) River basins of Turkey and location of Seyhan River Basin over the country, (b) Topography, (c) Drainage network of surface water courses and meteorological stations, (d) Areal precipitation distribution, (e) Sub-basins of river basin, and spatial distribution of cross-correlation calculated for annual precipitation of each station with respect to the basin-average

mountainous north. It has a dense drainage network of tributaries joining the Seyhan River before it discharges into the Mediterranean Sea. Precipitation is the highest in the central part of the river basin. Average annual total precipitation in the river basin is 641 mm, 67% of which falls during the winter and spring months under the influence of the Mediterranean low-pressure systems (Cavus and Aksoy 2019, 2020). The river basin drainage area is 22,042 km², and it accommodates approximately 2 million of population within the basin. About 900,000 ha of lands which cover approximately 41% in the basin are used for agriculture. Dry farming is practiced in 78% of the agricultural land and the rest is irrigated. With 2,546 industrial facilities, Adana has 98% of the industrial facilities in the basin and is the most concentrated province in terms of industry (GDWM 2019).

Monthly precipitation data of 19 meteorological stations operated by the State Meteorological Service (MGM) and the General Directorate of State Hydraulic Works (DSI) were obtained for the study. The stations are almost evenly distributed over the river basin (Fig. 1), and their record length varies between 10 and 57 years.

2.2 Major Dry Periods

A single time series was obtained from the average of the annual precipitation records of 19 meteorological stations for the period 1959–2016. The average of annual precipitation was calculated for each year t as

$$\bar{P}_t = \frac{1}{n_t} \sum_{i=1}^{n_t} P_i \quad t = 1, \dots, N \quad (1)$$

where P_i is annual precipitation at station i and n_t is the number of stations for which data exist at year t . The number of stations is changing for each year as we used the whole record period of each station not a common period of all. This was repeated for the length of the time series N . The overall average through the length of the time series was then taken by

$$\bar{P} = \frac{1}{N} \sum_{t=1}^N \bar{P}_t \quad (2)$$

The difference between the average in each year and the overall average of the time series was obtained as

$$P_t = \bar{P}_t - \bar{P} \quad t = 1, \dots, N \quad (3)$$

which was called either surplus or deficit depending on whether it takes a positive or a negative value, respectively.

The surpluses and deficits in the time series indicate that the river basin experienced major dry periods (Fig. 2). We identified six major dry periods in 1962–1965, 1970–1974, 1984–1986, 1989–1990, 2002–2008 and 2013–2015. A deficit that lasted 2-year long at minimum was defined as a *major dry period* in this study. This is in accordance with previous studies which found that a 2-year long dry period could impact on the region with important negative consequences; e.g., the 1989–1990 dry period (Altin et al. 2020).

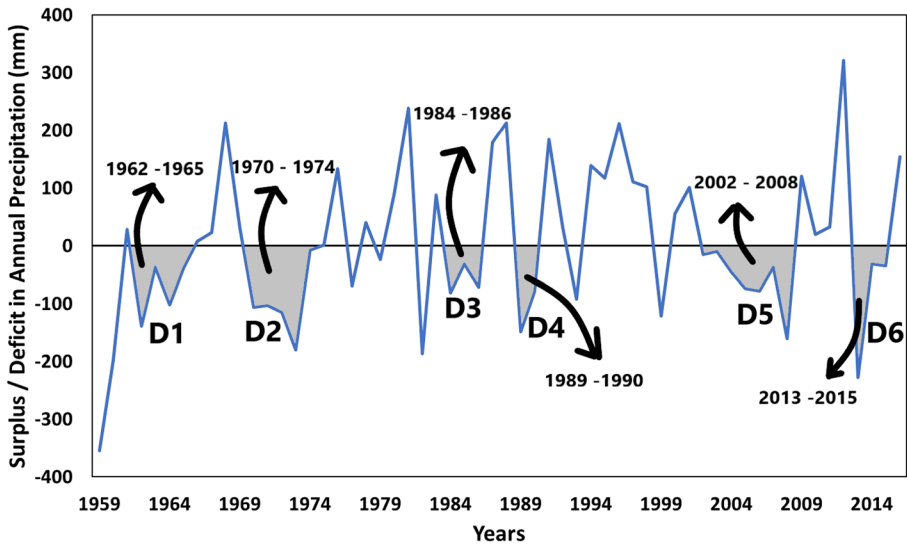


Fig. 2 Major dry periods identified from annual precipitation surplus and deficit time series in the Seyhan River Basin

2.3 Temporal Analysis of Major Dry Periods

In this study, drought was investigated based on SPI, which is one of the most commonly used drought indices due to its availability for diverse time scales and limited data needs. Precipitation is assumed to fit by Gamma distribution which can be alternated by other probability distribution functions (Stagge et al. 2015). Depending on the value of SPI, drought is categorized as mild ($-1.0 < \text{SPI} < 0$), moderate ($-1.5 < \text{SPI} \leq -1.0$), severe ($-2.0 < \text{SPI} \leq -1.5$), and extreme ($\text{SPI} \leq -2.0$). Temporal analysis of major droughts was performed through drought probability graphs. Drought probability is the likelihood of a drought event which is quantified as the frequency calculated from the SPI time series by counting number of months falling into a given drought category (Eris et al. 2020).

The Seyhan River Basin consists of four sub-basins (GDWM 2019) each represented by a station. In selecting representative stations, we focused on two criteria; (i) cross-correlation of the annual precipitation of stations with the basin average, (ii) time series length of their record to cover as many of the major dry periods as possible. The correlation of the meteorological stations with the basin average was calculated. It changes from one station to another within the range of 0.192 to 0.901. It increases in the central part of the basin where most of the stations are located and decreases northerly (Fig. 1e). The representative stations are 17351 for sub-basin 1, 17936 for sub-basin 2, 17837 for sub-basin 3, 6902 for sub-basin 4. It should be mentioned that representative stations of sub-basins 2 and 3 have the second highest correlation. They were preferred as they have longer periods of record to cover larger number of dry periods (4 dry periods each) than the stations with the highest correlation.

2.4 Temporal Analysis with Rolling Time Series

The key assumption of time series analysis that precipitation is stationary changes considerably due to climate change or variability. Rolling analysis is often used to assess the nonstationary of a time series (Zivot and Wang 2006). It is commonly used to back test a statistical model established on historical data to evaluate its stability and accuracy in prediction. The back testing works in the following way in this study:

The time series was divided into a reference period and a redefining event (Fig. 3). The portion before the major dry period (e.g., R1 in Fig. 3) was defined as the reference period, and the major dry period itself was called the redefining event. The analysis was made first using the time series until the major dry period starts (R1) to define the drought characteristics; it was then extended to the end of major dry period (the redefining event, R1 + L1). The time series was rolled to the next reference period (R2) and the redefining event (R2 + L2). This was repeated until the end of the last major dry period was reached. Occurrence probabilities of each drought categories were calculated for the collection of major dry periods and their reference periods to compare with the full-record of the time series.

Using SPI time series, major dry periods were analyzed (or revisited). The SPI time series were calculated for each reference period and the redefining event at different time scales. Comparison was made between SPIs calculated from the reference periods including major dry periods (Rn + Ln). With the use of the rolling time series in revisiting major dry periods, it has been possible to extract the change in the drought occurrence probability over time. This makes the concept of the ‘revisiting’ of this study clear/important for water managers before a dry period starts. The new aspect of this study might be significant considering a ‘rolling’ drought probability estimate that each drought event management would have had from the past until then.

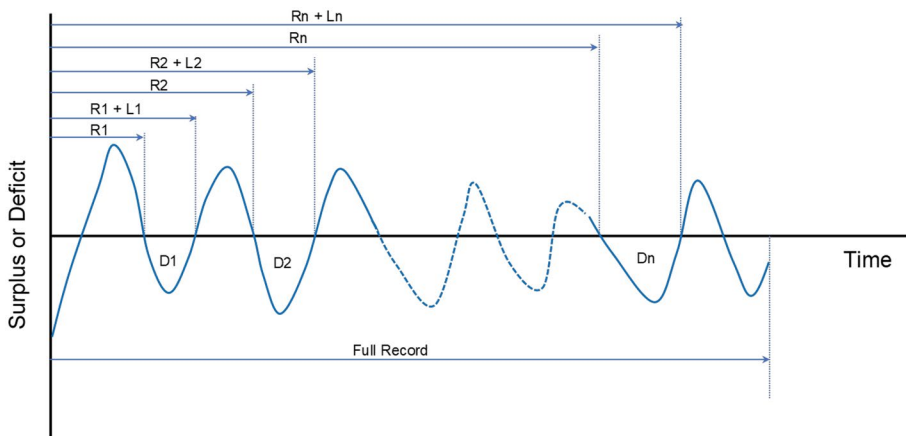


Fig. 3 Rolling time series analysis. D denotes the major dry period (redefining event), R and L show the lengths of each reference and major dry periods, respectively

3 Results

3.1 Characteristics of Identified Events

The SPI time series show temporal variation of major dry periods (Fig. 4), which illustrates similar patterns for each time scale with varying drought characteristics such as the duration, severity and intensity. In terms of the time scale, the frequency of SPI decreases with

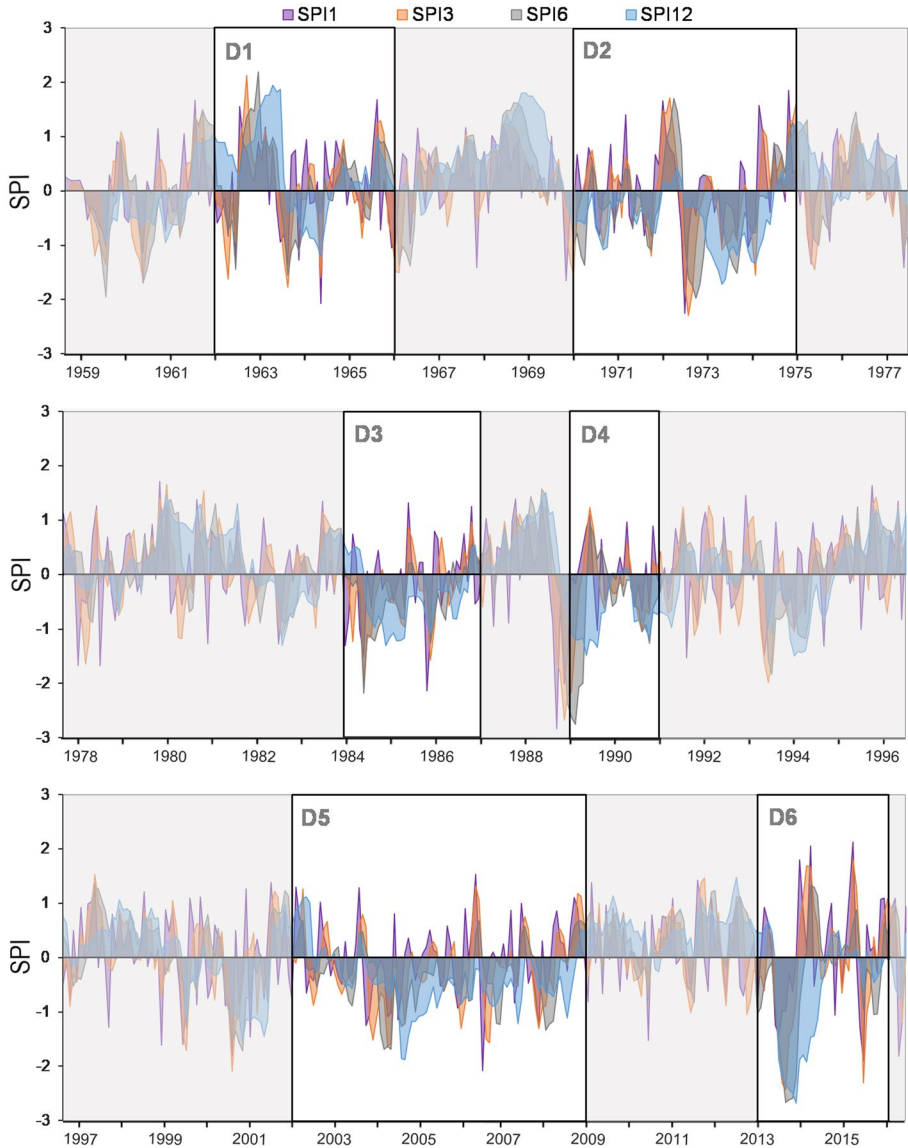


Fig. 4 SPI time series of major dry periods at 1, 3, 6 and 12-month time scales

moving from one-month time scale to longer scales. Wet and dry periods are frequent in shorter time scales. Wet periods are dominant between 1962–1963 in D1, 1971–1972 in D2, 1988–1989 in D4 and 2013–2014 in D6. In some of the major dry periods, these wet periods last up to one year at the longer time scales. For example, in D1, the year 1963 is mostly wet and the next year (1964) is dry.

3.2 Temporal Analysis

3.2.1 Major Dry Periods

Figure 5 shows how each drought category changes among major dry periods and in the full record period. Mild drought has the highest percentage for all major dry periods at each time scale. Its probability is the highest (60%) for station 17837 in D3 at SPI6. At the same station and at the same time scale, extreme drought reached the highest probability (25%) in D4. For station 17351 at SPI3, mild drought exceeds 50% in D2 while it is exactly 50% in D3; which means dry periods D2 and D3 have mild droughts at least for the half of their record lengths. Similarly, at least in half of the record lengths, dry periods D2 (50%) and D3 (52.8%) have been mild in SPI6. The number of mild droughts in half of the record length at minimum has increased to three (D3, 58.3%; D4, 50%; D5, 56%) in SPI12. This shows how the frequency of the mild drought category increases with increasing time scale. This is the case about the mild drought in one hand; on the other hand, the extreme drought has not been observed in some of the major dry periods. For example; D1, D2 and D6 have not experienced extreme drought in SPI1, and D1, D3 and D4 in SPI12 at the same station. D2 and D5 are two dry periods that have the highest probability of extreme and severe droughts in SPI12. With increasing time scale, more strengthened droughts change to less strengthened droughts although results do not show a systematic change in the probability of drought categories. However, in general, the probabilities of the drought categories show a similar character for all stations (Fig. 5).

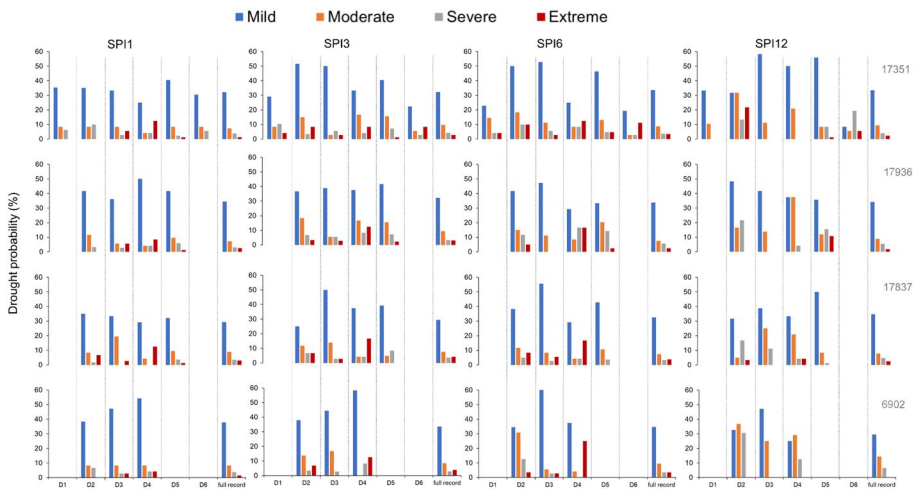


Fig. 5 Probability of drought categories for major dry periods and the full record (SPI1, SPI3, SPI6, SPI12)

3.2.2 Rolling Time Series

Figure 6 shows how the probability of each drought category changes among the reference periods, redefining events and in the full record period. The first reference period and redefining event (R1 and R1+L1) were skipped, because the number of meteorological stations with long precipitation time series is not sufficient. Mild drought has the highest percentage for all reference periods and redefining events, and it is the most frequent drought category at all-time scales. However, the percentage of mild droughts is lower when the reference period and redefining events are considered instead of taking major dry periods individually. For example, the probability of mild drought approached 40% for station 17351 in the second redefining event (R2+L2 in Fig. 6) at SPI6. At the same station and at the same time scale, the percentage of extreme drought reached (4%) in R5. For station 17936 at SPI12, mild droughts approached 40% in R2+D2, R3 and R3+D3 while no extreme drought was observed in these periods; which means mild droughts dominate. This situation can be observed in other meteorological stations; i.e., extreme droughts observed in short time scales changed to mild droughts as the time scale increases. At meteorological station 6902, mild and extreme droughts observed in short time scales changed to moderate and severe droughts in SPI12. This is the case about the mild and extreme droughts in one hand; on the other hand, the extreme drought has been consistently observed at all stations with a certain probability. For example; at stations 17351 and 17837, extreme droughts have almost been experienced at all-time scales; and at stations 17936 and 6902, extreme droughts are seen in SPI1, SPI3 and SPI6. There is no great increase or decrease in the probability of mild, moderate, severe and extreme droughts when the full record is considered.

4 Discussion

4.1 Temporal Analysis

The above results provide new insights into the temporal patterns of drought in the Seyhan River Basin. Although numerous studies on the drought analysis have been performed for the basin, none has focused on observed major dry periods. Examining major dry periods over the basin is a challenging task due to the lack of a common period of meteorological

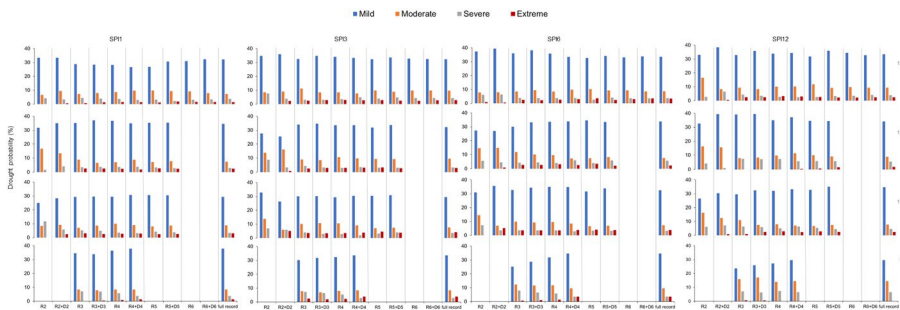


Fig. 6 Probability of drought categories based on the rolling time series analysis and the full record (SPI1, SPI3, SPI6, SPI12)

data and their limited availability. To overcome this limitation, we selected a representative station for each sub-basin to enable us to cover as many of the major dry periods as possible. The length of the data set is limited such that only one representative station covered the six major dry periods.

Over the last half century, Turkey experienced strengthened and widespread droughts in 1971–1974, 1983–1984, 1989–1990, 2007–2008 and 2013–2014 coinciding mostly with what we identified from the precipitation surplus and deficit time series although they are not exactly the same. Major dry periods identified in this study are in line with previous studies (Simsek and Cakmak 2010; Altin et al. 2020).

In the temporal analysis part of this study, significant differences were observed in the drought probabilities (e.g. between the mild and extreme droughts, and extreme droughts compared with moderate droughts). D4 was found to have the most strengthened droughts and D5 to have the longest drought duration. This finding disagrees with the previous studies performed on the river basin, which ignore the D4 major dry period although it was identified (Simsek and Cakmak 2010; Altin et al. 2020). Instead, previous studies emphasized D2, D5 and D6 due to their impacts on the society, economy and agriculture. Turkes (2012) explained that D5 was triggered in 1990s with a decrease in the frosty and snowy days and an increase in the temperature in the Eastern Mediterranean. Sonmez et al. (2005) indicated a similar climatological reasoning stating that a warming trend began to dominate the annual mean temperature in early 1990s.

A quantitative comparison shows the new insight this study brings. Sonmez et al. (2005) and Turkes and Tatli (2009) calculated SPI values at the country-scale, and Gumus and Algin (2017) analyzed the Seyhan and Ceyhan River Basin, the eastern neighbor. Results agree with previous studies in terms of timing of major dry periods. This study provides two insights: (i) A major dry period ignored because of its short duration could be as important as a long-lasting major dry period, (ii) A drought masked by the analysis of the whole SPI time series at the country or basin-scale can be prominent if a detailed analysis is made at the sub-basin scale. In addition, comparison of Figs. 5 and 6 shows that the probability of mild droughts has a notable decrease for all stations in the rolling time series analyses compared to the drought probability calculated from individual major dry periods. This is applicable at all-time scales. The probability of extreme droughts increases significantly with the use of individual major dry periods. The rolling time series analysis underestimates the drought probability compared to individual use of major dry periods. This is an important outcome to consider for practical purposes such as the drought management. Because severe and extreme droughts have higher occurrence probabilities when the dry period is taken in calculating the drought probabilities. This prevents underestimation of severe and extreme droughts and allows managers to take precautions against the drought in advance.

By using data from representative meteorological stations at the sub-basin scale, higher probabilities reaching 25% were calculated for moderate, severe and extreme droughts in major dry periods. This is a notable outcome that short extreme droughts masked by large-scale temporal analysis are indeed not ignorable in the river basin. This statement is supported with the results of Cook et al. (2016).

4.2 Significance and Importance for Practice

The study has potential to be used for regional drought management plans. It also sheds light on the need for such analyses for regional drought adaptation and mitigation. This is

an important issue to be resolved in the basin where agriculture represents an important livelihood for the population. Given the limitations that emerged on the determination of the representative stations, it would be advisable to consider additional data (e.g., remote sensing) in future studies to gain further insights into the temporal and spatial characteristics of drought. Although the river basin is prone to droughts and suffers from their effects, it does not have any tool to monitor and predict the drought in advance to take proper measures. Thus, we expect that the outputs of this study can significantly be used in the river basin-specific sectoral water allocation plan, drought management plan and drought early warning studies, and be improved for a possible extension to river basins with similar climatological characteristics.

4.3 Human-Water Relevance in Drought Management

All major dry periods identified in the basin are equally important, none being less important than any other no matter how long or severe they are. For example, D2 and D5 are important for their duration, D4 and D6 for their severity, and D1, D3 and D4 for their higher probability of severe and extreme drought categories. D2 was newsworthy emphasizing that agricultural activities stopped due to insufficient rainfall in the region (Hurriyet 2007). The low precipitation of D6 in 2013 affected also the year 2014. It has been indicated in the newspapers that it caused to reduce water level in the Seyhan River with more than 40% (IHA 2014). The local population in the river basin was affected by water shortages in cities, economic impacts, negative consequences on agriculture during both events (D2 and D6). It could be important to mention that drought in D2 has mostly affected the agricultural activities and energy sector while drought in D6 affected not only the agriculture and industry but also it heavily caused shortages in urban water supply system.

A few more droughts were observed in this region, but none has been as severe as D4 and D5 which had some consequences to accelerate the public institutions to take actions. Drought in 2008 is particularly important as it has been a milestone to initiate structural and non-structural solutions through the governance and gave an impetus to many institutional and legislative developments within the water policy agenda of Turkey. State authorities took some actions against the drought primarily by increasing supply, i.e., by exploiting groundwater, building dams and infrastructure for water storage to provide water mainly for population and agricultural irrigation. Even the farmers tried to take some drought mitigation actions individually. Whenever a drought is observed, reduction in agricultural products, pastures and forest productions; depletion in water levels in the rivers, lakes and reservoirs become unavoidable. Also, increase in fires, losses in livestock and wild animals come out. These are all direct consequences of drought which cause, for example, a decrease in agricultural products that, in turn, results in a decrease in farmers' income; an increase in the food price (economical effects). Besides, the rate of unemployment increases, tax revenues of the state decrease and finally migration starts (social effects). These cascading impacts or 'knock-on effects' show how widely the drought phenomena have affected the region. In order to avoid or minimize all these consequences, the Ministry of Food, Agriculture and Livestock subsidized farmer families by granting cash support. Monetary compensation by the government can only be considered a temporary solution mitigating these negative effects. Also, in order to take some precautions to drought, State Hydraulic Works (DSI) of Turkey restricted irrigation, encouraged night watering, and prevented a second crop cycle per year in the region. These precautions are

adaptation strategies which were developed to increase resilience to external drivers such as climate change, variability, natural and social events (Selek et al. 2016).

Each of these major dry periods was a kind of a 'redefining event' for water resources management such as the allocation and prioritizations, because people and managers took some actions after being failed in water supply during these drought events. An interesting management question would then be: What knowledge did the water managers not have before each drought? Could they have estimated the risk correctly with the data available before the drought event? What is the new estimated risk after these events?

These dry periods are important to reveal the importance of the time series analysis used in this study. Its importance come from the output obtained by the individual use of dry periods, which gives higher probability for more strengthened droughts compared to the nonstationary rolling time series and the stationary full record period. The above questions were tried to be answered with the use of rolling time series and the individual use of major dry periods. The final outcomes are (i) the rolling time series analysis is superior to the full record analysis to show the nonstationary evolution of drought occurrence probability, and (ii) the individual use of dry periods should be preferred not to underestimate the drought.

5 Conclusions

The aim of this study was to revisit major dry periods with different time series analyses by linking them with human-water relations. Major dry periods over the Seyhan River Basin were investigated with a methodology adapted specifically for the river basin where local meteorological data are limited. The results illustrate that:

1. The probability of mild drought dominates at each time scale and their frequencies increase with increasing time scale.
2. A significant change in the probabilities of drought categories was not found, instead, we observed no systematic change.
3. In the rolling time series analysis, the probability of mild droughts decreased in all stations compared to drought probability calculated from major dry periods.
4. The probability of the strengthened drought categories (severe and extreme droughts) is found higher when the dry periods are taken into account.
5. Major dry period in 1989–1990 is the most severe compared to the others. This makes it considerably important to take into account and to conclude that a short-duration drought can be as important as a long-duration drought. This outcome has provided a better understanding of droughts.
6. The non-stationary rolling time series or the stationary full-record time series analysis underestimate strengthened droughts. This is the current practice which should be replaced by the individual major dry period analysis with which higher probabilities are found for severe and extreme droughts.

Acknowledgements This study is supported by the DAAD "Research Grants – Bi-nationally Supervised Doctoral Degrees / Cotutelle" Program for which the authors are thankful. It is a contribution to the *Prediction under Change* Working Group under the Panta Rhei decade of International Association of Hydrological Sciences (IAHS).

Author Contributions Yonca Cavus: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Roles/Writing - original draft, Writing - review & editing. Kerstin Stahl: Funding acquisition, Project administration, Supervision, Writing - review & editing. Hafzullah Aksoy: Conceptualization, Data curation, Investigation, Methodology, Project administration, Supervision, Writing - review & editing.

Funding Open Access funding enabled and organized by Projekt DEAL. The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Declarations

Ethical Approval This paper has neither been published nor been under review for publication elsewhere.

Consent to Participate The authors have participated to the preparation and submission of this paper for a publication in *Water Resources Management*.

Consent to Publish The authors would like to publish their paper in *Water Resources Management*.

Competing Interest The authors have no relevant financial or non-financial interests to disclose, and they have no conflicts of interest to declare that are relevant to the content of this paper and its publication.

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