Estimation of meteorological drought indices based on AgMERRA precipitation data and station-observed precipitation data (Postprint)

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Abstract

Meteorological drought is a natural hazard that can occur under all climatic regimes. Monitoring the drought is a vital and important part of predicting and analyzing drought impacts. Because no single index can represent all facets of meteorological drought, we took a multi-index approach for drought monitoring in this study. We assessed the ability of eight precipitation-based drought indices (SPI (Standardized Precipitation Index), PNI (Percent of Normal Index), DI (Deciles index), EDI (Effective drought index), CZI (China-Z index), MCZI (Modified CZI), RAI (Rainfall Anomaly Index), and ZSI (Z-score Index)) calculated from the station-observed precipitation data and the MERRA gridded precipitation data to assess historical drought events during the period 1987-2010 for the Kashaf Rud Basin of Iran. We also presented the Degree of Dryness Index (DDI) for comparing the intensities of different drought categories in each year of the study period (1987-2010). In general, the correlations among drought indices calculated from the AgMERRA precipitation data were higher than those derived from the station-observed precipitation data. All indices indicated the most severe droughts for the study period occurred in 2001 and 2008. Regardless of data input source, SPI, PNI, and DI were highly inter-correlated ($R^2 = 0.99$). Furthermore, the higher correlations ($R^2 = 0.99$) were also found between CZI and MCZI, and between ZSI and RAI. All indices were able to track drought intensity but EDI and RAI showed higher DDI values compared with the other indices. Based on the strong correlation among drought indices derived from the AgMERRA precipitation data and from the station-observed precipitation data, MERRA precipitation data can be accepted to fill the gaps in the station-observed precipitation data in future studies in Iran. In addition, if tested by station-observed precipitation data, the MERRA precipitation data may be used for the data-lacking areas.

Full Text

Abstract

Meteorological drought is a natural hazard that can occur under all climatic regimes. Monitoring drought constitutes a vital and important part of predicting and analyzing drought impacts. Because no single index can represent all facets of meteorological drought, we adopted a multi-index approach for drought monitoring in this study. We assessed the ability of eight precipitation-based drought indices–SPI (Standardized Precipitation Index), PNI (Percent of Normal Index), DI (Deciles Index), EDI (Effective Drought Index), CZI (China-Z Index), MCZI (Modified CZI), RAI (Rainfall Anomaly Index), and ZSI (Z-Score Index)–calculated from both station-observed precipitation data and AgMERRA gridded precipitation data to evaluate historical drought events during the period 1987-2010 in the Kashafrood Basin of Iran. We also presented the Degree of Dryness Index (DDI) for comparing the intensities of different drought categories in each year of the study period (1987-2010). In general, the correlations among drought indices calculated from the AgMERRA precipitation data were higher than those derived from the station-observed precipitation data. All indices indicated that the most severe droughts for the study period occurred in 2001 and 2008. Regardless of data input source, SPI, PNI, and DI were highly inter-correlated (R^2 = 0.99). Furthermore, higher correlations (R^2 = 0.99) were also found between CZI and MCZI, and between ZSI and RAI. All indices were able to track drought intensity, but EDI and RAI showed higher DDI values compared with the other indices. Based on the strong correlation among drought indices derived from the AgMERRA precipitation data and from the station-observed precipitation data, we suggest that the AgMERRA precipitation data can be accepted to fill the gaps existing in the station-observed precipitation data in future studies in Iran. In addition, if tested by station-observed precipitation data, the AgMERRA precipitation data may be used for data-lacking areas.

Keywords: severe drought; degree of dryness; MDM (Meteorological Drought Monitoring) software; precipitation; intensity; Middle East

1 Introduction

Precipitation deficits over an extended period can be devastating to human life and health, water resources, and economies, and are commonly described as meteorological droughts [?]. Meteorological drought is characterized by lack of precipitation over weeks, months, or years [?, ?, ?]. Monitoring meteorological drought is a vital and important part of drought risk mitigation [?] on a global scale [?, ?]. In arid and semi-arid regions like Iran, monitoring meteorological drought is of critical importance for both agricultural and natural resource management. In addition, droughts may be exacerbated under projected global climate change, further highlighting the importance of drought monitoring [?].

For drought monitoring, various drought indices have been developed to describe the intensity of a drought, including SPI (Standardized Precipitation Index), PNI (Percent of Normal Index) [?], DI (Deciles Index), EDI (Effective Drought Index) [?], CZI (China-Z Index), MCZI (modified CZI), RAI (Rainfall Anomaly Index), and ZSI (Z-Score Index). Drought indices are calculated by a combination of climatic and meteorological variables, among which precipitation is the most important in defining the magnitude and intensity of a drought [?, ?]. Fortunately, station-observed precipitation data recorded over long historical periods are widely available [?]. Using those available data, Morid et al. [?] compared the performance of seven drought indices (DI, PNI, SPI, CZI, MCZI, ZSI, and EDI) for drought monitoring. They concluded that DI is responsive to rainfall events and EDI is sensitive to drought intensification.

Shahabfar and Eitzinger [?] compared six drought indices (SPI, PNI, CZI, MCZI, ZSI, and de Martonne aridity index) in six different climatic regions of Iran and concluded that ZSI, CZI, and MCZI could be used as meteorological drought predictors. Wu et al. [?] evaluated the SPI, CZI, and ZSI on 1-, 3-, 6-, 9-, and 12-month time scales using monthly precipitation totals for four locations in China and concluded that SPI, CZI, and ZSI were all useful for defining, detecting, and monitoring droughts.

Based on the NASA Modern Era Retrospective Analysis for Research and Applications (MERRA) outputs [?], the AgMERRA global gridded climate dataset (0.25° × 0.25° horizontal resolution; ~25 km) provided daily, high-resolution, and continuous meteorological datasets for the period 1980–2010 and was advocated to be useful for agricultural and meteorological projects [?, ?]. Bannayan et al. [?] evaluated the performance of the AgMERRA dataset to fill gaps existing in historical station-observed meteorological data for different climatic regions of Iran and concluded that the AgMERRA dataset can satisfactorily fill the gaps in station-observed data. Ceglar et al. [?] also found that the AgMERRA dataset has the best performance in reflecting the station-observed precipitation data in comparison with ERA-Interim (ERA, European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis), ERA-Interim/Land, and JRA-55 datasets.

In order to properly allocate water resources for agricultural, economic, and ecological sectors, researchers attempt to quantify the effects of droughts using many indices. In this study, precipitation-based drought indices calculated from different sources of data were utilized for monitoring meteorological drought in the Kashafrood Basin of Iran. The main objectives of this study are: (1) to compare the outputs of eight drought indices derived from the AgMERRA precipitation data and from the station-observed precipitation data; and (2) to present the Degree of Dryness Index (DDI) for evaluating meteorological drought intensity in the northeast of Iran.

2.1 Study Area

This study was conducted in the Kashafrood Basin (35°40 -36°03 N, 58°02 - 60°08 E; Fig. 1 [Figure 1: see original paper]), Khorasan Province in northeastern Iran. The Kashafrood Basin includes the Mashhad-Fariman, Mashhad-Chenaran, and Chenaran-Ghoochan plains, each of which has a weather station. The study area is characterized by a cool and dry climate. Physiographic details of the three weather stations are included in Table 1 .

Table 1 Characteristics of the three weather stations

Station	Latitude	Longitude	Elevation	Average Tmax (°C)	Average Tmin (°C)	Precipitation	Climate
Mashhad	36°16 N	59°38 E					Semi-arid
Ghoochan	37°04 N	58°30 E					Semi-arid
Golmakan	36°29 N	59°17 E					

Note: Tmax, maximum temperature; Tmin, minimum temperature.

2.2.1 SPI (Standardized Precipitation Index)

The SPI is the most popular drought index [?] and is a widely recognized index for characterizing meteorological droughts [?, ?]. McKee et al. [?, ?] defined SPI suitable for different timescales (1, 3, 6, 12, 24, and 48 months), with output values ranging from −2.0 to 2.0. Because precipitation data may be fitted by a gamma distribution, the SPI is calculated using a probability density function of the gamma distribution:

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

where Γ is the gamma function; x (mm) is the amount of precipitation ($x > 0$); α is the shape parameter ($\alpha > 0$); and β is the scale parameter ($\beta > 0$). More details can be found in Edwards and McKee [?] and Dogan et al. [?].

2.2.2 PNI (Percent of Normal Index)

The PNI was described by Willeke et al. [?] as a percentage of normal precipitation. It can be calculated for different time scales (monthly, seasonally, and yearly). PNI has been found to be rather effective for describing drought for a single region and/or for a single season [?]. PNI is calculated as follows:

$$\mathrm{PNI}_i = 100 \times \frac{P_i}{P}$$

where P_i is the precipitation in time increment i (mm), and P is the normal precipitation for the study period (mm).

2.2.3 DI (Deciles Index)

The DI was defined as a ranking of precipitation in a particular time interval over the entire historic period [?]. Specifically, monthly historical precipitation data are sorted from lowest to highest and divided into ten equal categories or deciles. Thus, precipitation in a given month can be placed into the historical context by decile.

2.2.4 EDI (Effective Drought Index)

The EDI is calculated on a daily time step and its values are standardized in a similar way to SPI values. The EDI was originally developed by Byun and Wilhite [?] to overcome some limitations of other indices. The value of EDI generally ranges from -2.5 to 2.5. Near-normal conditions are indicated when EDI ranges from -1.0 to 1.0, while extreme drought conditions are indicated when EDI is less than or equal to -2.0. Effective precipitation should be calculated first before obtaining the EDI:

$$EP_i = \sum_{m=1}^{n} \frac{P_m}{m}$$

where EP_i is the effective precipitation (mm), which represents the valid accumulations of precipitation; P_m is the precipitation over the previous m days (mm); and n is the duration of the preceding period (day). When $i = 365$, then EP_{365} shows available precipitation accumulated over 365 days. More details about the calculation of EDI can be found in Byun and Wilhite [?].

2.2.5 CZI (China-Z Index) and MCZI (Modified CZI)

The National Climate Center of China developed the CZI in 1995 as an alternative to the SPI [?] when mean precipitation follows the Pearson type III distribution. CZI is calculated as:

$$\mathrm{CZI}_{i,j} = \frac{\phi_{t,j}}{C_{s,i}} \times \left(\frac{C_{s,i}}{2} + 1\right)$$

where i is the time scale of interest and j is the current month; $\mathrm{CZI}_{i,j}$ means the CZI value of the current month (j) for period i; $C_{s,i}$ is the coefficient of skewness; and $\phi_{t,j}$ is the standardized variation. Further details can be found in

Wu et al. [?]. Furthermore, the MCZI can also be calculated using the formula above but substituting the median precipitation for mean precipitation.

2.2.6 ZSI (Z-Score Index)

The ZSI is occasionally confused with SPI. However, it is more analogous to CZI, but without the requirement for fitting precipitation data to either gamma distribution or Pearson type III distribution. ZSI can be calculated by the following equation:

$$\mathrm{ZSI} = \frac{P_i - \bar{P}}{\mathrm{SD}}$$

where $\bar{P}$ is the mean monthly precipitation (mm); P_i is precipitation in a specific month (mm); and SD is the standard deviation of any time scale (mm).

2.2.7 RAI (Rainfall Anomaly Index)

The RAI considers two anomalies: positive anomaly and negative anomaly. First, the precipitation data are arranged in descending order. The ten highest values are averaged to form a threshold for positive anomaly and the ten lowest values are averaged to form a threshold for negative anomaly. The thresholds are calculated by Equations 6 and 7, respectively:

$$\mathrm{RAI} = \pm 3 \left(\frac{p - \bar{p}}{\bar{p}_{\mathrm{extreme}} - \bar{p}} \right)$$

where p is the actual precipitation for each year (mm); $\bar{p}$ is the long-term average precipitation (mm); $\bar{p}_{\mathrm{extreme}}$ is the mean of the ten highest values of p for the positive anomaly and the mean of the ten lowest values of p for the negative anomaly.

2.3 Data Collection and Processing

Daily precipitation data from 1987 to 2010 were obtained from two sources: three weather stations and the AgMERRA gridded dataset (http://data.giss.nasa.gov/impacts/agmipcf/agmerra/). We used SPSS 16.0 software and MATLAB 2013a for data analysis. Furthermore, we used the C# language (Visual Studio 2013 and .NET Framework 4.5.1) to develop a software package for calculating the meteorological drought indices.

We developed the MDM (Meteorological Drought Monitoring) software package for calculating different precipitation-based meteorological drought indices. Normally, if different drought indices can be simultaneously calculated for a given time interval and also for a given region, drier-than-mean or wetter-than-mean conditions can be more confidently defined [?]. Thus, user-friendly software is a rather useful tool for calculating and comparing multiple locations, different timescales, and different data sources. The MDM software package is currently based on calculations from two sources of data covering the period of 1980–2010. The first is the weather station data file, which includes daily precipitation in Excel format. The second is a database of daily precipitation from AgMERRA. The user can click the map on the desired point in the package and calculate all indices at 0.25° grid location. Complete help instructions are included in the package describing all setup steps. Detailed instructions for data analysis and a description of MDM capabilities are available at https://www.agrimetsoft.com.

2.4 Degree of Dryness Index (DDI)

We classified dry months as those in which each of the aforementioned indices falls into one of three categories: extreme, severe, or moderate. For each year, we counted the frequency of months for the location of interest when each index fell into one of the three drought categories (i.e., extreme, severe, and moderate). For example, the SPI index for 1989 in Ghoochan had 1 month of extreme drought, 0 months of severe drought, and 2 months of moderate drought. We then applied multipliers of 3 for extreme drought, 2 for severe drought months, and 1 for moderate drought months to obtain a total yearly degree of dryness index (DDI) of 5 for SPI at Ghoochan station (i.e., DDI = (1 × 3) + (0 × 2) + (2 × 1) = 5). Then we averaged the DDI values from the three weather stations to get an average yearly degree of dryness index of 3 for SPI for station-observed precipitation data in 1989. The same method was used for the AgMERRA-derived index outputs, with the exception of the final averaging across sites. The DDI can be calculated by Equations 8 and 9:

$$\mathrm{DDI}_{st,y} = \sum_{int=1}^{3} (a_{int} \times N_{int,y})$$

$$\mathrm{DDI}_{y} = \frac{\sum_{st=1}^{N_{st}} \mathrm{DDI}_{st,y}}{N_{st}}$$

where $\mathrm{DDI}_{st,y}$ is the degree of dryness index of the station in each year; a_{int} is the intensity of drought, with 1 for moderate drought, 2 for severe drought, and 3 for extreme drought; $N_{int,y}$ is the number of dry months for each drought category in each year; DDI_{y} is the average value of degree of dryness index in each year for all stations; and N_{st} is the number of stations ($N_{st} = 3$ in this study).

2.5 Statistical Analysis

The performance of AgMERRA datasets was evaluated using five widely-used statistical indices: relative absolute bias (ABIAS), mean errors (ME), mean absolute error (MAE), Pearson' s correlation coefficient (r), and coefficient of determination (R^2). Specifically, ABIAS was computed to describe the absolute magnitude of systematic bias of the difference between the station-observed precipitation data and the AgMERRA precipitation data (Eq. 10). ME was selected to represent the average difference between the station-observed precipitation data and the AgMERRA precipitation data (Eq. 11). MAE was used to determine the average magnitude of the error (Eq. 12). Pearson' s correlation coefficient (r) was used to measure the degree of agreement between the two sources of data (Eq. 13). The coefficient of determination (R^2) described the proportion of the total variance in the station-observed precipitation data that can be explained by the AgMERRA precipitation data (Eq. 14). It ranges from 0 to 1, with higher values indicating stronger agreement.

$$\mathrm{ABIAS} = 100 \times \frac{\sum_{i=1}^{N} |Ag_i - St_i|}{\sum_{i=1}^{N} St_i}$$

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}(Ag_i - St_i)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Ag_i - St_i|$$

$$r = \frac{\sum_{i=1}^{N}(Ag_i - \overline{Ag})(St_i - \overline{St})}{\sqrt{\sum_{i=1}^{N}(Ag_i - \overline{Ag})^2 \sum_{i=1}^{N}(St_i - \overline{St})^2}}$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(Ag_i - \overline{Ag})(St_i - \overline{St})}{\sqrt{\sum_{i=1}^{N}(Ag_i - \overline{Ag})^2 \sum_{i=1}^{N}(St_i - \overline{St})^2}}\right]^2$$

where N is the total number of data sets for AgMERRA precipitation data or station-observed precipitation data; Ag_i and St_i are the AgMERRA precipitation data (mm) and station-observed precipitation data, respectively; and $\overline{Ag}$ and $\overline{St}$ are the average values of AgMERRA and station-observed precipitation data (mm), respectively.

3.1 Comparison of AgMERRA Precipitation Data and Station-Observed Precipitation Data

We first calculated the statistical indices (i.e., ABIAS, ME, MAE, R^2, and r) to compare the AgMERRA precipitation data with the station-observed precipitation data at three stations in the Kashafrood Basin. These results are presented in Table 2 at the monthly time scale. Figure 2 [Figure 2: see original paper] shows the relationships between average monthly precipitation over each selected grid box for the three stations (Mashhad, Ghoochan, and Golmakan) and the corresponding values from the three stations. These results show that there is good agreement between the station-observed precipitation data and the AgMERRA precipitation data, with $R^2 = 0.9025$ for Mashhad, $R^2 = 0.8437$ for Ghoochan, and $R^2 = 0.6924$ for Golmakan. As shown in Table 2, the ME values ranged from -2.20 to 0.39 mm; the ABIAS values ranged from 21.0% to 37.5%; and the r values ranged from 0.85 to 0.96. This indicates that the AgMERRA precipitation data are quite consistent with the station-observed precipitation data. Therefore, the AgMERRA precipitation data can be acceptable for monitoring meteorological droughts.

Table 2 Statistical indices between the AgMERRA precipitation data and the station-observed precipitation data for Mashhad, Ghoochan, Golmakan stations and for the Kashafrood Basin

Region	ABIAS (%)	MAE (mm)	ME (mm)	r	R^2
Mashhad					0.9025
Ghoochan					0.8437
Golmakan					0.6924
Kashafrood Basin	21.0–37.5		–2.20 to 0.39	0.85–0.96	

Note: ABIAS, relative absolute bias; MAE, mean absolute error; ME, mean errors; r, Pearson' s correlation coefficient.

3.2 Comparison of Drought Indices

The eight drought indices (i.e., SPI, PNI, DI, EDI, CZI, MCZI, RAI, and ZSI) were calculated for the three stations (Mashhad, Ghoochan, and Golmakan) from 1987 to 2010. For Mashhad station, there were close relationships between the AgMERRA-derived drought indices and the station-derived drought indices, with all correlation coefficients larger than 0.82 (Table 3 ; Fig. 3 [Figure 3: see original paper]). The Pearson' s correlation coefficients for SPI, PNI, and DI were more or less identical (0.91, 0.89, and 0.89, respectively). It should be noted that similar conclusions were drawn by Keyantash and Dracup [?], who found that SPI and DI are the two most robust indices for monitoring meteorological drought in Oregon. Quiring [?] recommended SPI, DI, and PNI as the best indices of meteorological drought. In our study, the trends of these three indices (SPI, DI, and PNI) were very similar (Fig. 3). The values of CZI, ZSI, and RAI were nearly the same for the observation period. In Mashhad, the trends of MCZI were somewhat different from those of CZI (Fig. 3). Morid et al. [?] also found that MCZI was a poor detector of meteorological drought. It should be particularly pointed out that 2008 was the driest year at Mashhad station during the study period (1987-2010), as suggested by all indices.

Table 3 Pearson' s correlation coefficients between the AgMERRA-derived drought indices and the station-derived drought indices for the three stations

Station	SPI	PNI	DI	EDI	CZI	MCZI	RAI	ZSI
Ghoochan								
Golmakan								
Mashhad	0.91	0.89	0.89					

Note: SPI, Standardized Precipitation Index; PNI, Percent of Normal Index; DI, Deciles Index; EDI, Effective Drought Index; CZI, China-Z Index; MCZI, Modified CZI; RAI, Rainfall Anomaly Index; ZSI, Z-Score Index.

For Ghoochan station, there was good correspondence between the AgMERRA-derived drought indices and the station-derived drought indices, with all correlation coefficients larger than 0.76 (Table 3; Fig. 4 [Figure 4: see original paper]). By comparing MCZI and CZI indices, we found that MCZI represented the range of wet years better than CZI, while CZI represented the dry years better than MCZI. Shahabfar and Eitzinger [**?**] described MCZI as a best performer during rainy seasons in mountainous and semi-mountainous areas. In general, SPI, PNI, DI, CZI, and ZSI showed similar trends (Fig. 4). Wu et al. [**?**] and Morid et al. [**?**] obtained similar outputs from SPI, CZI, and ZSI. In our study, the precipitation recorded by AgMERRA and the derived drought indices for years 2001 and 2002 were lower than the precipitation recorded at weather stations and the derived drought indices. All indices indicated that 2001 and 2008 were the driest years at Ghoochan station during the study period (1987–2010).

In contrast to Mashhad and Ghoochan stations, the correlations between the AgMERRA-derived drought indices and the station-derived drought indices for Golmakan station were not robust at all ($r < 0.65$; Table 3; Fig. 5 [Figure 5: see original paper]). For example, 1992 and 1993 were two years when the station-derived drought indices showed extreme drought while the AgMERRA-based drought indices showed normal conditions. This discrepancy was likely caused by the 300-m elevation difference between the Golmakan station and the nearest pixel of AgMERRA. For Golmakan, SPI, PNI, DI, and EDI showed good agreement between the AgMERRA-based drought indices and the station-derived drought indices in presenting wet and dry spells. The values of CZI, MCZI, RAI, and ZSI had similar trends (Fig. 5), with 1993 being the driest year at Golmakan station during the study period (1987–2010).

Pearson' s correlation coefficients among all indices derived from the AgMERRA precipitation data are shown in Table 4 , and the correlations from the station-observed precipitation data are shown in Table 5 . The correlation coefficient between EDI and RAI was the lowest (0.60 for station-observed precipitation data and 0.74 for AgMERRA precipitation data). The second lowest correlation was found between EDI and ZSI (0.68 for station-observed precipitation data and 0.76 for AgMERRA precipitation data). In general, the correlation coefficients among the drought indices obtained from the AgMERRA precipitation data are higher than those obtained from the station-observed precipitation data. In both the AgMERRA and station-observed datasets, SPI, PNI, and DI, as well as CZI and MCZI, and ZSI and RAI showed higher correlation coefficients. These results agree with the findings of Wu et al. [?], Dogan et al. [?], and Asefjah et al. [?]. Given the strong correlations between PNI, DI, and SPI ($R^2 = 0.99$), we only used SPI to define the number of dry months during the study period. Similarly, we only used CZI in the following analysis due to the high correlation between CZI and MCZI ($R^2 = 0.99$).

3.3 Calculation of Degree of Dryness Index (DDI)

As shown in Table 6 , DDI values from EDI and RAI suggested that the most severe drought year was 2001 over the entire study period (1987-2010). However, DDI values from SPI, CZI, and ZSI suggested that 2008 was the most severe drought year over the same period. In fact, the lowest average annual precipitation values recorded at these three stations were 173 mm in 2001 and 123 mm in 2008. It should be emphasized here that due to a significant reduction in rainfall, about 95% of rain-fed farms suffered severely from droughts in both 2001 and 2008 in Iran [?, ?, ?]. According to reports from the Ministry of Jihad-e-Agriculture [?], about 2.5×10^6 hm^2 of irrigated agricultural land, 4×10^6 hm^2 of rain-fed agricultural land, and 1.1×10^6 hm^2 of gardens were affected by the 2001 drought. In general, the data in Table 6 showed that 2001 and 2008 were the two driest years during the study period (1987-2010). However, the DDI values from EDI and RAI appear to be more sensitive to the station-observed droughts than the DDI values from other drought indices. The reasons may include: EDI is more sensitive to subtle changes in rainfall [?, ?, ?] and RAI can better identify positive or negative anomalies.

Although most of the drought indices are strongly cross-correlated and exhibit rather comparable seasonal and annual DDI trends, selecting a single most appropriate index of meteorological drought is still a difficult task, and the difficulty arises from various sources including the spatial variability of climates and the temporal scales of the intended applications [?, ?]. Therefore, a variety of indices should always be examined to select the best or better drought indices for a specific case study. Another consideration in drought index selection is the differences in index formulations, as SPI uses the gamma distribution in its structure while EDI does not.

Table 6 Average yearly Degree of Dryness Index (DDI) for five drought indices derived from the AgMERRA precipitation data and from the station-observed precipitation data across the Kashafrood Basin

Year	SPI (WS)	SPI (AgM)	CZI (WS)	CZI (AgM)	ZSI (WS)	ZSI (AgM)	EDI (WS)	EDI (AgM)	RAI (WS)	RAI (AgM)
2001										

Year	SPI (WS)	SPI (AgM)	CZI (WS)	CZI (AgM)	ZSI (WS)	ZSI (AgM)	EDI (WS)	EDI (AgM)	RAI (WS)	RAI (AgM)
2008										

Note: WS, weather station; AgM, AgMERRA.

4 Conclusions

In this study, using historical precipitation data from 1987 to 2010, we developed a software program to calculate and compare drought indices for monitoring drought in the Kashafrood Basin of Iran based on two different precipitation data sources: AgMERRA and station observation. We compared eight drought indices to track the drought history. Our comparison shows that all indices agree that the most severe droughts for the study period occurred in 2001 and 2008. High cross-correlation coefficients ($R^2 > 0.90$) were obtained among ZSI, CZI, and SPI, among SPI, DI, and PNI, and between CZI and MCZI in both data sources (AgMERRA and station observation). The DDI values from EDI and RAI appear to be more sensitive to the observed droughts than the DDI values from other drought indices. The consistent and significant agreements between the AgMERRA-based drought indices and the station-derived drought indices boost our confidence that the AgMERRA precipitation data can be used for filling gaps existing in the station-observed precipitation data. In addition, if tested by station-observed precipitation data, the AgMERRA precipitation data may be used for data-lacking areas.

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Note: Figure translations are in progress. See original paper for figures.