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ORIGINAL PAPER

Spatiotemporal analysis of drought by CHIRPS precipitation estimates

Hakan Aksu[1] · Yonca Cavus[2,3,4] · Hafzullah Aksoy[5] · Mehmet Ali Akgul[6,7] · Seyhmus Turker[1] · Ebru Eris[8]

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Abstract

Drought is one of the most devastating natural hazards causing considerable losses in all climatic zones of the world. It is one of the most complex and the least understood hazards at the same time because of its spatially heterogeneous and temporally variable character. Spatially dense and uniformly distributed ground-based meteorological data are needed for proper spatial and temporal drought analysis. In practice, such data are lacking in general due either to the nonexistence of ground stations or their uneven and scarce distribution over a region. This creates a great potential in the use of satellite precipitation estimates (SPEs) such as the long-period high-resolution Climate Hazards Group Infrared Precipitation with Station (CHIRPS) data in drought analysis. In this study, we aim to analyze drought over the Kucuk Menderes River Basin in the western part of Turkey by using the CHIRPS data, which were found highly correlated with precipitation in the local ground stations. The analysis was performed by considering the spatial variability and temporal change in the drought characterization based on the Standardized Precipitation Index (SPI) calculated at the 3-month (seasonal) timescale. Drought in the river basin was found to have a within-year variability from month to month, and a spatial variability over the basin in any given month. Also, an over-year variability with a decreasing trend exists, which could be considered a signal for more strengthened droughts in the future. The study eventually demonstrates how the CHIRPS SPEs could be useful in the spatial and temporal drought analysis for regions with limited ground-based meteorological data.

Keywords Drought · Satellite precipitation estimates · CHIRPS · Standardized Precipitation Index · Kucuk Menderes River Basin

1 Introduction

Long, accurate and reliable precipitation data from spatially dense meteorological networks are needed for hydrometeorological events including drought, which is one of the most dangerous natural hazards (Mishra and Singh, 2010) due to its negative impacts on society, economy and environment. For many regions in the world, number of stations is not yet at a level to reveal the spatial change, and they are not homogeneously scattered over the region of interest. Due to this limitation, the use of satellite technology has emerged (Zuo et al., 2019; Aksu and Arikan, 2017). Among the satellite products, satellite precipitation estimates (SPEs) have gained a great importance in hydrometeorological practice including drought analysis (Yilmaz et al., 2005a,b; Tote et al., 2015; Santos et al., 2017; Zambrano et al., 2017; Satge et al., 2019; Li et al., 2020; Wang et al., 2020). SPEs have high spatial and temporal resolution. They can be substituted for ground stations in a region for which they have been validated. A variety of SPEs are available, which namely,

✉ Ebru Eris
ebru.eris@ege.edu.tr

1 Department of Meteorological Engineering, Samsun University, Samsun, Turkey

2 Department of Civil Engineering, Beykent University, Istanbul, Turkey

3 Graduate School, Istanbul Technical University, Istanbul, Turkey

4 Environmental Hydrological Systems, University of Freiburg, Freiburg, Germany

5 Department of Civil Engineering, Istanbul Technical University, Istanbul, Turkey

6 Department of Geographic Information Systems, General Directorate of State Hydraulic Works, 6th Regional Directorate, Adana, Turkey

7 Department of Mining Engineering, Cukurova University, Adana, Turkey

8 Department of Civil Engineering, Ege University, Izmir, Turkey

are the Precipitation Estimation from Remote Sensing Information using Artificial Neural Network (PERSIANN; Hsu et al., 1997), the Microwave/Infrared Rain Rate Algorithm (MIRAA; Miller et al., 2001), the CPC MORPHing technique (CMORPH; Joyce et al., 2004), the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS; Funk et al., 2015), the Integrated Multisatellite Retrievals for GPM (IMERG; Huffman et al., 2015), the Tropical Applications of Meteorology using Satellite and ground-based observations (TAMSAT), the African Rainfall Climatology and Time series (TARCAT) (Tarnavsky et al., 2014), African Rainfall Climatology Version 2 (ARC v2.0) (Novella and Thiaw, 2013) and the TRMM Multi-satellite Precipitation Analysis (TMPA; Huffman et al., 2007). The accuracy of SPEs (CMORPH, IMERG, CHIRPS, PERSIANN, etc.) has recently increased by blending them with the ground-based measurements. The Food and Agriculture Organization (FAO) and the Global Historical Climate Network (GHCN) used the CHIRPS SPEs to obtain precipitation data for more than 20,000 ground stations.

Numerous studies have been performed to evaluate the accuracy of SPEs. For example, Khandu et al. (2016) evaluated three satellite-based products (TRMM, CMORPH, CHIRPS) to estimate rainfall in Bhutan. Similarly, Usman et al. (2018), Diem et al. (2019), Gupta et al. (2019) and Macharia et al. (2020) used four satellite products in Africa and India. Santos et al. (2019a, b), Neto et al. (2020) and dos Santos et al. (2021) presented case studies from Brazil; and Chen et al. (2021) from the Yangtze River Basin in China. CHIRPS combines the long-term infrared (IR) remote sensing data and ground-based observations. A few examples on the CHIRPS were made available by Katsanos et al. (2016), Guo et al. (2017), Gao et al. (2018), Perdigón-Morales et al. (2018) and Peng et al. (2020) among many others. The CHIRPS data overestimated precipitation in Mexico during summer and autumn seasons by up to 30% (Perdigón-Morales et al., 2018). The performance of the CHIRPS was examined in Turkey where SPEs were found consistent with the ground measurements in the southern and western parts of the country particularly (Aksu and Akgul, 2020). The CHIRPS data were not only substituted for the ground precipitation but also used in the streamflow forecasting (Sulugodu and Deka, 2019). It is even possible to use the CHIRPS data for the management of environmental conflicts in transboundary river basins (Minanabadi et al., 2020).

Besides the fast progress in the satellite data products, there is a comprehensive literature on the indices used in the drought research and practice. The drought indices are calculated from the so-called meteorological, agricultural and hydrological indicators such as precipitation, soil moisture and streamflow. Among the drought indices, the Standardized Precipitation Index (SPI; McKee et al., 1993) is commonly used as it takes various timescales into account and requires the precipitation data only for its quantification (Cavus and Aksoy, 2019, 2020; Eris et al., 2020). It has been suggested by the World Meteorological Organization (WMO, 2012) to the national meteorological organizations as a kind of standard for drought characterization.

In the common practice, drought indices are calculated using data recorded at the ground stations (Kalisa et al., 2020). However, in many cases, the ground stations are spatially sparse and unevenly distributed and their records might have been interrupted because of missing data. Drought analysis can therefore be made through the use of SPEs blended with the data of the existing ground stations. The scarcity in the ground data can thus be overcome with the high temporal and spatial resolution of the CHIRPS (Hinge et al., 2021). For example, droughts over Brazil, China and India were satisfactorily detected by the SPI calculated from the CHIRPS SPEs (Gao et al., 2018; Rivera et al., 2019; Wu et al., 2019; de Oliveira-Júnior et al., 2021).

The uneven poor spatial distribution of ground stations with interrupted records is not an uncommon situation in many regions over the world, and Turkey is not an exception. This is a problem that can be solved by using the SPEs (e.g., the CHIRPS), which is an important development for data scarce river basins. Despite their consistency with the ground measurements (Aksu and Akgul, 2020), no study exists yet using the CHIRPS SPEs for a basin-scale drought analysis in Turkey. Only a preliminary recent analysis was found at the country scale using a few meteorological stations, none from the Kucuk Menderes River Basin in this study (Aksoy and Sertel, 2021). The lack in the use of the CHIRPS SPEs gives an impetus to the motivation of this study which is based on the fact that (i) the CHIPRS SPEs have already been validated for the western part of Turkey, i.e., they are readily available to accompany the ground data, and (ii) there does not exist a study combining the CHIPRS SPEs with the drought indices for the region. The aim of this study is therefore to check if the CHIRPS SPEs can be substituted or not for the ground-station precipitation and also if they can reveal new insights for the spatial and temporal drought characteristics at the river basin scale. Thus, we focus on the use of the CHIRPS SPEs by verifying their performance to estimate the spatiotemporal behavior of meteorological drought in the western part of Turkey.

The study proceeds as follows: We start with introducing the study area and meteorological stations, and explain the CHIRPS data together with the bias correction method next. SPI is then given as the methodology to compare with the CHIRPS data. Results are discussed before the conclusions are finally listed.

2 Study area and meteorological stations

Kucuk Menderes River Basin was selected from the Aegean Region in the western part of Turkey for the case study (Fig. 1). The river basin has fertile agricultural lands as well as forests, seminatural areas and industrial regions (Aksoy, 2020). Agricultural lands cover nearly 41% of the river basin, 52% of which is irrigated while the rest is used for dry agriculture. Agricultural and industrial water needs are mostly supplied by groundwater resources (Yagbasan, 2016). The river basin is under the effect of Mediterranean climate with hot and dry summers, and warm and rainy winters. The annual average temperature is 16.3 °C and the annual total precipitation is 622 mm (Selek and Aksu, 2020). Precipitation is higher in the east and southeast parts of the river basin compared to the other parts.

Ground stations which have already been used in the production of the CHIRPS data were avoided to use in this study (see URL-1 for the list of stations used in the blending process to produce the CHIRPS data). Three stations (Selcuk, Kusadasi and Seferihisar) unused at the CHIRPS data production process were selected from the meteorological network of the State Meteorological Service (MGM) of Turkey. General information and statistical characteristics of the stations based on monthly precipitation data obtained from MGM for the period 2008–2018 are given in Table 1.

3 CHIRPS data and bias correction

The CHIRPS was developed for drought monitoring over regions with a scarce meteorological network and complex topography (Funk et al., 2014, 2015). It is an infrared-based quasi-global satellite precipitation dataset made

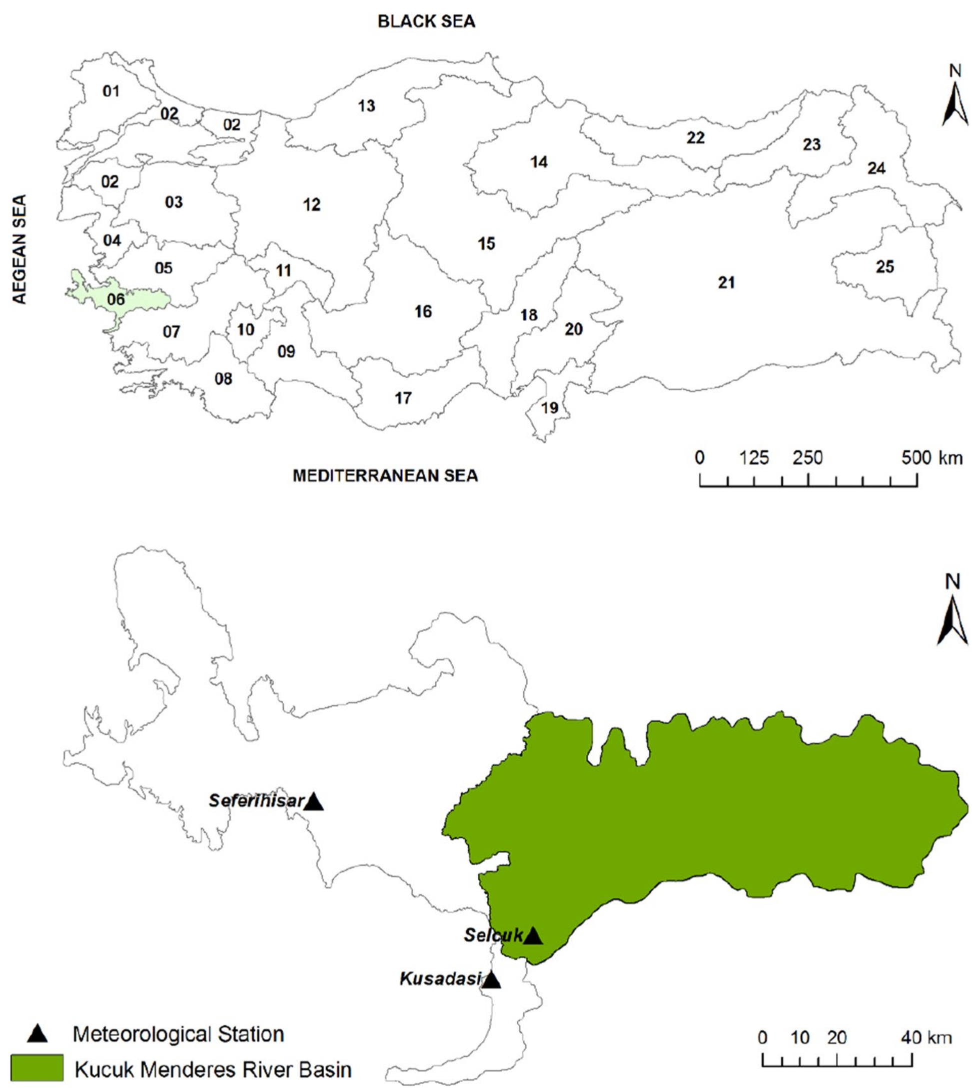

Fig. 1 Kucuk Menderes River Basin in Turkey and location of meteorological stations used in this study

Table 1 Meteorological stations and statistical characteristics of their annual precipitation (P_{mean}: average annual precipitation, P_{min}: minimum annual precipitation; P_{max}: maximum annual precipitation; St.Dev.: standard deviation of annual precipitation. C_v: coefficient of variation; C_s: coefficient of skewness; k: Kurtosis coefficient)

Station name	Observation period	Latitude	Longitude	Elevation (m)	P_{mean} (mm)	P_{min} (mm)	P_{max} (mm)	St. Dev. (mm)	C_v	C_s	k
Selcuk	2008–2018	37.9423	27.3669	18	685.0	447.4	901.5	123.8	0.18	-0.14	-0.21
Kusadasi	2008–2018	37.8597	27.2652	25	656.7	459.1	765.0	110.9	0.17	-0.84	-0.62
Seferihisar	2008–2018	38.1990	26.8350	22	684.3	387.2	979.1	159.1	0.23	0.34	0.58

of a blended product which combines the precipitation climatology, quasi-global satellite estimates and in-situ measurements. The records going back to 1981 at the daily, pentadal, dekadal and monthly temporal resolutions are freely downloadable (URL-2). It has a relatively high spatial resolution (0.05°) (Funk et al., 2015) providing an ideal precipitation dataset for drought monitoring and early warning system (Funk et al. 2015). However, the SPEs contain a bias due to several methodological and geographical reasons such as the cloud top temperature threshold, the lack of ground stations, the orography and the proximity to the sea among others (AghaKouchak et al., 2012; Yilmaz et al., 2005a, b). A bias correction is therefore applied to increase the performance of the SPEs in representing the ground-based measurements (Vernimmen et al., 2012).

Aksu and Akgul (2020) evaluated the performance of the CHIRPS SPEs over the western part of Turkey, and found a positive overall bias within a high-performance range. The CHIRPS SPEs were therefore preferred in this study. The CHIRPS version 2.0 was used at the monthly timescale with 0.05° spatial resolution for the period 2008–2018. A bias correction was applied as

$$P^* = a(P/P_0)^b \tag{1}$$

in which P^* is the bias-corrected precipitation, P is the precipitation (mm), P_0 is the reference precipitation (1 mm in this study), and a and b are parameters which were optimized by the generalized reduced gradient algorithm (Fylstra et al., 1998). Figure 2 shows the overall similarity between the bias-corrected SPEs of the meteorological stations and the ground-based monthly precipitation data. The overall performance of the bias-correction is high although it is reduced to an acceptable level when it is assessed at monthly scale as in the example provided for January in Fig. 3.

The Nash–Sutcliffe efficiency (NSE) coefficient and the determination coefficient (R^2) were used as the performance criteria to assess the similarity between the CHIRPS and the ground stations (Table 2). In rainy seasons, the CHIRPS and ground-based observations were found highly correlated while a very low performance was obtained in summer. The bias between the CHIRPS and the ground-based observations stems from the CHIRPS methodology which is affected from the constant cloud top temperature threshold among many other reasons as explained above. It is difficult for CHIRPS to replace days with no precipitation. This can be a particular reason for low NSE and R^2 in the summer season (June–August, Table 2). While the calibration provided no improvement in the summer, a minor improvement was added to the already high correlation of the uncalibrated SPEs in rainy months (Figs. 2 and 3, Table 2).

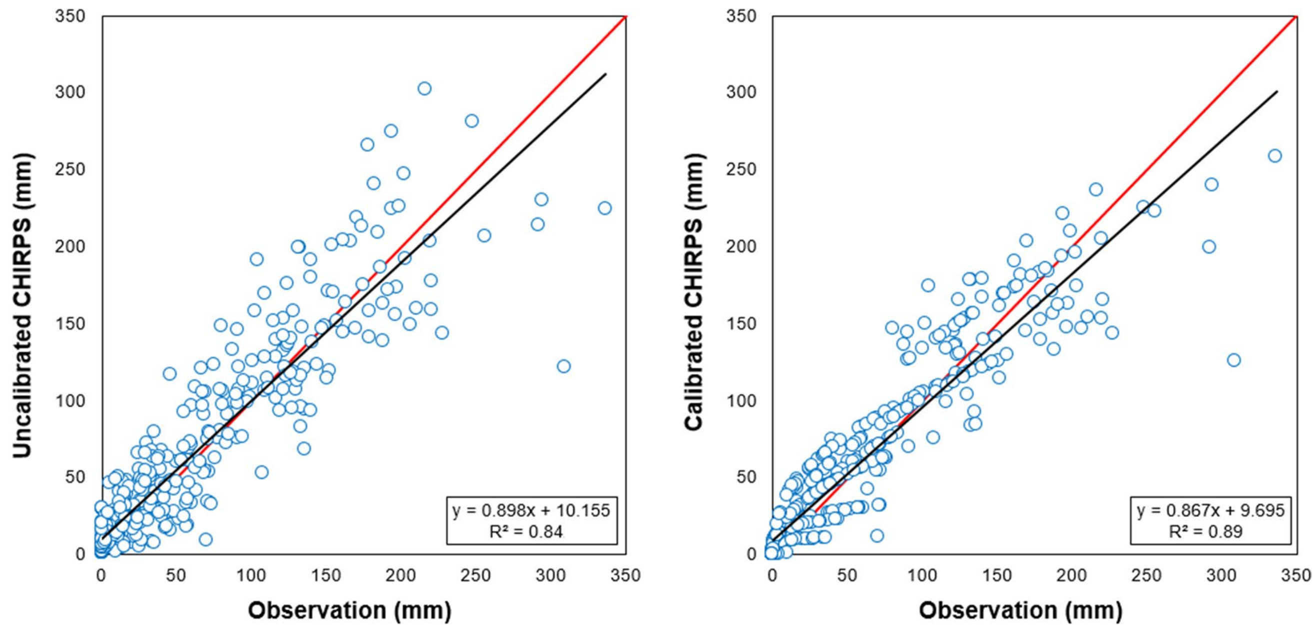

Fig. 2 Overall comparison of the uncalibrated and calibrated CHIRPS SPEs to the ground-based monthly precipitation of the selected meteorological stations (Red and black lines show the perfect fit and the best fit, respectively. Equation and determination coefficient are given for the best-fit regression.)

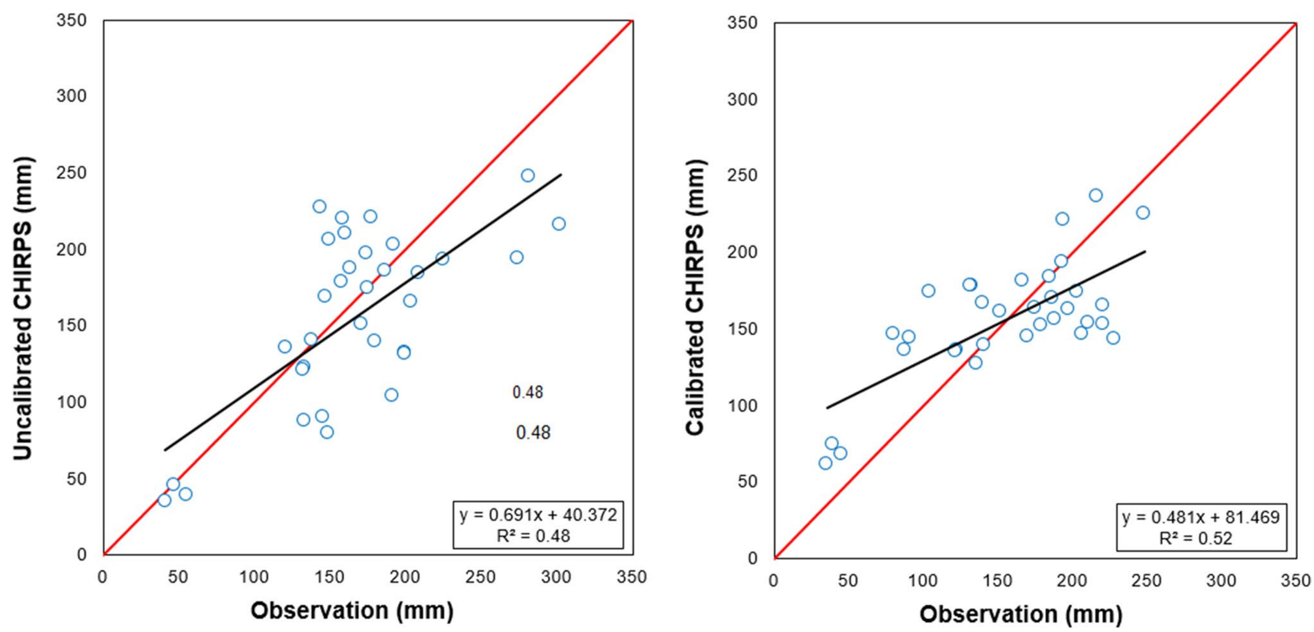

Fig. 3 Comparison of uncalibrated and calibrated CHIRPS SPEs to the ground-based precipitation in January of the selected meteorological stations (Red and black lines show the perfect fit and the best fit, respectively. Equation and determination coefficient are given for the best-fit regression.)

This is a good point showing that SPEs are similar enough to the ground-based precipitation and they need no significant improvement with bias correction. Thus, we understand that the CHIRPS SPEs validated by Aksu and Akgul (2020) for Turkey can be used for the Kucuk Menderes River Basin drought analysis in this study.

Table 2 The Nash–Sutcliffe efficiency (NSE) coefficient and the determination coefficient (R^2) calculated from the uncalibrated and calibrated CHIRPS SPEs and the ground-based monthly precipitation data

Performance criteria	January	February	March	April	May	June	July	August	September	October	November	December	Overall
NSE (Uncalibrated)	0.35	0.69	0.51	0.67	0.28	0.02	-5.22	-5.03	0.46	0.46	0.78	0.79	0.62
NSE (Calibrated)	0.51	0.75	0.73	0.71	0.48	0.16	0.02	0.02	0.44	0.60	0.77	0.86	0.77
R^2 (Uncalibrated)	0.48	0.75	0.68	0.75	0.41	0.07	0.02	0.02	0.50	0.50	0.84	0.82	0.84
R^2 (Calibrated)	0.51	0.75	0.73	0.72	0.48	0.17	0.02	0.02	0.50	0.60	0.80	0.86	0.88

Table 3 Drought categorization based on SPI

SPI	Drought category
$0 > \text{SPI} > -1.0$	Mild
$-1.0 \geq \text{SPI} > -1.5$	Moderate
$-1.5 \geq \text{SPI} > -2.0$	Severe
$-2.0 \geq \text{SPI}$	Extreme

4 SPI as the comparison methodology

SPI is a simple and stand-alone index used frequently for the determination of drought characteristics (McKee et al. 1993). It is calculated at timescales k = 1, 3, 6, 9, 12 and 24 months over which precipitation is accumulated. The 3-month timescale was taken into account in this study. Typically, precipitation is not normally distributed for the accumulation periods shorter than 12 months. It is presumed that precipitation has gamma distribution (Aksoy 2000), which is transformed into the standard normal distribution with zero mean and unit variance to calculate SPI as

$$SPI_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \tag{2}$$

where $x_{i,j}$ is precipitation in month j ($j = 1, 2, 3, \ldots, 12$) of year i ($i = 1, 2, \ldots, n$), μ_j the mean value of precipitation in month j, and σ_j the standard deviation of precipitation in month j. Drought is categorized as in Table 3, depending on the value of SPI averaged over the drought duration.

5 Results and discussion

In this study, drought was analyzed based on SPI_3 (the 3-month scale SPI) of the selected meteorological stations. We used SPI_3, because it demonstrates seasonal meteorological wet and dry periods; i.e., the surplus or deficit in precipitation accumulated in three previous months is reflected by the SPI_3 time series. SPI_3 calculated from the ground-based data and the CHIRPS SPEs show that the three meteorological stations exhibit a similar variability with a high correlation (Fig. 4). In the positive region, SPI_3 values of the CHIRPS SPEs are lower than the SPI_3 values calculated from the ground station data. It is the opposite in the negative region, SPEs provided higher SPI_3 than the ground data. This is mathematically equivalent to

$$\left|SPI_{CHIRPS}\right| < \left|SPI_{Ground}\right| \tag{3}$$

which means that SPI_3 values calculated from the CHIRPS-SPEs in dry periods estimate milder droughts than the ground data-based SPI_3 does.

SPEs poorly performed in summer (Table 2). The reason for this dissimilarity with the ground precipitation can be connected to the climate of the river basin with dry summer. Almost no rain has been recorded in July and August for the observation period while only about 2% of the total precipitation has been observed in June. The poor performance in summer may not be that important on the overall performance of the CHIRPS SPEs as about 98% of the total precipitation has been recorded in the well-performed autumn, winter and spring seasons (Fig. 5).

SPI_3 of the CHIRPS SPEs was illustrated over the Kucuk Menderes River Basin for each month (Fig. 6). This shows the within-year variability in the drought severity. Notice that the upper and lower limits of SPI_3 were fixed on the maps throughout the year for the comparability. April has the lowest SPI_3 reflecting the largest negative deviation from the normal precipitation accumulated over the 3-month period through February–April. The deviation in this particular month is important due to its significance primarily in agriculture as many crops cultivated in the river basin are grown in April during which they need water. The second lowest SPI_3 was calculated for September which is a month with significant amount of water consumption by the end of summer. Other months with negative SPI_3 are February, March, June, August and October in which agriculture might need water for irrigation depending on the crops

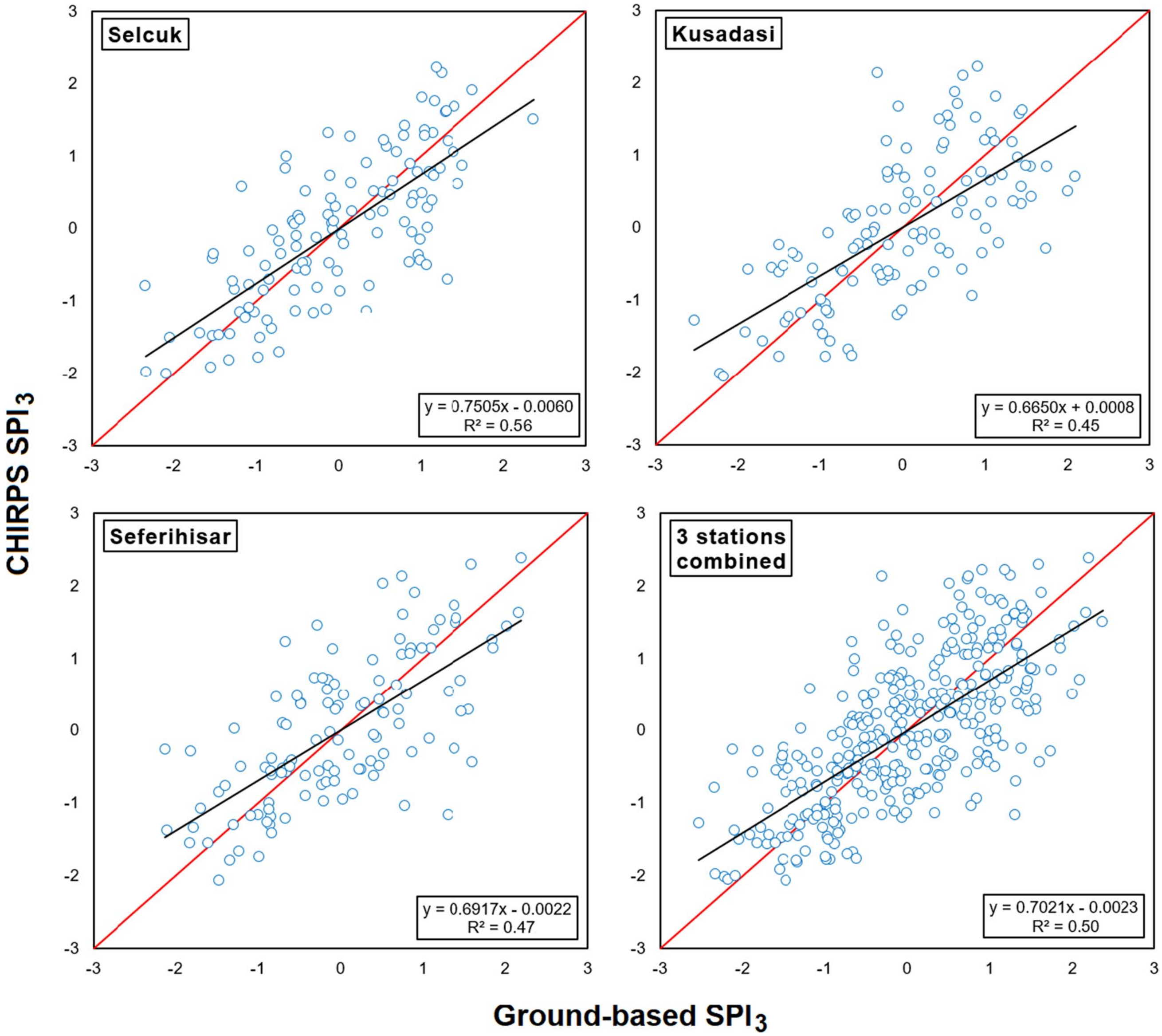

Fig. 4 SPI_3 calculated from the ground-based data and the CHIRPS SPEs for the selected meteorological stations (Red and black lines show the perfect fit and the best fit, respectively. Equation and determination coefficient are given for the best-fit regression.)

of the season. January, May, July, November and December have positive SPI_3 showing a surplus in precipitation. SPI_3 is maximized in November with accumulated precipitation in autumn through September–November.

Spatial variability over the river basin cannot be traced in Fig. 6 because of the fixed range of SPI_3 used throughout the year in the SPI_3 maps. For a clear visualization of the spatial variability, a variable range was used for SPI_3 in each month (Fig. 7). It is seen that the western half of the Kucuk Menderes River basin experiences moderate drought while the eastern half is under the effect of severe drought in April, the month with the minimum SPI_3. Also, a moderate drought is noticeable at the most eastern part of the river basin in the same month. In September, which is the month with the second least SPI_3, the western part of the basin becomes more prone to drought than its eastern. The eastern drought in the spring season has shifted to the west in autumn. This is an important information about the within-year spatial variability of drought for all water related sectors, including hydropower and agriculture. In June, mild drought affects the entire river basin with less severity in the east. In February and March, local hotspots

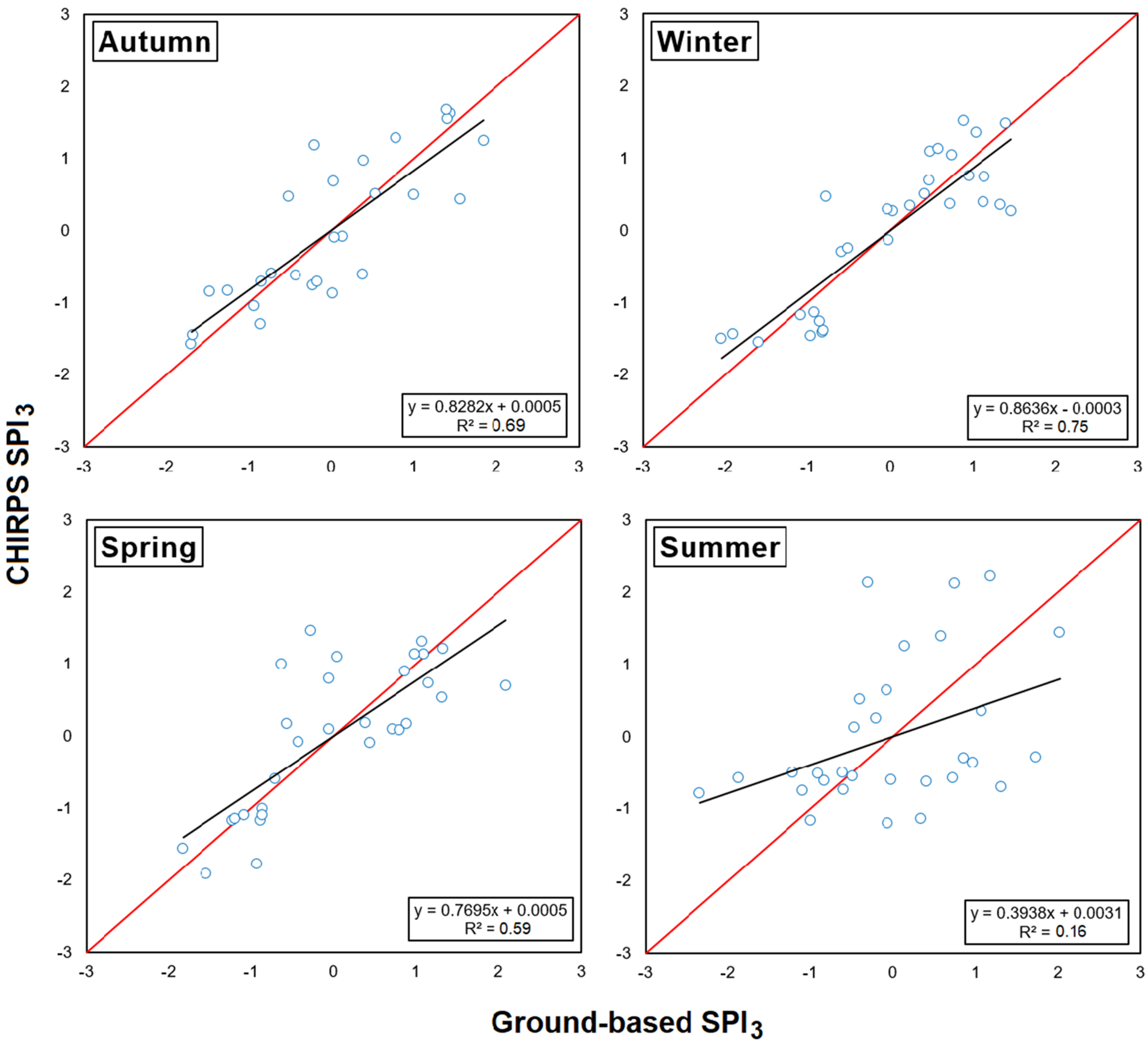

Fig. 5 Seasonal comparison of the CHIRPS and ground-based SPI_3 (Red and black lines show the perfect fit and the best fit, respectively. Equation and determination coefficient are given for the best-fit regression.)

with more severe droughts are scattered over the basin. The eastern part is under the effect of mild drought, while the western part is in transition to the moderate drought in August and September. The situation is reversed in October; the western part of the basin is under the effect of less severe droughts (mild drought) than the eastern part experiencing moderate drought. Thus, we understand that the entire river basin might experience drought at any severity depending on the months of the year.

In some months, the river basin experiences the same drought category with different severities in its different parts while it is affected by different drought categories in some others. It is even possible to observe that the river basin could be under the effect of both dry and wet conditions in the same month. Also, months which are totally wet exist. For example, in February and June, the river basin is under the effect of mild drought which is slightly less variable in February compared to June. For the remaining part of the year except for the totally wet

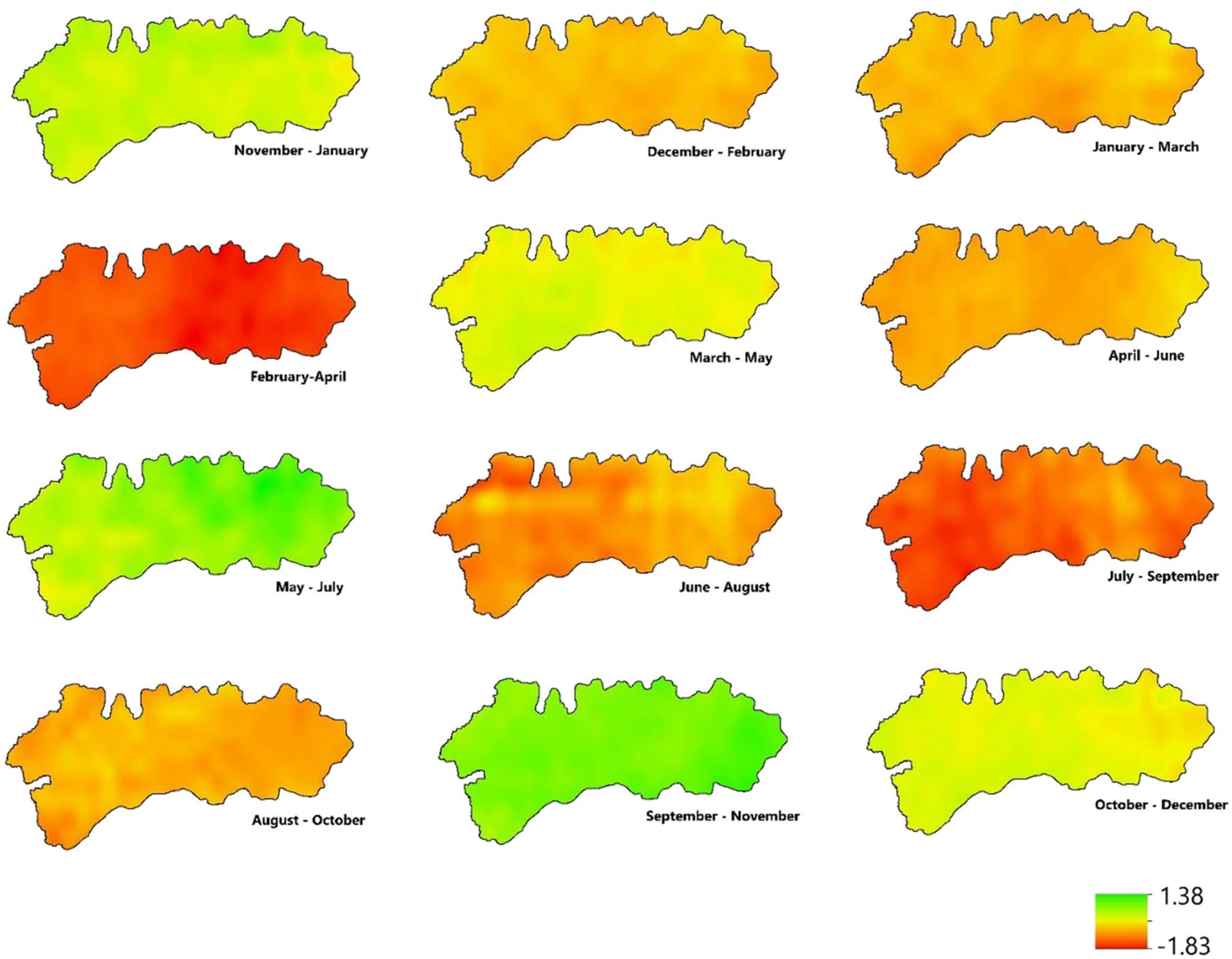

Fig. 6 Within-year variability in SPI_3 over the Kucuk Menderes River Basin for each month (a fixed range of $-1.83 \leq SPI_3 \leq 1.38$ was used for SPI_3 in the legend for all maps)

November, different drought categories were observed over the river basin in the same month (from mild to moderate drought in March and October, from mild to severe drought in August and September, from moderate to severe drought in April). Wet and dry conditions are experienced in January, May, July and December; i.e., the river basin is partly under wet conditions while other parts suffer from mild drought. Drought affects the western part of the river basin in July, and the eastern part in January, July and December. Variability in the drought severity is the largest in July, August and September. This shows how spatially variable the drought can be even in such a small river basin as the Kucuk Menderes. From Figs. 6 and 7, we found that the entire river basin is vulnerable to drought at different severities changing from month to month in time. We also observed that drought severity varied from one point to another in space for a given month despite the fact that the river basin is not large in size and does not have a complex topography.

Other than the within-year variability, it is also important to check if an over-year variability exists. It is seen from Fig. 8 that SPI_3 calculated from the precipitation data of the ground stations decreases over years. The decrease was checked with the Mann–Kendall trend test, showing that the meteorological stations have significant negative trends at 5 and 10% significance levels with the exception that the trend for the Seferihisar meteorological station was rejected at the 5% significance level. The significant negative trends can be counted as a future concern about the drought in the river basin.

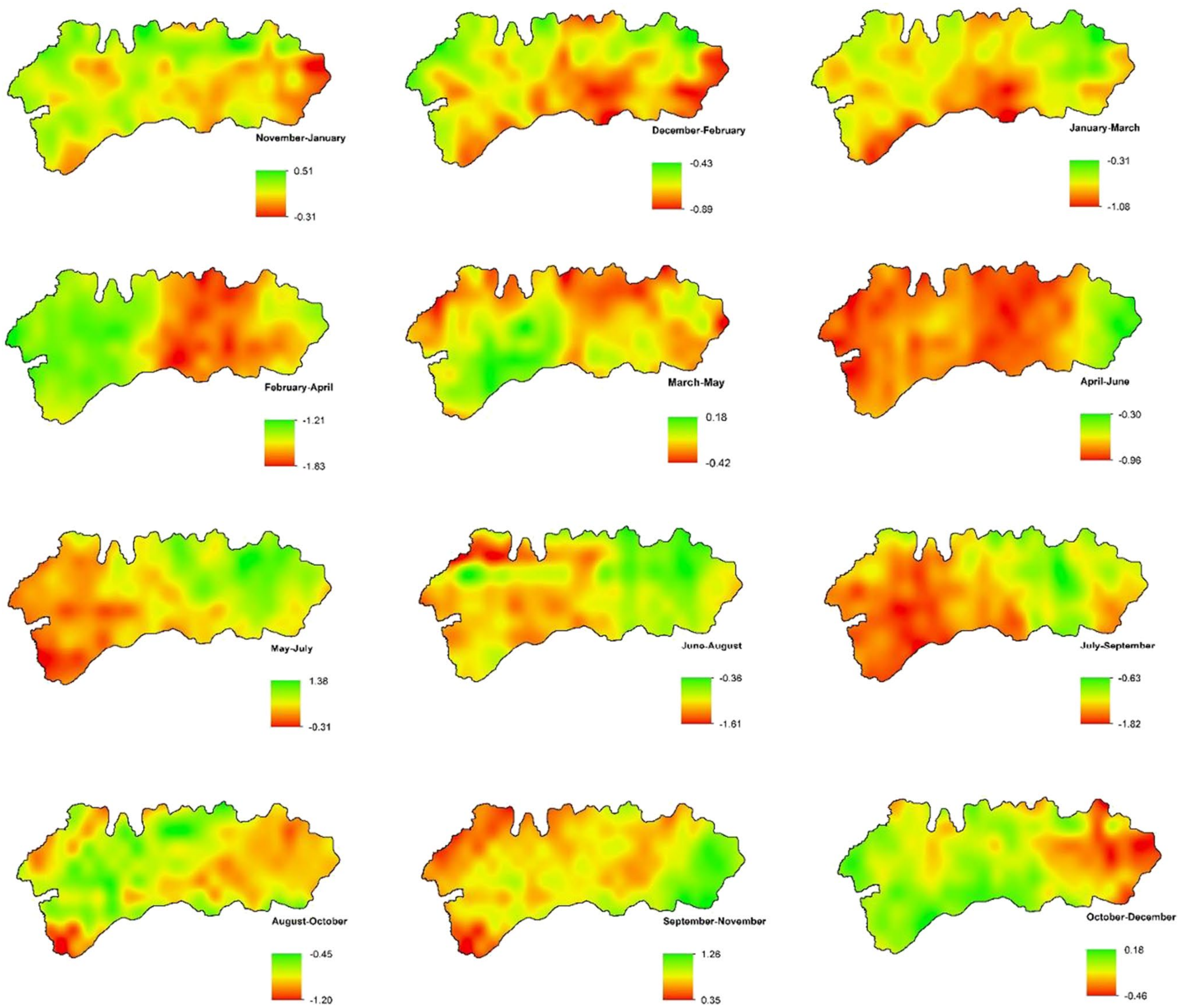

Fig. 7 Spatial variability in SPI_3 over Kucuk Menderes River Basin for each month (a variable range of SPI_3 was used for each month to trace the spatial variability)

6 Conclusions

This study was carried out over the Kucuk Menderes River Basin in the western part of Turkey based on the 3-month timescale SPI calculated from the CHIPRS SPEs and the monthly precipitation data of three meteorological stations in and around the river basin. Methodological and case study-specific conclusions achieved from the results are as follows:

1. The CHIRPS SPEs can define the spatial variability in the drought over a certain region. SPEs can replace for precipitation and they are eventually demonstrated to be handy tools to use in drought studies. This is the significance of the study which is more pronounced when a study area has a poor meteorological network or no meteorological stations at all.
2. Drought severity maps can be produced by using spatial interpolation techniques over the study area, which brings a gross uncertainty when limited number of ground stations with spatial uneven distribution are used. The uncertainty increases with the complexity in the terrain of the study area. The CHIRPS SPEs give an opportunity to greatly reduce this uncertainty thanks to their fine resolution.
3. The CHIRPS SPEs are found well consistent with the precipitation data of the ground stations in the Kucuk Menderes River Basin in western Turkey after a minor bias correction is applied with a simple algorithm.

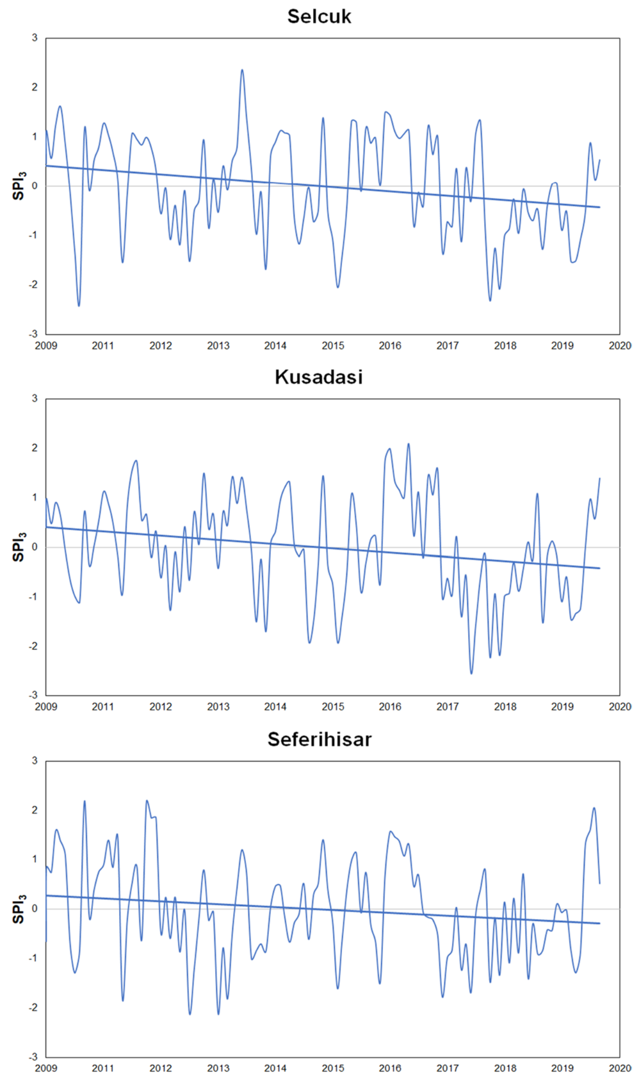

Fig. 8 The over-year variability of SPI_3 in selected meteorological station

4. From the spatial mapping of SPEs, it is seen that the Kucuk Menderes River Basin is under the effect of drought, which has a within-year variability. In more than half of the year, droughts of different categories affect the basin while in some months both wet and dry conditions are observed.
5. In the river basin, drought index carries a significantly decreasing over-year change that can be taken as a sign for more severe droughts in the future.

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Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflicts of interest/Competing interests The authors have no conflicts of interest to declare.

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