ORIGINAL PAPER

Analysis of hydrological drought indices in Alpine Zagros Mountains of Iran

Jahangir Porhemmat[1] · Majid Altafi Dadgar[2]

Abstract

The propagation of climatological drought to water cycle components, including soil moisture, surface, and groundwater resources, was investigated in upper Dez basin, southwestern Iran. Standardized precipitation index (SPI), standardized stream discharge index (SQI), standardized surface runoff index (SRI), standardized base flow index (SBFI), standardized groundwater level index (SGI), and standardized soil moisture index (SRI) were calculated for different time scales: 1-, 3-, 6-, 12-, 18- and 24-month. The correlation coefficient was used to analyze the relationship between indices. The results indicated that (1) comparing meteorological drought to hydrological drought showed the SQI correlated better with SPI than SBFI and SRI. The SRI and SPI correlated better when both indices had the same time scales, which emphasized that SRI can show the propagation of meteorological drought earlier than SQI and SBFI with a correlation coefficient (cc) equal to 0.74. (2) Correlation between the SPI and SGI resulted in the maximum correlation coefficient for SPI-24 and SGI-03 (maximum correlation coefficient (MCC) =0.63). This result revealed that seasonal depletion in groundwater table correlated stronger with more prolonged meteorological drought. (3) SGI showed stronger correlation than SBFI for considering groundwater drought. (4) Correlation between SPI and SSI showed a more substantial relation as the time scale was lengthened, and at deeper soil depths, CC tended to be constant. (5) Each drought index explains a part of drought and applying an individual index cannot describe the drought propagation well. The development of a method that can combine drought indices as an optimal one is recommended for the future.

Keywords Hydrological drought · Meteorological drought · Propagation · Upper Dez basin

Introduction

Drought is defined as dry conditions over a specific period. Drought impacts are not immediately obvious but develop slowly in comparison with natural disasters, such as floods, storms, and tornadoes (Bayissa et al. 2018; Ding et al. 2021). Drought damages occur in different aspects of the environment and economic, such as drying up of rivers, forest fires, organism and crop losses, and water shortage (Wilhite et al. 2007; Wang et al. 2021). Drought's characteristics must be investigated for reducing damages, early warning preparedness, and contingency planning (Wilhite 1993; Kogan 2000; Wilhite and Svoboda 2000; Arab and Elyasi 2010). Drought is mainly grouped into four major categories: meteorological, agricultural, hydrological, and socioeconomic, generally occurring in a particular order (Wilhite and Glantz 1985; Mishra and Singh 2010; Tu et al. 2018; Zuo et al. 2022). Meteorological drought which is induced by precipitation deficiency or water shortage (Tu et al. 2018) impacts soil moisture, i.e., agricultural drought (Wu et al. 2020), and consequently, low recharge from soil to streams, lakes, and groundwater causes hydrological drought (Mishra and Singh 2010; Zargar et al. 2011). Increasing the gap between the demand and supply of goods and commodities due to a water shortage refers to a socioeconomic drought (Wilhite and Glantz 1985; Zseleczky and Yosef 2014; Guo et al. 2019). Many indices have been developed and applied by researchers for monitoring drought. Details on different

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drought indices can be found in drought reviews (e.g. Mishra and Singh 2010; Zargar et al. 2011; Xu et al. 2015) and drought index books (Svoboda and Fuchs 2016; Dalezios et al. 2017). Some researchers have investigated drought characteristics by a single index (Morid et al. 2007; Miah et al. 2017; Shi et al. 2018; Yao et al. 2018; Forootan et al. 2019; Simsek 2021), and some studies have focused on the relationship between different drought indices (Jain et al. 2015; Bayissa et al. 2018; Mohammad et al. 2018; Zhao et al. 2019). Wang et al. (2019) studied correlation between meteorological and hydrological droughts in a basin in China and concluded that hydrological drought occurred later than meteorological droughts. Due to the complexity of the drought events and variation in meteorological and physical characteristics of any region, drought indices may vary from place to place (Jain et al. 2015). Therefore, it is necessary to understand the occurrence of drought at different temporal scales and recognize an appropriate drought index for interested region, which helps to alleviate drought-related disasters (Zhang et al. 2021). Drought events have intermittently occurred in different parts of Iran and have affected the country harmfully, including water resources and ecological, biological, agricultural, social, and economic aspects over the past decades (Rahmaninan 2000). Geographical and seasonal changes of precipitation amount in different parts of Iran, varying from 50 to 1500 mm, led to various drought phenomena (Abbaspour and Sabetraftar 2005). Due to this variety of the spatio-temporal distribution of precipitation and the frequent occurrence of drought in Iran, it is necessary to study this phenomenon to manage water resources. This necessity is vital in the southwestern Iran, including Dez catchment, where most of the water demands are supplied from surface water resources. Therefore, this study aims at evaluating and comparing the performance of six drought indices to acquire a better knowledge of drought propagation. The results can help to inform future early warning and monitoring systems for hydrological and agricultural droughts.

Data and methods

Study area

The study area is upper Dez basin located in the southwestern of Iran, which spreads over three provinces, with an area of 16,150 km^2. Upper Dez is located between 48° 20′ to 50° 20′ N and 32° 30′ to 34° 7′ E (Fig. 1). Climate conditions vary from north to south and west to east due in part to the difference between minimum (−31 °C) and maximum average temperatures (47.8 °C). The average annual evaporation is 1985 mm, and the average annual sunshine of 3020 h. The altitude ranges from 490 to 4260 m above sea level (a.s.l) with an annual precipitation of 500 mm. Cropland (32.5%), forest (32.5%), and pastures (35.0%) mainly cover the area. There

are two main aquifers in the region, named Droud-Borujerd aquifer, where the average depth to groundwater table ranges from 0.5 to 46 m, and the Azna-Aligudarz aquifer, where groundwater depth ranges from 1 to 53 m. Aligudarz, Azna, Darud, and Borujard are the region's most important cities, with a population of 713,430 people. The main activity in this region is agriculture, which is mainly affected by drought.

Datasets

Stream flow discharge, precipitation, groundwater level records, and soil moisture were the hydrological and meteorological data used to analyze the drought indices. Daily discharge data from hydrometry stations and monthly groundwater level records were obtained from National Iranian Water Resources Management Company archive (https://data.wrm.ir). Also, the daily precipitation was obtained from both National Water Resources Management Company and Meteorological Organization of Iran data banks (https://www.irimo.ir/far/index.php). Drought indices, variables, and dataset are summarized in Table 1. For monitoring standardized precipitation index (SPI) and standardized stream flow index (SQI), 35 years of monthly time series on discharge and climatological parameters were supplied (Table 1). The spatial distribution of drought was investigated at nine selected climatic stations, which involved the same time series length as the stream flow gauging data. Daily base flow and direct runoff data were separated and used to investigate the standardized surface runoff index (SRI) and base flow index (SBFI). Soil moisture data (SM) obtained from the GLDAS CLM dataset at 1° × 1° per month (Rodell and Beaudoing 2007) was applied to monitor the standardized soil moisture index (SSI). The standardized groundwater level index (SGI) was monitored using data obtained from 75 observation wells during 2003–2017 (Fig. 1). Time series of groundwater levels in each observation well were used to generate the groundwater unit hydrograph (GUH) for both aquifers. Then SGI was calculated in terms of GUH fluctuations.

Methodology

Drought indices

The drought indices applied depict three of drought categories: meteorological, agricultural, and hydrological droughts. The drought indices were the standardized precipitation index (SPI) (McKee et al. 1995), standardized runoff index (SRI) (Shukla and Wood 2008), standardized stream flow index (SQI) (Nalbantis and Tsakiris 2009), standardized base flow index (SBFI), standardized soil moisture index (SSI) (Xu et al. 2018), and standardized groundwater level index (SGI) (Kubicz 2018b; Halder et al. 2020). The drought indices were selected based on data availability, simple algorithm,
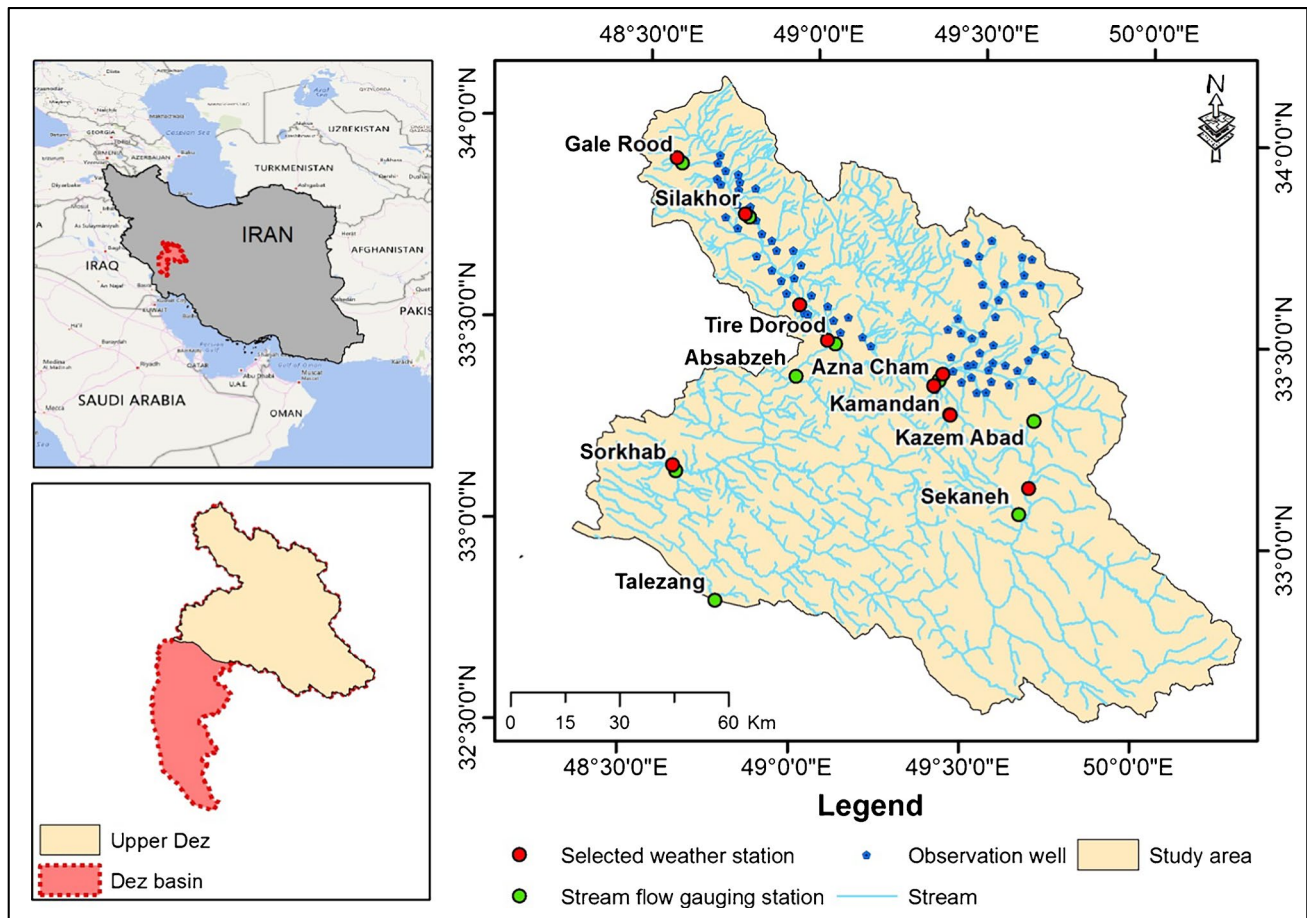
Fig. 1 Location map of study area

Table 1 Drought indices, variables, and time series of dataset

Drought index	Variable	Time series	Standardization
SPI	Precipitation	1982–2017	Standardized by the mean and standard deviation
SRI	Surface runoff	1982–2017	
SQI	Total runoff	1982–2017	
SBFI	Base flow	1982–2017	
SSI	Soil moisture	1999–2017	
SGI	Groundwater level	2003–2017	

and applicability to monitoring drought propagation. Drought indices were calculated using Eq. (1):

$$DI_{i,k} = \frac{x_{i,k} - \bar{x}_k}{S_k} \tag{1}$$

where $DI_{i,k}$ is the standardized drought index, $x_{i,k}$ stands for the variable values, $\bar{x}_k$ is for the mean, and S_k is for the standard deviation of variables at year i, and kth period, respectively. Equation (1) is applied to all drought indices based on the concept used by McKee et al. (1993) for SPI, who

suggested applying the procedure to other drought-related variables. Drought indices were calculated for different time scales, including 1-, 3-, 6-, 9-, 12-, 18-, and 24-month periods and spatial distribution over the region. The drought classification based on *DI* is shown in Table 2 (McKee et al. 1993).

Drought correlation analysis

The Pearson correlation method was used to analyze the relationship between the three major drought categories.

Table 2 SPI values corresponding to different categories of drought severity (after McKee et al. 1993)

Level	Drought classification	SPI values
1	Mild drought	$-1.00 < SPI \leq 0.00$
2	Moderate drought	$-1.50 < SPI \leq -1.00$
3	Severe drought	$-2.00 < SPI \leq -1.50$
4	Extreme drought	$SPI \leq -2.00$

The Pearson coefficient (Eq. 2) is a criterion that shows linearity between two datasets and has been used in many similar studies (Jain et al. 2015; Ding et al. 2021). The correlation coefficient (CC) was calculated between all drought indices, and the maximum coefficient was selected to show differences in response to spatial and temporal variation in the drought types.
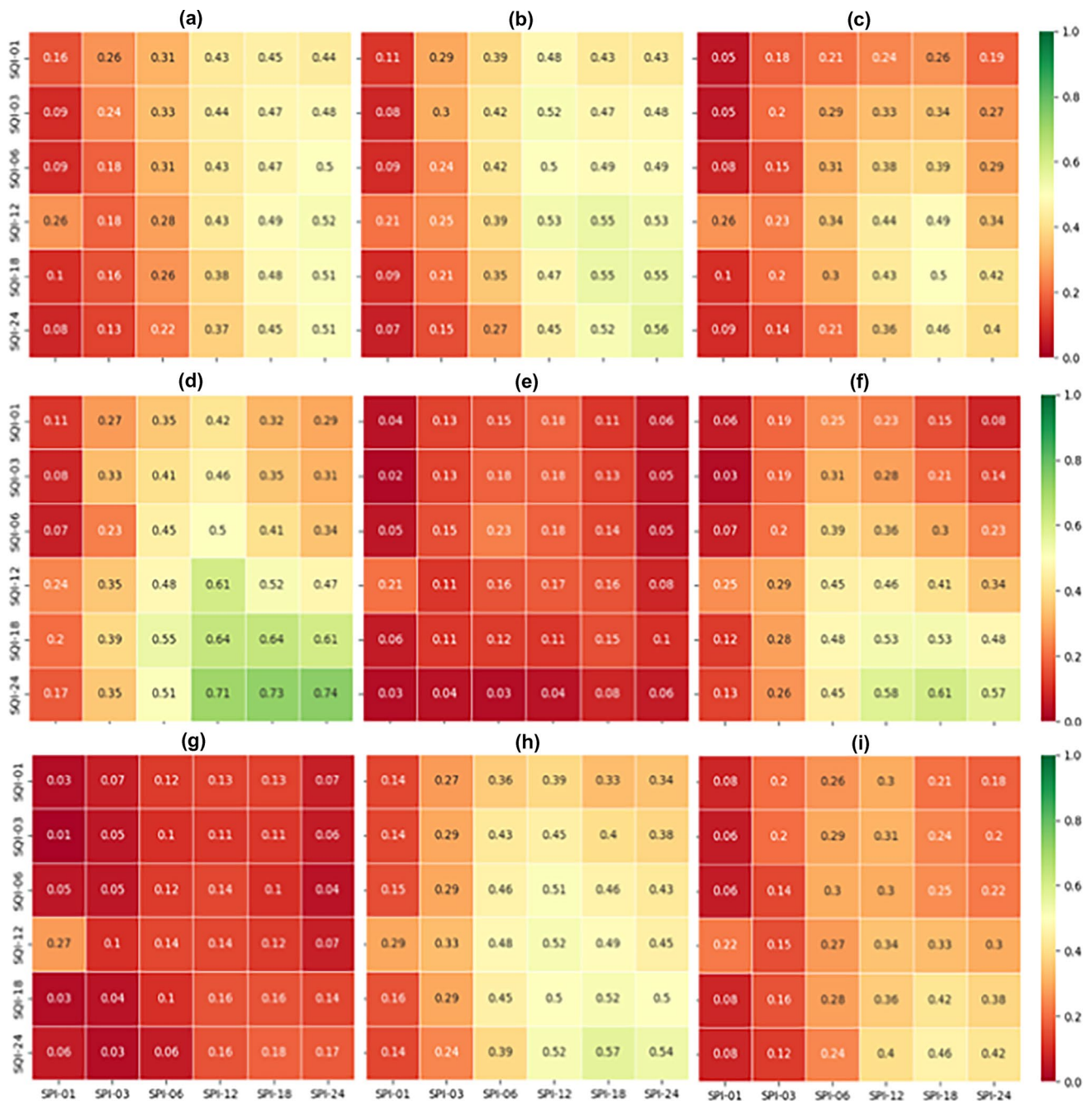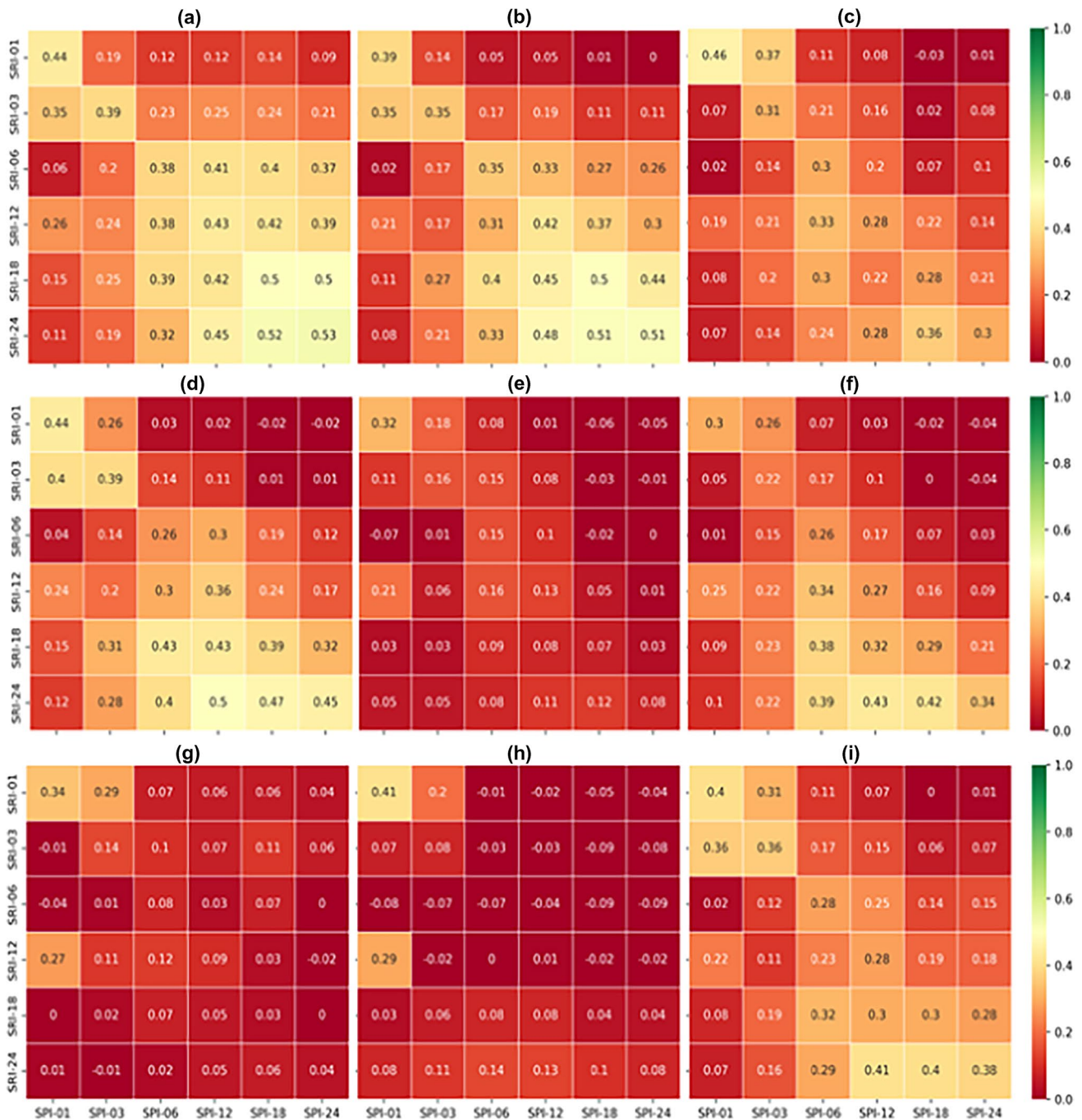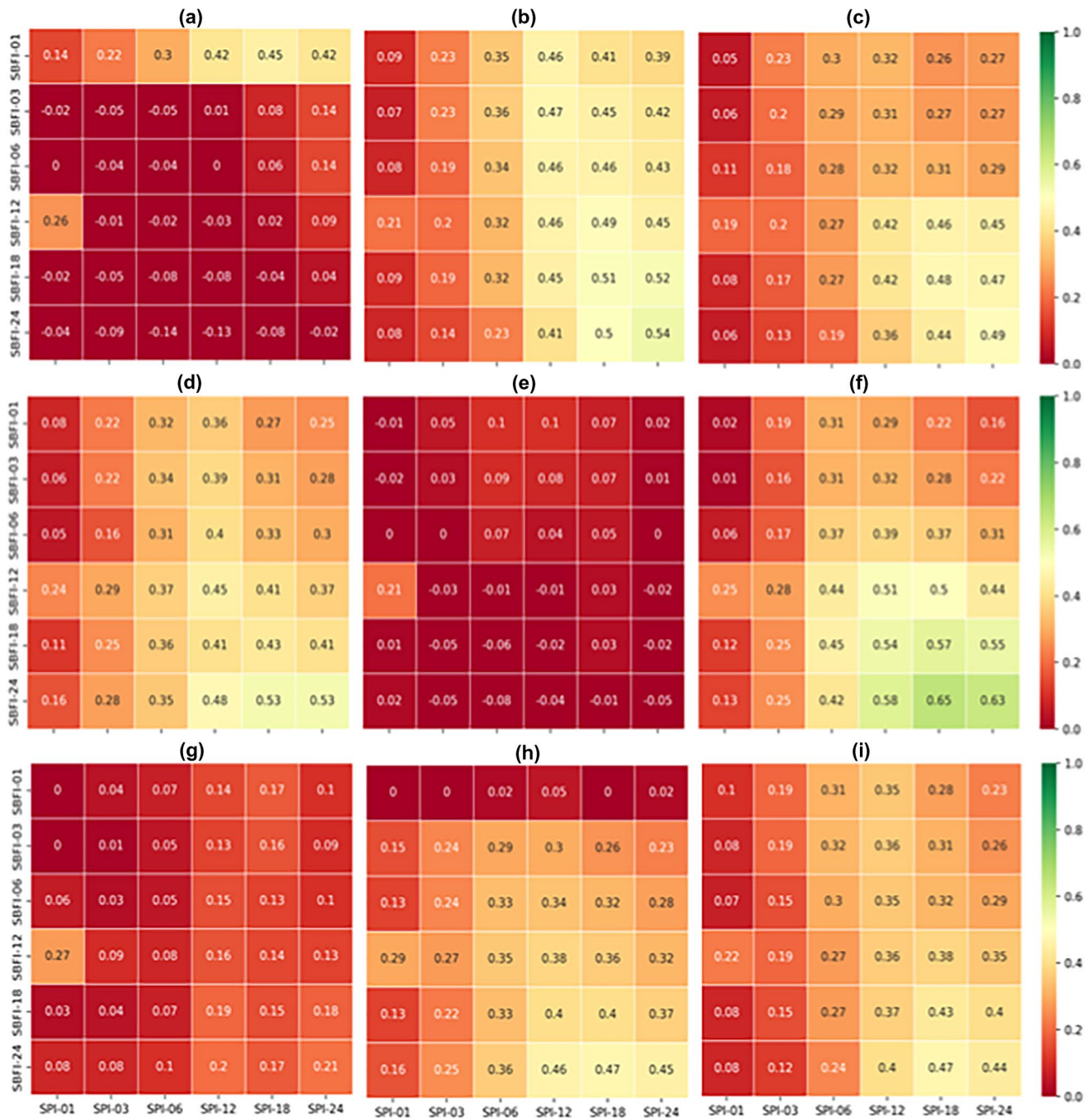

Fig. 2 Pearson correlation coefficient between SPI and SQI for 1-, 3-, 6-, 12-, 18-, and 24-month time scales at different sub-basins: Azna Cham (**a**), Tire Dorood (**b**), Absabzeh (**c**), Sorkhab (**d**), Kazem Abad (**e**), Kamandan (**f**), Gale Rood (**g**), Sekaneh (**h**), and Silakhor (**i**)

$$r = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{S_x} \right) \left(\frac{y_i - \bar{y}}{S_y} \right), \tag{2}$$

where n stands for the number of dataset values, x_i and y_i are the values of the arrays, $\bar{x}$ and $\bar{y}$ are the mean of two arrays, and S_x and S_y are the standard deviation of two arrays.

Results and discussion

Relation between meteorological and hydrological droughts

The maximum correlation coefficient (MCC) was used to investigate propagation between meteorological (SPI) and hydrological droughts (SQI, SRI, and SFBI) for 1-, 3-, 6-, 12-, 18-, 24-month temporal scales. Figure 2 shows the heat map of the correlation coefficient between the SPI and SQI for the selected meteorological stations. From Fig. 2, as the time scale was lengthened, the MCC responded strongly, and the MCC for SQI reached when both indices were compared for the 24-month time scale (CC=0.74). Because the SQI is based on total stream flow, so there might be a specific lag time with the SPI. To find the general lag time between SPI and SQI, the MCC was extracted by averaging each row of the heat map grid (Table 3). Results showed the MCC ranged from 0.05 to 0.53, which is dominantly related to 12-month SPI. This

behavior is in convenient with the results of the previous study (Bayissa et al. 2018). As expected, the lowest CC belonged to SPI-1 with SQI-24. This discrepancy might be related to the attenuation of the 1-month precipitation effect on the 24-month discharge of the basin. Additionally, the MCC value was spatially related to the Sorkhab flow gauging station, located downstream of the basin. Conversely, upstream stations showed the lowest correlation, such as Gale Rood and Kazem Abad (Fig. 2). It suggests that low-discharge rivers may not be a good indicator for hydrological drought assessment.

Correlation between surface runoff index (SRI) and SPI showed that the best CC was reached when both indices had the same time scales (Fig. 3). For example, in most of the sub-basins, SPI-1 correlated better with SRI-1 or SPI-3 correlated better with SRI-3 and so on. Consequently, SRI responded faster to the propagation of meteorological drought than SQI because SRI was only based on direct runoff. These findings support the results of research by Li et al. (2016), who reported a slight time lag between SPI and SRI. The MCC was found downstream in the Sorkhab region (Fig. 3d), possibly due to the accumulation of runoff concentrates toward downstream and interflow delay effects. The SRI index at the 1-month time scale explained better hydrological drought among the other time scales. As a result, the SRI can be used as a useful complement to the SPI on monthly to seasonal time scales (Shukla and Wood 2008).

Table 3 Average correlation coefficient for different SPI time scales (1-, 3-, 6-, 12-, 18-, and 24-month) for each period of hydrological drought indices

Station name	Average SPI correlation coefficient								
	Azna Cham	Tire Dorood	Absabzeh	Sorkhab	Kazem Abad	Kamandan	Gale Rood	Sekaneh	Silakhor
SQI-1	0.34	0.36	0.21	0.29	0.11	0.16	0.09	0.31	0.21
SQI-3	0.34	0.38	0.23	0.32	0.11	0.19	0.07	0.35	0.22
SQI-6	0.33	0.37	0.24	0.33	0.13	0.26	0.09	0.38	0.21
SQI-12	0.36	0.41	0.31	0.45	0.15	0.37	0.14	0.43	0.27
SQI-18	0.31	0.37	0.29	0.51	0.11	0.40	0.11	0.40	0.28
SQI-24	0.29	0.34	0.29	0.53	0.05	0.43	0.11	0.40	0.29
SRI-1	0.18	0.11	0.17	0.12	0.08	0.10	0.14	0.08	0.15
SRI-3	0.28	0.21	0.14	0.18	0.08	0.08	0.08	−0.01	0.19
SRI-6	0.30	0.23	0.14	0.17	0.03	0.12	0.03	−0.07	0.16
SRI-12	0.35	0.30	0.23	0.25	0.10	0.22	0.10	0.04	0.20
SRI-18	0.37	0.36	0.22	0.34	0.05	0.25	0.03	0.05	0.24
SRI-24	0.35	0.35	0.23	0.37	0.08	0.32	0.03	0.10	0.28
SBFI-1	0.32	0.32	0.24	0.25	0.06	0.20	0.09	0.01	0.24
SBFI-3	0.02	0.33	0.24	0.27	0.05	0.22	0.07	0.24	0.25
SBFI-6	0.02	0.33	0.25	0.26	0.03	0.28	0.09	0.27	0.25
SBFI-12	0.05	0.35	0.33	0.35	0.03	0.40	0.15	0.33	0.29
SBFI-18	−0.04	0.35	0.31	0.33	−0.02	0.41	0.11	0.31	0.28
SBFI-24	−0.08	0.32	0.28	0.39	−0.03	0.44	0.14	0.36	0.29

The correlation coefficient between standardized base flow index (SBFI) and SPI increased as the time scale for SPI lengthened (Fig. 4). Generally, the trend of relation between SBFI and SPI was similar to the SQI and SPI relation. Base flow in most of the sub-basins correlated better with more extended time scales of the SPI. However, the SBFI index was expected to respond with a lag time to meteorological droughts. The correlation coefficient was different spatially because SBFI depends on many catchment factors, such as permeability of soil layers, catchment area, and location of rivers in snow-dominated regions (Sutanto and Van Lanen 2022).

Mean values of hydrological drought index were calculated by averaging the correlation coefficient of all the

Fig. 3 Pearson correlation coefficient between SPI and SRI for 1-, 3-, 6-, 12-, 18-, and 24-month time scales at different sub-basins: Azna Cham (**a**), Tire Dorood (**b**), Absabzeh (**c**), Sorkhab (**d**), Kazem Abad (**e**), Kamandan (**f**), Gale Rood (**g**), Sekaneh (**h**), and Silakhor (**i**)
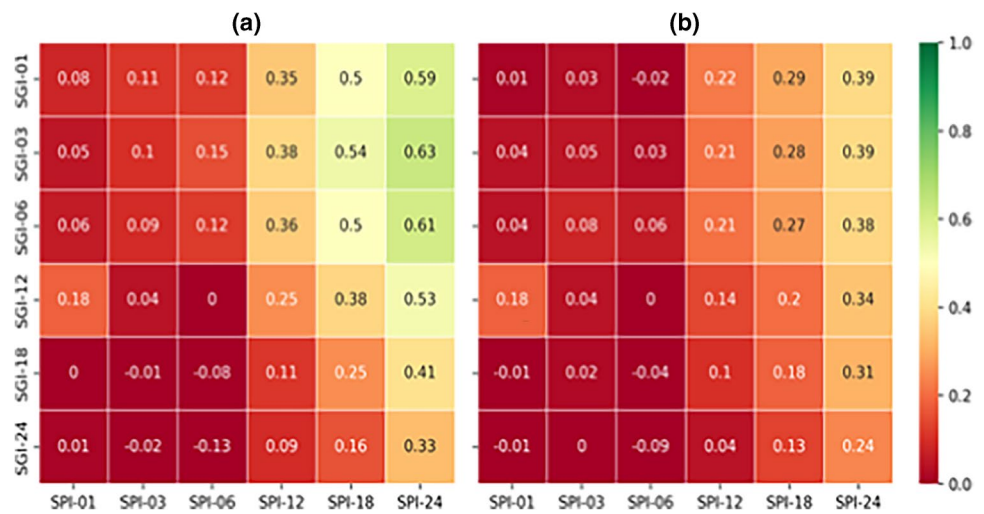
SPI time scales (1-, 3-, 6-, 12-, 18-, and 24-month) corresponding to each of the hydrological index time scales. In the other words, the values of each row in the heat map were averaged for each sub-basin and presented in Table 3. Results showed that SRI had the weakest averaged correlation coefficient over the region. This does not mean that SRI is not correlated to meteorological drought. It reveals several factors, for example, seasonal water harvesting and consuming for agricultural demands, independent from precipitation and affecting the SRI. However, the SRI showed drought propagation faster than SQI and SBFI, although it had low CC. The most significant averaged correlation coefficient was reached using SQI, and in the region, SQI better described propagation of meteorological drought than SRI and SBFI.

Fig. 4 Pearson correlation coefficient between SPI and SBFI for 1-, 3-, 6-, 12-, 18-, and 24-month time scales at different sub-basins: Azna Cham (**a**), Tire Dorood (**b**), Absabzeh (**c**), Sorkhab (**d**), Kazem Abad (**e**), Kamandan (**f**), Gale Rood (**g**), Sekaneh (**h**), and Silakhor (**i**)
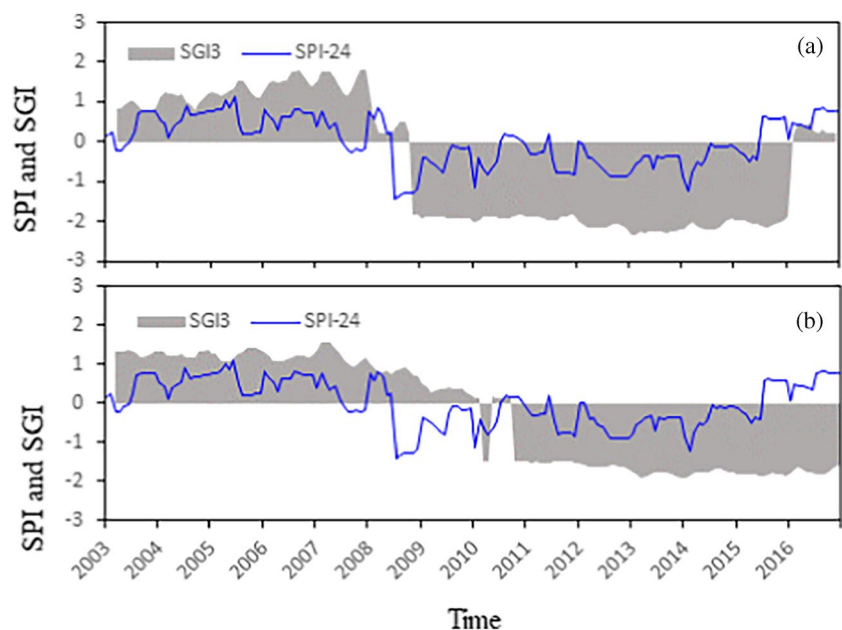
Relation between SPI and SGI droughts

The spatial average of the SPI was calculated for the corresponding period of the SGI time scales to show the effects of meteorological drought propagation on groundwater level decline. Statistically, the correlation coefficient values increased when the SPI time scale extended from 1 to 24 months which is consistent with the study by Kubicz (2018a). When the same time scales were compared, longer time scales showed weaker correlation coefficient (Fig. 5). For example, the maximum correlation coefficient was achieved between SPI-24 and SGI-03 for both aquifers (MCC=0.63 and 0.39) which means that seasonal decreasing in groundwater table correlated stronger with more extended meteorological drought. Comparing SGI and SBFI

for investigating groundwater drought, the SGI showed a stronger correlation. The simultaneous MCC between SPI and SGI is presented in Fig. 6. As it can be found, several periods with normal, moderate, and severe drought events have taken place during the long-term time series of precipitation. A sever meteorological drought was monitored from 2008 to 2009, reflecting slightly to considerable groundwater level delays. The lag time varied from 3 to 9 months in Droud-Borujerd and Azna-Aligudarz aquifers, respectively. Recorded precipitation deficits from 2008 reflected a continuous declining trend of groundwater level trend in the study area. The results of propagation drought from meteorological to groundwater showed that if it is impossible to monitor groundwater drought, the SPI-24 indicator can be used to investigate the risk of groundwater resource drought.

Fig. 6 Plots of SPI-24 versus SGI-3: Droud-Borujerd (**a**) and Azna-Aligudarz (**b**) aquifers

Relation between SPI and SSI droughts

The standardized soil moisture index (SSI) was calculated based on the GLDAS CLM dataset per month, which corresponded to different soil layers, including 0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm. Figure 7 shows the correlation coefficient between the spatially average SPI 1- to 24-month time scales and corresponding SSI for different soil depths. At the topsoil (0–10 cm), MCC (r > 0.7) was found for time scales 18- and 24-month (Fig. 7a). The correlation between the SSI-1 and all the SPI time scales was relatively constant and low (r <0.12). The fluctuation of soil moisture at the ground surface is affected by many factors, such as root water uptake and evaporation. Therefore, the topsoil moisture conditions cannot be a good indicator for agricultural drought. For the middle soil depths (10–40 and 40–100 cm), results of correlation coefficient were almost similar (Fig. 7b and c), showing the MCC = 0.71 for SPI time scales 1-, 18-, and 24-month. At deeper depths, correlations tend to be constant at longer time scales of SSI. For the deepest soil layer (100–200 cm), MCC = 0.85 corresponded to SSI-12 and SPI-1 (Fig. 7d). It might be related to the reason that the soil moisture drought occurs more continuously, whereas meteorological drought occurs frequently but in short period.

Conclusion

Understanding their relationship is essential to investigate drought propagation among meteorological, hydrological, and agricultural draughts. The SPI, SRI, SQI, SBFI, SSI, and SGI were applied to investigate the drought types in the upper Dez basin southwest of Iran. The correlation and propagation among the drought types were analyzed. The main conclusions reached as follows:

(1) Results of comparing the SPI and SQI showed longer time scale of SPI correlated better with SQI and the highest correlation was reached when both indices had the same time scale of 24 months (CC=0.74). Comparing the SPI and SRI showed that the best CC was found when both indices had the same time scales, and conversely, the CC was increased between SBFI and SPI as the time scale for SPI increased.

(2) Correlation between SPI and SGI resulted in the MCC between SPI-24 and SGI-03: MCC = 0.63 and MCC = 0.39 for Droud-Borujerd and Azna-Aligudarz aquifers, respectively. This result revealed seasonal depletion in the groundwater table correlated stronger with more extended meteorological drought. In deficit of groundwater drought monitoring, the SPI-24 indicator can be used to investigate the risk of groundwater resource drought.

(3) Correlation between SPI and SSI was better as time scales increased, and at deeper soil depths, correlations tend to be constant. For the deepest soil layer (100–200 cm), MCC = 0.85 corresponded to SSI-12 and SPI-1. Correlations between SPI-SQI and SPI-SSI were stronger to reveal propagation from climatological drought.

Our results have important implications for adequate drought warning and prevention, and future studies should combine drought indices to extract an optimal index for predicting water resources situation.
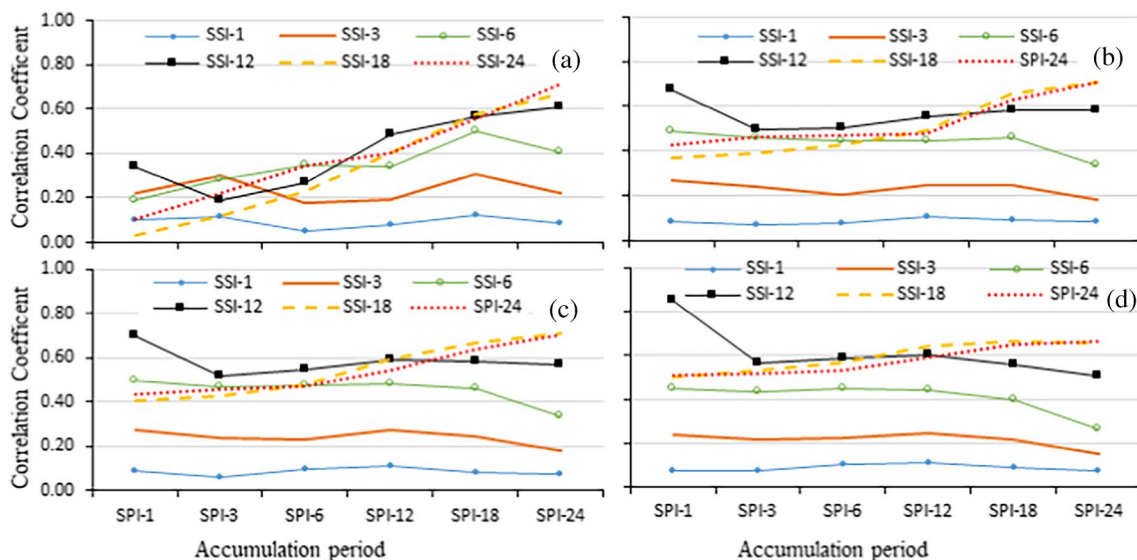
Fig. 7 Correlation coefficient between spatially average SPI for different time scales with SSI at 10 cm (**a**), 40 cm (**b**), 100 cm (**c**), and 200 cm (**d**) depths

Declarations

Conflict of interest The authors declare no competing interests.

References

Abbaspour M, Sabetraftar A (2005) Review of cycles and indices of drought and their effect on water resources, ecological, biological, agricultural, social and economical issues in Iran. Int J Environ Stud 62:709–724

Arab D, Elyasi A, Tavakoli far H, Karamouz M (2010) Developing an integrated drought monitoring system based on socioeconomic drought in a transboundary river basin: a case study. World Environ Water Res Congress 2010: 2754-2761.

Bayissa Y, Maskey S, Tadesse T, Van Andel SJ, Moges S, Van Griensven A, Solomatine D (2018) Comparison of the performance of six drought indices in characterizing historical drought for the Upper Blue Nile Basin. Ethiopia Geosci 8:81

Dalezios NR, Tarquis AM, Eslamian S (2017) Droughts. In: Dalezios NR (ed) Environmental hazards methodologies for risk assessment and management. International Water Association Publishing, London UK, pp 177–210

Ding Y, Xinglong Gong X, Xing Z, Cai H, Zhou Z, Zhang D, Sun P, Shi H (2021) Attribution of meteorological, hydrological and agricultural drought propagation in different climatic regions of China. Agric Water Manag 255:106996

Forootan E, Khaki M, Schumacher M, Wulfmeyer V, Mehrnegar N, van Dijk A, Brocca L, Farzaneh S, Akinluyi F, Ramillien G, Shum C, Joseph A, Mostafaie A (2019) Understanding the global hydrological droughts of 2003–2016 and their relationships with teleconnections. Sci Total Environ 650:2587–2604

Guo Y, Huang S, Huang Q, Wang H, Fang W, Yang YY, Wang L (2019) Assessing socioeconomic drought based on an improved multivariate standardized reliability and resilience index. J Hydrol 568:904–918

Halder S, Roy MB, Roy PK (2020) Analysis of groundwater level trend and groundwater drought using standard groundwater level index: a case study of an eastern river basin of West Bengal, India. SN Appl Sci 2:1–24

Jain VK, Pandey RP, Jain MK, Byun HR (2015) Comparison of drought indices for appraisal of drought characteristics in the Ken River Basin. Weather Clim Extreme 8:1–11

Kogan FN (2000) Contribution of remote sensing to drought early warning. In: Wilhite DA, Wood DA (eds) Early warning systems for drought preparedness and drought management. World Meteorological Organization, Geneva, pp 75–87

Kubicz J (2018a) The application of standardized precipitation index (SPI) to monitor drought in surface and groundwaters. E3S Web Conf 44:00082

Kubicz J (2018b) TLM method and SGi index as an indicator of groundwater drought. Acta Scientiarum Polonorum, Formatio Circumiectus, p 17

Li J, Zhou S, Hu R (2016) Hydrological drought class transition using SPI and SRI time series by loglinear regression. Water Resour Manag 30:669–684

McKee TB, Doesken NJ, Kleist J (1995) Drought monitoring with multiple time scales. In: Proceedings of the ninth conference on applied climatology. American Meteorological Society, Dallas TX, pp 233–236

McKee TB, Doesken NJ, Kleist JR (1993) The relationship of drought frequency and duration to time scales. In: 8th Conference on Applied Climatology, Anaheim CA. American Meteorological Society, 17-22 January 1993, pp 179–184

Miah MG, Abdullah HM, Jeong C (2017) Exploring standardized precipitation evapotranspiration index for drought assessment in Bangladesh. Environ Monit Assess 189:547

Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol 391:202–216

Mohammad AH, Jung HC, Odeh T, Bhuiyan C, Hussein H (2018) Understanding the impact of droughts in the Yarmouk Basin, Jordan: monitoring droughts through meteorological and hydrological drought indices. Arab J Geosci 11:103

Morid S, Smakhtin V, Bagherzadeh K (2007) Drought forecasting using artificial neural networks and time series of drought indices. Int J Climatol 27:2103–2111

Nalbantis I, Tsakiris G (2009) Assessment of hydrological drought revisited. Water Resour Manag 23:881–897

Rahmaninan D (2000) Challenge with drought without community planning is not possible. In: Seasonal magazine mahab Godse

Rodell M, Beaudoing HK (2007) GLDAS CLM Land Surface Model L4 3 hourly 1.0 x 1.0 degree Subsetted V001. In: NASA/GSFC/HSL. Goddard Earth Sciences Data and Information Services Center (GES DISC), Greenbelt, Maryland, USA

Shi H, Chen J, Wang K, Niu J (2018) A new method and a new index for identifying socioeconomic drought events under climate change: a case study of the East River basin in China. Sci Total Environ 616:363–375

Shukla S, Wood AW (2008) Use of a standardized runoff index for characterizing hydrologic drought. Geophys Res Lett 35:1–7. https://doi.org/10.1029/2007GL032487

Simsek O (2021) Hydrological drought analysis of Mediterranean basins. Turkey Arabian J Geosci 14:2136

Sutanto SJ, Van Lanen HAJ (2022) Catchment memory explains hydrological drought forecast performance. Sci Rep 12:2689. https://doi.org/10.1038/s41598-022-06553-5

Svoboda M, Fuchs B (2016) Handbook of drought indicators and indices. In: WMO 1173, p 45

Tu X, Wu H, Singh VP, Chen X, Lin K, Xie Y (2018) Multivariate design of socioeconomic drought and impact of water reservoirs. J Hydrol 566:192–204. https://doi.org/10.1016/j.jhydrol.2018.09.012

Wang J, Wang W, Cheng H, Wang H, Zhu Y (2021) Propagation from meteorological to hydrological drought and its influencing factors in the Huaihe River Basin. Water 13:1985. https://doi.org/10.3390/w13141985

Wang L, Yu H, Yang M, Rui Y, Gao R, Wang Y (2019) A drought index: the standardized precipitation evapotranspiration runoff index. J Hydrol 571:651–668. https://doi.org/10.1016/j.jhydrol.2019.02.023

Wilhite D, Svoboda M (2000) Drought early warning systems in the context of drought preparedness and mitigation, in early warning systems for drought preparedness and drought management. In: Proceedings of an Expert Group Meeting held 5-7 September, 2000, vol 1037, Lisbon Portugal WMO/TD No, pp 1–21

Wilhite DA (1993) Drought assessment, management, and planning: theory and case studies. Kluwer Academic Publishers, p 293. https://doi.org/10.1007/978-1-4615-3224-8

Wilhite DA, Glantz MH (1985) Understanding: the drought phenomenon: the role of definitions. Water Int 10:111–120

Wilhite DA, Svoboda MD, Hayes MJ (2007) Understanding the complex impacts of drought: a key to enhancing drought mitigation and preparedness. Water Resour Manag 21:763–774

Wu B, Ma Z, Yan N (2020) Agricultural drought mitigating indices derived from the changes in drought characteristics. Remote Sens Environ 244:111813. https://doi.org/10.1016/j.rse.2020.111813

Xu K, Yang D, Yang H, Li Z, Qin Y, Shen Y (2015) Spatio-temporal variation of drought in China during 1961–2012: a climatic perspective. J Hydrol 526:253–264. https://doi.org/10.1016/j.jhydrol.2014.09.047

Xu Y, Wang L, Ross KW, Liu C, Berry K (2018) Standardized soil moisture index for drought monitoring based on soil moisture active passive observations and 36 years of north American land data assimilation system data: a case study in the southeast United States. Remote Sens 10:301

Yao N, Li Y, Lei T, Peng L (2018) Drought evolution, severity and trends in mainland China over 1961-2013. Sci Total Environ 616:73–89

Zargar A, Sadiq R, Naser B, KhanFaisal I (2011) A review of drought indices. Environ Rev 19:333–349

Zhang H, Ding J, Wang Y, Zhou D, Zhu Q (2021) Investigation about the correlation and propagation among meteorological, agricultural and groundwater droughts over humid and arid/semi-arid basins in China. J Hydrol 603:127007. https://doi.org/10.1016/j.jhydrol.2021.127007

Zhao P, Lü H, Wang W (2019) Fu G (2019) From meteorological droughts to hydrological droughts: a case study of the Weihe River Basin China Arabian. J Geosci 12:364. https://doi.org/10.1007/s12517-019-4524-8

Zseleczky L, Yosef S (2014) Are shocks really increasing? A selective review of the global frequency, severity, scope, and impact of five types of shocks. Intl Food Policy Res Inst

Zuo DD, Hou W, Zhang Q, Yan PC (2022) Sensitivity analysis of standardized precipitation index to climate state selection in China. Adv Clim Chang Res 13:42–50. https://doi.org/10.1016/j.accre.2021.11.004