Effects of different reference periods on drought index estimations for 1901-2014

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Abstract**.** This study aims to understand how different reference periods (i.e., calibration periods) of climate data used to estimate drought indexes influence regional drought assessments. Specifically, we investigate the influences of different reference periods on historical drought characteristics such as trends, frequency, intensity and spatial extent using the standard precipitation evapotranspiration index (SPEI) with a 12-month lag (SPEI-12), which was estimated from the datasets of the climate research unit (CRU) and the University of Delaware (UDEL). For the 1901–1957 (P1) and 1958–2014 (P2) estimation periods, three different types of reference periods are used: P1 and P2 together, P1 and P2 separately and P1 only. Focusing on East Asia, Europe, the United States and West Africa, we find that the influence of the reference period is significant in East Asia and West Africa, with dominant drying trends from P1 to P2. The reference period influenced the assessment of drought characteristics, particularly the severity and spatial extent, whereas the influence on the frequency was relatively small. Finally, self-calibration, which is the most common practice for indexes such as the SPEI, tends to underestimate the drought severity and spatial extent relative to the other approaches used in this study. Although the conclusions drawn in this study are limited to two global datasets, they nevertheless highlight the need for clarification of the reference period in drought assessments to better understand regional drought characteristics and their temporal changes, particularly under climate change scenarios.

1 Introduction

Drought is a complex, slow onset and natural phenomenon that affects more people than any other hazard and seriously influences water resources, agriculture, society and ecosystems (Hagman, 1984; Wilhite, 2002; Ionita et al., 2015). As drought impacts are largely nonstructural and spread over relatively large regions, the onset and end of a drought, as well as its severity, are often difficult to determine (Wilhite, 2002). Furthermore, based on recent changes in the 21st century and projected climate warming, such drought phenomena will likely worsen (Sheffield and Wood, 2008; Dai, 2010). Sheffield et al. (2012) stated that severe and prolonged drought events have been observed since the 1970s, and these changes are related to higher temperatures and lower precipitation.

Drought can be defined and explained using absolute or relative terminology, allowing these terms or measures to be compared to each other (Dai, 2011; Trenberth et al., 2014). Absolute terms such as the amount of precipitation, the amount of soil moisture and other metrics can be used. The relative measures include the

Palmer drought severity index (PDSI), the standardized precipitation index (SPI), the standardized precipitation and evapotranspiration index (SPEI) and others. Vicente-Serrano et al. (2010) and Vicente-Serrano and Beguería-Portugués (2003) suggested that drought indices are not as useful because they are based on standardized or normalized shortages relative to average conditions at a given station and or in a specific period. Nevertheless, various drought indices have been widely used in many drought studies.

Dracup et al. (1980) suggested three components of drought: duration, magnitude (average water deficiency) and severity (cumulative water deficiency). Such concepts have been applied to various drought indices to analyze historical characteristics. Wang et al. (2011) defined the intensity-duration-frequency of droughts with the SPI, standardized runoff index (SRI), standardized soil water index (SSWI) derived from observations and future regional climate change projections in central Illinois. To evaluate how well global climate models simulate observed drying or wetting trends, Nasrollahi et al. (2015) applied the Mann-Kendall trend test to the SPIs derived from global observational climate data, in this case, the dataset from the climate research unit (CRU), and 41 predictions of global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). Similarly, Tan et al. (2015) utilized climate data from 22 meteorological stations in Ningxia, a well-known food production area in Northwest China, and performed Mann-Kendall trend tests with the SPI and SPEI. The degrees of increasing drought frequency and intensity varied with the stations in the study region. Furthermore, Touma et al. (2015) used data from 15 GCMs in CMIP5 and assessed the likelihood of changes in the spatial extent, duration and number of occurrences of four drought indices, including the SPI, SPEI, and others.

Estimating a drought index requires a calibration step. Specifically, historical data such as precipitation data should be fitted to a specific probability distribution function (PDF) and used to estimate drought indices. A few previous studies addressed the issue of the data period in the calibration step (e.g., Karl et al., 1996; Dubrovsky et al., 2009). While it is common to use self-calibrated indices (i.e., using the same dataset for calibration and index estimation), some studies suggest calibration using reference climate data to allow for an intercomparison of the index among stations or different periods (Dubrovsky et al., 2009). Such reference periods (i.e., calibration periods) of climate data are particularly important in climate change studies. It was previously noted for the self-calibrated PDSI that trends toward more extreme conditions are amplified when the calibration period does not include recent data, including the recent effects of climate change (van der Schrier et al., 2013; Trenberth et al., 2014). Still, few studies have clarified their approaches to calibration.

Therefore, we aim to understand how a different reference period (i.e., calibration period) of climate data influences regional drought assessment. Specifically, we investigate the influences of different reference periods on historical drought characteristics such as trends, frequency, intensity and spatial extents with the SPEI estimated using two historical global climate datasets from the CRU and the University of Delaware (UDEL). This study shows that the reference periods influence the assessment of drought characteristics, particularly the severity and spatial extent, while its influence on the frequency is relatively small. These influences are especially significant in regions with dominant drying trends such as East Asia and West Africa. These findings suggest that the reference period should be clarified in drought assessments for a better understanding of regional drought characteristics and their temporal changes.

2 Materials and methods

2.1 Study area and climate data

We investigate the drought characteristics over the Northern Hemisphere with a focus on four different regions: East Asia (EA), Europe (EU), the United States (US) and West Africa (WA) (Fig. 1). We perform the analyses based on the spatially distributed patterns over those regions, as well as their averages, but without distinguishing the sub-regions based on the climate characteristics. Two widely used global observational datasets from the CRU and UDEL are utilized in this study. From these two datasets, monthly precipitation and temperature data with a spatial resolution of 0.5° are used from 1901 to 2014.

This study uses the latest CRU dataset (CRU TS3.10), as described in Harris et al. (2014). The principal sources of the CRU data are the World Meteorological Organization (WMO) in collaboration with the US National Oceanographic and Atmospheric Administration (NOAA). Covering all land areas between 60°S and 80°N at a spatial resolution of 0.5°, the dataset includes global monthly climate data for ten variables: precipitation, mean temperature, diurnal temperature range, minimum and maximum temperature, vapor pressure, cloud cover, rain days, frost days and potential evapotranspiration. The dataset is derived from archives of climate station records with extensive manual and semi-automated quality control measures.

The UDEL dataset (V 4.01, Willmott and Matsuura, 2001) is also used in this study. The dataset includes gridded monthly precipitation and temperature data at a spatial resolution of 0.5° across the land over the globe. The dataset was compiled from sources including the Global Historical Climatology Network (GHCN) and the Global Surface Summary of Day (GSOD). To interpolate the station values to the grid, climatologically aided interpolation (CAI) and traditional interpolation were used for precipitation and digital elevation model (DEM)-assisted interpolation, traditional interpolation and CAI for temperature. In this work, traditional interpolation is a spherical version of Shepard's algorithm, which employs an enhanced distance weighting method (Shepard, 1968; Willmott et al., 1985).

2.2 Meteorological drought index

Various drought indices have been used to understand different types of droughts, including meteorological drought, agricultural drought and hydrological drought (Heim, 2002). For meteorological droughts, the indices include the PDSI (Palmer, 1965), the SPI (McKee et al., 1993) and the SPEI (Vicente-Serrano et al., 2010). As different studies have used different meteorological drought indices (Seneviratne, 2012; Sheffield et al., 2012; Trenberth et al., 2014; Nasrollahi et al., 2015; Touma et al., 2015), this study focuses on the SPEI. Devised by Vicente-Serrano et al. (2010), the SPEI has the advantage of considering the effects of temperature variability on drought relative to the SPI (Naumann et al., 2014) because potential evapotranspiration (PET) can be calculated from air temperature based on the Thornthwaite method (1948). The SPEI uses the amount of precipitation minus PET and fits the data to the log-logistic PDF. Here, we summarize the steps in estimating the SPEI based on monthly precipitation and temperature data. The detailed procedure for estimating the SPEI was presented by Vicente-Serrano et al. (2010).

Step 1: Estimate the water surplus or deficit in month j (D_j) using the difference between precipitation (P_j) and potential evapotranspiration (PET_j).

$$D_j = P_j - PET_j \tag{1}$$

Here, the potential evapotranspiration is estimated based on the Thornthwaite method (1948), which requires the monthly temperature, latitude, day and month.

Step 2: Estimate the accumulated difference ($X_{i,j}^{k}$) over timescale k in a given month j and year i. For example, the accumulated difference for a month in a particular year with a 12-month timescale is calculated as follows.

$$X_{i,j}^{k} = \sum_{l=13-k+j}^{12} D_{i-1,l} + \sum_{l=1}^{j} D_{i,j}\,, \qquad if\ j < k \tag{2}$$

$$X_{i,j}^{k} = \sum_{l=j-k+1}^{j} D_{i,l}\,, \qquad if\ j \geq k \tag{3}$$

Step 3: Fit the accumulated difference to a log-logistic distribution as follows:

$$F(X) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{4}$$

where $F(X)$ is the cumulative probability function of a three-parameter log-logistic distribution and α, β and γ represent the scale, shape and origin parameters, respectively. For model fitting, the L-moment procedure (Hosking, 1990) is employed, as it is one of the most robust and easy-to-use approaches.

Step 4: Estimate the SPEI based on the estimated $F(X)$. The SPEI can be derived from the standardized values of $F(X)$ and the classical approximation of Abramowitz and Stegun (1965) following Vicente-Serrano et al. (2010). The estimated drought index is classified as shown in Table 1 for moderate, extreme and very extreme cases. In this study, we focus on the SEPI with a 12-month lag (SPEI-12). SPEI can be estimated for different lag times, such as 1, 3, 6, 9, 12 and 24 months.

2.3 Temporal trends and statistical characteristics

This study investigates various measures of historical droughts, including trend, frequency, severity and spatial extent (Lloyd-Hughes and Saunders, 2002; Wang et al., 2011; Hoerling et al., 2012; Seneviratne, 2012; Trenberth et al., 2014; Touma et al., 2015).

The temporal trend is investigated with a nonparametric and monotonic trend test based on the S-statistic (Mann, 1945; and Kendall, 1976) as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{5}$$

$$sgn(x_j - x_i) = \begin{cases} +1, & (x_j - x_i) > 0 \\ 0, & (x_j - x_i) = 0 \\ -1, & (x_j - x_i) < 0 \end{cases} \tag{6}$$

where sgn is the sign function and n is the sample size. The statistical significance of the trend can be predicted by a Z test as follows:

$$Z = \begin{cases} (S-1)/\sigma_s\,, & if\ S > 0 \\ 0, & if\ S = 0 \\ (S+1)/\sigma_s\,, & if\ S < 0 \end{cases} \tag{7}$$

$$\sigma_s = \sqrt{\left(n(n-1)(2n+5) - \sum_{j=1}^{q} t_j(t_j-1)(2t_j+5)\right)/18} \tag{8}$$

where σ_s is the square root of S in the case that the x values include potential ties, q is the number of ties in the dataset and t_j is the amount of data in the jth tie group. A trend in the data does not exist for $Z < Z_{\alpha/2}$ at significance level α.

For the frequency, severity and spatial extent of drought, different measures have been defined and used in past studies (e.g., Wang et al., 2011; Touma et al., 2015) because it is not straightforward to define these quantities in practice. For example, Touma et al. (2015) defined the duration, occurrence and spatial extent of drought to investigate the drought changes with 15 CMIP5 models throughout the world in the 21st century. The duration of drought was defined as the consecutive period below a certain drought status. The occurrence of droughts was defined as the total number of droughts in the period of interest. Additionally, the spatial extent of drought was defined as the percentage of grid points below the given drought level, in which the corresponding drought index was less than the given drought category in each month.

In this study, we define three measures of droughts based on the SPEI-12: (1) the drought frequency is the ratio between the total number of drought events, which is defined as SPEI-12 ≤ -1, and the total number of effective grid points; (2) the severity is the lowest estimate of the regional monthly average SPEI-12 with moving windows with periods of 1 to 12 months; here, regional averages are estimated in the four study regions depicted in Fig. 1; and (3) the spatial extent is the number of grids with annual SPEI-12 ≤ -1.0 relative to the total number of grids.

2.4 Design of data analysis

To understand the influence of the reference period (i.e., calibration period) on the drought index, three different types of reference periods are used to estimate the SPEI-12 with the CRU and UDEL data. To separately analyze the drought characteristics in the estimation periods of 1901–1957 (P1) and 1958–2014 (P2), different sets of reference periods are used (Table 2). Here, we assume that the mean climates of P1 and P2 are different to some extent because of global climate and environmental changes, which will be discussed further in Section 3. For the first type of reference period (Ref1), we calibrate the distribution of a specific PDF (Step 3 in Section 2.2) using data from 1901 to 2014, which is used to estimate the SPE12 for the P1 and P2 estimation periods. For the second type of reference period (Ref2), calibrations are performed separately for P1 and P2; thus, so-called self-calibrated indices are derived. For the third type (Ref 3), we calibrate the distribution using the data from P1 (i.e., 1910–1957) and then use this distribution for both estimation periods.

3 Results and discussion

3.1 Spatial and temporal patterns of climate variables

Precipitation, air temperature and PET are investigated because they are used to estimate the SPEI values (Figs. 2 and 3 and Table 3). As noted, the SPEIs are estimated based on the distribution of D (Eq. 1), and the air temperature is directly related to PET because we use the Thornthwaite approach to estimate PET. The selected regions have different climate features (Fig. 2), and the EA and WA regions exhibit relatively wide ranges of mean precipitation, ranging from almost zero to more than 2000 mm per year. In terms of mean air temperature, it is clear that WA is generally quite warmer than other regions. Thus, a relatively high PET is observed in WA. Furthermore, the mean precipitation, air temperature and PET are quite similar between CRU and UDEL.

To investigate the temporal changes in precipitation, air temperature and PET, we compared the means and standard deviations between the two periods (i.e., P1 and P2) in Table 3 and performed a Mann-Kendall trend test (Fig. 3). Table 3 presents different temporal patterns of precipitation depending on the region, and all temporal patterns of air temperature are increasing. Additionally, the annual precipitation in EA slightly decreased from 637.19 mm to 635.52 mm based on CRU (-0.2%) and from 659.67 mm to 649.21 mm based on UDEL (-1.6%). Moreover, in WA, the annual precipitation decreased substantially from 698.49 mm to 666.59 mm based on CRU (-4.6%) and from 734.84 mm to 676.11 mm based on UDEL (-8.0%). However, the annual precipitation increased in EU (25.17 mm (5.4%) based on CRU and 14.14 (3.5%) mm based on UDEL) and the US (37.78 mm (3.7%) based on CRU and 24.92 mm (2.1%) based on UDEL).

The average change in air temperature between P1 and P2 based on CRU (UDEL), which was 0.59 (0.37)°C in EA, 0.50 (0.27)°C in EU, 0.32 (0.05)°C in the US and 0.35 (0.26)°C in WA, was generally greater than the difference between CRU and UDEL. The annual average temperature increased from EA (6.16°C) to EU (6.99°C) to the US (10.59°C) to WA (10.52°C) in P1. Consequently, the increasing ratios of annual average temperature based on CRU (UDEL) were 9.70 (5.92)%, 7.18 (3.85)%, 3.06 (0.47)% and 1.33 (0.98)% in EA, EU, the US and WA, respectively. Such changes in air temperature directly influence changes in PET, as we used the Thornthwaite approach to estimate PET.

The average annual increases in PET based on CRU and UDEL in P2 were higher than those in P1, including increases of 17.09 mm and 9.08 mm based on CRU and UDEL in EA, 26.42 mm and 14.20 mm based on CRU and UDEL in EU, 17.11 mm and 2.42 mm based on CRU and UDEL in the US and 111.80 mm and 95.37 mm based on CRU and UDEL in WA. This trend was observed because air temperature is the main factor used to estimate PET in this study. Consequently, the increasing ratios of annual PET based on CRU (UDEL) were 2.5 (1.3)%, 4.4 (2.4)%, 2.4 (0.3)% and 5.9 (4.9)% in EA, EU, the US and WA, respectively.

The Mann-Kendall trend tests for annual precipitation, annual average temperature and annual PET were also performed, as shown in Fig. 3. The data reflect whether these variables showed statistically increasing, decreasing or no trends. For annual precipitation in EA, the areal extent with an increasing trend was almost twice that with a decreasing trend based on CRU, but the areal extent with a decreasing trend based on UDEL was broader than that with an increasing area. In EU and the US, the areal extent with an increasing trend was clearly larger than that with a decreasing area based on both CRU and UDEL. However, in WA, the areal extent with a decreasing trend was larger than that with an increasing trend based on both CRU and UDEL. These patterns were generally more severe for CRU than for UDEL. For annual average air temperature and PET, CRU produced increasing trends over most regions. Similar patterns were observed for UDEL, but the areal extent of the decreasing trend was slightly larger than that of CRU.

3.2 Temporal patterns of drought index

The drought index (i.e., SPEI-12) is estimated for two periods, P1 and P2, with three different reference periods (Table 2), as described in Section 2.4. Fig. 5 shows the temporal variations in SPEI-12 based on the reference periods (Ref1, Ref2 and Ref3) and datasets (CRU and UDEL) used in the two periods. In the US and EU, the SPEI-12 averages are very similar in the two periods, with values of 0.005 (P1) and 0.118 (P2) in the US and -0.011 (P1) and -0.001 (P2) in EU. In EA, the SPEI-12 averages for the three different reference periods slightly decrease from P1 to P2, whereas the deviations in SPEI-12 increase markedly. In WA, the averages and deviations in SPEI-12 significantly decrease and increase, respectively, from P1 to P2. Furthermore, the variances in SPEI are relatively small in P1 compared to those in P2 in EA and WA, while no noticeable differences in the variances are observed in EU and the US. This result may attributed to the lack of ground-based observations before 1950 (i.e., most of P1) (Becker et al., 2013; Vittal et al., 2013; Nasrollahi et al., 2015), and such limited data availability plays a role in reducing the SPEI variance in P1 in EA and WA. Based on regional averages, the role of the reference period is not clear; thus, we investigate the spatial patterns of SPEI-12 hereafter.

Based on the Mann-Kendall trend test of annual SPEI-12 from 1901 to 2014, we determine the increasing (i.e., wetting), decreasing (i.e., drying) or no trend areas of the regions (Fig. 6). First, the spatial distribution of SPEI-12 trends is identical between Ref1 and Ref3, and that in Ref2 is different. Ref1 and Ref2 use different calibration datasets but are similar in using one dataset for the two estimation periods; however, Ref2 uses different calibration datasets for different estimation periods (Table 4). Therefore, SPEI-12 of Ref2 exhibits relatively smaller areas of wetting and drying trends in the first and second periods relative to those of Ref1 and Ref3.

Regarding the temporal characteristics in different regions, the following are our findings for Ref1 and Ref3. In WA, drying trends are clearly dominant. In EU, drying trends are scattered over the domain. In the US, wetting trends are scattered in the eastern region, and drying trends can be observed in the southwestern region. In EA, the drying trends are clearly in the western region.

Based on the grid-level trend analyses of precipitation, air temperature, PET and SPEI-12, we categorize each grid cell based on increasing, decreasing or neutral trends for each variable (i.e., precipitation, air temperature, PET and SPEI-12). For SPEI-12, increasing and decreasing trends represent wetting and drying trends. We present the ratio of each case relative to the total number of cases (i.e., total number of effective grid cells in all four regions), as shown in Fig. 7. First, the SPEI-12 trends are the same between Ref1 and Ref3, as the estimation periods share one reference period in both Ref1 and Ref3, while each estimation period uses its own reference period in Ref2. Thus, the values of SPEI-12 are different in both cases, but the trends (i.e., relative values) are the same. Second, precipitation and air temperature exhibit neutral (or no) trends (in the center panel; presumably stationary climate), and the grid percentages of different trends in SPEI-12 vary between Ref1/Ref3 and Ref2. However, the ratio is relatively small, as most grid cells display increasing temperature and PET trends. Finally, based on neutral precipitation and increasing air temperature and PET trends in most grid cells, the numbers of cells with neutral and drying SPEI-12 trends are notably different between Ref1/Ref3 and Ref2.

Increasing temperature and PET trends can be observed in most regions; thus, it is important to consider the associated impact on SPEI, particularly because we use the Thornthwaite approach to estimate PET.

3.3 Frequency, severity and spatial extent of drought

In this section, we examine how the reference periods play a role in assessing the frequency, severity and spatial extent of drought using SPEI-12. The definitions of frequency, severity and spatial extent of drought used in this study are clarified in Section 2.3, and they may differ in different studies.

As explained above, a drought event occurs when the monthly SPEI-12 is estimated to be at or below -1.0 based on the drought duration-frequency relationship. For each drought event in a grid cell, the duration is how long the SPEI-12 stays at or below -1. The frequency is the ratio between the total number of drought events and the number of effective grid points in each region (Fig. 8). We find that the drought events with longer durations (prolonged right tails in the plot) occur more frequently in P2 than in P1 in all regions. However, we do not find any particular differences between the three different reference periods except in WA. The drought frequencies differ among the three reference periods. The frequencies of Ref2 and Ref3 are higher than those of Ref1 in P1, and slight differences in the frequency among the three reference periods are observed throughout the 12-month duration of P2.

We examine how the severity of drought varies with the moving window size for the average monthly SPEI-12. Fig. 9 shows the most severe SPEI-12 estimates, which are defined as the lowest values among the regional monthly averages of SPEI-12 in the moving windows from 1 month to 12 months. In EU and the US, we find no large differences between the SPEI-12s for Ref1, Ref2 and Ref3 in the same period. In these regions, the most severe SPEI-12s in P1 are higher than those in P2. Such findings are seemingly inconsistent with the recently observed severe drought events in the US and EU, but they are reasonable because we examine the regionally averaged indices and not the local extremes of SPEIs. Additionally, the results are consistent with Fig. 4. In the US, the increase in precipitation is higher than that in PET, which increases D (Eq.1). In EU, the increase in PET is higher than that in precipitation; thus, D decreases in terms of the average, but the lower extreme of D slightly increases. Therefore, the most severe drought events are less severe in P2 compared to those in P1. Nonetheless, such changes in SPEI-12 values according to the relative changes between P and PET reflect the important role of air temperature in drought severity, particularly because the Thornthwaite approach is used in this study.

In EA and WA, different patterns can be observed for the most severe SPEI-12 values. The annual precipitation and air temperature (and thus PET) exhibit regionally scattered decreases and widespread increases, respectively (Fig. 3). Consequently, the droughts in 1958–2014 are more severe than those in P1. Furthermore, the severities vary significantly with the calibration period in EA and WA, where the changes in precipitation and air temperature between the two periods are considerable.

The spatial extents of droughts for annual SPEI-12 ≤ -1.0 are examined by sorting the results in ascending order (Fig. 10). We count the numbers of grid points with SPEI-12 values less than -1.0 in each period (i.e., P1 and P2) and divide them by the number of effective grid cells in the region to derive the spatial extent, i.e., the grid percentage of droughts. Then, the annual time series of the spatial extent are sorted in ascending order. No specific patterns are evident in EU and the US. In EA and WA, the spatial extents are generally broader in P2 than in P1. In particular, the spatial extents in 1958–2014 clearly diverge based on the different calibration periods, suggesting the importance of the calibration method (i.e., reference periods in assessing the droughts in a region).

To understand how the drought characteristics would change if the reference period is dry or wet, we compare the spatial extent of drought (%) for dry and wet cases in EA, EU, the US and WA. We define dry and wet cases based on the water surplus or deficit D (Eq. 1). Then, we compare D values between the reference period and estimation period. A value of D in the estimation period less than that in the reference period represents a dry case, i.e., the estimation period is drier than the reference period. We perform such analyses only in Ref1 for the estimation periods of 1901-1957 (P1) and 1958-2014 (P2) and a reference/calibration period from 1901-2014 (P1+P2). For dry and wet cases, we quantify the spatial extent (%) according to the three different drought levels (D1, D2 and D3, which denote the cases of SPEI < -1.0, SPEI < -2.0 and SPEI < -3.0, respectively) in the four regions.

As presented in Table 5, the average D in P1 or P2 (estimation period) is smaller than that in P1+P2 (reference period), and it is considered to the dry case. For example, in EA, the D values in P2 and P1+P2 are -4.89 mm/month and -5.07 mm/month, respectively; thus, it is a dry case. Then, for each case, the spatial extent of drought, i.e., the number of drought grid cells relative to the total number of effective grid cells, is analyzed, as shown in Fig. 11. The spatial extent of drought tends to be larger in dry cases than in wet cases in most regions, particularly in WA. However, we also note there are a few exceptions, which may be attributed to the fact that we use regionally averaged values of D. Thus, we cannot consider the grid-level variability in D values.

3.4 Case studies using historical drought events

SPEI-12s with different reference periods are evaluated for historical drought events selected in each region to investigate how different reference periods influence the drought assessments of historical events. One drought event is chosen for each region as follows: 1) in EA, droughts that occurred in northern China in 2001 are chosen, and these events caused economic losses of USD 1.52 billion (Zhang and Zhou, 2015); 2) in EU, we chose a 2003 drought that was caused by the European heat wave and spread over the majority of Europe (Stagge et al., 2013; Spinoni et al., 2015); 3) in the US, we chose 2012 as the period of study as drought in that year was the most extensive drought over half of the US since the 1930s, and it caused economic losses of USD 31.2 billion (Smith and Katz, 2013; National Climate Data Center, 2015); and 4) in WA, the drought in 1984 was chosen because it was one of the most severe droughts that has occurred in Sahel countries (Gommes and Petrassi, 1994; Rojas et al., 2011; Masih et al., 2014).

By estimating SPEI-12 for a chosen year in each region, we can compare the magnitudes of SPEI values (Figs. 12, 13, 14 and 15). Here, the annual SPEI-12 values based on monthly climate data from January to December in each year are first calculated. Then, the SPEI-12 values for a chosen year are examined in detail. All SPEI-12 values in different reference periods reflect the drought status because we chose specific years with drought events. In general, all cases reveal that the SPEI-12 estimates in Ref2 are relatively high (i.e., wet), and those in Ref3 are relatively low (i.e., dry) in EA and WA, where drying temporal trends are clear. In particular, several extreme values (i.e., out of the scale range in Figs. 12-15) of SPEI-12 in Ref3 cases highlight the importance of the reference period. If a reference period is based on a certain time (P1 in this study, i.e., Ref3), the drought events in the estimation period may be beyond the range in which the distribution is calibrated for the index. Essentially, for Ref3, it is assumed that not only the stationarity of the climate but also that the entire probability distribution of droughts is sampled in this period.

Furthermore, the percentage of the spatial extent of drought, i.e., the number of drought grid points relative to the total number of grid points, is assessed for different drought thresholds (Table 6). In most cases, the spatial extents of drought with the SPEI less than a certain threshold, such as -1, -2 or -3 (i.e., D1, D2 and D3 as in Table 1) are the greatest in Ref3 among the three cases with different reference periods. These results and the spatial extents are consistent with the SPEI-12 results estimated above. In addition, higher percentages of severe droughts events, which are defined based on low thresholds, such as SPEI-12 values less than -2 or -3, were observed in Ref3 compared to those in Ref1 and Ref2 in all regions of EA, EU, the US and WA.

4 Conclusions

This study seeks to understand how a different reference period (i.e., calibration period) of climate data for estimating the drought index can influence regional drought assessment. Specifically, we investigate the influences of different reference periods on historical drought characteristics such as trends, frequency, intensity and spatial extents using SPEI-12 and the CRU and UDEL datasets. For the 1901–1957 (P1) and 1958–2014 (P2) estimation periods, three different types of reference periods are used. In the first case, data from 1901 to 2014 (P1+P2) are used for both estimation periods. In the second case, data from P1 and P2 are used separately for the estimation periods of P1 and P2, respectively (self-calibrated). In the final case, data from P1 (1910–1957) are used for both estimation periods.

Focusing on the EA, EU, US and WA regions, we find that the influence of the reference period is significant in regions with dominant drying trends from P1 to P2, such as EA and WA. Additionally, the results suggest that it is necessary to quantify the trends of climate variables such as precipitation and air temperature as the first step in selecting a reference period. We find that the reference period influences the assessment of drought characteristics, particularly the severity and spatial extent, based on the two datasets; however, their influence on the frequency is relatively small. Finally, self-calibration, the most common practice associated with indexes such as the SPEI, tends to underestimate the drought severity and spatial extent relative to the other approaches examined in this study.

This study highlights the need for clarifying the reference period in drought assessments to better understand regional drought characteristics and their temporal changes, particularly under climate change scenarios. This study, which was based on historical data, may yield different results at the local scale, and similar studies based on historical data or climate change scenarios in different regions would undoubtedly strengthen our findings. We note that this study focuses on the temporal aspects of calibration data (i.e., calibration period). As briefly mentioned in the Section 1, by using data from a particular station or grid, the average calibration values could permit a meaningful comparison of drought indexes at different locations. In conjunction with temporal considerations, spatial issues should be addressed in future studies.

Acknowledgements

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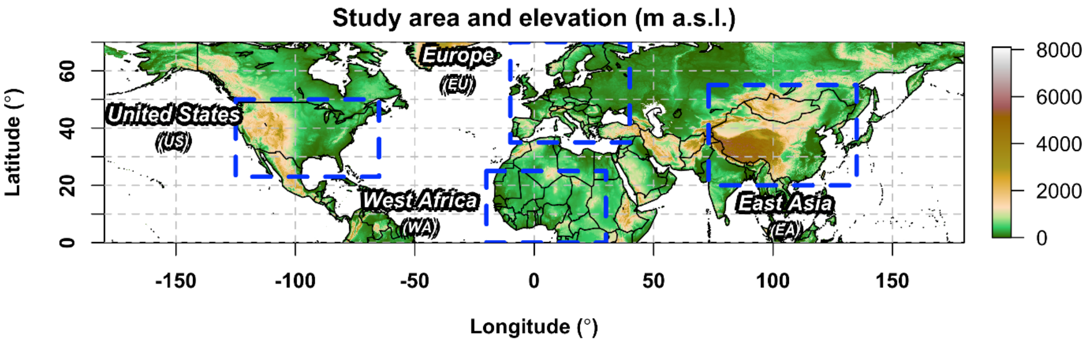

Figure 1. Study areas and elevation

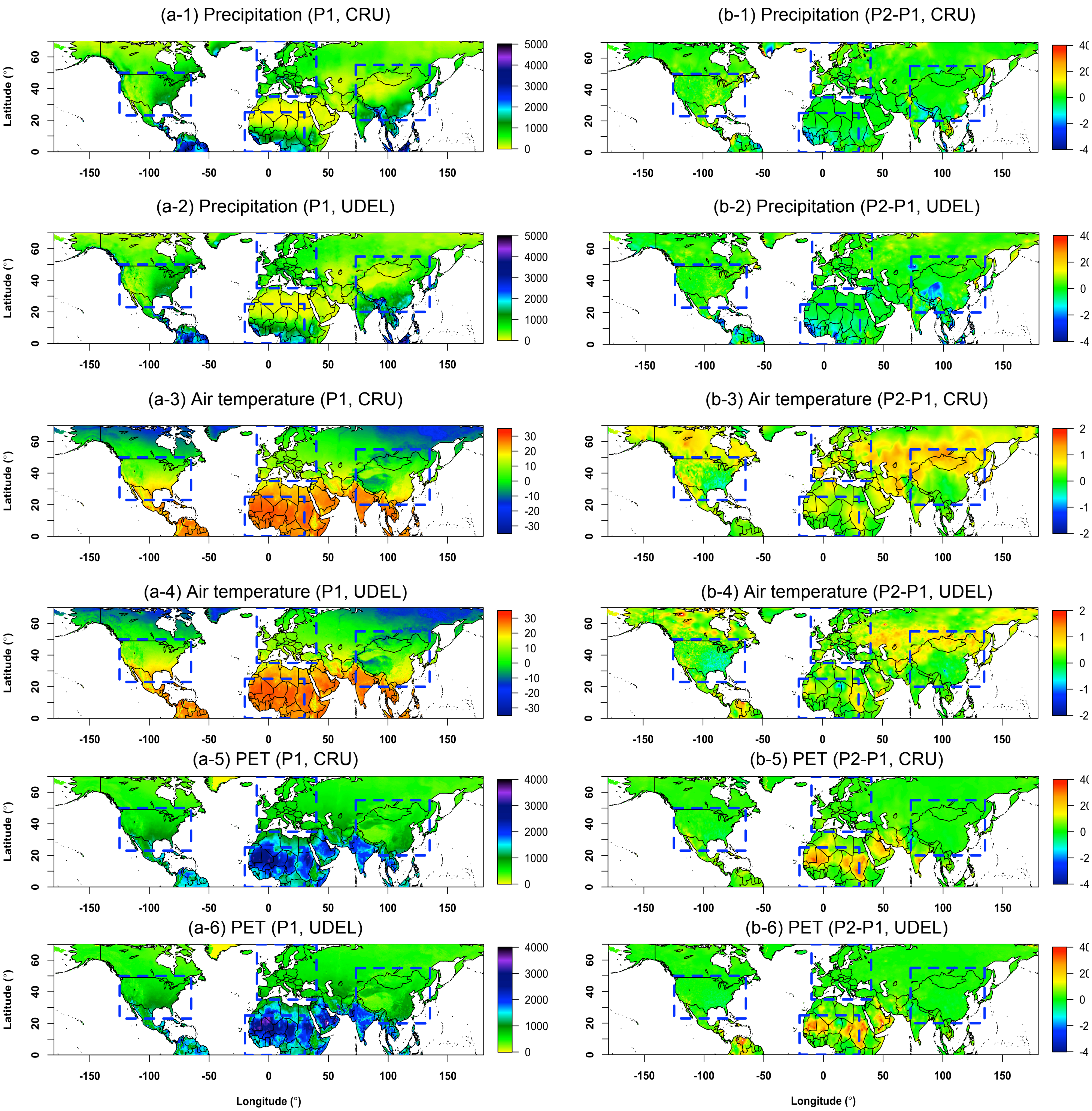

Figure 2. Annual precipitation (mm), annual average temperature (°C) and annual PET (mm) based on the CRU and UDEL datasets in P1 and the difference between P1 and P2

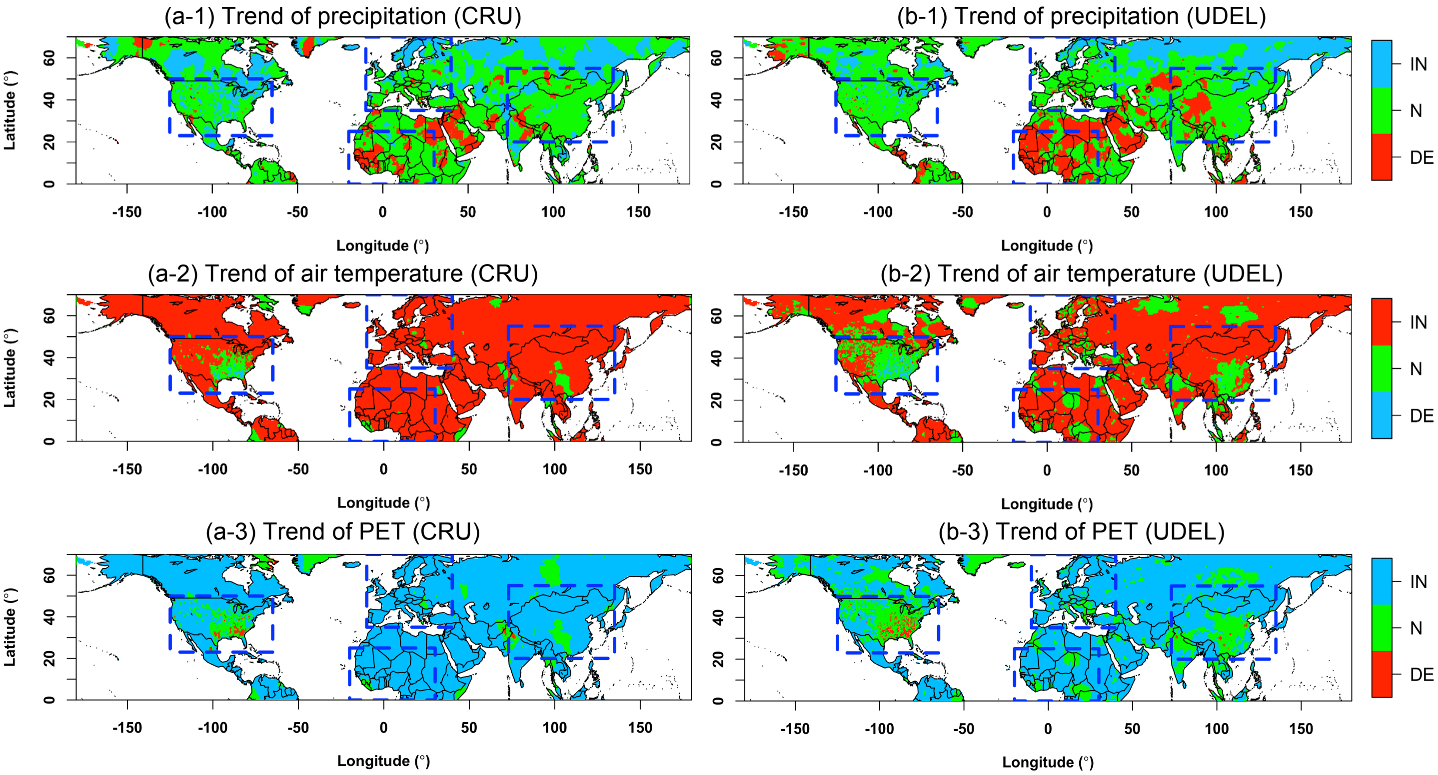

Figure 3. Trends in annual precipitation, annual averaged temperature and annual PET based on the CRU and UDEL datasets. PR and TA denote precipitation and temperature, respectively, and IN, N and DE indicate increasing, no trend and decreasing, respectively.

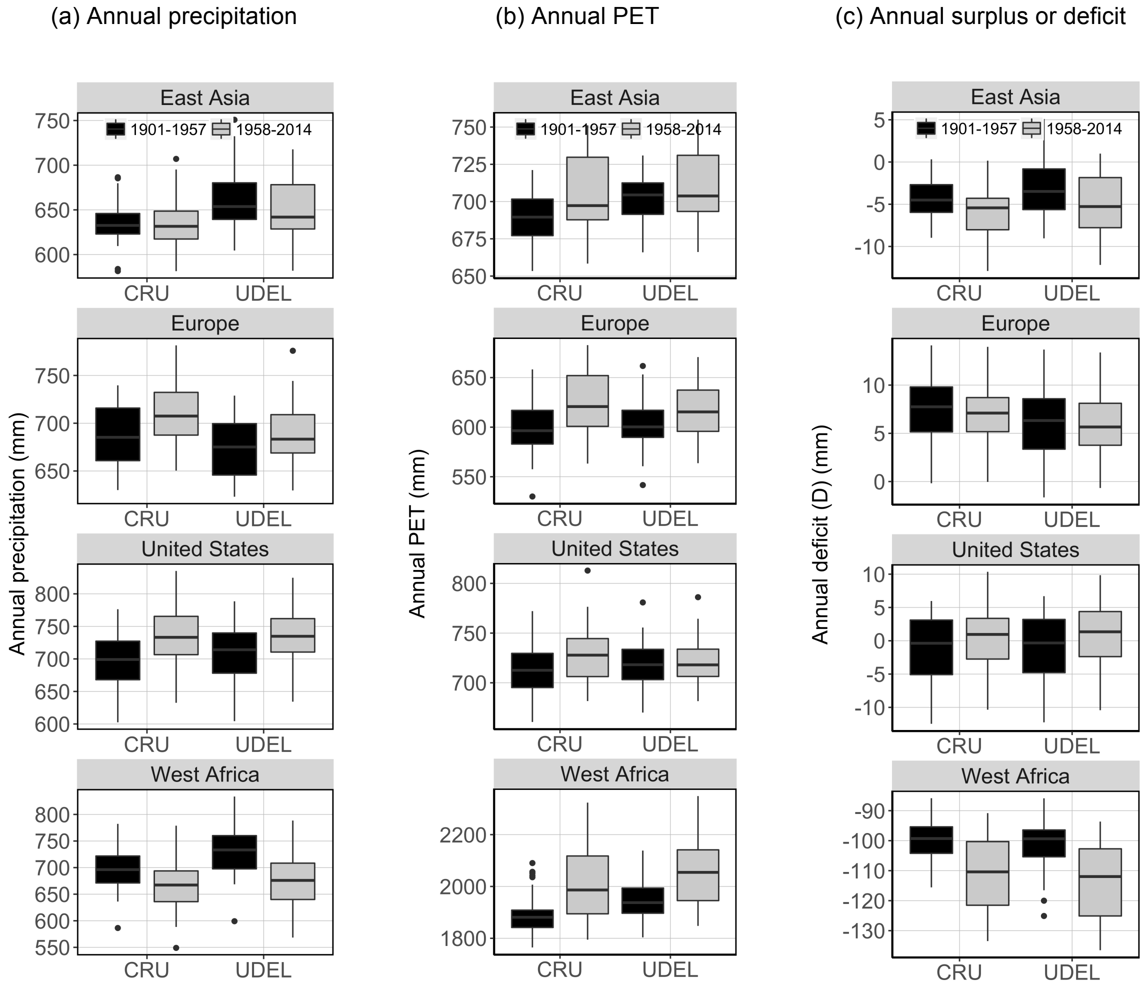

Figure 4. Temporal variations in annual precipitation, PET and surplus or deficit (D) depending on two datasets (CRU and UDEL) and periods (1901-1957 and 1958-2014). In the box plots, the center line represents the median value; the top and bottom of each box represent the 25th and 75th percentile of the data, respectively; and the dots represent outliers.

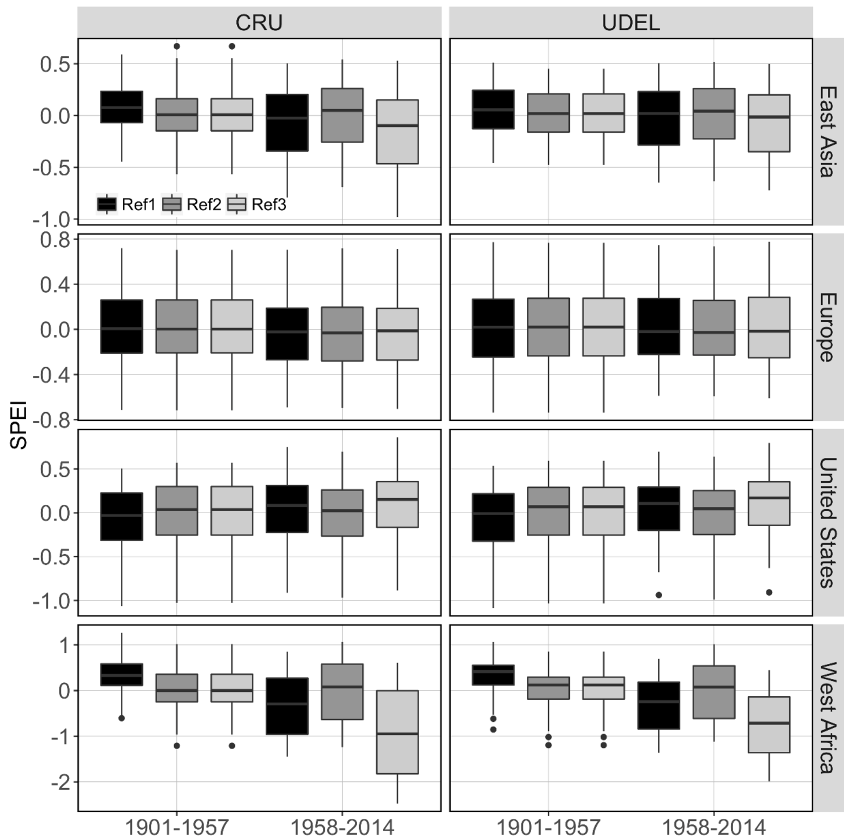

Figure 5. Temporal variations in SPEI-12 for three different reference periods (Ref1, Ref2 and Ref3) based on the CRU and UDEL datasets from 1901–1957 and 1958–2014. In the box plots, the center line represents the median value; the top and bottom of each box represent the 25th and 75th percentile of the data, respectively; and the dots represent outliers.

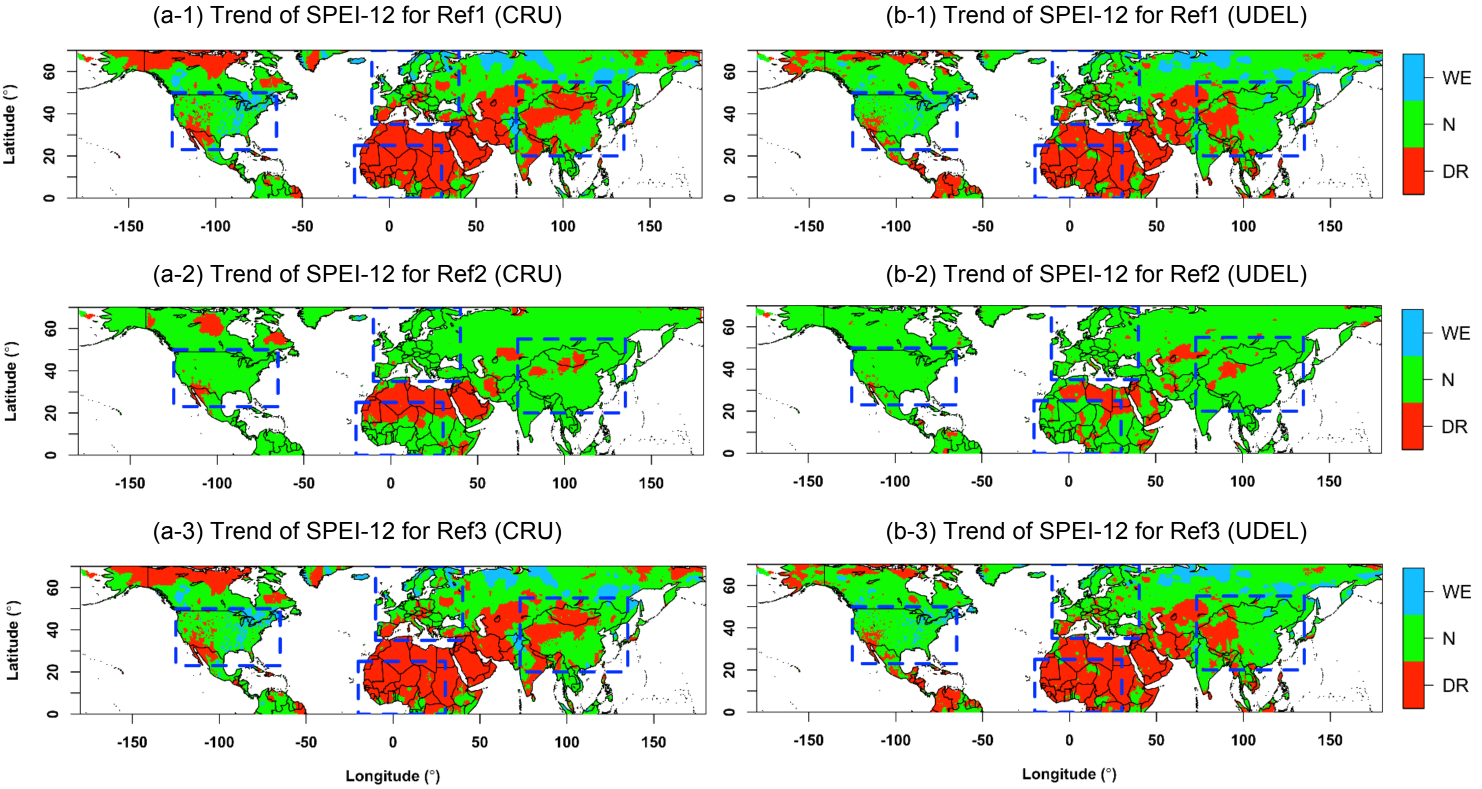

Figure 6. SPEI-12 trends in three different reference periods (Ref1, Ref2 and Ref3) based on the (a) CRU and (b) UDEL datasets. WE, N and DR denote wetting, no trend and drying, respectively.

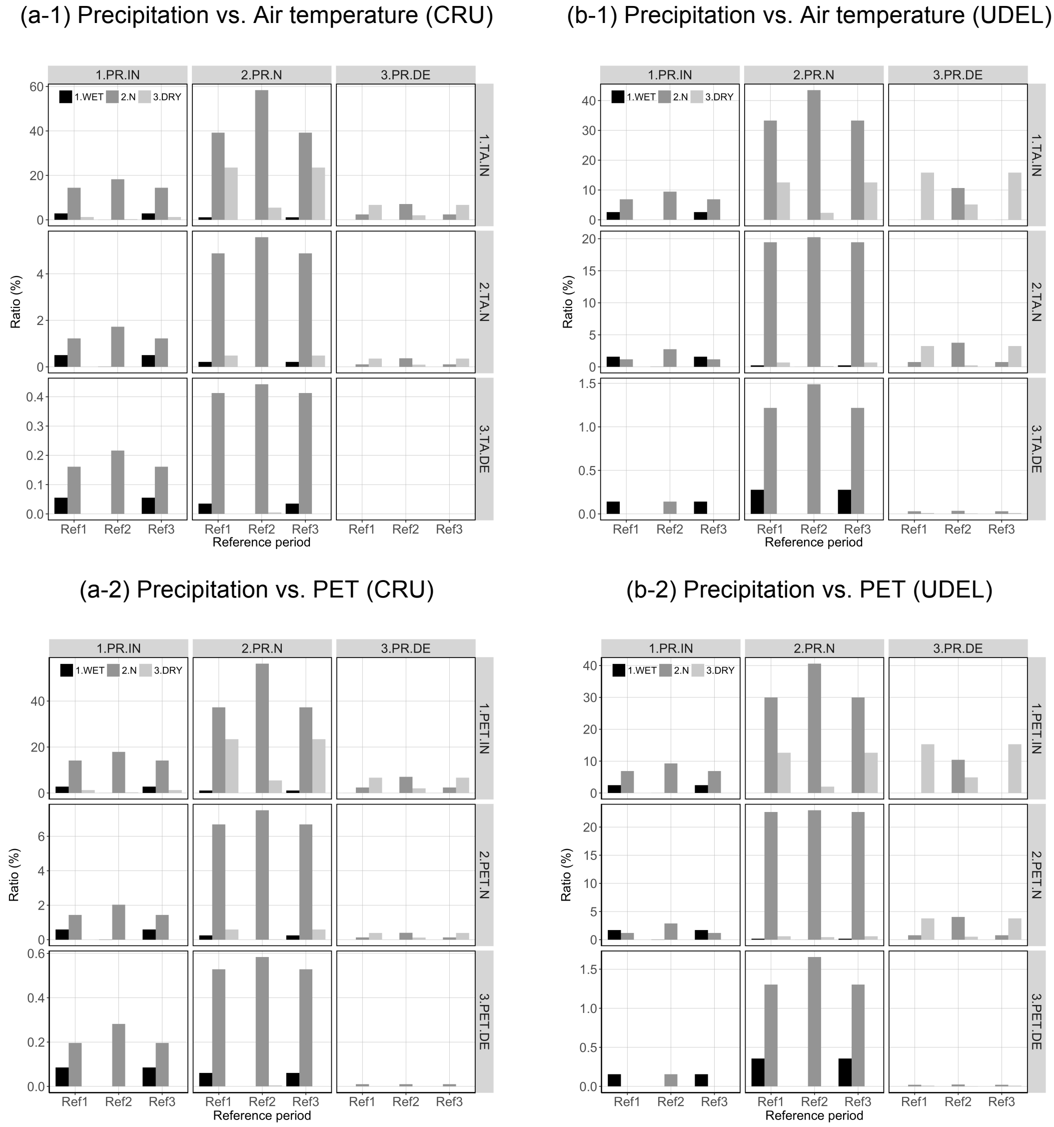

Figure 7. The SPEI-12 trends for three different reference periods (Ref1 to Ref3) based on the CRU and UDEL datasets for trends of monthly precipitation and temperature (or PET) in the four zones

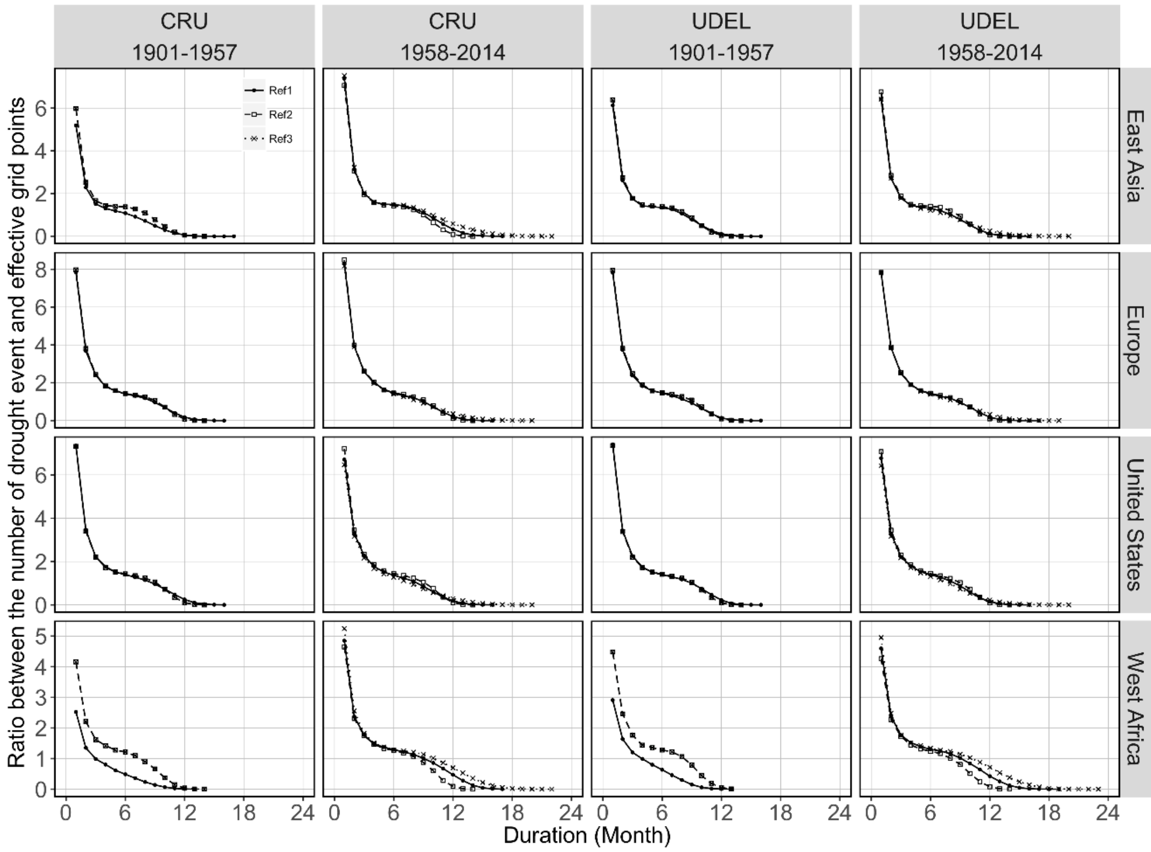

Figure 8. Ratio between the number of drought events and the number of effective data grid points based on the CRU and UDEL datasets from 1901–1957 and 1958–2014

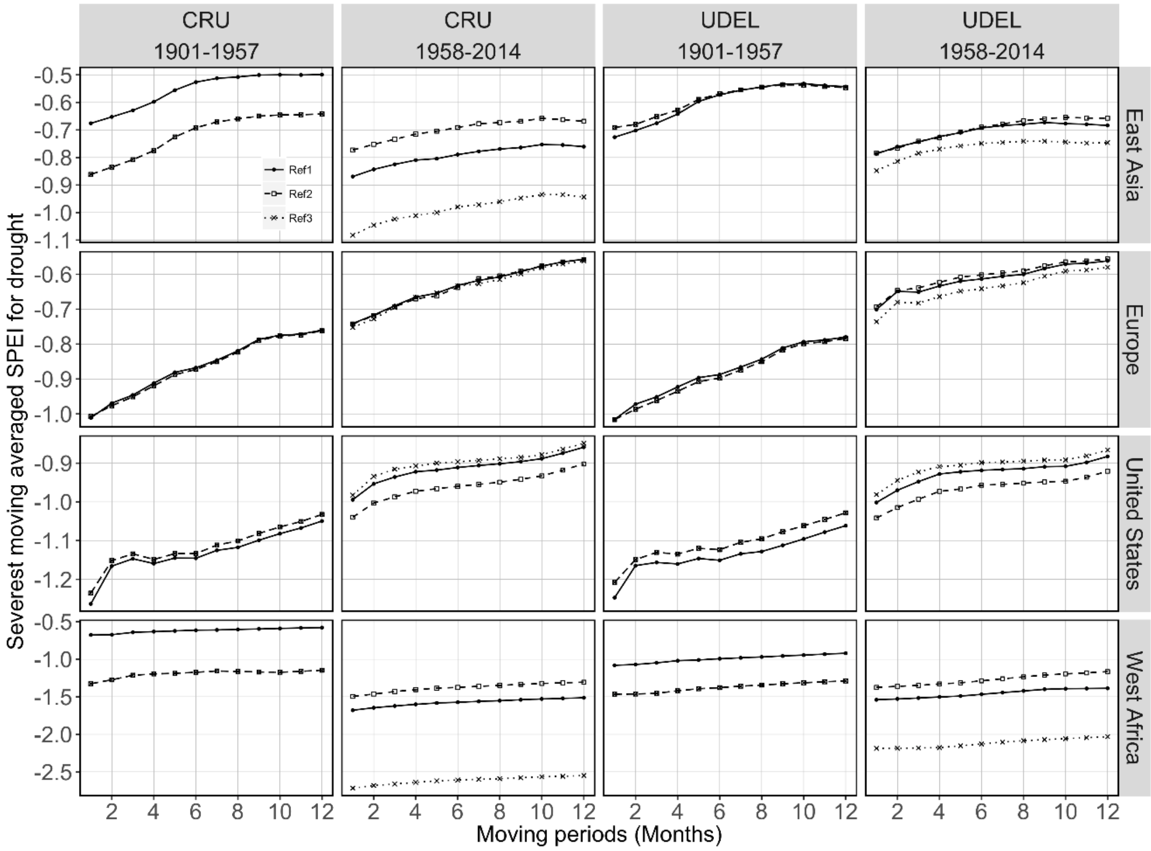

Figure 9. Most severe moving average of regional SPEI-12 for 1–12 months in three different reference periods (Ref1, Ref2 and Ref3) based on the CRU and UDEL datasets from 1901–1957 and 1958–2014

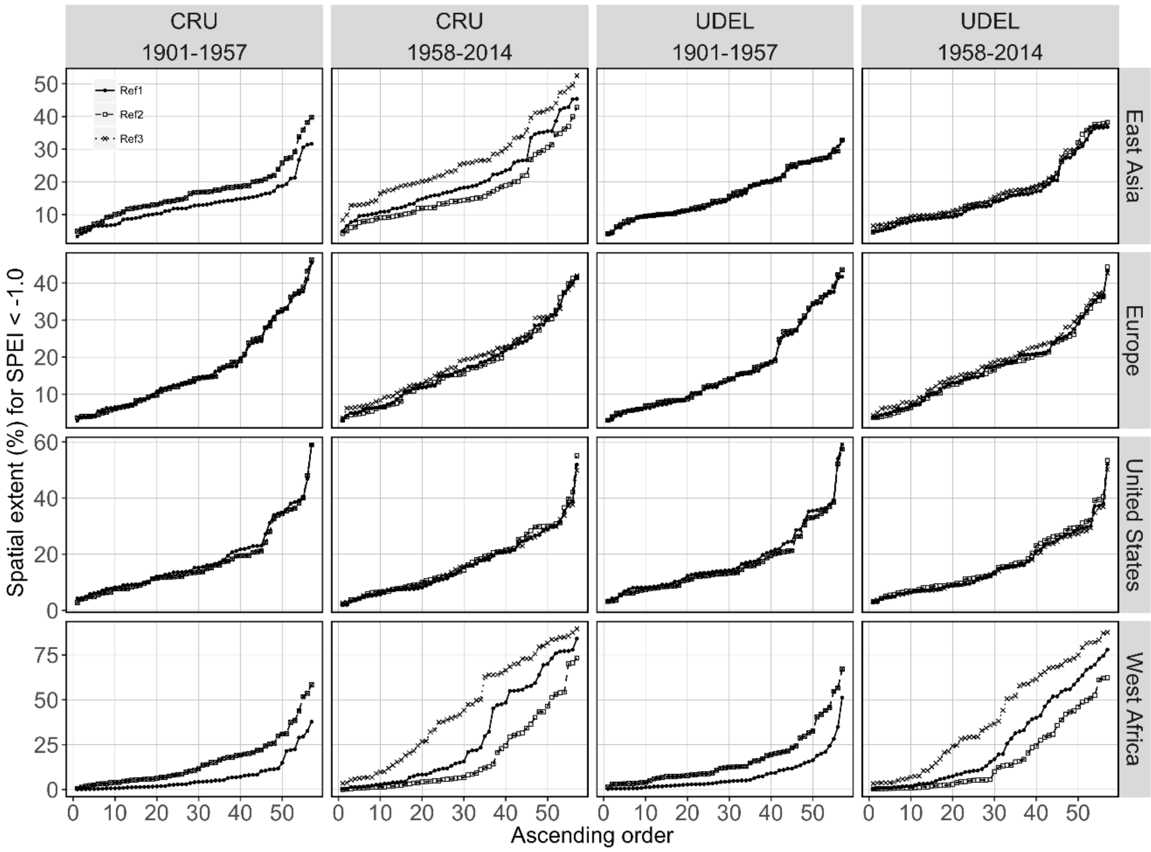

Figure 10. Spatial extent (%) of SPEI-12 < -1.0 for three different reference periods (Ref1, Ref2 and Ref3) based on the CRU and UDEL datasets from 1901–1957 and 1958–2014

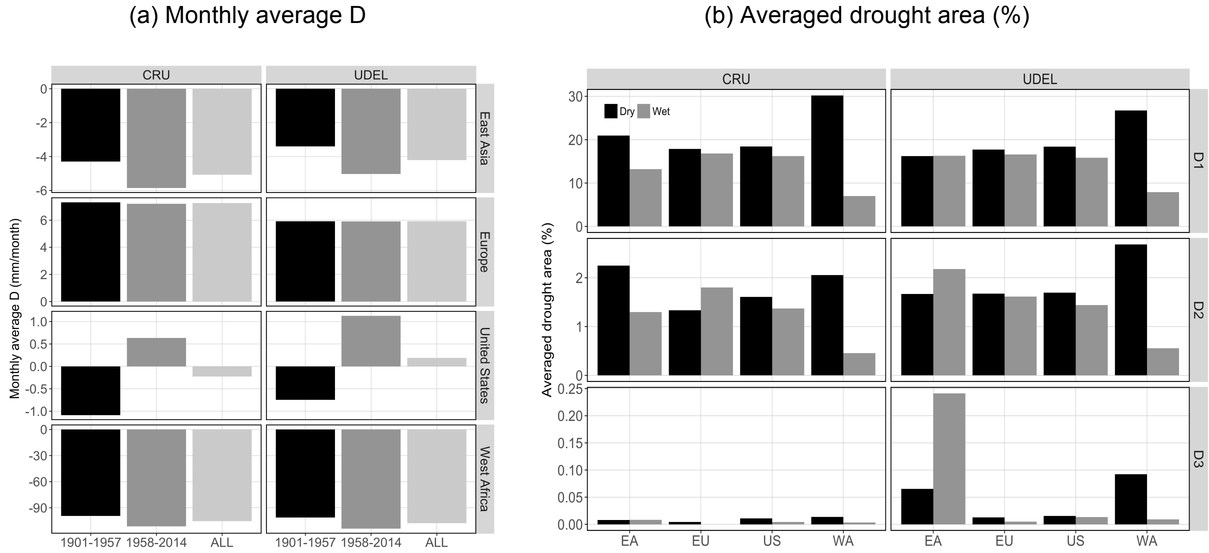

Figure 11. Monthly average D in Eq. (1) and average drought area depending on two datasets (CRU and UDEL) and four zones (EA, EU, US and WA) for the Ref1 condition (In Fig. 10(a), "ALL" denotes the period from 1901-2014. In Fig. 10(b), dry status means that the monthly average D in the assessment period is less than that in the reference period, and wet status denotes that the monthly average D in the assessment period is greater than that in the reference period based on the Ref1 condition.

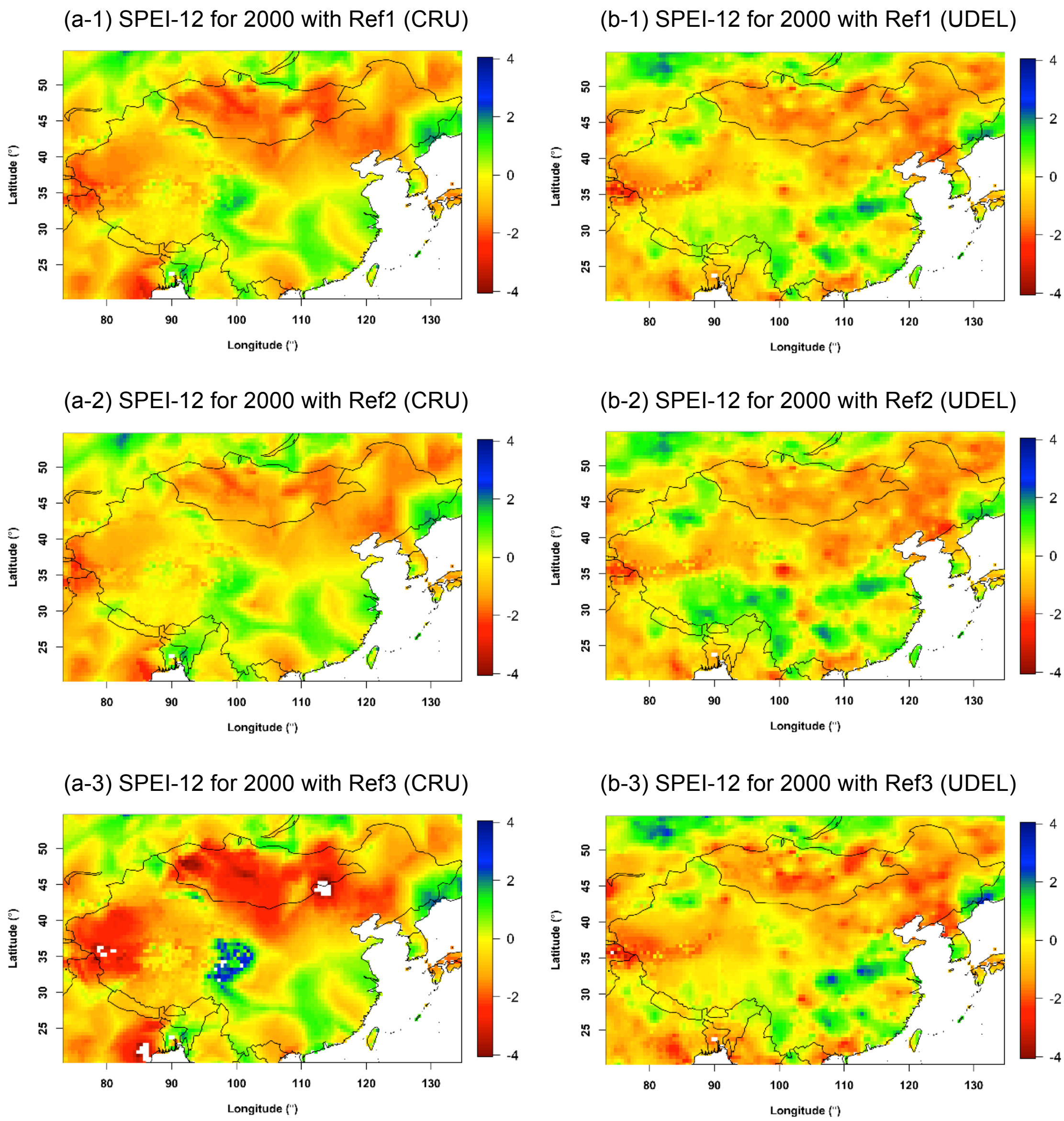

Figure 12. SPEI-12 for three different reference periods (Ref1, Ref2 and Ref3) based on the (a) CRU and (b) UDEL datasets in East Asia in 2000

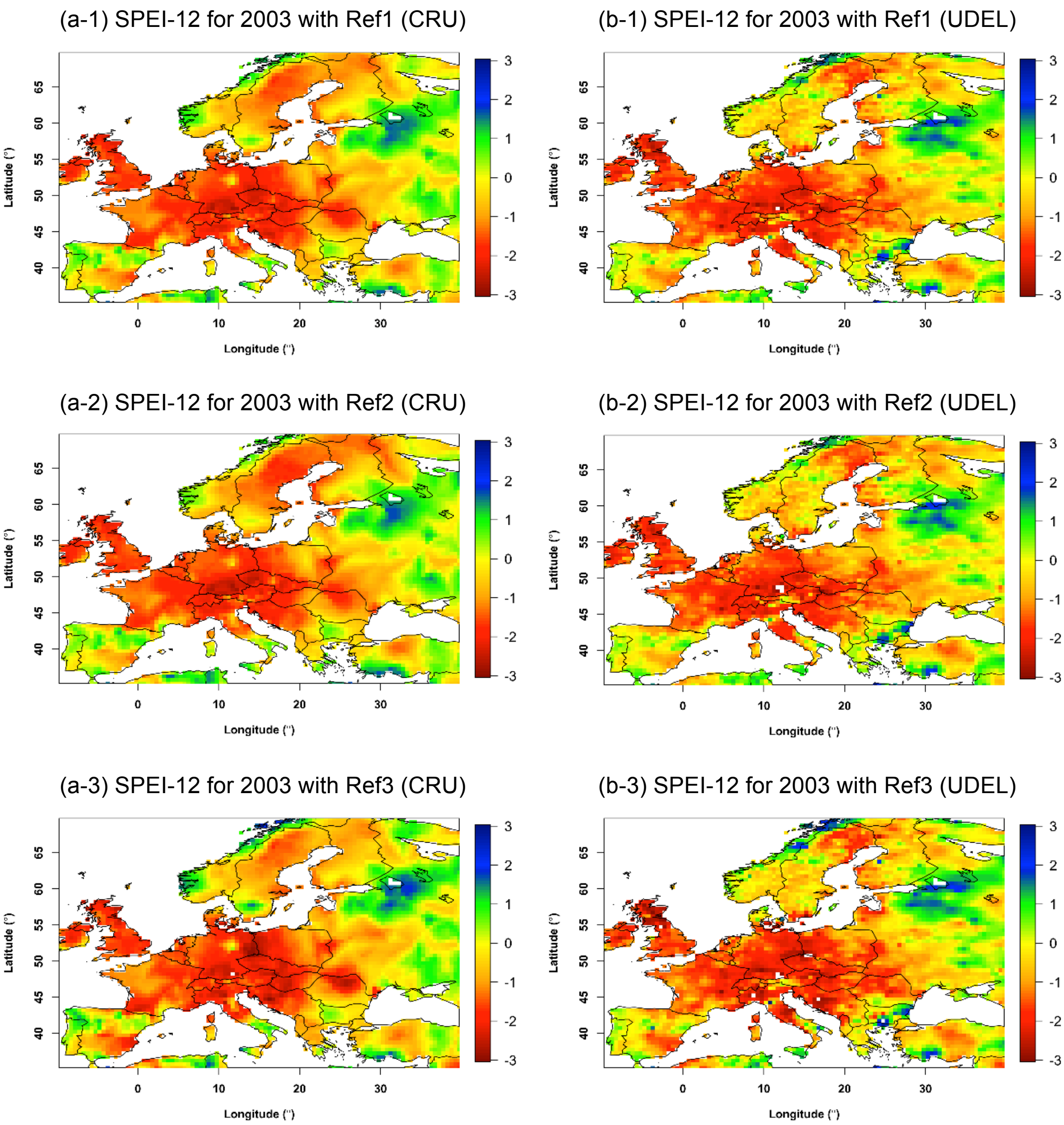

Figure 13. SPEI-12 for three different reference periods (Ref1, Ref2 and Ref3) based on the (a) CRU and (b) UDEL datasets in Europe in 2003

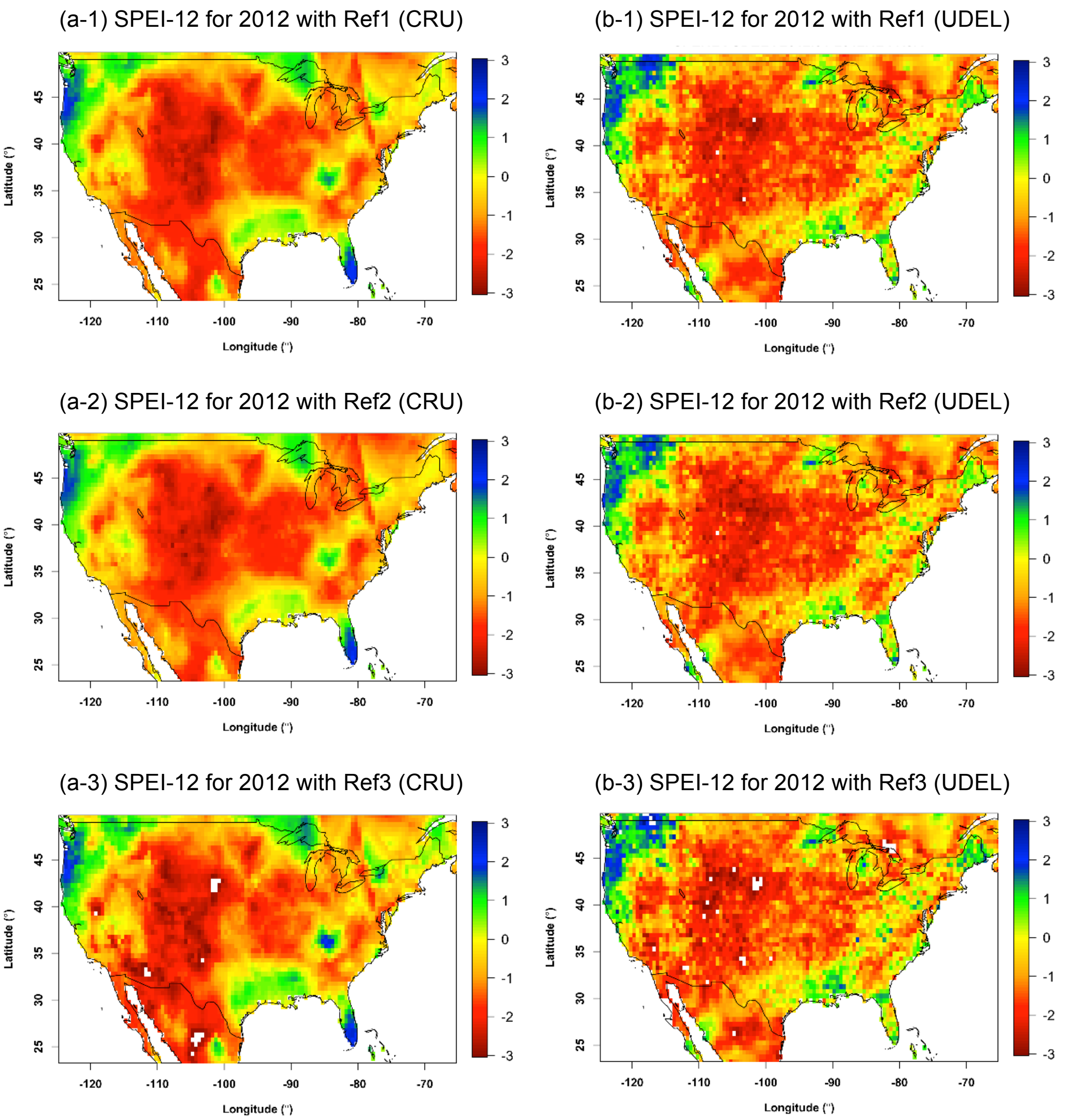

Figure 14. SPEI-12 for three different reference periods (Ref1, Ref2 and Ref3) based on the (a) CRU and (b) UDEL datasets in the United States in 2012

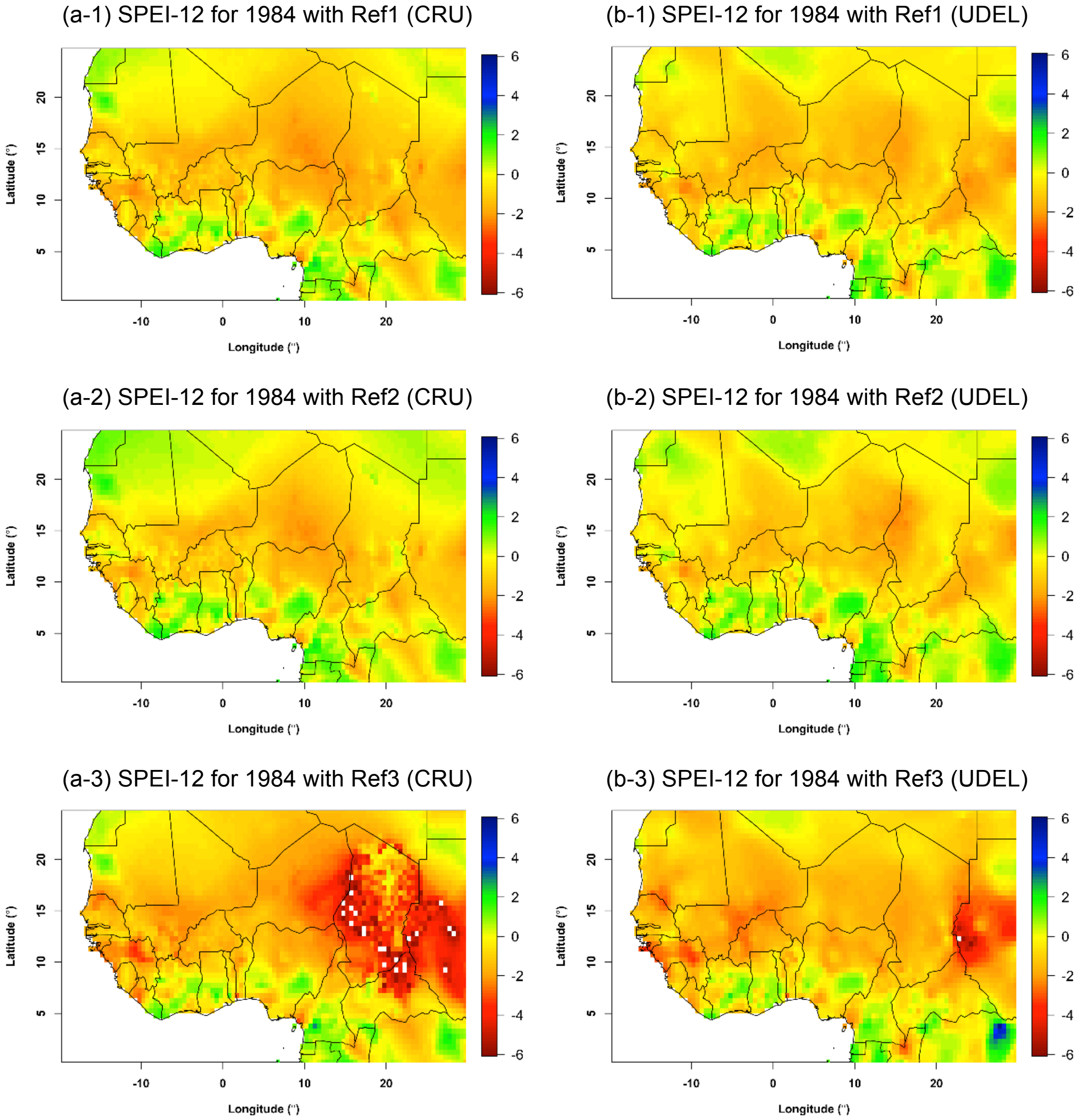

Figure 15. SPEI-12 for three different reference periods (Ref1, Ref2 and Ref3) based on the (a) CRU and (b) UDEL datasets in West Africa in 1984

Table 1. Classification of dry status in this study (Mckee et al., 1993)

Category	Description	SPEI
D1	Moderate dry	≤ -1.0
D2	Extreme dry	≤ -2.0
D3	Very extreme dry	≤ -3.0

Table 2. Estimation and calibration periods for the SPEI

Type	Estimation Period	Calibration Period
Ref1	1901–1957	1901–2014
	1958–2014	
Ref2	1901–1957	1901–1957
	1958–2014	1958–2014
Ref3	1901–1957	1901–1957
	1958–2014	

Table 3. Mean and standard deviation (STD) of precipitation and air temperature in different regions

			CRU		UDEL	
			1901–1957	1958–2014	1901–1957	1958–2014
Annual precipitation (mm)	EA	Mean	637.19	635.52	659.67	649.21
		STD	22.36	30.05	30.67	31.76
	EU	Mean	685.86	711.03	674.17	688.31
		STD	31.08	32.43	30.97	31.16
	US	Mean	698.44	736.22	709.50	734.42
		STD	43.31	41.48	44.06	41.55
	WA	Mean	698.49	666.59	734.84	676.11
		STD	36.87	43.84	44.89	48.00
Annual average air temperature (°C)	EA	Mean	6.08	6.67	6.25	6.62
		STD	0.28	0.52	0.31	0.48
	EU	Mean	6.96	7.46	7.02	7.29
		STD	0.56	0.68	0.55	0.64
	US	Mean	10.46	10.78	10.59	10.64
		STD	0.45	0.50	0.43	0.43
	WA	Mean	26.27	26.62	26.40	26.66
		STD	0.25	0.48	0.26	0.41
Annual potential evapotranspiration (mm)	EA	Mean	688.69	705.78	700.44	709.52
		STD	16.06	23.92	15.65	22.73
	EU	Mean	598.06	624.48	603.15	617.35
		STD	24.86	31.66	23.46	28.54
	US	Mean	711.49	728.60	718.48	720.90
		STD	23.84	26.28	22.59	21.28
	WA	Mean	1889.57	2001.37	1948.91	2044.28
		STD	72.61	136.96	78.17	129.94

Table 4. Spatial extent (%) (the number of grid points relative to the total number of effective grid points) in each region for different trends of SPEI-12 values based on different reference periods

Zone	CRU						UDEL					
	Ref1		Ref2		Ref3		Ref1		Ref2		Ref3	
	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry
EA	2.5	36.3	0.0	8.0	2.5	36.5	3.4	23.2	0.0	7.7	3.4	23.2
EU	10.4	24.9	0.0	1.7	10.4	24.9	5.3	15.8	0.0	2.2	5.3	15.8
US	18.6	16.2	0.0	67	18.6	16.2	11.3	9.7	0.1	3.1	11.3	9.7
WA	0.0	90.2	0.0	40.4	0.1	89.8	0.0	90.9	0.0	19.5	0.0	90.9

Table 5. Monthly average D (mm/month) in four study regions

	CRU			UDEL		
	P1	P2	P1+P2	P1	P2	P1+P2
EA	-4.29	-5.85	-5.07	-3.40	-5.03	-4.21
EU	7.32	7.21	7.26	5.92	5.91	5.92
US	-1.09	0.64	-0.23	-0.75	1.13	0.19
WA	-99.26	-111.23	-105.24	-101.17	-114.01	-107.59

Table 6. Spatial extent (%) (the number of grid points in each drought category relative to the total number of grid points) for major drought events

Zone	Period	Type	CRU			UDEL		
			Ref1	Ref2	Ref3	Ref1	Ref2	Ref3
EA	2000	D1	32.63	27.48	38.80	26.81	27.39	29.62
		D2	2.45	0.75	14.64	0.92	0.73	2.64
		D3	0.05	0.00	1.83	0.04	0.01	0.07
EU	2003	D1	37.58	39.10	36.68	35.30	34.67	36.61
		D2	5.33	3.97	7.68	5.93	4.82	8.50
		D3	0.00	0.00	0.02	0.02	0.10	0.22
US	2012	D1	52.16	55.01	50.02	54.69	56.32	52.92
		D2	11.97	11.90	15.74	10.36	11.76	11.63
		D3	0.02	0.00	0.53	0.09	0.05	0.87
WA	1984	D1	44.06	31.04	62.18	37.13	27.15	57.78
		D2	3.42	1.87	28.62	2.07	1.72	13.80
		D3	0.00	0.00	14.30	0.00	0.00	2.99