

Spatiotemporal Analysis of Drought by CHIRPS Precipitation Estimates

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Abstract

Drought is one of the most devastating worldwide natural hazards that can occur in all climatic zones and cause considerable losses affecting many water-needing sectors. It is also one of the most complex and least understood hazards due to its high heterogeneity in space and variability in time. Therefore, for a proper spatial and temporal drought analysis, spatially dense and uniformly distributed ground-based precipitation data are needed. In practice, such data are generally lacking either due to missing data or to the nonuniform and scarce spatial distribution of ground stations. This gives a great potential to the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) data with a long period and high resolution for using in drought studies. The CHIRPS data also allow to tackle with the problem of sparse, unevenly distributed and erratic ground stations. Based on the CHIRPS data, the study aims to assess the drought condition over Kucuk Menderes River Basin in the western part of Turkey. The analysis was performed considering the seasonality as well as the spatial and temporal change in the drought characterization based on the Standardized Precipitation Index (SPI) calculated at 3-month (seasonal) time scale. Results showed that the CHIRPS and ground stations were highly correlated except for summer despite the overall good performance in the basin. The CHIRPS can properly capture drought characteristics. Droughts have a within-year variability in time and an insignificant variability in space over the basin while the over-year variability shows a significant decreasing trend which could be a signal for more severe droughts after being accumulated over years in the future. The study demonstrates the usefulness of CHIRPS in drought analysis due to the fact that ground-based data are still not at a level dense and long enough to understand the process precisely both in time and space.

1. Introduction

Precipitation is the integral part and main driving agent of global water budget. It is therefore important to comprehensively study at various spatial scales ranging from a watershed (Vaheddoost and Aksoy, 2017) to a region (Ferrari et al., 2013) or to a country (Dahamsheh and Aksoy, 2007), and at temporal scales ranging from minutes to days, weeks, month and years (Unal et al. 2004). In order to capture the spatial and temporal variability in precipitation, it is essentially important to have spatially-dense and temporally-long, accurate and reliable precipitation data. It becomes more important when the issue concerned is drought, now being one of the most harmful natural hazards (McKee et al., 1993, Mishra and Singh, 2010) due to its negative effects on the society, economy and environment. Drought is mainly categorized by its impacts on various sectors. It starts with precipitation deficit as meteorological drought and propagates into agricultural and hydrological droughts, and finally into its socioeconomical and environmental types (van Loon, 2015). A significant increase is reasonably expected in the frequency, duration and intensity of natural hazards including droughts due to the foreseen climate change (IPCC, 2013) after which natural or anthropogenic disturbances become indisputable in hydrometeorological variables. Thus, a great interest has been observed on drought not only to understand the process itself or to develop methodologies but also to extend its effect on the society, economy and environment.

Precipitation data at meteorological stations on the ground are generally used in conventional drought studies. However, number of ground stations in a certain region or across a river basin is generally not at a level to reveal the spatial change in meteorological variables, and they are not homogeneously distributed nor are they available for common users in many regions around the world. Due to limitations in the spatial distribution of meteorological stations and deficiencies in the temporal availability of the data, satellite technology has emerged (Zuo et al., 2019). Accordingly, an increasing trend has been observed on the use of satellite technology in recent years (Aksu and Arikan, 2017). Among the satellite products, satellite precipitation estimates (SPEs) have gained an obvious great importance as they are used in a number of hydro-climatological applications including drought (Yilmaz et al., 2005a,b; Tote et al., 2015; Santos et al., 2017, 2019a,b; Zambrano et al., 2017; Satge et al., 2019; Li et al., 2020; Wang et al., 2020).

A variety of SPEs are available now thanks to the progress in the satellite technology. They are Precipitation Estimation from Remote Sensing Information using Artificial Neural Network (PERSIANN) (Hsu et al., 1997), Microwave/Infrared Rain Rate Algorithm (MIRAA) (Miller et al., 2001), CPC MORPHing technique (CMORPH) (Joyce et al., 2004), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (Funk et al., 2014, 2015a,b), Integrated Multisatellite Retrievals for GPM (IMERG) (Huffman et al., 2015), Tropical Applications of Meteorology using Satellite and ground-based observations (TAMSAT) African

Rainfall Climatology and Time series (TARCAT) (Tarnavsky et al., 2014), African Rainfall Climatology Version 2 (ARC v2.0) (Novella and Thiaw, 2013), and TRMM Multi-satellite Precipitation Analysis (TMPA) (Huffman et al., 2007) among others. SPEs can provide high spatial and temporal resolution, yet a performance assessment based on ground station measurements is required before an application is made over a region. They can be substituted for ground stations in the region for which they are once validated.

Numerous studies have been performed to evaluate the accuracy of SPEs regionally or globally (Aghakouchak, 2015; AghaKouchak et al., 2015), and a great effort has been witnessed in the literature. As a few examples to mention, Khandu et al. (2016) evaluated three satellite-based products (TRMM, CMORPH, CHIRPS) to estimate rainfall in Bhutan by correcting bias with the gamma distribution method. Similarly, Diem et al. (2019), Macharia et al. (2020) and Usman et al. (2018) used four satellite products each in different countries in Africa; and Gupta et al. (2019) in India. Santos et al. (2019a, b), Neto et al. (2020) and dos Santos et al. (2020) presented case studies from Brazil, and Chen et al. (2020) from the Yangtze River Basin in China.

Among the above SPEs, CHIRPS combines the long-term infrared (IR) remote sensing data and ground-based observations. Thus, it is relatively long enough (more than 30 years) to use for drought monitoring as well as other climatological applications. The performance of CHIRPS varies from region to region. A few recent examples on CHIRPS have been made available by Katsanos et al. (2016), Guo et al. (2017), Gao et al. (2018), Perdigon-Morales et al. (2018), and Peng et al. (2020) among many others. They are used not only to replace for ground precipitation data but it has found that they also have a useful potential in streamflow forecasting (Sulugodu and Deka, 2019). It is even possible to use them for the management of environmental conflict in transboundary river basins (Minanabadi et al., 2020). The performance of CHIRPS data was evaluated over Turkey as well, and SPEs were found consistent with ground measurements in the western and southern parts of the country particularly (Aksu and Akgul, 2020) within which Kucuk Menderes River basin, the study area of this research, is located.

Besides the fast progress in the satellite products providing SPEs, there is a wide and common methodology based on indicators or indices used in research and practiced by meteorological services when the drought is concerned. The methodology uses either meteorological or hydrological variables (i.e., precipitation, streamflow, temperature) called indicators or indices calculated from the indicators themselves. Among numerous drought indices so far developed in the literature, Standardized Precipitation Index (SPI; McKee et al., 1993) is the most commonly used due to its availability for diverse time scales and needing only precipitation (Cavus and Aksoy, 2019, 2020; Eris et al., 2020) as the input. It has therefore been suggested by the World Meteorological Organization (WMO, 2012) to national meteorological organizations as a standard for drought characterization.

In the common application, drought indices are calculated based on data recorded at the ground stations. However, as in many cases, the ground stations are sparsely and unevenly distributed over the study area, and they might not have uninterrupted long records. This creates problems in performing a proper spatial and temporal drought analysis (Kalisa et al., 2020). This is the case for Kucuk Menderes River Basin in western Turkey which is greatly important for agriculture and hence requiring water to irrigate agricultural lands, i.e. the river basin is not well equipped with ground stations (Eris et al., 2020). SPEs which blend the remote-sensed data with existing ground-based measurements could be proposed as an alternative solution to overcome this difficulty. Aksu and Akgul (2020) have validated the CHIRPS SPEs for Turkey and concluded that they were performed well in the western part of the country particularly. The scarcity of ground stations combined with the availability of the well performed SPE has been the motivation for this study which aims at (i) evaluating the performance of CHIRPS at the 3-month time scale over the Kucuk Menderes River basin; and (ii) mapping the spatio-temporal variability over the river basin by using SPI. The study proceeds as follows: First, study area and meteorological stations are introduced, CHIRPS data and bias correction method are explained next. SPI as the comparison methodology is then given, followed by the assessments and comparison of the CHIRPS with ground stations. Spatio-temporal analysis of the drought is made before the conclusions are listed at the end.

2. Study Area And Meteorological Stations

Turkey is divided into 25 administrative hydrological basins; some coincides with a river basin while others are composed of several river sub-basins. The administrative Kucuk Menderes Basin (numbered 06 in the upper panel, Figure 1) in the Aegean Region, the western part of Turkey, selected for the case study is in the form of the latter which accommodates the Kucuk Menderes River basin (Figure 1 lower panel) and a few more sub-basins each being home to several rivers individually flowing into the Aegean Sea in the western half and southern cape of the administrative basin. The Kucuk Menderes River Basin exhibits the Mediterranean climate (with an average temperature of 16.3 °C); thus, summers are hot and dry, and winters warm and rainy. Precipitation is higher in the east and southeast compared to other parts of the basin (with an average annual total of 622 mm) (Selek and Aksu, 2020). In the river basin, there exist productive agricultural lands as well as forest, semi-natural areas and industrial areas (Aksoy, 2020). Agricultural lands cover nearly 41% of the river basin, 52% of which is irrigated. The rest is used for dry agriculture. Almost all water needs for irrigation and industry are supplied by groundwater resources (Yagbasan, 2016). It has therefore been a prominent study area for which water allocation and drought management plans have been prepared by state-owned organizations (TUBITAK, 2010; GDWM, 2016, 2017) and research studies have been performed (Eris et al., 2020).

Three meteorological stations in and around the Kucuk Menderes River basin as in the layout in Figure 1 were selected to use in the validation process. The meteorological stations are listed in Table 1 in which their names are given together with their coordinates and elevation. Also, statistical characteristics - the mean (P_{mean}), minimum (P_{min}) and maximum (P_{max}) values, standard deviation, and coefficients of variation (C_v), skewness (C_s) and kurtosis (k) - calculated from the monthly precipitation time series of the available observation period are given. Monthly precipitation data for the meteorological stations were obtained from the State Meteorological Service (MGM with its Turkish acronym) of Turkey.

Table 1 General characteristics of meteorological stations

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	57.08	0	294.0	65.14	1.14	1.28	0.95
Kusadasi	2008-2018	37.8597	27.2652	25	54.72	0	336.1	63.99	1.16	1.40	2.01
Seferihisar	2008-2018	38.1990	26.8350	22	57.02	0	308.7	68.91	1.20	1.47	1.87

There are a number of meteorological stations in the Kucuk Menderes River Basin. For example; Eris et al. (2020) has listed five meteorological stations in the river basin and eight around; 13 in total, all with uninterrupted data length of 10 years at minimum. Many others are available in the river basin most of which has been used in the production of CHIRPS data which prevented their re-use in this study. This explains the reason why this study was accomplished with these three particular meteorological stations.

3. Chirps Data And Bias Correction

CHIRPS was developed by U.S. Geological Survey (USGS) and the Climate Hazards Group at University of California Santa Barbara for drought monitoring over regions with scarce observation networks and complex topography (Funk et al., 2014, 2015 a,b; URL-1). CHIRPS is an IR-based quasi-global satellite precipitation dataset. It has a relatively higher spatial resolution (0.05°) than other SPEs (Funk et al., 2015a,b), long records (dating back to 1981) at daily, pentadal, dekadal and monthly temporal resolutions, which are all freely downloadable (URL-1). It is a blended product which combines precipitation climatology, quasi-global satellite estimates and in-situ measurements. The accuracy of SPEs has recently increased by blending them with the ground-based measurements (CMORPH, IMERG, CHIRPS, PERSIANN etc.). The Food and Agriculture Organization (FAO) and Global Historical Climate Network (GHCN) used CHIRPS SPEs to obtain precipitation data from more than 20,000 ground stations.

CHIRPS is an ideal precipitation dataset for drought monitoring and warning (Funk et al. 2015a, b) although SPEs contain bias over many regions of the World as a result of the methodology they use which is affected by a number of reasons such as cloud top temperature threshold, lack of ground stations, duration as well as geographical reasons such as orography, proximity to the sea, etc. (AghaKouchak et al., 2012; Yilmaz et al., 2005a, b). Therefore, a bias correction should be applied to increase the performance of SPEs in representing the ground-based measurements (Vernimmen et al., 2012). Aksu and Akgul (2020) evaluated the performance of CHIRPS SPEs over Turkey, and found a positive bias within a high-performance range over the western Anatolia including the Kucuk Menderes River basin. At monthly time scale, a negative bias was calculated for May and June, a strong positive bias for July and August, and a positive bias of 20% from November through April all across the river basin. Bias varied spatially in September and October over the river basin when the season changes from dry summer to wet winter. Based on the already available validation (Aksu and Akgul, 2020), the CHIRPS SPEs were selected to use in this study for drought analysis in Kucuk Menderes River Basin. SPEs from CHIRPS version 2.0 were used and referred to as CHIRPS shortly here. Monthly time scale data with 0.05° spatial resolution of CHIRPS was chosen to analyze drought conditions between 2008 and 2018.

As the case study of Aksu and Akgul (2020) has shown, CHIRPS SPEs may overestimate precipitation up to 20% annually while a monthly bias may vary substantially. Bias correction was therefore applied at monthly time scale on the three meteorological stations used in this study by

$$P^* = a(P/P_0)^b \quad (1)$$

in which P^* is the bias corrected precipitation, P is precipitation (mm), P_0 is reference monthly precipitation (1 mm in this study), and a and b are constants which were optimized by the generalized reduced gradient algorithm (Fylstra et al., 1998).

Within the framework of the case study, comparison of the bias-corrected monthly SPEs of the selected meteorological stations with the ground-based precipitation data is displayed in Figure 2, and, in order to show how they behave in a particular month, the comparison was made for January in Figure 3 as an example. The performance of the bias-correction is quite high when an overall comparison is made although it is reduced at monthly level as in January, which is still at a considerably acceptable level.

Comparison between the CHIRPS and ground stations was made in terms of Nash-Sutcliff Efficiency coefficient (NSE) and determination coefficient (R^2) as in Table 2. During rainy seasons, CHIRPS and ground-based observations are highly correlated; while CHIRPS shows very low performance in summer. The difference between CHIRPS and ground-based observations stems from the applied algorithm. The constant cloud top temperature threshold is an important reason of the bias correction. CHIRPS has also a difficulty to detect zero precipitation values. This is the reason why NSE and R^2 are low in June, and particularly in July and August. Figures 2 and 3, and Table 2 suggest that calibration does not increase the correlation in summer but only provides a minor improvement in rainy months as the correlation was already significantly high with the uncalibrated SPEs. This is a good point indeed showing that SPEs are already quite similar to the ground-based precipitation and no significant improvement is needed to validate them. It is possible to connect this statement with the validation study of Aksu and Akgul (2020) who found that CHIRPS SPEs work well for Turkey, particularly for its western part where Kucuk Menderes River Basin is located.

Table 2 Performance statistics (NSE and R^2) of uncalibrated and calibrated CHIRPS SPEs with ground-based monthly and annual precipitation data

Performance Statistics	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
NSE (Uncalib)	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 (Calib)	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 (Uncalib)	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 (Calib)	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

4. Spi As The Comparison Methodology

With the help of SPI calculated by using only monthly precipitation data, dry periods can be determined as well as wet periods. SPI can be calculated for various time scales such as 1, 3, 6, 9, 12, 24, 48 months. Precipitation is typically not a normal distribution process for the accumulation periods shorter than 12 months particularly but this can be overcome by applying a transformation to its distribution (McKee et al., 1993). Precipitation data sets are assumed to fit gamma probability distribution function (Aksoy, 2000), which is then transformed into the standard normal distribution with zero mean and unit variance. Once the transformation is made, the SPI is then calculated by

$$SPI_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \quad (2)$$

where $x_{i,j}$ is precipitation in the j^{th} month ($j = 1, 2, 3, \dots, 12$) of the i^{th} year ($i = 1, 2, \dots, n$), μ_j mean value of precipitation in the j^{th} month, and σ_j standard deviation of precipitation in the j^{th} month. SPI is calculated for various time scales. The short-, medium-, and long-term meteorological droughts are characterized by the respective time scale as recommended by the World Meteorological Organization (WMO) (Hayes et al. 2011). SPI is typically used to determine drought category depending on its severity as in Table 3.

Table 3 Drought categorization based on SPI (WMO, 2012)

SPI	Drought Category
$-0.99 < SPI \leq 0$	Mild
$-1.0 < SPI \leq -1.49$	Moderate
$-1.5 < SPI \leq -1.99$	Severe
$-2.0 \geq SPI$	Extreme

5. Results And Discussion

Results of the case study are presented based on SPI values at the 3-month time scale (SPI_3) for the selected meteorological stations. The reason for using SPI_3 among other shorter and longer time scales is that, SPI_3 demonstrates seasonal meteorological drought for each month of the year; i.e., surplus or deficit in the 3-month accumulated precipitation in each month of the year is reflected by the SPI_3 time series. Scatter diagrams of SPI_3 calculated from the ground-based data and CHIRPS SPEs are given in Figure 4. The three meteorological stations have shown similar variability, also their SPI_3 values demonstrated a high correlation with SPI_3 calculated from SPEs of CHIRPS. Selcuk meteorological station shows higher correlation than Kusadasi and Seferihisar both close to each other. When the three stations are taken altogether, the correlation is still quite significant (Figure 4).

When the best-fit line of the scatter diagram is considered together with the perfect-fit line, one point which is common to the three meteorological stations is that, SPI values calculated from the CHIRPS SPEs are lower in the positive region of the scatter diagram than SPI values calculated from precipitation observed at the meteorological station. It is the vice versa in the negative region; i.e., higher SPIs were calculated from the SPEs. This statement is mathematically equivalent to

$$|SPI_{CHIRPS}| < |SPI_{Obs}| \quad (3)$$

which means that SPI values calculated from the SPEs in the dry periods estimate milder droughts than the ground-based SPI. This is important to know in advance for providing proper safety measures against drought in terms of preparedness, mitigation and risk management in the drought management plans of a region or river basin when CHIRPS-based SPEs are used.

Any bias between SPEs and ground station precipitation will affect SPI as it is calculated by using precipitation. SPEs performed poorly in summer (Table 2) while other seasons had much better similarities between SPEs and ground-based precipitation. The reason for the dissimilarity of the summer season is connected to the no-rain character of the climate in the river basin. Mostly no rain is recorded in July and August while it is about only 2% of the total precipitation in June. The poor performance of summer with almost no-rain may not be that important and should not be considered a deficiency in making a decision on the overall performance of the CHIRPS SPEs due to the fact that autumn, winter and spring seasons through which about 98% of the total precipitation is recorded perform quite well (Figure 5).

In this study, drought analysis was demonstrated by using SPI_3 calculated from CHIRPS SPEs of which spatial variability over the Kucuk Menderes River Basin was given for each month in Figure 6. SPI_3 is based on precipitation accumulated over three months. It is an important index to use for meteorological drought at seasonal time scale. In order to understand the within-year variability, i.e., to rank months depending on how severe a drought they experience, a fixed color legend of SPI_3 was used throughout the year for the maps in Figure 6. It is seen that April has the lowest SPI_3 showing that precipitation accumulated through February-April is the least in the year while it is maximized in November after precipitation in autumn from September through November is accumulated. The least amount of precipitation in April is significantly important to consider for sectors such as agriculture primarily due to its significance in the river basin. September has the second least SPI_3 when water consumption is quite significant for many sectors by the end of summer. Other months with negative SPI_3 smaller in absolute value are February, March, June, August and October in which lands might need irrigation depending on the agricultural products of the season. Remaining months (January, May, July, November and December) have positive SPI_3 showing no drought but wet periods instead.

When the same range of SPI_3 was used in the legend for the maps in Figure 6, the variation of SPI_3 over the river basin is not visible to understand the spatial variability as it seems as if almost uniformly distributed. However, it is important to demonstrate the variation by using a variable color scaling in each month to clearly demonstrate the spatial variability of SPI_3 as in Figure 7. When the spatial variability is checked month-by-month (Figure 7), it is seen in April, the month with the most severe drought, e.g., the lowest SPI_3 , that lower values of SPI_3 are concentrated in the eastern half of the river basin although it tends to get higher values at the most east. In other words, the eastern half of the river basin mostly experiences drought more severely (in the severe drought category) than the western half which observes moderate drought due to less accumulation of the 3-month precipitation in April. In September, which is the month with the second least SPI_3 , the western half of the river basin becomes more prone to drought but less severe than April. This is a significant piece of information showing that the eastern part of the river basin is more likely to be affected by drought in April (spring) while it is the western part in September (autumn). That is, drought shifts from east to west when the deficit in the 3-month precipitation is considered for April and September. Such information on the spatial variability over time is important for all sectors, not only for water-using sectors such as hydropower but also for water-consuming sectors such as agriculture. The drought-prone western part of the river extends to a larger area in June, the drought covers almost the entire river basin. In February and March, hotspots with more severe droughts are observed rather than a spatially concentrated extension over the river basin. The western part of the river

basin is more critical in August while it is the eastern part in October experiencing less severe droughts compared to the above-named months. It seems that other months have no drought.

When an overall analysis of Figures 6-7 is made, it is possible to express that drought might be experienced in any part of the river basin at any severity depending on the months of the year. This shows that pre- or post-drought measures as well as measures during the drought are important to take throughout the year for the entire river basin without being concentrated in one particular part. Anti-drought measures readily available for the entire river basin might concentrate over a partial area or at a hotspot due to the fact that drought may not uniformly affect the river basin at monthly scale. However, the difference in the severity in Figure 7 is not that significant. To clarify this, it is meaningful to compare Figures 6 and 7 for April. Figure 6 shows that the entire river basin is under the effect of a severe drought which could be more effective in the eastern part (see Figure 7). However, it is important to notice that the spatial variability over the river basin is not that significant. It is finally meaningful to understand the significant within-year temporal variability in the drought in Kucuk Menderes River Basin (Figure 6) with less spatial variability over the river basin. It can also be stated that the entire Kucuk Menderes River Basin is vulnerable to drought at different severities changing from month to month but with no significant difference from one point to another in the river basin, which is not large in size and not complex in topography to experience a variable climate and to show a significant spatial variability in drought.

Other than the within-year variability, it is also important to check if an over-year variability exists. It is seen from Figure 8 that SPI_3 calculated from precipitation of the ground stations decreases over years. They were checked with the Mann-Kendal trend test at 5 and 10% significance levels. The SPI_3 time series of the meteorological stations were found to have significant negative trends at both levels with the exception that the existence of trend was rejected at 5% for Seferihisar. The significant negative trends should be concerned and pre-drought measures should have already been set within the scope of drought risk management before the risk turns into a crisis in the river basin. The significance of this study is that the CHIRPS SPEs permit one to draw spatial variability over a certain region, e.g., a river basin such as Kucuk Menderes in this study, with no dense meteorological network or no meteorological station at all, provided that the CHIRPS data have been validated before. This is possible as the CHIRPS SPEs are available at monthly time interval over a grid with a spatial resolution of 0.05° and have been validated by Aksu and Akgul (2020).

6. Conclusions

The study was carried out over Kucuk Menderes River Basin in the western part of Turkey based on the 3-month time scale SPI calculated from the CHIRPS SPEs and the monthly precipitation data of three ground meteorological stations. Following conclusions were achieved from the results:

1. CHIRPS SPEs are found well consistent with precipitation data of ground stations after a minor bias correction is applied with a very simple algorithm. However, SPEs in summer season are less similar to the ground-based precipitation. This is not a deficiency in advertising SPEs as a tool to use in data-scarce or no-data areas from climates with clear seasonality where negligible precipitation is recorded in summer season.
2. The simple bias correction algorithm worked quite well to correct bias in the SPEs. However, if a more precise correction is required to increase the representativeness of SPEs, alternative algorithms can be applied. This should be performed particularly for wet seasons with high amount of precipitation to improve the capability of SPEs in replicating the drought characteristics of these particular seasons over the study area.
3. Drought severity maps can be produced by using spatial interpolation techniques over the study area, which brings a gross uncertainty depending on the number and spatial variation of ground stations. The uncertainty increases with the scarcity of meteorological stations over complex terrain-study areas. It is greatly reduced thanks to the fine resolution-CHIRPS data when SPEs are used.
4. Having SPEs available in hand allows one using them in drought studies. This could be considered as one of the benefits of SPEs provided that they are validated for the study area.

5. From the spatial mapping of SPEs, it is seen that Kucuk Menderes River Basin in western Turkey is vulnerable to drought with significant within-year variability meaning that more severe droughts are experienced in some months than others. Once a drought is observed, the entire river basin is affected due to the insignificant spatial variability although minor local changes can be observed. Drought in the river basin carries an over-year variability significantly decreasing as a sign for more severe future droughts.

Following statements are important to mention in summary, for the significance and the future of this study: SPEs are well developed tools to use for hydro-meteorological purposes. Drought over a study area can be monitored by accurate satellite products such as SPEs from CHIRPS. Due to the spatially-precise availability of SPEs, satellite-based drought methodologies become advantageous to apply not only in research but also in practice.

7. Declarations

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Figures

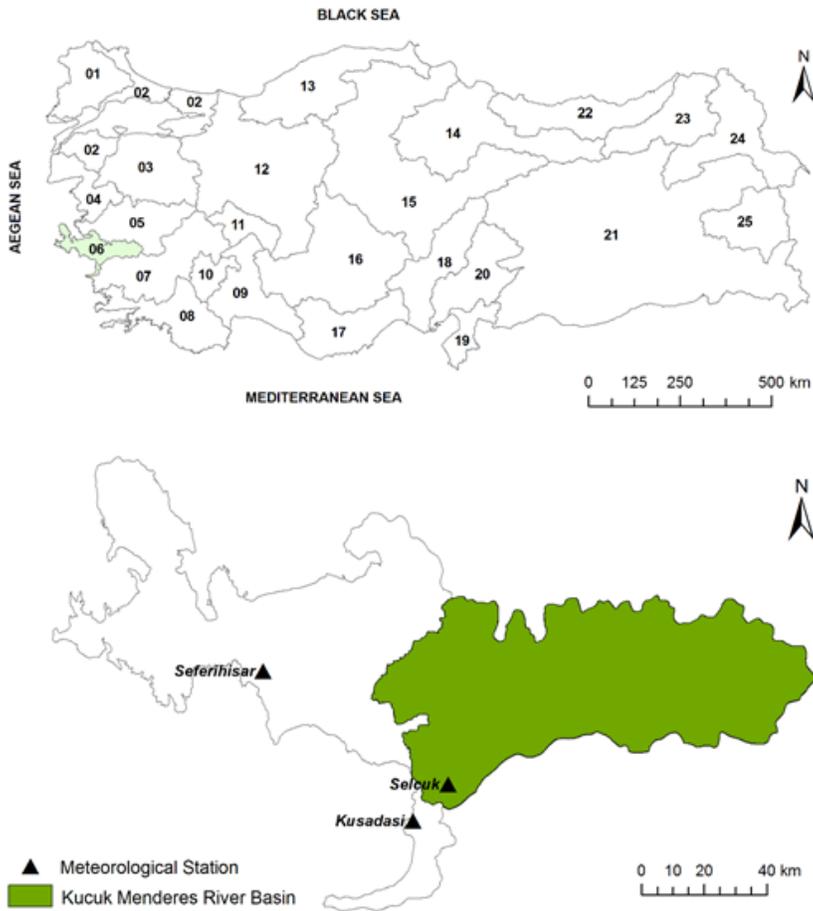


Figure 1

Kucuk Menderes River Basin in the western part of Turkey and location of the meteorological stations

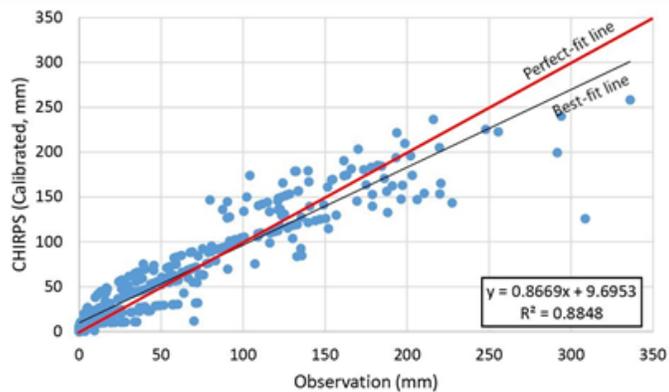
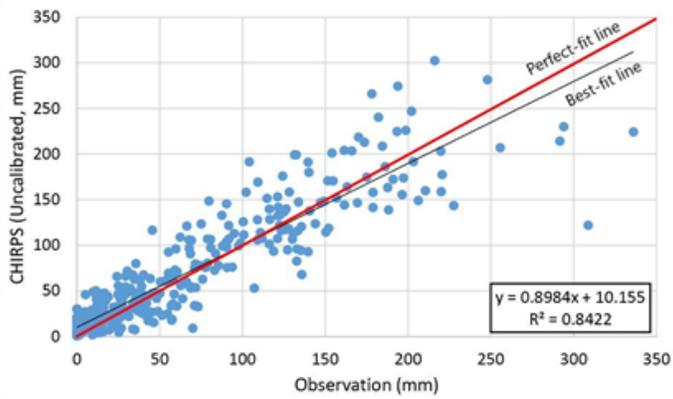


Figure 2

Scatter diagram of uncalibrated (upper panel) and calibrated (lower panel) CHIRPS SPEs compared to the ground-based precipitation of the selected meteorological stations in Kucuk Menderes River Basin

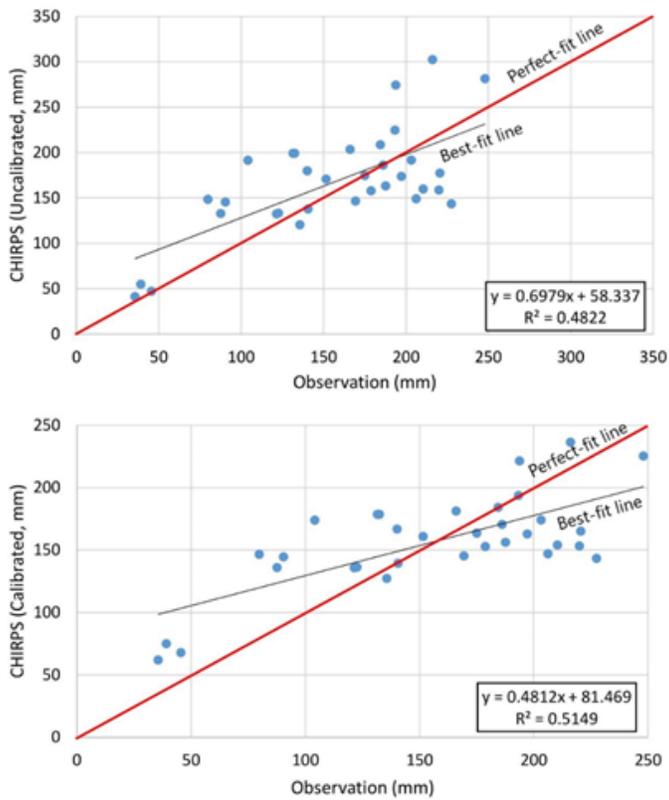


Figure 3

Scatter diagram of uncalibrated (upper panel) and calibrated (lower panel) CHIRPS SPEs compared to the ground-based precipitation in January of the selected meteorological stations in Kucuk Menderes River Basin

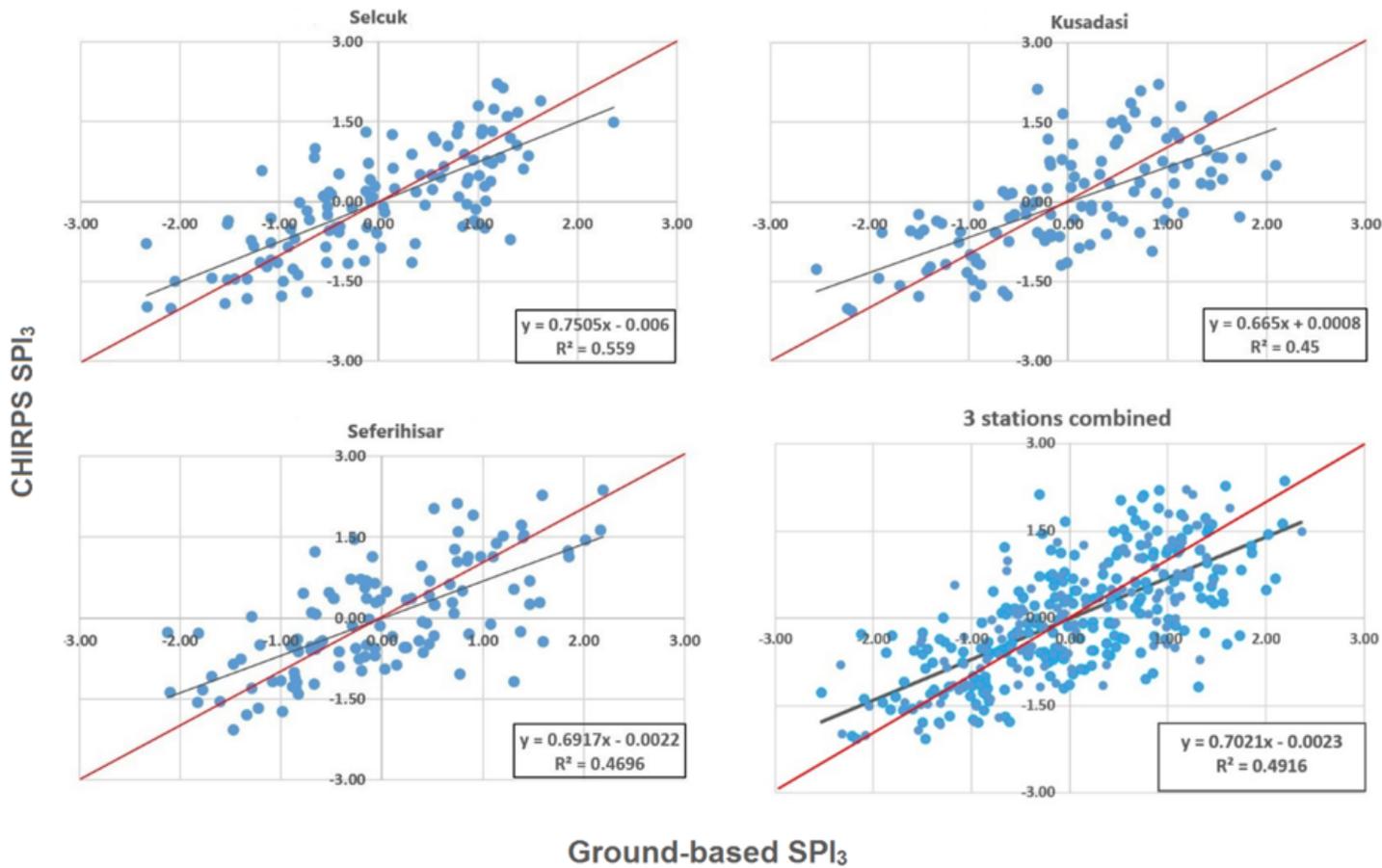


Figure 4

SPI₃ calculated from monthly precipitation of the ground-based observations vs. SPI₃ calculated from the CHIRPS SPEs for selected meteorological stations (Black line shows the best-fit, red line the perfect fit)

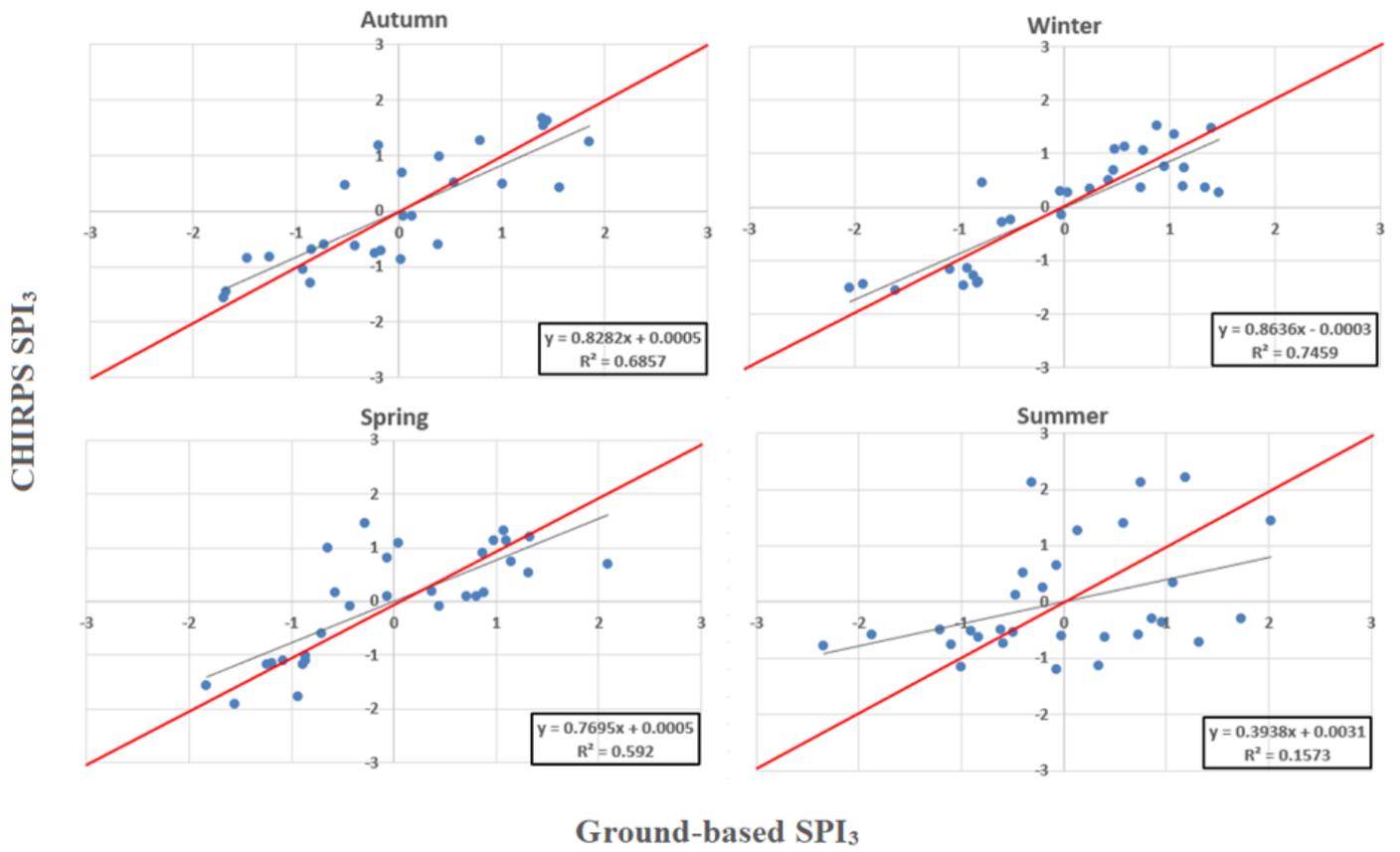


Figure 5

Season-by-season comparison of CHIRPS SPI₃ and ground-based SPI₃ (Black line shows the best-fit, red line the perfect fit)

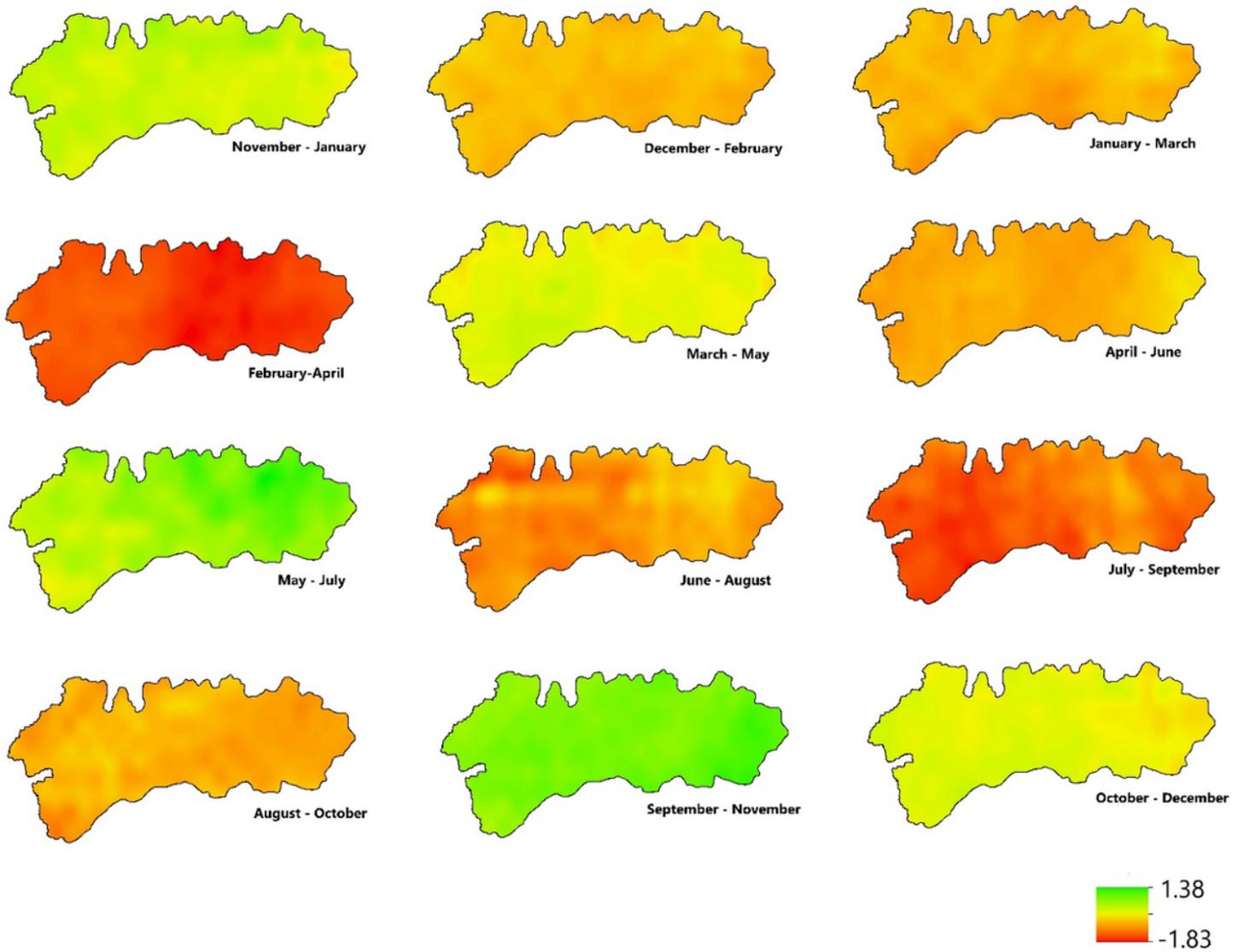


Figure 6

Within-year variability in SPI3 over the Kucuk Menderes River Basin for each month of the year (a fixed range of $-1.83 < \text{SPI3} < 1.38$ is used in the legend for all maps)

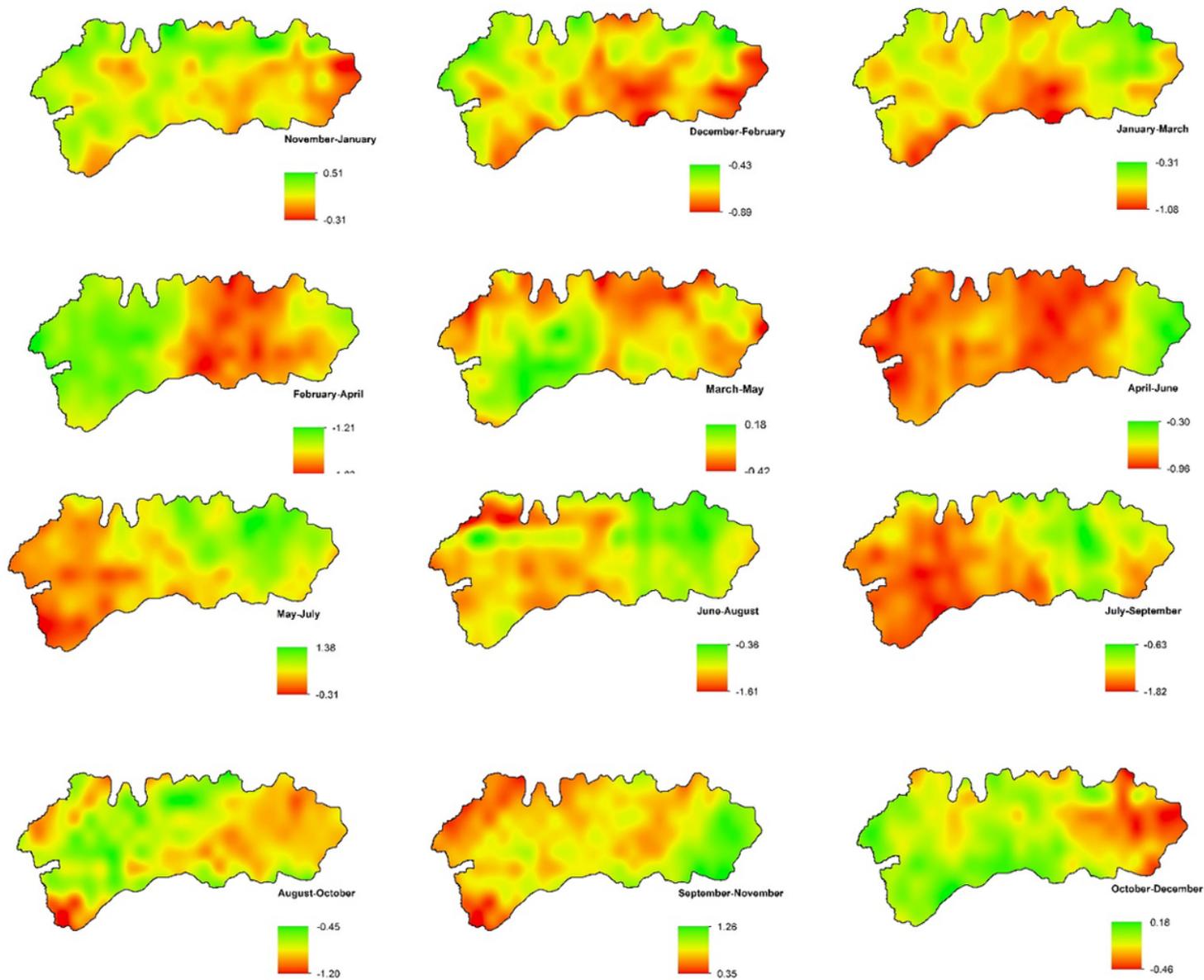


Figure 7

Spatial variability in SPI3 over Kucuk Menderes River Basin for each month of the year (a variable range of SPI3 was used for each month to get the precision in the spatial variability)

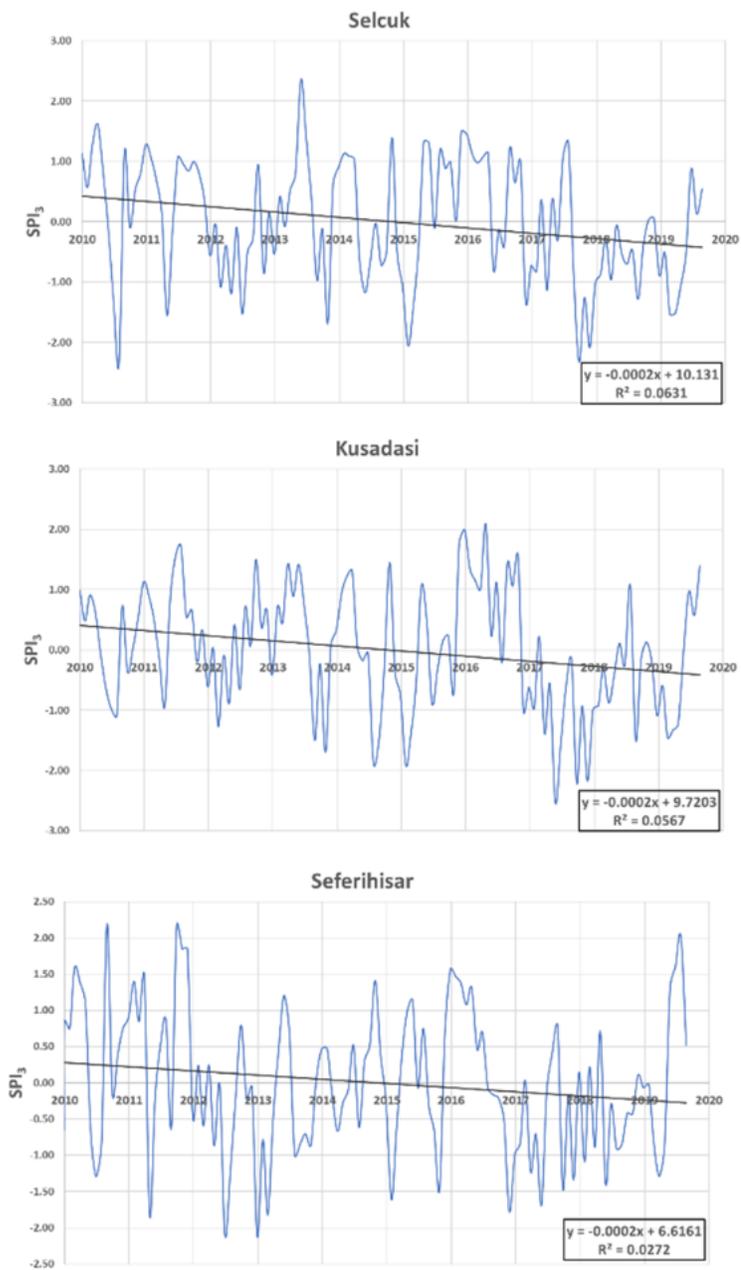


Figure 8

The over-year variability of the drought index (SPI₃) in each meteorological station