Journal of Hydrology 470–471 (2012) 255–268

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Comparison of multi-monthly rainfall-based drought severity indices, with application to semi-arid Konya closed basin, Turkey

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ARTICLE INFO

Article history:
Received 12 May 2012
Received in revised form 20 July 2012
Accepted 1 September 2012
Available online 12 September 2012
This manuscript was handled by Geoff Syme, Editor-in-Chief

Keywords:
Drought indices (DIs)
Drought severity
Effective Drought Index (EDI)
Konya closed basin
Rainfall

SUMMARY

Many drought indices (DIs) have been introduced to monitor drought conditions. This study compares Percent of Normal (PN), Rainfall Decile based Drought Index (RDDI), statistical Z-Score, China-Z Index (CZI), Standardized Precipitation Index (SPI), and Effective Drought Index (EDI) to identify droughts in a semi-arid closed basin (Konya), Turkey. Comparison studies of DIs under different climatic conditions is always interesting and may be insightful. Employing and comparing 18 different timesteps, the objective of comparison is twofold: (1) to determine the effect of timestep for choosing an appropriate value, and (2) to determine the sensitivity of DI to timestep and the choice of a DI. Monthly rainfall data obtained from twelve spatially distributed stations was used to compare DIs for timesteps ranging from 1 month to 48 months. These DIs were evaluated through correlations for various timesteps. Surprisingly, in many earlier studies, only 1-month time step has been used. Results showed that the employment of median timesteps was essential for future studies, since 1-month timestep DIs were found as irrelevant to those for other timesteps in arid/semi-arid regions because seasonal rainfall deficiencies are common there. Comparing time series of various DI values (numerical values of drought severity) instead of drought classes was advantageous for drought monitoring. EDI was found to be best correlated with other DIs when considering all timesteps. Therefore, drought classes discerned by DIs were compared with EDI. PN and RDDI provided different results than did others. PN detected a decrease in drought percentage for increasing timestep, while RDDI overestimated droughts for all timesteps. SPI and CZI were more consistent in detecting droughts for different timesteps. The response of DI and timestep combination to the change of monthly and multi-monthly rainfall for a qualitative comparison of severities (drought classes) was investigated. Analyzing the 1973–1974 dry spell at Beysehir station, EDI was found sensitive to monthly rainfall changes with respect to cumulative rainfall changes, especially more sensitive than other DIs for shorter timesteps. Overall, EDI was consistent with DIs for various timesteps and was preferable for monitoring long-term droughts in arid/semi-arid regions. The use of various DIs for timesteps of 6, 9, and 12 months is essential for long term drought studies. 1-month DIs should not be used solely in comparison studies to present a DI, unless there is a specific reason. This investigation showed that the use of an appropriate timestep is as important as the type of DI used to identify drought severities.

1. Introduction

A drought is a prolonged period of water deficit, and usually occurs when an area does not receive significant precipitation for a sustained period of time, say several months (Chen et al., 2009; Linsely et al., 1959). Droughts can be classified into four categories as meteorological, hydrological, agricultural and socio-economic (American Meteorological Society, 1997; Palmer, 1965; White and Walcott, 2009). The preparedness and planning for a drought depend on the information about its areal extent, severity and duration (Mishra and Singh, 2011). This information can be obtained through drought monitoring that is usually done with the use of drought indices (DIs) which provide information to decision makers about drought characteristics. Thus, these indices can be used to initiate drought action plans. Prediction of droughts is useful for early warning that may reduce the response time and consequently the impact of a drought.

Palmer (1965) introduced probably the first comprehensive DI, known as the Palmer drought severity index (PDSI). Earlier DIs were drought-definition specific but PDSI involves precipitation, temperature and soil moisture in a water balance model. PDSI

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http://dx.doi.org/10.1016/j.jhydrol.2012.09.003

gained prominence from the 1960s to the 1990s. Since then many other DIs have been developed to quantify drought conditions throughout the world. Heim (2002) reviewed PDSI and many other DIs which were widely used in the last century in order to consider them for use nationwide for national drought assessment in the USA.

Keyantash and Dracup (2002) reviewed 14 well-known DIs which have been used for assessing the severity of meteorological, hydrological, and agricultural droughts. A weighted set of criteria, consisting of robustness, tractability, transparency, sophistication, extendibility and dimensionality, was created for evaluation of DIs. Barua et al. (2011) also applied the same set of evaluation criteria except for dimensionality. Ntale and Gan (2003) identified eight assessment criteria: (1) statistical properties and variability of DIs; (2) detailed analysis of a major historical drought; (3) adaptation of DIs to local climate; (4) unbounded index values; (5) spatial invariability; (6) flexible timestep; (7) data requirement and availability; and (8) interpretability. These assessment criteria reflect some similarities to those of Keyantash and Dracup (2002). According to these assessment criteria, Standardized Precipitation Index (SPI) was found to be the best choice for detecting droughts with many advantages, including fewer data requirements, ability of computation for any timestep, and interpretability. Keyantash and Dracup (2002) also found SPI as a highly valuable estimator of drought severity. A good DI (Barua et al., 2011; Keyantash and Dracup, 2002; Ntale and Gan, 2003) might be robust (responsive as well as not temperamental), tractable (requisite of a low level of numerical computation, fewer variables, and less extensive database), transparent (understandable by both the professionals and the general audience), sophisticated (comprehensive approach for conceptual merits), and extendable (inferable to further studies and scenarios). Ntale and Gan (2003) modified the properties of PDSI, the Bhalme–Mooley index (BMI), and SPI to determine the most appropriate index for detecting the initiation, evolution, termination and severity of droughts in East Africa. Mishra and Singh (2010) and White and Walcott (2009), among others, have pointed advantages and limitations of different indices.

Morid et al. (2006) compared seven DIs for drought monitoring in the Tehran province of Iran. Percent of Normal (PN), Rainfall Deciles (RDs), Statistical Z Score (Z-Score), Standardized Precipitation Index (SPI), China-Z Index (CZI), Modified China-Z Index (MCZI), and Effective Drought Index (EDI) were used. These DIs are all rainfall-based indices and are able to quantify both dry and wet cycles. Comparisons showed that SPI and EDI performed better in detecting the onset of drought, and these were recommended to the Tehran drought monitoring system. However, EDI was more responsive to the initiation of a drought. This study is enlightening and currently one of the most exhaustive comparison studies of DIs. Smakhtin and Hughes (2007) introduced a software package (Spatial and Time Series Information Modeling – SPATSIM) for automated estimation, display, and analyses of meteorological DIs from monthly rainfall data. This software calculates five different DIs, including RD, EDI, SPI and deviations from the long-term mean and median values, to allow a quantitative assessment of meteorological droughts. Pandey et al. (2008) used SPATSIM to investigate historical drought severity in Orissa (India) and found EDI to be better than any other DI.

For many regions, especially semi-arid regions, limited knowledge is available about the diurnal and seasonal cycles of land surface interactions. Semi-arid areas pose a challenge due to large contrasts between dry and wet conditions within a temporal cycle (Schuttemeyer, 2005). A meteorological drought is generally an indicator of other drought types with below normal precipitation, and usually occurs first before other drought types do. The seasonality and climatological conditions vary by location. Drought severity may differ from site to site under different climatic conditions, hence, as many as applications of DIs and their comparisons are beneficial for specific regions in the world. Droughts in arid and semi-arid regions are arduous to monitor, and cause crucial impacts. Patel et al. (2007) computed a 3-month timestep SPI (actually computed Z-Score) using 23 years of monthly rainfall data from 160 stations in arid and semi-arid regions of Gujarat (India) to evaluate the usefulness of a DI for quantifying the effects of drought on food grain productivity and analyze temporal and spatial meteorological drought risk.

Several studies (Guttman, 1998; Morid et al., 2006; Pandey et al., 2008; Paulo and Pereira, 2006; Smakhtin and Hughes, 2007; Wu et al., 2001) have indicated that there is an advantage in considering more than one DI for drought studies. Comparing and combining different DIs may help: (1) characterize droughts, (2) examine the sensitivity and accuracy of DIs, (3) investigate the correlation between them, and (4) explore how well they cohere with each other in the context of a specific objective.

A DI itself might be robust, but the incorporated timestep is also important for sensitivity analysis. The uniformity of the required data for the computation of DIs provides a fair competition for comparison. Morid et al. (2006) used monthly rainfall data for six indices except EDI for which daily rainfall data was used. In addition, only 1-month timestep was applied to six DIs. The DIs which Heim (2002) used were dependent on numerous parameters and properties of data. Keyantash and Dracup (2002) used RDDI with one timestep, and SPI was used with only 1-month timestep. Barua et al. (2011) also applied only 1-month timestep to PN and SPI. The DI and timestep combination would influence the DI response to the change of monthly and multi-monthly rainfall. Hence, the sensitivity of drought investigation depends on the timestep of DI used. This study compares multi-monthly DIs to better identify a drought and to monitor its severity in a semi-arid Konya closed basin, Turkey. This paper is intended to assess correlation between DIs for different timesteps and, to investigate the response of DIs with different timesteps to droughts. The objective of this study therefore is to investigate the variability of DI and timestep combinations, and evaluate their dependability and effectiveness in determining the severity and evolution of droughts. Seasonal rainfall deficiencies are common in semi-arid/arid regions, so the results might be extendable to similar regions.

2. Drought indices

PDSI and some other popular DIs which demand other parameters as input, such as temperature, soil humidity, etc. were not used in this study because monthly rainfall data is the most easy-to-access meteorological data. Actual rainfall datasets were used for 1-month DI calculations and multi-monthly rainfall datasets were created from monthly values for multi-monthly DI timesteps. Six DIs which Morid et al. (2006) used except MCZI were adopted. MCZI is a modified version of CZI and the only difference is that MCZI uses median rainfall instead of mean, and was not used in this study following Morid et al. (2006) and Wu et al. (2001). All DIs were abbreviated with index name and subscript denoting the timestep, for example, a 1-month SPI was abbreviated as SPI_1 and a 24-month CZI as CZI_{24}.

2.1. Percent of normal by mean

The percent of normal by mean (PN-Mean) is a simple index for detecting a drought and can be effective when used in a single region or for a season (Barua et al., 2011; Hayes, 2000; Morid et al., 2006; Smakhtin and Hughes, 2007). PN-Mean is not able to determine the frequency of departures from normal but due to its simple calculation PN-Mean is well suited for weather broadcasting and general audience.

2.2. Rainfall decile based drought index

The Rainfall Decile based Drought Index (RDDI) has been developed (Gibbs and Maher, 1967) to monitor droughts, and has been commonly used in drought studies (Barua et al., 2011; Keyantash and Dracup, 2002; Lana and Burgueno, 2000; Morid et al., 2006; Pandey et al., 2008; Smakhtin and Hughes, 2007), especially in Australia (Mpelasoka et al., 2008; Simmonds and Hope, 2000). Discussing Australia's vulnerability to climate variability and limitations of adaptive capacity, Mpelasoka et al. (2008) compared two DIs for their potential utility in water resource management: (1) rainfall decile-based DI as a measure of rainfall deficiency and (2) soil-moisture decile-based DI as a measure of soil-moisture deficiency attributed to rainfall and potential evaporation. Both of these indices were used to investigate future droughts in Australia under various climate change scenarios. An increase in drought frequency associated with global warming was demonstrated by both indices, except for the western part of Australia. Increases in the frequency of soil-moisture-based droughts were greater than increases in meteorological drought frequency.

2.3. Statistical Z Score

The Statistical Z Score (Z-Score) is a dimensionless quantity derived by subtracting the population mean from an individual rainfall value and then dividing the difference by the population standard deviation. This conversion process is called standardizing or normalizing. Z-Score indicates how many standard deviations a rainfall value is above or below the mean. It is not the same as SPI, because it does not require adjusting the data to fit gamma or Pearson type III distribution which causes the Z-Score to not represent shorter dry periods as well as SPI does. Z-Score is frequently computed in drought studies (Akhtari et al., 2009; Komuscu, 1999; Morid et al., 2006; Patel et al., 2007; Tsakiris and Vangelis, 2004; Wu et al., 2001). To differentiate it from SPI, Z-Score is sometimes called the standardized monthly precipitation (SMP) (Sirdas and Sahin, 2008). Since the original SPI (Mckee et al., 1993) has been commonly used to fit a gamma distribution, calling as Z-Score or SMP instead of SPI for further studies is better when the distribution type is normal. Others (Guttman, 1999; Ntale and Gan, 2003; Vicente-Serrano et al., 2004) have used the Pearson type III distribution which is sometimes referred to as the 3-parameter gamma distribution for SPI calculations.

2.4. China-Z index

The China-Z Index (CZI) assumes that precipitation data follow the Pearson Type III distribution and is related to Wilson–Hilferty (Wilson and Hilferty, 1931) cube-root transformation from chi-square variable to the Z-scale (Kendall and Stuart, 1977). CZI has been used since 1995 by the National Climate Centre of China to monitor moisture conditions throughout the country. Wu et al. (2001) investigated the relationship between SPI, CZI, MCZI, and Z-Score, using monthly rainfall data from 1951 to 1998 at four stations in China. Morid et al. (2006) also used CZI and MCZI in a comparative study. Both investigations reported that SPI, CZI and Z-Score performed similarly. Wu et al. (2001) concluded that major advantages of CZI and Z-Score against SPI were: (1) simpler calculation and (2) allowance for missing data, which makes Z-Score and CZI more flexible for regions where rainfall data are often incomplete.

2.5. Standardized precipitation index

McKee et al. (1993) developed the Standardized Precipitation Index (SPI) to identify and monitor local droughts. Paulo and Pereira (2006) distinguished droughts from other water scarcity conditions and constructed a framework for understanding the general characteristics of droughts as hazards and disasters. For characterizing droughts, they described three main DIs: theory of runs, the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI), and applied them to local and regional droughts in the Alentejo region of Portugal. SPI is essentially a standardizing transformation of the probability of observed precipitation and can be computed for a precipitation total observed over any desired duration (1, 3, 6, 12, 24, 48 month SPI, etc.); short term durations of the order of months are important for agriculture, while long term durations spanning seasons or years are important for water supply management, water resources planning, and hydrological studies. The responsiveness to emerging precipitation deficits of SPI was found more reliable for shorter timesteps (Edwards and McKee, 1997; Guttman, 1998; Hayes et al., 1999; Wu et al., 2001).

Although SPI is more suited to monitoring meteorological and hydrological droughts rather than agricultural droughts, its flexibility in selecting time periods that correspond with growing seasons and crop times does make it useful to inform on some aspects of agricultural droughts (White and Walcott, 2009). Due to its rainfall-only data requirement, simplicity of calculations, decent reliability, and ability to address a variety of drought related issues, SPI has been used extensively in Turkey (Durdu, 2010; Keskin et al., 2009; Sonmez et al., 2005; Touchan et al., 2005; Turkes and Tatli, 2009), Mediterranean region (Lana and Burgueno, 2000; Lana et al., 2001; Paulo and Pereira, 2006; Salvati et al., 2009; Vicente-Serrano et al., 2004), United States (Budikova, 2008; Guttman, 1999; Hayes, 2000; Hayes et al., 1999; Heim, 2002; Keyantash and Dracup, 2002), and other parts of the world (Edossa et al., 2010; Mishra and Singh, 2009; Ntale and Gan, 2003; Pandey et al., 2008; Patel et al., 2007; Roudier and Mahe, 2010; Stricevic et al., 2011; Zhai et al., 2010).

2.6. Effective drought index

Byun and Wilhite (1999) developed the Effective Drought Index (EDI) to detect a drought and its beginning, end, and accumulation stress. Other concepts introduced through EDI were effective precipitation (EP) which is the sum of precipitation with a time-dependent reduction function, and (PRN) precipitation needed for return to normal conditions. EDI in its original form is calculated with a daily timestep (Akhtari et al., 2009; Kalamaras et al., 2010; Kim and Byun, 2009; Kim et al., 2009; Morid et al., 2006; Roudier and Mahe, 2010), unlike many other DIs. However, its principle can be extended to monthly rainfall data (Morid et al., 2007; Pandey et al., 2008). Smakhtin and Hughes (2007) developed a software which uses monthly algorithm. Akhtari et al. (2009), and Roudier and Mahe (2010) found EDI difficult to calculate. Although reasonable, EDI has not received much attention. EDI has a drought classification similar to SPI, as shown in Table 2.

3. Study area and data

Konya closed basin, with an area of 53,850 km^2, is located in Central Anatolia and occupies 7% of the total area of Turkey (Fig. 1). Although the basin is mainly a plateau at 900–1050 m above sea level, its altitude varies from 900 m to 3534 m. It has a population of 3.2 million inhabitants, equally divided between cities and rural areas. The Central Anatolian Plateau, which itself is also a closed basin, has several drainless areas. Two of these areas

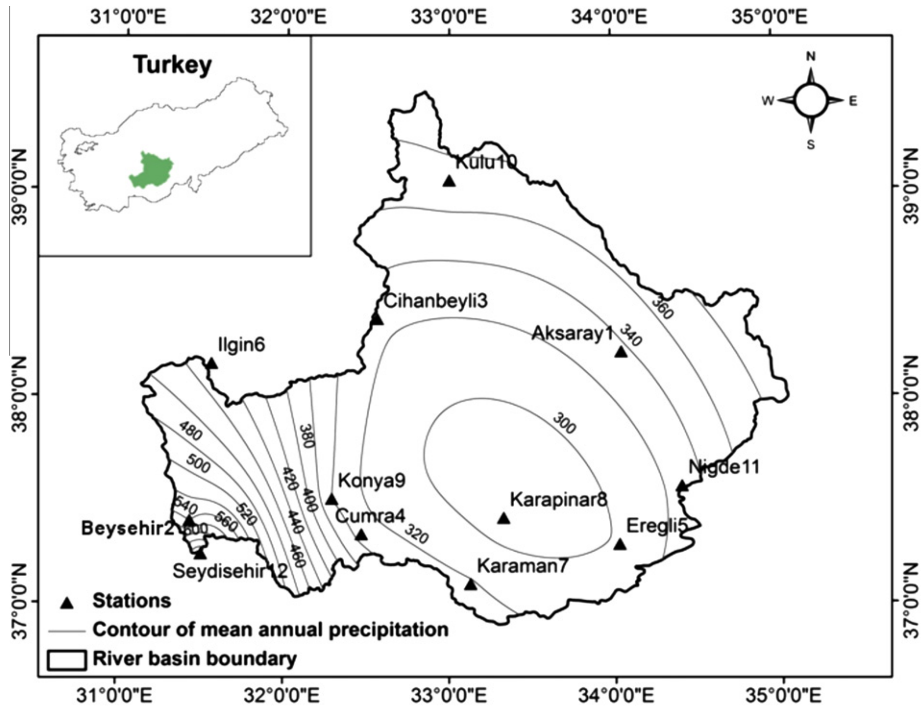

Fig. 1. Study area showing location of meteorological stations.

have large lakes: Tuz (Salt) Lake and Beysehir Lake which is the largest freshwater lake in Turkey and is the main source of drinking water in the basin. Tuz Lake is the second largest lake in the country after Van Lake and is the third saltiest lake in the world. The basin has rich fauna and flora biodiversity, with 2 national parks, 12 important bird areas, 8 important plant areas, and big colony of Greater Flamingos. The basin is now recognized as one of the Global 200 Eco-regions. Meke Maar lake and Kizoren sinkhole are within the basin and listed in Ramsar List of Wetlands of International Importance. The main threats to the basin are agricultural practices based on wild irrigation and illegal wells and the lack of long-term conservation strategies, resulting in the loss of natural wetland functions, decrease in groundwater level, habitat loss and soil salinity, which are further exacerbated by recurring droughts in the basin. However, there have not been many drought studies conducted in the basin; this paper attempts to undertake a more comprehensive study involving six DIs with various timesteps.

A minimum of 30 years of data are needed to accurately calculate most of the DIs used. Monthly rainfall data from twelve stations, shown in Fig. 1, were obtained from Turkish State Meteorological Service (TSMS). The longer the length of record used in DI calculation, the more reliable DI values will be, especially for long timesteps to capture the signals of climate variability (Wu et al., 2005). Therefore, the length of record to be used in DI calculation is recommended to be as long as possible, but some stations in Konya closed basin started recording by 1972, hence the best mutual period dataset (from 1972 to 2009) of 38 years was used. Longer period of data might have been used for those few stations for which longer period of records were available, but in this case the length of data may affect the results of comparison. This study aims at the accuracy of response of DI and timestep combination to the change of monthly and cumulative rainfall in a semi-arid area (particularly Konya closed basin). So, equal length of data for each station was used to ensure a fair comparison.

Statistical characteristics of rainfall along with station locations are shown in Table 1. The mean annual rainfall varied from 286 mm to 740 mm during the period of record. Every station received less than 500 mm of precipitation annually, except station 12 (Seydisehir). If Seydisehir station was excluded, the annual rainfall varied from 286 mm to 485 mm and the basin average was

Table 1
Meteorological stations in Konya closed basin.

Stations	Elevation (m)	Coordinates		Statistics of annual rainfall series (1972–2009)					
		Lat.	Long.	Mean (mm)	Max (mm)	Min (mm)	St.D	Skewness	Kurtosis
(1) Aksaray	965	38.23	34.05	338	506	229	74	0.50	−0.43
(2) Beysehir	1129	37.41	31.43	485	623	317	91	−0.49	−0.88
(3) Cihanbeyli	969	38.39	32.56	320	500	185	72	0.09	−0.23
(4) Cumra	1013	37.35	32.47	319	502	177	69	0.32	0.08
(5) Eregli	1044	37.30	34.03	296	439	140	60	−0.07	0.54
(6) Ilgin	1034	38.17	31.55	423	584	236	79	−0.26	0.01
(7) Karaman	1025	37.11	33.13	326	513	213	70	0.59	0.25
(8) Karapinar	1004	37.43	33.33	286	413	172	60	0.39	−0.27
(9) Konya	1031	37.52	32.29	317	500	176	74	0.02	−0.38
(10) Kulu	1010	39.06	33.00	379	548	219	75	0.03	−0.20
(11) Nigde	1211	37.58	34.41	325	461	193	66	−0.11	−0.07
(12) Seydisehir	1131	37.25	31.50	740	1127	475	153	0.20	−0.29

Table 2
Classes of drought indices (wet classes are not displayed).

	Extreme drought (−3)	Severe drought (−2)	Moderate drought (−1)	Normal (0)
RDDI (%)	⩽10	10–20	20–30	30–70
PN (%)	⩽40	40–55	55–80	80–100
Z-Score	⩽−2.00	−1.99 to −1.50	−1.49 to −1.00	−0.99 to 0.99
SPI	⩽−2.00	−1.99 to −1.50	−1.49 to −1.00	−0.99 to 0.99
EDI	⩽−2.00	−1.99 to −1.50	−1.49 to −1.00	−0.99 to 0.99
CZI	⩽−2.00	−1.99 to −1.50	−1.49 to −1.00	−0.99 to 0.99

347 mm and median was 325 mm of rainfall. The standard deviation of rainfall at each station was similar to that at other stations, being about 15% of station's maximum rainfall value and 20% of station's mean rainfall.

4. Methodology

This study emphasizes data requirements and availability (Ntale and Gan, 2003) and tractability (Barua et al., 2011; Keyantash and Dracup, 2002) of a DI. Six rainfall based DIs (PN, RD, Z-Score, CZI, SPI, and EDI) were used with monthly rainfall data of 38 years (456 months).

- There were no missing data in the TSMS dataset from January-1972 to December-2009.
- Calculation of each DI for 1-month timestep resulted in 456 rows of DI values. For multi-monthly calculations, e.g., 12-month timestep, the first cumulative rainfall value was calculated from the preceding 12 months (the first value was December-1972), so each DI was calculated from December-1972 to December-2009, resulting in 445 rows of DI values.
- These calculations were made for all 12 stations, involving five indices (PN, RDDI, Z-Score, SPI, CZI) for eighteen different timesteps (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 18, 24, 30, 36, and 48 months).
- DIs were abbreviated with index name and subscript denoting the timestep. (For instance, Z-Score$_{48}$ is for 48-month timestep of Z-Score.)
- EDI was calculated only once (no timestep) per station because it is a timestep independent index, determined as weighted rainfall over a year. EDI values started from January-1973 to December-2009 (444 rows) for each station.
- All DI values were converted to integer values to allow comparing drought classes. The meaning of integers was "−3" for Extreme Drought (ED), "−2" for Severe Drought (SD), "−1" for Moderate Drought (MD), "0" for Normal season, as seen in Table 2, and "+1" for all kinds of wet seasons. For instance, if the SPI value of a month is −1.54, this indicates severe drought and it would be converted to "−2" as integer, or the RDDI value is 8%, then this reflects extreme drought and would be converted to "−3".

Correlations between DIs were computed using these integers. Although Z-Score, SPI, EDI and CZI have the same range of numerical values (Table 2), this conversion is essential to determine drought classes indicated by PN and RDDI and compare with other DIs. This conversion is also important for a qualitative comparison of severities (drought classes).

4.1. Calculation of DIs

Methodology for computation of each DI is now discussed.

4.1.1. PN-Mean

Computation of PN-Mean involves two steps. First, the mean value ($\bar{x}$) for the month or season of the year is found. Second, actual rainfall value (x_i) is divided by the mean ($\bar{x}$) and multiplied by 100 to get the PN-Mean in percent.

$$\text{PN-Mean}(\%) = \frac{x_i}{\bar{x}}100 \tag{1}$$

4.1.2. RDDI

Deciles are calculated from actual rainfall. First, rainfall values of each calendar month (or group of months) are ranked from lowest to highest and a cumulative frequency distribution is constructed. The distribution is then split into 10 deciles (10% slices). The first decile that has the top rainfall values indicates wettest months in the series, the last decile indicates driest months in the series, the last decile indicates wettest months, and other deciles show the range from the driest to wettest months. RDDI is often grouped into ten classes (classes by each decile) and is shown as integers from 1 to 10. It is also common to classify RDDI into five classes, two deciles per class. RDDI was classified into 10 classes in this paper. To synchronize with other indices, three of them which correspond to wet classes are not shown in Table 2.

4.1.3. Z-Score

The standard deviation is the unit of measurement of the Z-Score which allows comparison of observations from different normal distributions. Notation 'Z' is used, because the normal distribution is also known as the "Z distribution." The Z-Score is defined for each timestep as the difference between moving cumulative rainfall (x_i) and the multi-monthly rainfall average ($\bar{x}$), divided by the standard deviation (σ):

$$\text{Z-Score} = \frac{x_i - \bar{x}}{\sigma} \tag{2}$$

If the case is 1 month timestep then x_i is the monthly rainfall of the specific month and $\bar{x}$ is the rainfall average of that specific month in the time series. Moreover, x_i is the total rainfall of a specific month and two preceding months when the case is 3-month timestep, then $\bar{x}$ is the time series average of total rainfall for that specific 3 month period.

4.1.4. CZI

CZI is calculated as:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

$$C_s = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{n \times \sigma^3} \tag{4}$$

$$\text{CZI} = \frac{6}{C_s}\left(\frac{C_s}{2}\text{Z-Score} + 1\right)^{1/3} - \frac{6}{C_s} + \frac{C_s}{6} \tag{5}$$

where σ is the standard deviation, n is the number of observations, and C_s is the skewness coefficient. The calculation of x_i and $\bar{x}$ is same as of Z-Score.

4.1.5. SPI

To calculate SPI, first a frequency distribution of rainfall data for the selected time scale is constructed. Second, a theoretical probability density function is fitted to the empirical rainfall frequency distribution. Rainfall data of most climatic zones may be fitted by a gamma distribution, although the best distribution type may vary with temporal and spatial scale. Third, equiprobability transformation from the fitted distribution to the standard normal distribution is applied to have a zero mean and unit variance, which represents SPI. The transformed distribution allows to determine the extent of rainfall deficit which facilitates comparison of spatial drought conditions for monitoring droughts at various temporal scales, since SPI is the normalization of rainfall data.

This study also used the gamma distribution which is defined by its probability density function:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \tag{6}$$

The maximum likelihood method was used to estimate the optimal values of the α (shape) and β (scale) parameters as:

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \quad \text{and} \quad \beta = \frac{\bar{x}}{\alpha} \tag{7}$$

where $\bar{x}$ represents the sample statistic, the rainfall average,

$$A = \ln(\bar{x}) - \frac{\Sigma \ln(x)}{\text{n}} \tag{8}$$

and n is the number of observations. The obtained parameters were then used to derive the cumulative probability function as

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx \tag{9}$$

The rainfall dataset may contain zero values, since the gamma distribution is undefined for zero rainfall, then the cumulative probability of zero and nonzero rainfalls, $H(x)$, was calculated as

$$H(x) = q + (1 - q)G(x) \tag{10}$$

where q is the probability of zero rainfall.

If m is the number of zeros present in the dataset, then q is estimated by m/n. The cumulative probability is then transformed into a standardized normal distribution so that the SPI mean and variance are 0 and 1, respectively.

4.1.6. EDI

EDI is a function of PRN, the amount of precipitation necessary for recovery from the accumulated deficit since the beginning of a drought. PRN stems from monthly EP and its deviation from the mean for each month. The first step is the calculation of EP, defined as a function of current month's rainfall and weighted rainfall over a year. If P_i is rainfall and N is the duration of preceding period, then EP for the current month is:

$$EP = \sum_{m=1}^{N}\left[\left(\sum_{i=1}^{m} P_i\right)/m\right] \tag{11}$$

Then, mean ($\overline{EP}$) and standard deviation of the EP values for each month are calculated and the time series of EP values is converted to deviations from the mean (DEP):

$$DEP = EP - \overline{EP} \tag{12}$$

The PRN values are then calculated as:

$$\text{PRN} = \text{DEP}/\sum_{i=1}^{N}\frac{1}{i} \tag{13}$$

The summation term is the sum of the reciprocals of all the months in the duration N. Finally EDI is calculated as

$$\text{EDI} = \text{PRN}/\sigma_{\text{PRN}} \tag{14}$$

where σ_{PRN} is the standard deviation of the relevant month's PRN values.

4.2. Comparison of DIs

DI values were converted to integers to present drought classes (Table 2) for 5 indices for 18 timesteps, and plus EDI (5 indices × 18 time steps + EDI = 91). Ninety-one columns each representing DI timesteps were created with the data of 456 rows that denote months of 38-years of record. This resulted in 12 (number of stations) worksheets consisting of 91 columns by 456 rows. The Pearson correlation coefficient was computed pair-wise between the columns of the same worksheet to create the correlation matrix (Table 3). As an instance of computation, PN_1 was paired with SPI_1 and the Pearson correlation coefficient (0.59) was computed for this pair, this formed one cell in the matrix. PN_1 paired with EDI and all timesteps of all DIs (PN_1, RDDI_1, CZI_1, SPI_1, …, PN_{48}, RDDI_{48}, CZI_{48}, Z-Score$_{48}$, SPI_{48}) which formed a row with 91 cells in matrix. And then for the next row of the matrix, RDDI_1, was paired with all timesteps of all DIs. Thereafter, a correlation matrix [91 × 91] was created for all timesteps of all DIs as seen on Table 3. All calculations were made for each station (worksheet) and then relevant results were averaged to obtain the final result to represent the basin.

5. Results and discussion

5.1. Relationship between drought indices

After creating the correlation matrix as mentioned above, the highest cumulative correlation coefficient was found for EDI, far higher than others. Fig. 2 shows the distribution of correlations by timesteps. Five different indices were combined for each timestep seen on the axes. The median timesteps (8, 9, 10, 11, 12 months) showed better correlation (>0.55), while lower and higher timesteps showed less correlation. There were two reasons for this: (1) Median timesteps had better correlation with both lower and higher timesteps (longer range was correlated), while lower/higher timesteps were only correlated with nearby timesteps; and (2) the strength of the relationship between median timesteps with closer timesteps was stronger (shorter range was highly correlated). However, EDI showed dramatically higher correlations with most of the timesteps, and this made EDI the best correlated DI overall. Very high pair-wise correlation (>0.90) was obtained between Z-Score, CZI, and SPI for the same timesteps.

In order to investigate the relationship among timesteps, the average of 91 correlation coefficients for a particular timestep of a DI was computed to represent its timestep average correlation against all DIs (average of each column of matrix, e.g., the average of the column of SPI_1 reflects how SPI_1 is correlated with all timesteps of DIs; presented by first circle bullet in Fig. 3, and SPI_2 is presented by second circle bullet, and so on. PN_{12} is presented by the diamond located by the timestep of 12-month on the axis). The correlation coefficients of five various indices for the same timestep (for instance, as 1-month group; PN_1, RDDI_1, Z-Score$_1$, CZI_1, SPI_1, thereafter other groups formed out of each timestep) were grouped and averaged (18 averages of 5 correlation coefficients; each average represents the correlation of one timestep

Table 3
Partial sample of 91 by 91 matrix for pair-wise Pearson correlation coefficients between indices.

	PN_1	$RDDI_1$	Z-Score$_1$	CZI_1	SPI_1	PN_2	$RDDI_2$		PN_{48}	$RDDI_{48}$	Z-Score$_{48}$	CZI_{48}	SPI_{48}
PN_1	1.00	0.92	0.59	0.60	0.59	0.67	0.64	...	0.07	0.09	0.07	0.07	0.08
$RDDI_1$	0.92	1.00	0.65	0.62	0.60	0.65	0.66	...	0.08	0.10	0.09	0.09	0.09
Z-Score$_1$	0.59	0.65	1.00	0.92	0.88	0.45	0.49	...	0.06	0.08	0.06	0.06	0.06
CZI_1	0.60	0.62	0.92	1.00	0.93	0.44	0.47	...	0.05	0.07	0.06	0.06	0.06
SPI_1	0.59	0.60	0.88	0.93	1.00	0.45	0.47	...	0.05	0.07	0.05	0.05	0.05
PN_2	0.67	0.65	0.45	0.44	0.45	1.00	0.92	...	0.10	0.13	0.11	0.11	0.12
$RDDI_2$	0.64	0.66	0.49	0.47	0.47	0.92	1.00	...	0.12	0.15	0.14	0.14	0.14
Z-Score$_2$	0.49	0.51	0.55	0.53	0.54	0.65	0.69	...	0.09	0.11	0.10	0.10	0.10
CZI_2	0.51	0.52	0.53	0.52	0.52	0.69	0.70	...	0.09	0.11	0.09	0.09	0.09
SPI_2	0.51	0.51	0.52	0.51	0.53	0.69	0.68	...	0.08	0.10	0.08	0.08	0.09
	...	...	...	...	...	...	...		...	...	...	...	...
PN_{48}	0.07	0.08	0.06	0.05	0.05	0.10	0.12	...	1.00	0.73	0.60	0.60	0.60
$RDDI_{48}$	0.09	0.10	0.08	0.07	0.07	0.13	0.15	...	0.73	1.00	0.81	0.82	0.82
Z-Score$_{48}$	0.07	0.09	0.06	0.06	0.05	0.11	0.14	...	0.60	0.81	1.00	0.97	0.98
CZI_{48}	0.07	0.09	0.06	0.06	0.05	0.11	0.14	...	0.60	0.82	0.97	1.00	0.97
SPI_{48}	0.08	0.09	0.06	0.06	0.05	0.12	0.14	...	0.60	0.82	0.98	0.97	1.00

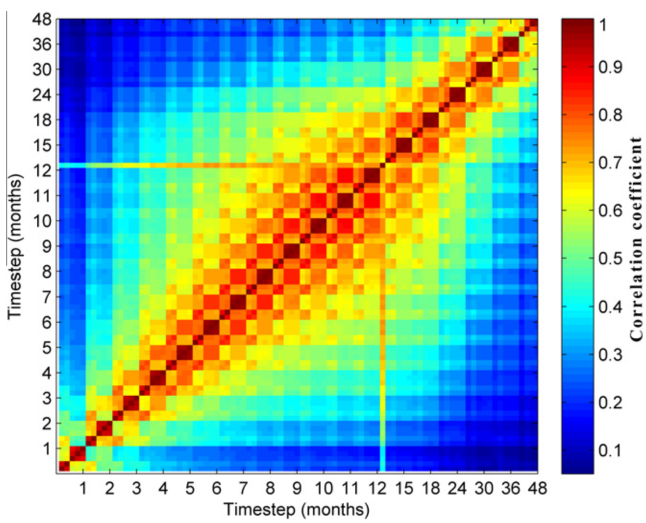

Fig. 2. Correlation between drought indices for various time steps. Each time step consists of five different indices (1 pixel for each DI in the order of PN, RDDI, Z-Score, CZI, SPI. Preceding 5 pixels represent each time step. EDI allocates 1 pixel which is separately located right after 12-month time step). Ordinate and abscissa interpret same 91 DIs to present mutual correlation coefficient.

independently of DI). The average correlation coefficient computed from all DIs for each timestep is timestep average of DIs, shown by continuous line in Fig. 3. As can be seen from the figure there was not much difference between DI correlations with the same timestep which means average correlation of a DI with particular timestep against all time steps of DIs had similar average correlation with other DI of the same timestep (PN_1, $RDDI_1$, Z-Score$_1$, CZI_1, SPI_1. They were all similar).

As expected, median timesteps (5-month to 18-month) had better correlations (>0.5) with other timesteps. On the other hand, a drought is an accumulation of water deficiencies by time, so multi-monthly analysis would be a better indicator, especially for semi-arid/arid regions because short-term/seasonal water deficiencies are common in these areas. A 1-month timestep has been commonly used in DI comparative studies (Barua et al., 2011; Keyantash and Dracup, 2002; Morid et al., 2006;). Timestep influence is also essential while comparing the robustness of DIs. It is clear that the least correlation is for 1-month, followed by 48-month and 2-month timesteps. It would be beneficial to not only use lower timesteps, but to involve at least 6-month and 9-month timesteps of any DI while studying short/long term drought in a semi-arid region.

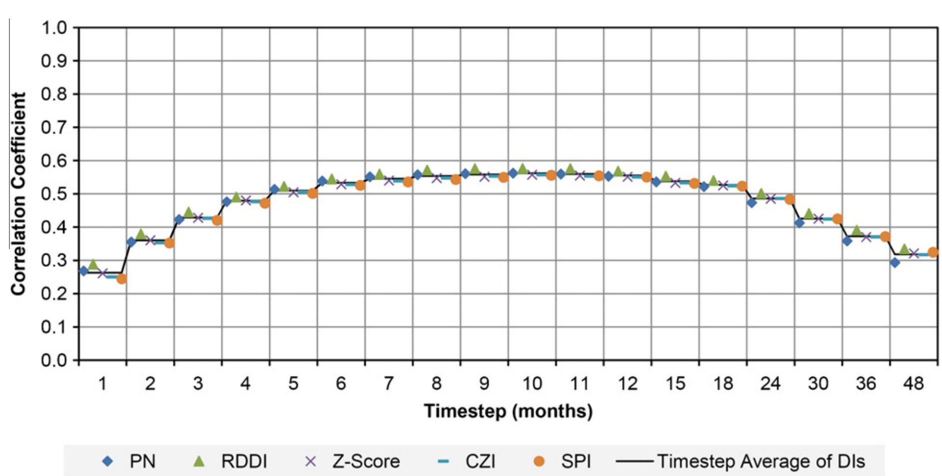

Fig. 3. Average correlation coefficient of a particular DI by timesteps against all timesteps of all DIs.

To consider which timesteps of indices may better match a particular DI, 91 correlation coefficients from all timesteps of all DIs (the column of that particular DI) were extracted from the matrix, then the rows were grouped according to their timesteps. Fig. 4 shows four particular DIs (EDI, Z-Score$_3$, SPI$_{12}$, and CZI$_{24}$) besides timestep average of DIs that was already present in Fig. 3. The similarity of correlation curves was detected for different/same DIs for the adjoining timesteps. Therefore, Z-Score$_3$ was selected to reflect the response of lower timesteps, SPI$_{12}$ for median timesteps and CZI$_{24}$ for higher timesteps in Fig. 4. All lower timesteps of any DI (like Z-Score$_3$) were left-skewed, while higher timesteps of any DI (like CZI$_{24}$) were right-skewed.

Although EDI's curve was platykurtic and did not have distinct peaks, EDI had the best correlation with the timesteps of 7, 8, 9, 10 and 11 months. EDI's average coefficients for these timesteps were higher than 0.72, while the timestep averages were around 0.55. Average coefficients of EDI for each timestep were approximately 0.15 point higher than any timestep averages before 24-month. EDI started being less sensitive with other DIs after 24-month timestep.

Ordinarily, EDI was highly correlated with lower timesteps than other DIs, except Z-Score$_3$ (and others which are not shown in figure). Z-Score$_3$ had significantly higher correlations than EDI for 2 and 3-month timesteps, and had peak for 3-month timestep, because of Z-Score$_3$ Z-Score$_3$ (1.00), Z-Score$_3$ CZI$_3$ (0.95), and Z-Score$_3$ SPI$_3$ correlation (0.93). Z-Score$_3$ did not show the same high correlations with PN$_3$ (0.69) and RDDI$_3$ (0.73), although they were computed for the same timestep. Z-Score$_3$ was better correlated than timestep average for pre-5-month timesteps, then the correlation dramatically decreased.

The same timestep of Z-Score, SPI and CZI had similar results, but PN and RDDI did not. SPI$_{12}$ had slightly lower but very similar correlations with timestep average till 7-month, after then the correlation increased, and peaked for 12-month timestep. SPI$_{12}$ had only better correlation than EDI for 10, 11, 12, and 15 month timesteps. SPI$_{12}$ was very similar to EDI for timesteps higher than those timesteps, and EDI was better (approximately 0.2 point higher) for pre-9-month timesteps. CZI$_{24}$ had only better correlations than EDI, when the timestep was higher than 18-month, and EDI had better correlations for the rest.

5.2. Comparison of drought classes indicated by DIs

The highest cumulative correlation coefficient in matrix was found for EDI in earlier section. EDI showed higher correlations with most of the timesteps of DIs, and EDI was found to be the best correlated DI overall. Individually each station's best correlated index was also found to be EDI.

After calculation of DIs, to do the second phase of analysis, these values were grouped with respect to their drought classes to compute the percentages in the time series. For instance, if a DI value was indicating extreme drought in 10 months out of 456 months, then the extreme drought percentage in that time series would be 2.2%. This part of study discusses comparisons of DIs with EDI (EDI was used as a reference, since EDI was best correlated with all timesteps of all DIs overall). Each comparison in this part illustrated with one figure to better convey the results. These figures not only compare with EDI but they also show the changes for timesteps of their own index. On the other hand, multiplex or pair-wise comparisons can be made from Figs. 5–9, to evaluate the results of DIs and also to consider the discrepancies among them.

5.2.1. Comparison of Z-Score with EDI

Fig. 5 shows that Z-Score$_1$ detected no extreme drought, and very low severe drought (1%) rate. The total percentage of any class of droughts indicated by EDI (19.1%) was higher than that of Z-Score for any timestep. Moderate droughts were found similarly by EDI (11.6%) and Z-Score (10.4%, average of timesteps); only Z-Score$_3$ (11.8%) and Z-Score$_4$ (12.6%) detected higher rates than did EDI. Extreme and severe droughts for all timesteps were underestimated by the Z-Score. The timesteps over 4 months tended to be more reliable, and Z-Score$_6$ to Z-Score$_{12}$ were evaluated as they responded in a better way. Z-Score$_1$ to Z-Score$_4$ were less consistent, and Z-Score$_1$ was the worst and detected no extreme drought, 1.0% severe drought and 9.8% moderate drought (10.8% was found as the total of all times with any class of drought).

5.2.2. Comparison of SPI with EDI

EDI had a greater total drought (sum of ED + SD + MD) percentages (19.1%) than for any timestep of SPI which means EDI resulted in more values indicating any drought classes than did SPI (Fig. 6).

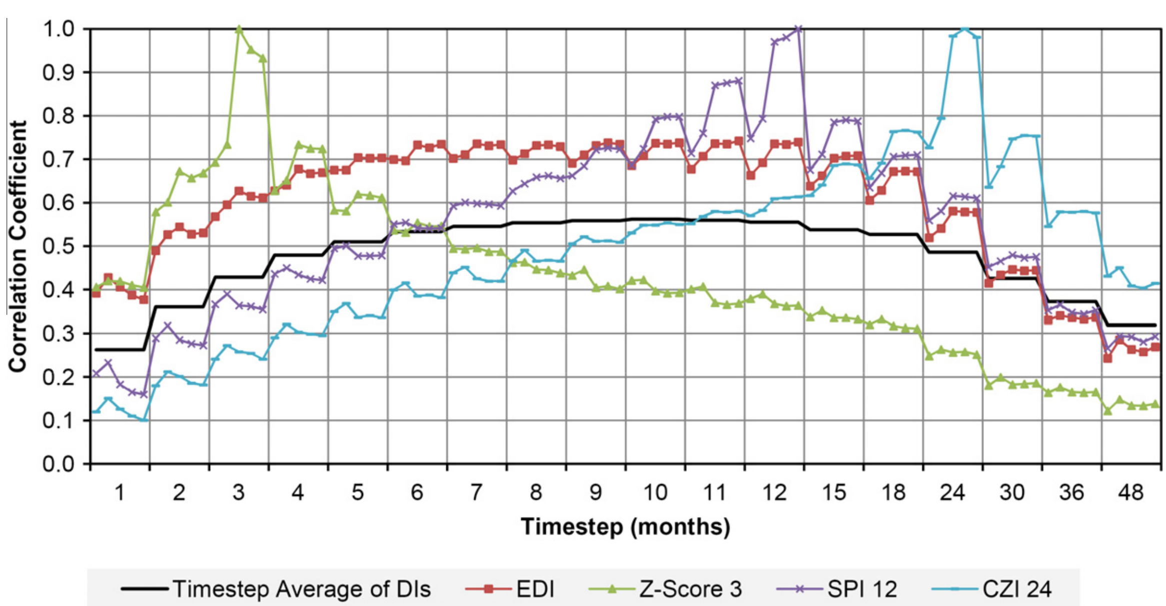

Fig. 4. Correlation coefficient between DIs and timesteps.

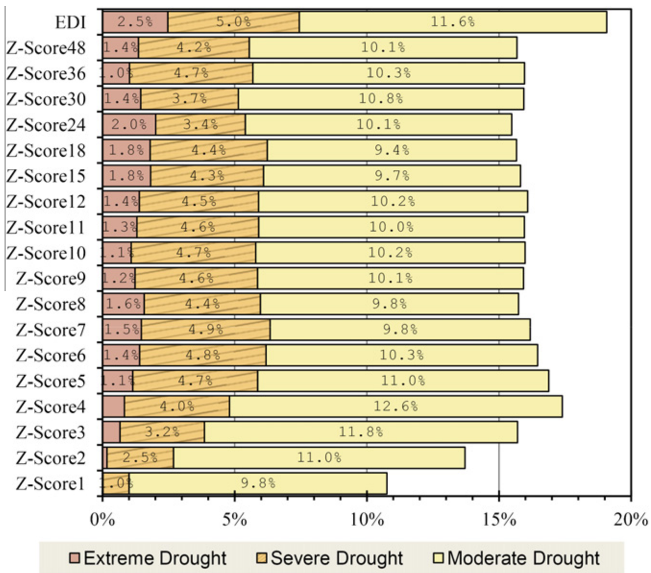

Fig. 5. Drought class percentages by EDI and Z-Scores as an average of 12 stations in Konya closed basin for the 1972–2009.

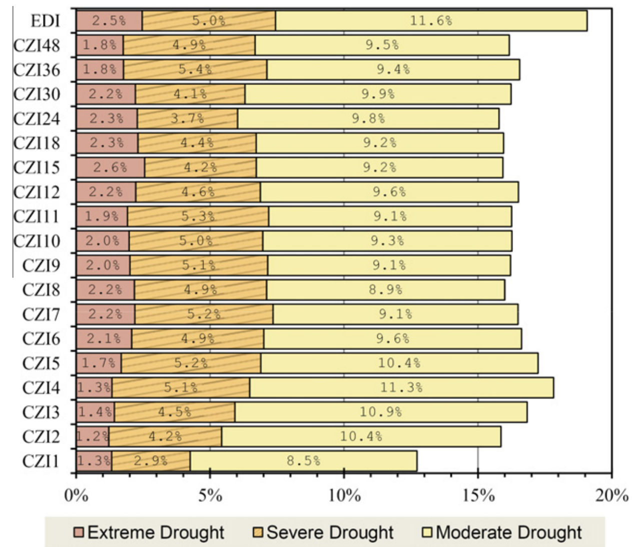

Fig. 7. Drought class percentages by EDI and CZIs as an average of 12 stations in Konya closed basin for the 1972–2009.

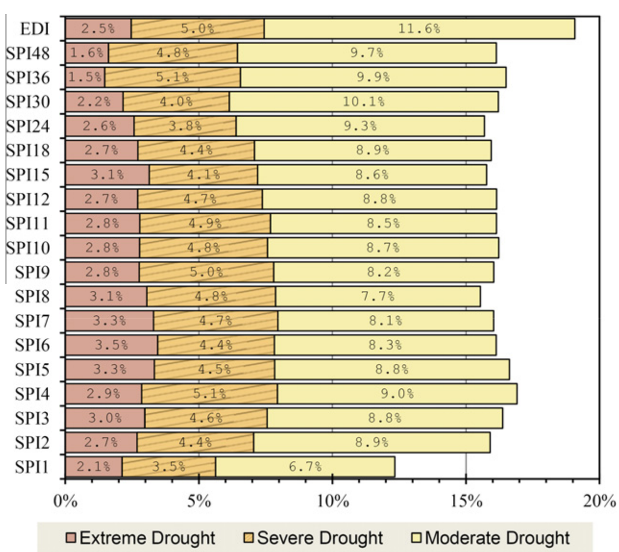

Fig. 6. Drought class percentages by EDI and SPIs as an average of 12 stations in Konya closed basin for the 1972–2009.

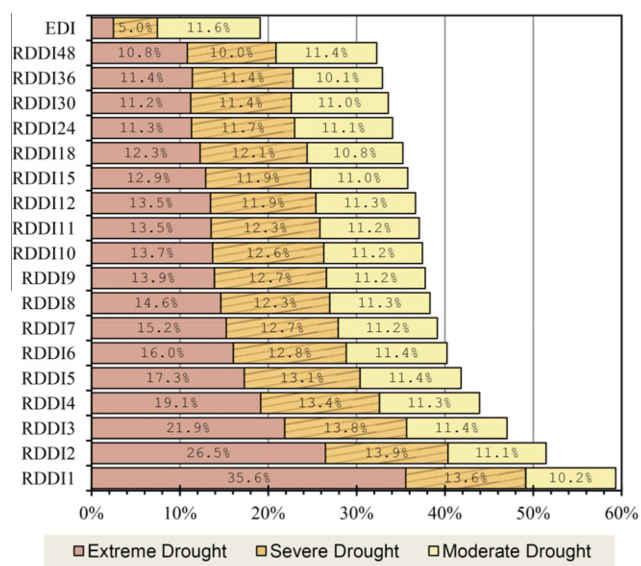

Fig. 8. Drought class percentages by EDI and RDDIs as an average of 12 stations in Konya closed basin for the 1972–2009.

Therefore, a large portion of these overestimated droughts belonged to moderate droughts (11.6%). Severe droughts had also been overestimated by EDI (except SPI_4 and SPI_{36}). An interesting part of Fig. 6 shows EDI underestimated extreme droughts than did any SPI, from SPI_2 to SPI_{24}. The highest rate of extreme drought was detected by SPI_6. EDI detected 2.5% extreme drought, while SPI_5, SPI_6, and SPI_7 detected 3.3%, 3.5%, and 3.3%, respectively. Drought classes detected by EDI were most similar to those by SPI_{10}, SPI_{11} and SPI_{12}. SPI_1 was less consistent and detected 2.1% extreme drought, 3.5% severe drought and 6.7% moderate drought (12.3% was found as the total of all times with any class of drought). Extreme drought percentages increased from SPI_1 to SPI_6 and then decreased, but SPI_{15} responded differently in this trend.

5.2.3. Comparison of CZI with EDI

CZI underestimated extreme droughts in all cases (Fig. 7), except CZI_{15} (2.6%). CZI_{15} detected a slightly higher rate of extreme drought than nearby timesteps as did SPI_{15}. The rate of extreme droughts was found similar for each timestep within the range of 6 months to 30 months (mean = median = 2.2%). Severe droughts were close but mostly slightly higher than by EDI (5.0%) between CZI_4 and CZI_{11}. Moderate droughts were always slightly underestimated by CZIs. The total percentage of any class of droughts indicated by any timestep of CZI was lower than EDI's total (19.1%). All analyses entailing CZI_6 to CZI_{12} responded similarly and consistently. CZI_1 was less consistent and detected 1.3% extreme drought, 2.9% severe drought and 8.5% moderate drought (12.7% was found as the total of all times with any class of drought).

5.2.4. Comparison of RDDI with EDI

RDDI was similar to EDI for only moderate droughts for all timesteps, but results were irrelevant for other drought classes. In Fig. 8, RDDI detected from a minimum 32.3% ($RDDI_{48}$) to a maximum of 59.3% ($RDDI_1$) of the sum of any drought class which

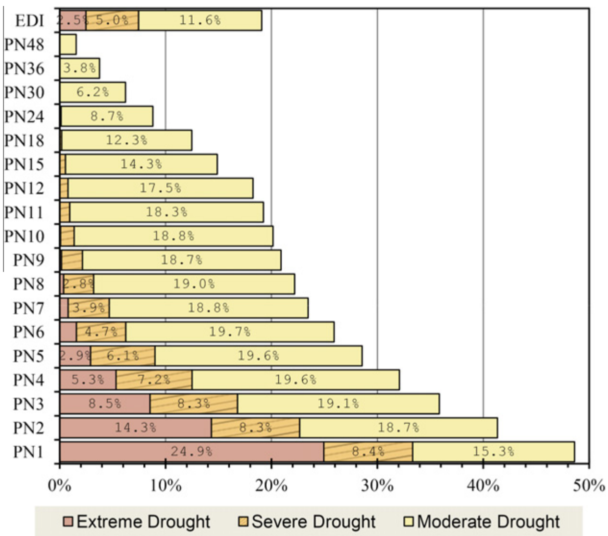

Fig. 9. Drought class percentages by EDI and PNs as an average of 12 stations in Konya closed basin for the 1972–2009.

may be considered inappropriate. RDDI for all timesteps detected far higher extreme and severe droughts but RDDI for lower timesteps found radically high extreme and severe droughts compared to EDI. Severe and moderate drought percentages were more consistent and slightly higher than 10% (deciles) for any timestep.

5.2.5. Comparison of PN with EDI

PN found dramatically decreasing total drought percentages of any class with the increase of timestep that can be clearly seen in Fig. 9; this was also the case for extreme and severe droughts. No extreme droughts were detected by PN_{11} to PN_{48}. For lower timesteps drought events were overestimated but underestimated for higher timesteps. The variability of PN with the change in timestep was found to be the highest among all DIs. PN was also found as the most irrelevant DI to other DIs. PN_5 and PN_6 might be the best match with EDI.

As the results of multiplex and pair-wise comparisons from Figs. 5–9; Z-Score, SPI, and CZI detected the sum of all drought classes around 15% which was an underestimation according to EDI (19.1%). The three indices showed similar response, especially SPI and CZI, for timesteps of 6 to 12 months, although Z-Score always underestimated extreme droughts but overestimated moderate droughts. SPI detected higher extreme drought rates than did CZI for all timesteps except for 36 and 48 month timestep. Z-$Score_4$, SPI_4, CZI_4 found the highest total percentages of any class of drought for all timesteps. Various timesteps of SPI and CZI were more consistent to other timesteps of same DI, besides the fact that all DIs for 1-month timestep were irrelevant to other timesteps.

5.3. Spatial variability of droughts detected by EDI

There is a variety of drought severity from one station to another, although the entire area of Konya closed basin have suffered similarly from extreme drought events. Fig. 10 reflects this variety in the basin showing spatial distribution of drought severities besides the rainfall data shown in Table 1. Station 8 is the driest (average annual rainfall of 286 mm) region of the basin and EDI found this station having the lowest rate of extreme (0.5%) and severe (3.4%) droughts but one of the highest rates of moderate droughts. EDI found the following stations most affected from extreme and severe droughts (ED + SD): station 6 (10.4%), station 11 (9.7%), station 10 (9.1%), and least affected stations were station 8 (3.9%), station 3 (5.2%), station 2 (6.4%). Station 12 is located in the southwestern part of the basin and in the wettest region with the average annual rainfall of 740 mm which is slightly more than double of other stations. Nevertheless, station 12 responded similarly as did other stations.

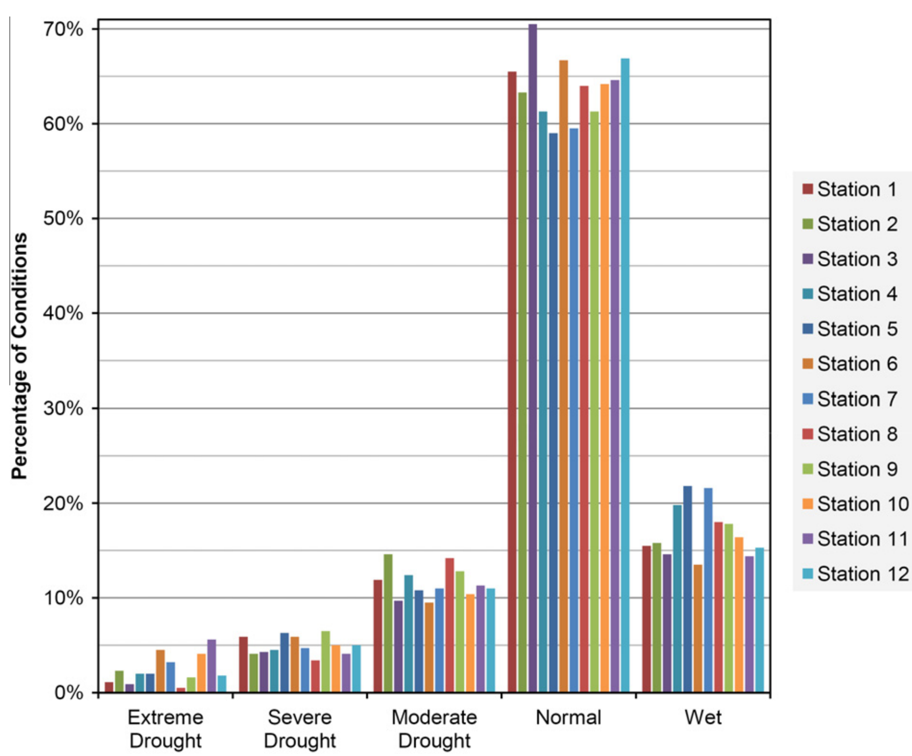

Fig. 10. Droughts found by EDI in Konya closed basin for the 1972–2009 (stations ordered respectively from left to right).

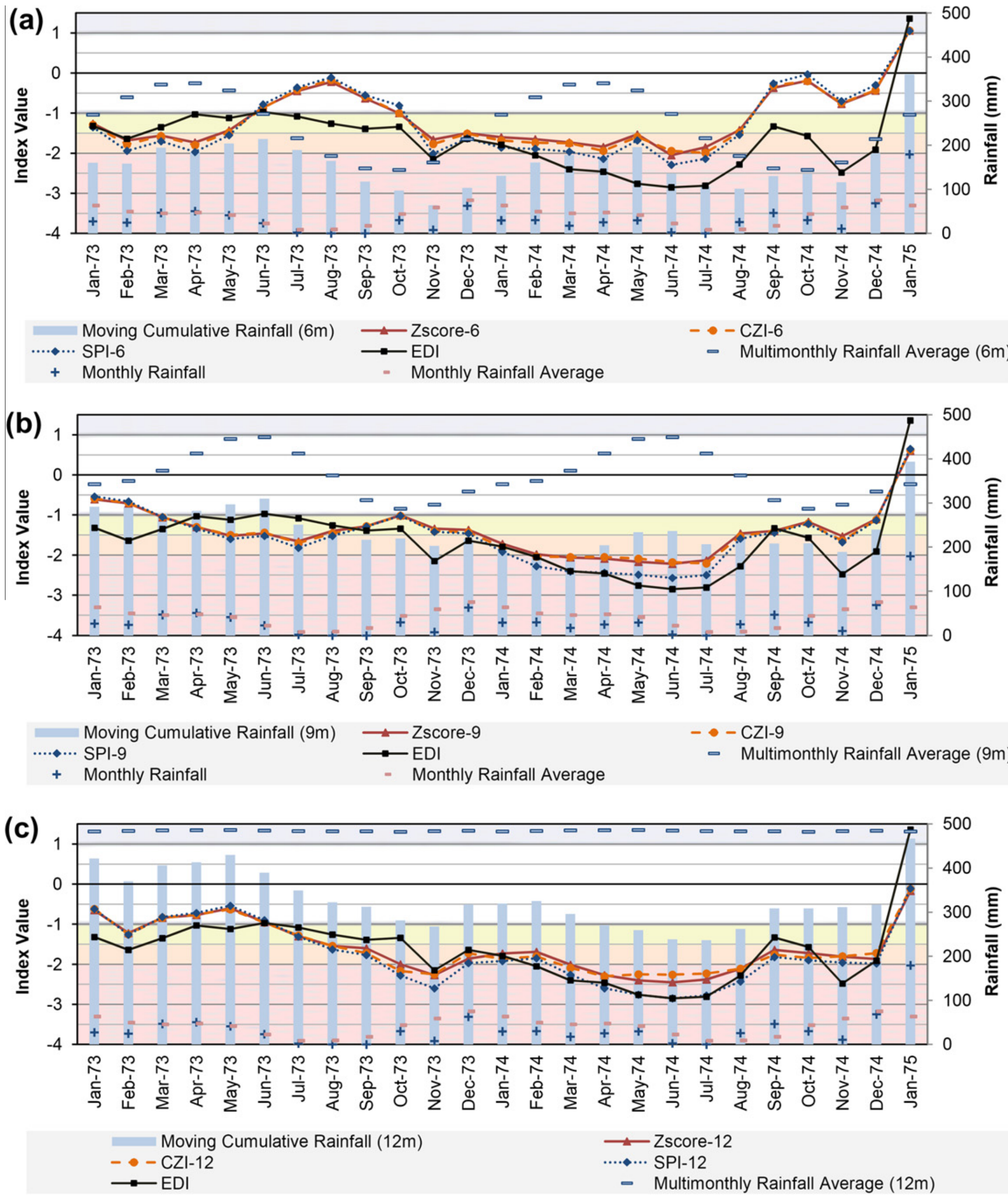

Fig. 11. Time series of drought indices and rainfall at Station 2 (Beysehir), timesteps of: (a) 6 months, (b) 9 months, and (c) 12 months.

Table 4
Pair-wise Pearson correlation coefficients of indices with same timestep for 1973–1974 dry spell at station 2 (EDI is timestep independent).

	Timestep (months)							
	3 (%)	6 (%)	7 (%)	8 (%)	9 (%)	10 (%)	11 (%)	12 (%)
EDI-SPI	51.5	68.5	74.0	77.8	82.3	86.0	86.4	83.1
EDI-CZI	54.1	70.9	76.1	79.8	83.4	86.0	84.7	81.7
EDI-Z-Score	56.8	72.1	77.3	79.4	82.9	86.9	87.7	84.0
SPI-CZI	99.3	99.4	99.3	99.3	99.2	98.6	98.5	98.6
SPI-Z-Score	97.7	99.2	99.4	99.4	99.5	99.6	99.7	99.8
CZI-Z-Score	99.1	99.8	99.8	99.7	99.7	99.0	98.6	98.7
EDI-Average(SPI-CZI-Z-Score)	54.2	70.5	75.8	79.0	82.9	86.3	86.3	82.9

5.4. Comparison using historical droughts (event based)

It is known that the basin was affected by rainfall deficiencies in the years of 1973–1974, 1984–1985, and 1989, 1993–1994, 2000–2001, 2004–2005 and 2007. As a result of this study; the 1973–1974 drought was the most severe drought with the longest duration. Although the 1993–1994 drought lasted almost as long as 1973–1974 drought did, its severity was not as great as of

1973–1974. The severity and duration of droughts in years 1989 and 2000–2001 were not as severe and long as the 1973–1974 drought. In this part of study; EDI, and selected timesteps of SPI, CZI and Z-Score were used to determine how they responded to historical monthly and multi-monthly precipitation deficiencies. PN and RDDI were avoided here because both did not demonstrate significant success in this section and also in earlier sections.

DIs were evaluated to see how they responded as time series to monthly rainfall data to better distinguish their responses by the change of rainfall. Multi-monthly cumulative rainfall data was also involved to understand the DI response better. Fig. 11 shows a dry spell of 1973–1974 at station 2 (Beysehir). DI values went below -1 on January 1973 and negative values continued for 24 months till December 1974. This period was the longest and most severe dry spell, and affected all stations. Using index values of EDI, SPI, CZI and Z-Score (lines) and rainfall variables, Fig. 11 depicts the 1973–1974 drought for station 2. SPI, CZI and Z-Score were used with timesteps of 6-month (Fig. 11a), 9-month (Fig. 11b), and 12-month (Fig. 11c). The same EDI was used for all three figures. There are four rainfall variables involved: monthly rainfall (the rainfall received in that month), monthly rainfall average (repeats every same month), moving cumulative rainfall representing the sliding sum of rainfall of preceding months relevant to timestep, and multi-monthly rainfall average- the average of the sum of particular months (this also repeats every same month). For instance, if the case is 3-months; the March value presents the dataset average of the total of January, February and March rainfalls. If the case is 12-months, then the March value presents the dataset average of the total rainfall of March and preceding 11 months (Fig. 11c).

Fig. 11(a) shows three essential differences between EDI and SPI_6, CZI_6, Z-$Score_6$ series. The first one was between March 1973 and August 1973, where EDI responded increasingly on April 1973 while other indices were decreasing. The monthly rainfalls received in March and April 1973 were just meeting the monthly averages, but 6-month cumulative rainfalls were well below 6-month rainfall averages (184 mm of rainfall, 54% of the average, received in 6 months whilst the 6-month average was 341 mm for April), so EDI was not able to detect 6-month rainfall deficiency very well for this month. Monthly rainfall (41 mm) again almost met its average value (42 mm) on May 1973; this led 6-month cumulative rainfall (204 mm, 63% of the average) to its 6-month average (324 mm). SPI_6, CZI_6 and Z-$Score_6$ responded as initiation of recovery from the deficiency, but EDI was not there yet. EDI and others responded in the same way on June 1973, while the monthly rainfall just met its average (23 mm), leading to cumulative rainfall (214 mm) to its average (271 mm). July 1973 (2.2 mm) and August 1973 (0.1 mm) monthly rainfalls were below their averages (8.5 mm, 9.4 mm, respectively), but the 6-month cumulative rainfall (164 mm, 93% of the average) almost achieved its average (176 mm) on August 1973. EDI decreased by the monthly rainfall deficiencies in July and August 1973, while SPI_6, CZI_6 and Z-$Score_6$ were increasing to catch up with the cumulative average. SPI_6, CZI_6 and Z-$Score_6$ increased to almost give the termination signal of the drought (reaching index value of zero), then indices decreased again by the monthly rainfall deficiency on September 1973 and also by the increase of cumulative rainfall deficiency. The second different response of EDI was on May 1974, EDI was decreasing while others were increasing. Monthly rainfall (30 mm) was still below its average (42 mm), but cumulative rainfall of preceding 6 months was getting better for May 1974 (received 60% of its average), because there was more deficiency in April 1974 (51% of its average). EDI responded with more sensitivity to monthly rainfall changes with respect to cumulative rainfall changes. The third different response of EDI was on October 1974, and again EDI was decreasing while others were increasing. The cumulative rainfall (135 mm) reached 94% of its average (144 mm), so EDI did not get that signal because monthly rainfall was 30 mm, comprising 68% of its average (44 mm).

SPI_6, CZI_6 and Z-$Score_6$ responded almost the same way for this dry spell (Table 4); on the other hand this tiny discrepancy between their responses played an important role as well. CZI_6 did not go below the threshold level of -2 in this dry spell period of 1973–1974, got -1.99 as the lowest value on July 1974, yet CZI_6 did not indicate this drought event as extreme drought, but a severe drought. Z-$Score_6$ pointed this event as an extreme drought by going below the threshold (-2.05) only once on June 1973. SPI_6 detected this dry spell as an extreme drought by the excess of threshold level within the 1973–1974 period, on November 1973 (-2.01), April 1974 (-2.14), June 1974 (-2.29) and July 1974 (-2.14), total four times. EDI also identified this dry spell as extreme drought. EDI went below -2 on November 1973, between February 1974 and August 1974 for 7 months, and November 1974. EDI found severities much higher than did SPI_6, CZI_6 and Z-$Score_6$ for the period of March to December 1974.

The best logically correlated timestep of SPI, CZI and Z-Score with EDI was 6 to 12-month timesteps (Fig. 4) in general. Pair-wise Pearson correlation coefficients were computed for all DIs with the same timesteps to numerically compare DI values. The lowest pair-wise correlation among the same timesteps of SPI, CZI and Z-Score for 1973–1974 dry spell was for SPI_3 to Z-$Score_3$, as shown in Table 4. SPI, CZI and Z-Score were significantly comparable, as seen from Fig. 11. Ten and eleven month timesteps of SPI, CZI and Z-Score were most comparable to EDI for 1973–1974 dry spell as shown in Table 4 (86.3%, as the average correlation of EDI with SPI_{10}, CZI_{10} and Z-$Score_{10}$). However, 3, 6, 9, and 12-month timesteps of DIs are more often used by researchers.

SPI_9, CZI_9 and Z-$Score_9$ did not respond as did EDI on March–April 1973, but most important responses of DIs in Fig. 11(b) were on July to December 1973 and November 1974. EDI did not detect accurately that cumulative rainfall deficiency was decreasing till October 1973, so EDI was decreasing, while others were increasing. EDI responded with sensitivity when monthly rainfall was 8 mm in November 1973, which is 14% of its average (59 mm). SPI_9, CZI_9 and Z-$Score_9$ did not respond similarly to this significant monthly rainfall deficiency. A similar case repeated on November 1974 when the monthly rainfall (11 mm) was 19% of its average (59 mm). Severity of the drought increased between February 1974 and August 1974, although SPI_9, CZI_9 and Z-$Score_9$ responded in a better way than did DIs with 6-month timestep (Fig. 11a), yet worse than 12-month timestep DIs (Fig. 11c). SPI_{12} responded very similarly to EDI within this evolution period of drought for 7 months. SPI_{12} also responded with high sensitivity to sudden monthly rainfall deficiency on November 1973, but was not as sensitive as EDI for November 1974. Annual rainfall average (multi-monthly rainfall average for 12 months) was 484 mm for Station 2. 12-month cumulative rainfall of 281 mm received on October 1973, which was 58% of annual rainfall average, and this deficiency led SPI_{12}, CZI_{12} and Z-$Score_{12}$ to indicate an extreme drought, but EDI did not. Next month (November 1973), 268 mm cumulative rainfall received (55% of annual rainfall), and also monthly rainfall deficiency from its average was also significant, therefore all DIs, including EDI, responded sensitively and they all went below -2 index value. 9 and 12-month timesteps of SPI, CZI and Z-Score identified the 1973–1974 dry spell as an extreme drought.

6. Conclusions

The number of rain gauge stations should be increased for Konya closed basin to have an accurate spatial distribution. The period of record length is a key factor for best results. The following conclusions can be drawn from this study:

- Comparison of numerical values of DIs and comparison of corresponding drought classes lead to slightly different results.
- Creating a comprehensive figure which involves monthly rainfall and multi-monthly rainfall variables and their averages may help better analyze drought characteristics and also DI responses.
- 1-month indices are least correlated to droughts in arid/semi-arid regions, because short-term/seasonal water deficiencies are common there. 1-month DIs should not be used solely in comparison studies to present a DI unless there is a specific reason. This study shows that timesteps of 6-month, 9-month and 12-month of a DI are essential to identify droughts. Future studies which investigate droughts in arid/semi-arid regions would involve multi-monthly analysis within the range of 5 to 18 months to have better indicators. A more reliable future drought projection within a particular basin can be sought from the correlation of various indices for different timesteps.
- PN and RDDI for variable timestep are less consistent. Therefore, the use of PN and RDDI may not be helpful in comparison studies if the purpose of their use is not set previously.
- Z-Score is an easy-to-calculate index and it responds similarly to complex SPI and CZI, but it is a little bit less consistent to its own timesteps.
- EDI is preferable for monitoring long term droughts in arid/semi-arid regions even if the input is monthly rainfall data. EDI is recommended for use in comparison studies, since it is timestep independent index and has good correlations with various timesteps of other DIs.
- DIs may be better in assessing droughts when used with many timesteps even while considering a short or long term drought. 6 or 9-month timestep of DI might be a better indicator for even short term droughts in arid/semi-arid regions.
- Using selected timesteps after a comparison study would be a better signal of seasonality and for sensitive drought identification for a particular basin or a climatical condition.
- Which timestep used is as important as what DI is used while identifying droughts. However, EDI is coherent with many timesteps of DIs, so it should be incorporated with any DI to monitor droughts.
- EDI is more sensitive to monthly rainfall changes with respect to multi-monthly cumulative rainfall changes. Resemblance between the sensitivity of EDI and that of others increases from 3-month to 12-month timestep.

Acknowledgments

The authors are grateful to C. Prakash Khedun and anonymous reviewers for their useful comments and suggestions. This research was partially derived from the first author's PhD dissertation and funded by Selcuk University Scientific Research Project Fund (BAP-09101028). Higher Educational Council of Turkey supported the first author under the PhD research scholarship program during his stay at Texas A&M University. The authors would like to acknowledge and thank Turkish State Meteorological Service for providing rainfall datasets.

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