Spatiotemporal Characteristics of Drought in Central Asia from 1981 to 2020

Yu Sun 1,2,3, Xi Chen 1,2,3,4,*, Yang Yu 1,2,3,4, Jing Qian 1,2,4,5, Min Wang 1,2,3,4, Shuangyan Huang 1,2,3,4, Xiuwei Xing 1,2,3,5, Shiran Song 1,2,3,4 and Xiaolin Sun 1,2,3,4

1 State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China
2 University of Chinese Academy of Sciences, Beijing 100049, China
3 Research Center for Ecology and Environment of Central Asia, Chinese Academy of Sciences, Urumqi 830011, China
4 Key Laboratory of GIS & RS Application Xinjiang Uygur Autonomous Region, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China
5 Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China

* Correspondence: chenxi@ms.xjb.ac.cn

Abstract: Drought is a meteorological phenomenon that threatens ecosystems, agricultural production, and living conditions. Central Asia is highly vulnerable to drought due to its special geographic location, water resource shortages, and extreme weather conditions, and poor management of water resources and reliance on irrigated agriculture exacerbate the effects of drought. In this study, the latest version of the Global Land Data Assimilation System was employed to calculate the Standardized Precipitation Evapotranspiration Index at different time scales during the period from 1981 to 2020. The varimax Rotated Empirical Orthogonal Function was applied for subregional delineation of drought patterns in Central Asia, and various methods were employed for a comparative analysis of the spatiotemporal characteristics of drought in these Central Asian subregions. The results show that drought patterns vary considerably in the Central Asian subregions. Over the past 40 years, alternating wet and dry conditions occurred in Central Asia. North Kazakhstan experienced more drought events with lower severity. East and west differences appear after 2001, the west becoming drier and the east becoming wetter. Some regions near lakes, such as Balkhash, Issyk-Kul, and the Aral Sea, suffer from droughts of long duration and high severity. In the Tianshan region, droughts in the northern slopes occur more frequently, with shorter durations and higher intensity and peaks. Northwestern China and western Mongolia have extensive agricultural land and grasslands with highly fragile ecosystems that have become progressively drier since 2001.

Keywords: drought characteristics; SPEI; Central Asia; GLDAS; Run Theory

1. Introduction

Drought is a complex, underestimated, and devastating natural phenomenon [1,2], with large impacts on the economy [3], agricultural production [4], water supply [5], energy production [6,7], human health [8], and natural ecosystems [9,10]. As a hyper-arid region, Central Asia has a typical continental climate, with scarce precipitation, high evapotranspiration, and extremely uneven precipitation distribution. Over the past few decades, Central Asia has experienced a significant increase in temperature and a slight decrease in precipitation, and poor management of water resources and reliance on irrigated agriculture have caused much of Central Asia to be highly vulnerable to drought [11–17]. According to the KU Leuven Emergency Events Database (EM-DAT), the northwest of China was severely affected during the severe drought event of 2000–2001. In the same period, serious losses in total agricultural production were reported in Tajikistan [18]. These areas are also vulnerable to salinization and threatened by the spread of dust, sandstorms, and winds [9]. Therefore, there is an urgent need to study drought in Central Asia.
Generally, droughts can be divided into four types: meteorological drought, agricultural drought, hydrological drought, and socio-economic drought. Drought indices are available for monitoring regional drought conditions. Over the past few decades, many excellent drought indices have been developed and widely used for drought monitoring, including the Palmer drought severity index (PDSI) [19], the Rainfall Deciles (RD) [20], the Crop Moisture Index (CMI) [21], the Standard Precipitation Index (SPI) [22], the China-Z Index (CZI) [23], the self-calibrating PDSI (sc-PDSI) [24], and the Standardized Precipitation Evapotranspiration Index (SPEI) [25]. Developed by McKee et al. [22], the SPI has many advantages, including simple calculation, multiple time scales, and adaptability to different regions. However, the SPI only uses precipitation input without considering temperature and evaporation, and the accuracy of the precipitation dataset affects the SPI accuracy [26,27]. The SPEI is calculated using the water balance equation, which is the difference between precipitation and potential evapotranspiration. It not only considers the sensitivity of temperature and evaporation to drought [25], but also retains the characteristics of multiple time scales and comparability. In addition, SPEI is based on statistical indices over long periods, requiring only climate-related information and no assumptions about the system characteristics of the underlying model. Temperature and evaporation are becoming increasingly important factors in drought monitoring, so SPEI is widely used to determine and characterize drought occurrence and development at regional and global scales [28–34].

Despite the progressively increasing risk of drought in Central Asia, research on drought has remained limited. Guo [10] examined the spatial and temporal distribution patterns of drought in Central Asia based on the SPEI at multiple time scales calculated from the CRU dataset for 1966–2015. Li [35] found a drying trend in Central Asia based on PDSI from 1965 to 2014. Hu [36] calculated multiple drought indices for Central Asia over the period from 1950 to 2015 and explored the major drought drivers. Ta [37] analyzed the patterns of dry and wet conditions and calculated the frequency of droughts in the five Central Asian countries. Most of the studies on Central Asia are centered on national scales. Attention to subregional scales is still lacking, resulting in an inadequate analysis and ineffective policy design. Previous studies in general using datasets with a spatial resolution of 0.5° may lead to poor characterization of drought. The lack of understanding of drought characteristics at the subregional scale, such as frequency, time of occurrence, severity, intensity, and drought area, may lead to an incomplete understanding of drought. In this study, the overall objective is to characterize and plot the spatiotemporal evolution of drought distribution at the subregional scale in Central Asia by calculating SPEI on multiple time scales based on the Global Land Data Assimilation System (GLDAS) dataset from 1981 to 2020. The objectives are (1) to identify subregions with distinct drought subregion characteristics by using the Rotated Empirical Orthogonal Function (REOF) and the Empirical Orthogonal Function (EOF) and (2) to use multiple methods to compare subregional drought characteristics, including drought spatial trends, drought temporal evolution, subregional drought events and their properties, and drought periodicity.

2. Materials and Methods

2.1. Study Area

As the only route between Europe and Asia and the core area of the Silk Road Economic Belt, Central Asia includes northwestern China, western Mongolia, and five Central Asian countries (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan) (Figure 1). The region is bordered by the Caspian Sea to the west, the Hexi Corridor and Mongolia to the east, the Kunlun Mountains and the Iranian Plateau to the south, and Russia to the north. The region experiences a typical continental climate with scarce precipitation, high evapotranspiration, and extremely uneven precipitation distribution. The topography of Central Asia is complex, with high terrain in the east and low terrain in the west, including high mountains (Tian Shan, Altay Shan), plateaus (Pamir Plateau), hills (Kazakh hills), plains (Turan Plain), and basins (Tarim Basin, Junggar Basin). Central Asia is highly vulnerable to
drought due to its special geographic location [38], water resource shortages, extreme weather conditions [36,38,39], high agriculture dependence [38,40], and fragile ecosystem [13,14].

Figure 1. Digital Elevation Model (DEM) of Central Asia. (Note: the base map is made based on the standard map (GS(2020)4632) approved by the National Bureau of Surveying and mapping geographic information, and the base map is not modified.)

2.2. Dataset

Compared with traditional observational data or other remote sensing data, grid datasets play an important role in characterizing drought, with better representativeness and continuous spatial and temporal availability. The Global Land Data Assimilation System (GLDAS) [41,42] dataset is developed by the American Goddard Space Flight Center and Environmental Forecast Center, combining satellite measurements and ground data to produce four land surface models, namely, CLM, Mosaic, Noah, and VIC, and GLDAS providing three-hourly and monthly datasets with spatial resolution of 0.25° and 1.0°. Considering the lack of sufficient meteorological measuring stations in Central Asia, the monthly precipitation and evapotranspiration data at 0.25° × 0.25° spatial resolution from the latest version of GLDAS–Noah are used to analyze the drought characteristics in this study during the period from 1981 to 2020. As GLDAS-2.0 covers the period from 1948 to 2014, while GLDAS-2.1 covers the period from 2000 to present, and the GLDAS-2.0 and GLDAS-2.1 products are “open-loop” (i.e., no data assimilation), we used GLDAS-2.0 and GLDAS-2.1 to study the drought situation in Central Asia.

2.3. Methods

2.3.1. The Standardized Precipitation Evapotranspiration Index (SPEI)

In order to monitor and quantify drought conditions, the Standardized Precipitation Evapotranspiration Index (SPEI) is used as a drought index [26]. Based on the simple water balance equation, the SPEI is calculated by the difference between precipitation and potential evapotranspiration. The calculation process is as follows.

The first step, the difference between monthly precipitation ($P_j$) and evapotranspiration ($PET_j$) is calculated as,

$$D_j = P_j - PET_j$$  \hspace{1cm} (1)

where $j$ is the month number, and $D_j$ is the difference between precipitation in month $j$ ($P_j$) and potential evapotranspiration in month $j$ ($PET_j$).
The second step is aggregating and normalizing the sequence of accumulation of $D_j$ at different time scales, and water surplus or deficit is represented by the results. The following represents the accumulated difference for one month in a particular year $i$, with a 12-month time scale,

$$\begin{align*}
  X^k_{ij} &= \sum_{l=13-k+j}^{12} D_{l-1} + \sum_{l=1}^{j} D_{lj}, \text{ if } j < k \\
  X^k_{ij} &= \sum_{l=j-k+1}^{j} D_{lj}, \text{ if } j \geq k
\end{align*}$$

(2)

where $X^k_{ij}$ is the accumulated difference between $P_j$ and $PET_j$ at the $k$-month time scales in the $j$th month of the $i$th year. By normalizing $X^k_{ij}$, three-parameter log-logistic distribution can be used to calculate the Standardized Precipitation Evapotranspiration Index (SPEI),

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

(3)

where $\alpha$, $\beta$, and $\gamma$ are the scale, shape, and origin state, respectively. By fitting using the linear moment method, the three parameters can be obtained.

The cumulative probability of a definite $X^k_{ij}$ and the SPEI is calculated as follows.

$$p = 1 - F(x)$$

(4)

$$w = \begin{cases} 
\sqrt{-2 \ln p} & \text{if } p \leq 0.5 \\
\sqrt{-2 \ln(1 - p)} & \text{if } p > 0.5
\end{cases}$$

(5)

$$\text{SPEI} = \frac{C_0 + C_1 w + C_2 w^2}{1 + d_1 w + d_2 w^2 + d_3 w^3} - w$$

(6)

The constants $C_0$, $C_1$, $C_2$, $d_1$, $d_2$, and $d_3$ are defined in the study [25]: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

Generally, the SPEI values have different sensitivities at different time scales on dry/wet performance. Due to the flexibility of time scales, SPEI is widely used to assess various types of drought, including short- and long-term meteorological droughts [22]. In this study, SPEI at different time scales (SPEI3, SPEI6, and SPEI12 represent 3-month, 6-month, and 12-month time scales, respectively) are used to describe short-, medium-, and long-term meteorological droughts.

2.3.2. EOF and REOF

The statistical and exploratory method of EOF is proposed to identify and extract spatiotemporal patterns of geophysical variables by reducing a dataset containing many variables to one containing a few new variables [43–49]. Specifically, EOF analysis within the climate field is applied to identify and extract possible spatial variability and evolutionary patterns by calculating the eigenvalues and eigenvectors based on a spatially weighted anomaly covariance matrix. Most commonly, the spatial weights are expressed as the cosine of the latitude. Variables can be expressed in EOF by extending the orthogonal functions in the space and time domains as follows.

$$Z(x, y, t) = \Sigma PC(t) \times EOF(x, y)$$

(7)

where $Z(x, y, t)$ represents the space–time field of SPEI12, $PC$ represents the matrix of the time series, and EOF$(x, y)$ represents the principle loading components, also known as the spatial pattern. The correlation between the original data and the component fraction time series can be represented by the few normalized eigenvectors. To ensure the robustness of calculations and the adequacy of SPEI12, we use Bartlett’s test of sphericity [50] and the Kaiser–Meyer–Olkin test (KMO) [51] in this study.
However, the spatial distribution pattern delineated using the EOF method does not clearly reflect the drought characteristics in different subregions and makes it difficult to regionalize to an area of similar drought conditions. To optimize and simplify localized drought patterns, the method of varimax rotated EOF analysis is applied to regionalization. Varimax rotation maximizes the squared correlation variance between rotated loading patterns (REOFs) and SPEI12, and simplifies spatial patterns with similar time variations. Compared to EOF, the rotation variance contribution is more uniformly distributed. North’s rule of thumb is used to select the number of EOFs to be rotated.

2.3.3. Sen’s Slope and Modified Mann–Kendall Test

To capture monthly drought trends and significance level, we used Sen’s slope and the modified Mann–Kendall (MMK) test. The non-parametric Mann–Kendall significance test (MK) can be used to calculate the significance of trends in time series [52–54]. The method is recommended by the World Meteorological Organization (WMO) and widely applied to evaluate the significance of trends in various hydro-meteorological and vegetation datasets [55–60], because there is no requirement for normality and no limitations on missing values in the data series. Therefore, the MK test tends to underestimate the sample variance when studying the serial correlation of time series. Hamed and Rao [61] formulated a variance correction approach of the MMK based on the effective sample size to improve trend analysis; one study [56] proved that MMK is more reasonable and robust.

The Theil–Sen slope analysis is a robust non-parametric method [56]. It allows missing values, is not required to obey a certain distribution, and is not disturbed by outliers. The Theil–Sen slope has been shown to accurately quantify the verification slope of MK trend analysis [62–65]. The formula is as follows:

$$\beta = \text{Median} \left( \frac{x_j - x_i}{j - i} \right), \forall j > i$$

(8)

where $1 < i < j < \beta$, and $\beta$ is the drought trend from 1981 to 2020.

In this study, Sen’s slope and the MMK method are applied to determine the significance at a 0.05 level.

2.3.4. Run Theory

Yevjevich [66] proposed the Run Theory for capturing drought characteristics. A run is defined as the continuous part of a time series variable, where the run has similar characteristics or all values of the run are below a selected threshold. According to the relevant studies [39,67,68], drought events are defined as three consecutive months with negative SPEI and a minimum value of less than $-1$. In addition, if there are less than three months between different drought events, they will be considered one drought event. The definition of drought events helps to quantify droughts and improve drought early warning systems. As shown in Figure 2, when there is a continuous negative run, the drought event and drought characteristics are defined and described according to the Run Theory, including drought frequency (DF), drought duration (DD), drought severity (DS), drought intensity (DI), and drought peak (DP). DF represents the frequency of drought. DD represents the number of months the drought event lasts, and DS represents the sum of the absolute values of SPEI in drought events. DI represents the average of SPEI values over the drought duration, measured as the drought severity divided by the drought duration, and DP represents the absolute value of the lowest SPEI during the drought event.

$$S = \sum_{i=1}^{DD} |\text{SPEI}_i|$$

(9)

$$\text{DI} = \frac{\sum_{i=1}^{DD} |\text{SPEI}_i|}{\text{DD}}$$

(10)
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![Figure 2. Definition of a drought event based on the Run Theory.](image)

In order to study the spatial and temporal characteristics of droughts at the grid scale, the drought characteristics are calculated in each grid, including mean drought duration (MDD), mean drought severity (MDS), mean drought intensity (MDI), and mean peak value (MDP). The percentage of drought area (PDA) represents the percentage of drought area in a region during a drought event. PDA is crucial to the study of drought characteristics, especially if different degrees of drought occur in different subregions.

\[
MDD = \frac{\sum_{j}^{N} DD_j}{N} \tag{12}
\]

\[
MDS = \frac{\sum_{j}^{N} DS_j}{N} \tag{13}
\]

\[
MDI = \frac{\sum_{j}^{N} DI_j}{N} \tag{14}
\]

\[
MDP = \frac{\sum_{j}^{N} DP_j}{N} \tag{15}
\]

\[
PDA = \frac{\sum_{j}^{N} DA_j}{AREA} \tag{16}
\]

where $N$ is the number of drought events during the study period, $j$ is a drought event, DA is the number of grids in which the drought event occurs, and AREA is the total number of grids.

2.3.5. Continuous Wavelet Transform (CWT)

To identify and describe the dominant localized variations in time series, wavelet transform analysis formulated on the theory of Fourier transform by decomposing data into time-frequency space is widely used in the field of climate and hydrological change [55,69–73]. In particular, CWT overcomes the inability to combine the time and frequency domains and offers various advantages such as self-adjusting time resolution, the flexibility of mother wavelets, and suitability for non-stationary time series [74]. Morlet mother waves are used in wavelet analysis as they produce reasonable temporal and frequency fields, and CWT is adopted to study the periodicity of drought in this study. In addition, CWT is tested by the Monte Carlo method at the 0.05 level of statistical significance.
3. Results

3.1. Regionalization and Spatial Variability of Droughts

In order to obtain reliable partitioning, we use the REOF method, which aims to minimize the mode complexity by making the large loadings larger and the small loadings smaller. Based on the REOF method, the monthly SPEI12 from 1981 to 2020 is used to determine subregional drought patterns with distinctive features. To evaluate the accuracy and reasonableness of the results, Bartlett’s test and the KMO test are used on the SPEI12 series. The results show that the SPEI12 is well suited for REOF regionalization analysis due to its low Bartlett test p-value (<0.01) and high KMO test value (0.76). According to the North test and the eigenvalues in the scree plot, the regionalization of the seventh eigenvector value is not robust enough, and the first six linearly uncorrelated principle components (PCs) with a cumulative percentage of 50.6% are selected to obtain a more stable pattern (Table 1).

| Methods | Component | PC1  | PC2  | PC3  | PC4  | PC5  | PC6  |
|---------|-----------|------|------|------|------|------|------|
| EOF     | Variance (%) | 21.59 | 8.02 | 7.64 | 5.55 | 4.22 | 3.78 |
|         | Cumulative (%) | 21.59 | 29.61 | 37.25 | 42.8 | 47.02 | 50.8 |
| REOF    | Variance (%) | 12.86 | 10.61 | 8.84 | 7.26 | 5.73 | 5.25 |
|         | Cumulative (%) | 12.86 | 23.47 | 32.31 | 39.57 | 45.3 | 50.55 |

To verify the reasonableness of the indexes in the six regions, Spearman’s rank correlation coefficient is employed to test the correlation between PCs and the mean SPEI in the subregions. A high score ($r > 0.52$) means that the subregions are suitable for studying the region’s drought characteristics (Figure 3). For convenience, the regions are named according to their location in Central Asia: North Kazakhstan (NK), the Hexi Corridor (HX), the Southwest (SW), Tian Shan (TS), the Southeast (SE), the Northeast (NE).

![Figure 3](image-url)  
Figure 3. The first six components of the REOF variation based on SPEI12. Subplots (a–f) represent the six component results of REOF and also the partitioning basis. The r score is the Spearman correlation coefficient value between the PC score and the six subregions of SPEI12.

Identifying drought patterns at subregional scales is essential for understanding drought development in the different subregions in Central Asia. Compared to REOF, the EOF analysis is better suited to be used to study possible spatial patterns of variability and how they change with time. Based on the EOF method, the North test, and the scree plot of eigenvalues, the first six EOFs are selected. They explain more than 50.8% of the total variance (Table 1). As shown in Figure 4, the six EOFs models based on SPEI12 calculations have significant differences, and the patterns of the subregions validate the rationality of
REOF regionalization. This first component (EOF1) explains the most variance (21.59%) and serves as a reference for the spatial distribution of droughts in Central Asia. According to the spatial mode of EOF1, positive values are found in almost all the main regions, and negative values are observed in NE and the local area of SE, where the variation range of the drought is sensitive and might result in drought anomalies in subregions. Combined with the time coefficients, Central Asia experienced alternating dry/wet periods for the past 40 years. The second component (EOF2) clearly reflects the antiphase distribution, forming the northern and southern part in Central Asia, mainly affected by latitude and atmosphere circulation. The slight downward time coefficient indicates a decreasing wetting trend after 2001 in the NK region, while the other regions become slightly drier, especially the SW and the east of SE. EOF3 mainly shows a high negative center for NE and TS, indicating that NE is affected by the same climate as TS, and the subregions become relatively drier after 2001. EOF4 has a reverse distribution to the eastern and western parts, showing a trend of high east and low west, and indicating that NK and most of the SW area are clearly wetter before 2001, and a gradual trend of relative drought is observed after 2001. In addition, the central region of SW, especially in the Aral Sea region, shows an opposite pattern to the other regions of SW. Both EOF5 and EOF6 show an east–west inverse distribution, but with the difference that EOF5 divides the subregions into two parts: one negative, including NE, HX, and the eastern of TS and NK, and the other positive, especially SW and the west of NK and TS. EOF6 shows the center of high negative values in the NE and HX subregions. Combined with the time coefficient of slight decline, the subregions of SW and the west of NK and TS, except for the Aral Sea, are significantly drier after 2001, while the NE and HX subregions show similar wet and dry conditions after 2001 as they are both in the eastern part of the TS and experience the same climatic influences.

Figure 4. The first six components of the EOF variation based on SPEI12. Subplots (a1–f1) represent the six component results of EOF, (a2–f2) represent the time coefficients.

In general, the subregions have distinct drought patterns and differences in drying and wetting trends. Specifically, NK shows a wetting trend during the whole study period, but the wetting trend decreases after 2001, while there is a difference between east and west, with the east becoming wetter and the west become drier. This east–west discrepancy is also present in a related study [10]. Most regions of the SW become wetter between 1981 and 2001, and after 2001, a wet/dry reversal occurs, but the Aral Sea basin becomes relatively wetter after 2001. The subregions of NE and HX show similar drought patterns. These subregions have large and concentrated areas of agricultural land and grassland with high ecological vulnerability. HX becomes wetter from 1981 to 2001 and drier after 2001. EOFs in the NE show a different pattern from other regions; the NE becomes drier after 2001.
and 2001 and relatively wetter after 2001. TS shows a clear north-south difference in EOF5, becoming wetter from 1981 to 2001, and most of the region becoming drier after 2001.

3.2. Characterization and Description of Droughts

3.2.1. Spatial Trends and Characteristics of Droughts

Due to changes in drying and wetting trends in Central Asia around 2001, we divide the drought trend into two parts to further observe and understand the evolution of SPEI at different time scales. Figure 5 shows the drought trends in different subregions using Sen’s slope and the modified Mann–Kendall test. The color bar represents the magnitude of the slope, and the red (blue) color represents the drying (wetting) trend. The dots indicate significant drying (wetting) at the 0.05 significance level.

Drought trends in different subregions show similar trends at different time scales. It is interesting to note the similarity between Figures 4a1 and 5g,h,i, verifying the consistency of the conclusions of the different methods. The overall wetting trend in Central Asia from 1981 to 2020 is caused by the combination of local drying trends (SPEI3, SPEI6, and SPEI12 account for 28%, 21%, and 18% in Central Asia, respectively) and wetting trends (SPEI3, SPEI6, and SPEI12 account for 72%, 78%, and 82% in Central Asia, respectively). In particular, considerable wetting trends are seen in the subregions of NK, SW, and HX, with wetting area proportions of about 97.9%, 95.5%, and 97.6% for the SPEI12 time scale, respectively. There is a significant drying trend in the NE with a dry area ratio of 85.2%. The TS and SE subregions have relatively complex patterns with mixed wetting and drying trends. In addition, the wetting area ratios are 63.9% and 68.8% for the SPEI12 time scale in central SE and the local part of TS. The spatial patterns at different time scales are similar for the 1981–2001 period and the 2001–2020 period. Compared to the patterns during the 1981–2001 period, the spatial wetting or drying patterns reverse after 2001. There are two clear changes in the spatial pattern of drought worth noting. One is the change in wetting trend with the wet area for SPEI12 from 68.6% to 40.3%, mainly in TS, HX, the west of NK, and the north of SW. The other change is an area of increased drying trend for SPEI12, from 31.4% to 59.7%.
Based on the Run Theory method in each grid, the drought spatial characteristics are shown in Figure 6. It can be clearly observed that the spatial distribution of drought characteristics is broadly similar in different subregions as the time scale increases. Overall, DF decreases from 8–34 times in SPEI3 to 2–23 times in SPEI12, while MDD and MDI show increasing trends, with MDD increasing from 4–10 times in SPEI3 to 8–44 times in SPEI12 and MDI increasing from 3.01–7.11 in SPEI3 to 4.58–35.09 in SPEI12. The spatial distribution patterns of MDI and MDP at different time scales seem to be random and complex.

Figure 6. Spatial patterns of drought characteristics for SPEI3, SPEI6, and SPEI12. Subplots (a–o) represent drought characteristics at different scales (SPEI3, SPEI6, and SPEI12).

The NK region is marked by higher DF and lower MDD and MDS, indicating that the subregion experiences more drought events with lower severity. In addition, east–west differences appear in SPEI6. Most of the SW subregion is similar to western NK. However, the local areas near lakes in SW with higher MDD and MDS and lower DF suffer from droughts of long duration and heavy severity. Similar drought conditions are found in the basins of SE and TS subregions such as Lake Balkhash and Issyk-Kul. This means that the regions near lakes suffer from droughts of long duration and high severity [75–79]. The HX and NE subregions have high MDI and MDP, but not high MDD and MDS, indicating that the drought events in these regions are of short duration, but high drought peak and intensity. For the TS subregion, differences between the north and south slopes can be clearly seen in SPEI6; droughts in the northern slopes are characterized by lower MDD and MDS and higher DF, MDI, and MDP, indicating that droughts in the northern slopes occur more frequently and are of shorter duration and higher intensity and peak.
In general, the Central Asian regions show a wetting trend from 1981 to 2020, while a drying trend is observed in most areas after 2001. This drying trend was also reported in other studies [35]. There are marked differences in drought characteristics among the subregions of Central Asia. Most of the SW subregion and NK experience more drought events with lower severity. The local areas near lakes in the SW, TS, and SE suffer from droughts of long duration and high severity. There is a clear north–south difference in the TS region; droughts on the northern slopes occur more frequently and are of shorter duration and higher severity. Furthermore, droughts in HX and NE are similar to those on the southern slopes of TS, with short duration, high drought peak, and high drought intensity.

3.2.2. Drought Temporal Evolution

The analysis of the evolution of drought over time contributes to the understanding of drought variability at subregional scales. Figure 7 shows the temporal evolution of droughts at different time scales in six different subregions. To obtain the linear and nonlinear characteristics of SPEI at different time scales, linear trend lines and local regression (LOESS) are fitted. The linear trend is marked with red solid lines, and the 5-year and 10-year LOESS curves (LOESS5, LOESS10) are marked with blue and green solid lines, respectively. The pink dashed line represents the occurrence of a drought pattern shift in 2001 according to the EOF analysis. The gray filled rectangles indicate the four most severe drought events for the SPEI12 time scale.

The NE and SE subregions become drier during the study period with a linearly decreasing trend in SPEI values. The other regions (NK, TS, HX, and SW) become wetter, which is consistent with Figure 5. The 5-year and 10-year LOESS curves have similar fluctuation trends; as the time scale increases, the amplitude and frequency of SPEI decrease and the wet/dry trend tends to be clearer. Based on LOESS curves, most subregions experience droughts in the 1990s, and the overall trend changes in Central Asia are consistent with other studies [10,16]. NK, SW, and TS have similar fitted curves, clearly showing that they become wetter after 2001. HX shows a dry-to-wet trend from 1981 to 2001 and fluctuates significantly after 2001, consistently with other studies showing that the northwest of China has been getting wetter since 1986 [48]. From 1990 to 1995, a significant wetting trend is observed in all subregions of Central Asia, which is consistent with the findings of precipitation anomalies in another study [16].

Gray filled rectangles show drought events occurring at similar times in different subregions, including NE, SE, and HX from 1999 to 2003, and NE, NK, TS, and SE from 2005 to 2009. Almost all subregions in Central Asia are affected by drought from 1981 to 1985 and from 1993 to 1997. These drought events have also been documented in related studies [10,80]. Severe and prolonged drought events have devastated the agriculture and economy of Central Asia [37,81,82].

Drought Area is an important indicator of the severity of drought events, and can also indicate the frequency of various types of droughts. To further understand the temporal evolution of drought, the trend in percent change of Drought Area is shown in Figure 8 for six subregions with different time scales for different degrees of drought. The yellow, orange, and red areas indicate the area percentage of Moderately dry, Severely dry, and Extremely dry. The blue and green solid lines represent local regression (LOESS) lines for 5 and 10 years. The gray filled rectangles indicate the four most severe drought events.
3.2.2. Drought Temporal Evolution

The analysis of the evolution of drought over time contributes to the understanding of drought variability at subregional scales. Figure 7 shows the temporal evolution of droughts at different time scales in six different subregions. To obtain the linear and non-linear characteristics of SPEI at different time scales, linear trend lines and local regression (LOESS) are fitted. The linear trend is marked with red solid lines, and the 5-year and 10-year LOESS curves (LOESS5, LOESS10) are marked with blue and green solid lines, respectively. The pink dashed line represents the occurrence of a drought pattern shift in 2001 according to the EOF analysis. The gray filled rectangles indicate the four most severe drought events for the SPEI12 time scale.

Figure 7. Temporal evolution of drought for the values of SPEI3, SPEI6, and SPEI12 in Central Asia and six subregions. Subplots (a–u) represent the drought trend in Central Asia and six subregions at different time scales (SPEI3, SPEI6, and SPEI12).
Figure 8. Temporal evolution of percentage of drought area for SPEI3, SPEI6, and SPEI12 over six subregions. Subplots (a–r) represent the percentage change of drought area at different time scales (SPEI3, SPEI6, and SPEI12).

The percentage of drought area at different time scales shows similar trends, and the fitted curves gradually flatten as the time scale increases. The percentage of severe drought and extreme drought area show a decreasing trend with time. It is worth noting the relative increase in the severity and frequency of drought events in each subregion over the past decade, as also found in other studies [49]. The NK, SW, TS, and HX subregions are more severely affected by drought and show larger areas of drought before 2001, but the area of drought decreases after 2001.
decade, as also found in other studies [49]. The NK, SW, TS, and HX subregions are more severely affected by drought and show larger areas of drought before 2001, but the area of drought decreases after 2001.

3.2.3. Drought Periodicity

The wavelet power spectrum and global wavelet spectrum after Morlet wavelet transform based on SPEI12 are shown in Figure 9. The periodicity of drought change in the six different subregions is mainly concentrated between 2 and 16 years. Considerable variations exist between the power patterns in different subregions.

![Wavelet power spectrum and global wavelet spectrum after Morlet wavelet transform based on SPEI12.](image)

Figure 9. Wavelet power spectrum and global wavelet spectrum after Morlet wavelet transform based on SPEI12. Subplots (a1–f1) represent wavelet power spectrum in different subregions, (a2–f2) represent global wavelet spectrum in different subregions.

In general, there is a relative stability of the drought recurrence periodicity across subregions. For NE, a 2–5-year periodicity with increasing amplitude is found in 1982–2000, and the periodicity of drought tends to stabilize at 2–3 years in 2007–2015. Similarly, the 2–5-year bands are distributed in 1983–2008 for SE, 2004–2017 for NK, and 1997–2018 for TS. The 2–5-year periodicity in different subregions reaches a significance level of 0.05. The wavelet power of around 9–16 years is detected at a significance level of 0.05 from 1991 to 2015 for NK, 1981 to 2001 for HX, and 1984 to 2020 for SW. Unlike other subregions with increasing amplitude, there are decreasing amplitudes in NK and TS, and these occur after 1990.

4. Discussion

Drought is a devastating natural phenomenon connecting several spheres, namely, atmosphere, hydrosphere, biosphere, and anthroposphere, with significant impacts on the economy, agricultural production, water supply, energy production, human health, and natural ecosystems. In this study, we explored the spatiotemporal characteristics of drought in Central Asia from 1981 to 2020. For a clearer illustration, we summarize the results obtained by different methods in Table 2.
The impact of drought on agriculture and food security is devastating. The northern part of Kazakhstan (NK) shows a wetting trend throughout the study period, but the wetting trend diminishes after 2001, with the east becoming relatively wetter and the west relatively drier; this is similar to the findings in related studies [10,40]. In particular, we found that the frequency of severe short-term droughts in the region increased over the past 20 years (Figure 8). This may have affected the country’s agriculture, especially as most of the country’s land is used for growing crops and raising livestock. For most rain-fed agricultural areas in Central Asia, droughts can cause considerable losses. During the past decade, the severity and frequency of drought events have increased relatively in some subregions, particularly in large concentrated agricultural lands and grasslands (HX, TS, and NE) in northwestern China and western Mongolia, which have high ecological
vulnerability [12,72]. High severity and frequent short-term droughts can result in reduced crop yields, ecological degradation, and other problems [76]. According to EM-DAT, the northwest of China (HX and NE) was severely affected by the severe drought event of 2000–2001. In the same period, Tajikistan (SE) reportedly lost USD 800 million in gross agricultural production [18], equivalent to 5% of GDP in that year. In Uzbekistan (SW), approximately 600,000 people in the most affected areas required assistance in the supply of food, drinking water, and agricultural resources [83], and the cultivation of water-intensive crops, such as rice, was even banned in parts of the country in 2000 and 2001. Drought has a direct effect on crop biomass [84,85]. More directly, drought stress during the growth phase of crops greatly reduces crop yields, and severe drought has a strong relationship with significant crop yield reduction in drought-prone areas.

The other obvious finding is that the drought has greatly damaged the areas near the lakes and the local water cycle. Drought in the Aral Sea region has different characteristics from most of the SW region (EOF4, Figures 5 and 6 and Table 2). The shrinkage of the Aral Sea is considered to be caused by a decrease in rainfall and intensification of human activities [75–79], including irrigation and damming. Compared to the 1960s, the remaining volume of water in the Aral Sea is about 10%, which is undoubtedly a disaster involving all the basin countries [75,77]. Drought events occurred in these regions with high severity and long drought duration, especially from 1998 to 2002, where extremely low precipitation was accompanied by a marked decrease in lake area and water volume [77]. Continuous drought is highly destructive to lake and wetland systems and limits the productivity of terrestrial ecosystems [9]. With the occurrence of drought, streamflow decreases by 2–5% in the Syr Darya Basin and by 10–15% in the Amu Darya Basin [77]. In extremely dry years, there can be a 25–50% reduction in runoff. However, the amount of irrigation in the same period increases. The flow to the Aral Sea currently is only 2 km³/year, a 35% to 40% decrease compared to normal years [9,18,75]. According to Figures 7 and 8, the percentage of drought area in the SW has increased and the area became drier in the past five years. A similar situation occurred in the TS and SE areas near the lakes, such as Lake Balkhash and Issyk-Kul. This situation should draw attention from policy makers to avoid more serious damage. Most of the arid and semi-arid regions in Central Asia are prone to drought-related soil salinization and are threatened by the spread of sand, dust, dust storms, and strong winds [76,86]. The environmental problems caused by drought will be further aggravated by the lack of water resources [9].

It should be noted that this study examined only the drought in Central Asia from 1981 to 2020, and the limitations of this study are due to the limitations of the GLDAS data—we needed to splice two different versions of datasets, which may have introduced uncertainties. In addition, drought occurs due to a combination of causes, which are not elucidated in this paper. The results of this paper may help understand the structure of drought at the subregional scale and provide scientific support for the mitigation of drought effects in Central Asia. For example, the drying trend in almost all subregions since 2001 and the increase in drought duration and severity in the Aral Sea, Balkhash, and Issyk-Kul regions should draw the attention of policymakers. The six subregions could be considered separately in the regional drought risk management and the relevant drought characteristics could be incorporated into regional drought modeling and forecasting. Future studies can further analyze the impact of drought trends on a seasonal scale from environmental and economic perspectives.

5. Conclusions

Based on the GLDAS dataset, the SPEI was calculated on multiple time scales, including SPEI3, SPEI6, and SPEI12. The EOF and REOF methods were used for drought regionalization and to explore the spatial patterns of drought distribution and describe and plot drought characteristics (drought frequency, drought duration, drought severity, drought intensity, drought peaks, and percentage of drought area). Drought characteristics were analyzed according to the Run Theory for the period from 1981 to 2020. The drought
trends were analyzed using the method of Sen’s slope and MMK. Finally, the drought periodicity was calculated based on a wavelet analysis. The main findings of the study are as follows.

1. Based on REOF, Central Asia was divided into six subregions: north Kazakhstan (NK), the Hexi Corridor (HX), the southwest (SW), Tian Shan (TS), the southeast (SE), and the northeast (NE).

2. NK showed a wetting trend during the whole study period, but the wetting trend decreased after 2001. Most of the SW subregion, similar to western NK, became wetter from 1981 to 2001, with a wet/dry reversal after 2001. The subregions of NE and HX showed similar drought patterns. Both areas have large and concentrated areas of agricultural land and grassland with high ecological vulnerability. HX became wetter from 1981 to 2001 and drier after 2001. EOFs in the NE showed a different pattern from other regions, becoming drier from 1981 to 2001 and relatively wetter after 2001. TS showed a clear north–south difference in EOF5, becoming wetter from 1981 to 2001 and most of the region becoming drier after 2001. SE showed no significant overall trend and similar patterns to neighboring regions.

3. Central Asia regions experienced a wetting trend from 1981 to 2020, and a drying change in most of the area after 2001. The NK subregion experienced more drought events with lower severity, and east–west differences appeared after 2001, the west becoming drier and the east becoming wetter. Most of the SW subregion is similar to western NK, but the local areas near lakes in the SW, TS, and SE suffered from droughts of long duration and high severity. The TS region had a clear north–south difference, with more frequent droughts of shorter durations and higher severity on the northern slopes. HX and NE are similar to the southern slope of TS, with droughts of short duration, high drought peak, and drought intensity. The SE experienced more frequent and intense droughts, especially over the past two decades, gradually becoming drier.

4. Droughts in Central Asia between 1981 and 2001 were more widespread and of longer duration, especially during the 1981–1985 and 1993–1997 drought events. The drought trends in the NK, SW, TS, and HX subregions were similar, with larger areas being affected by the occurrence of droughts. After 2001, the severity and frequency of drought events increased relatively in each subregion, with shorter durations and reduced drought area. Severe drought events included the NE, SE, and HX from 1999 to 2003 and the NE, NK, TS, and SE from 2005 to 2009. In the past decade, most subregions, such as the NE, TS, HX, and SE, showed an increase in the area of drought.

5. Considerable variations were found between the power patterns in different subregions. The periodicity of drought change in the six different subregions was mainly concentrated between 2 and 16 years.

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