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Unraveling Projected Changes in Spatiotemporal Patterns and Drought Events across Mainland China Using CMIP6 Models and an Intensity–Area–Duration Algorithm

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Abstract: In the context of global warming, temperature increases have led to frequent drought events and a sharp increase in economic losses and social risks. In this study, five medium- and high-emission scenario models, the SSP245 and SSP585, CMIP6 monthly scale temperature and precipitation datasets under different global warming contexts (1.5 °C and 2 °C), and the 1984–2014 weather station observations were selected. The latter dataset was used to improve the ability of the CMIP6 to simulate surface drought accuracy. A standardized precipitation–evapotranspiration index dataset was generated. The latest intensity–area–duration framework was adopted to identify regional drought events by considering their continuity and spatial dynamic characteristics. The parameters of intensity, area, and duration were used to characterize the dynamic evolution of drought events. Under the medium- to high-emission scenario model, with a continuous increase in global temperature to 1.5 °C, in the southeastern Qinghai–Tibet Plateau (QTP) and southern Xinjiang (XJ) there is a significant increase in intensity, extent, and duration of drought events and some drought exacerbation in northeastern China. Under the high-emission SSP585 scenario model, the severity of these drought events is reduced when compared with the SSP245 scenario model, but this also shows an increasing trend, especially with the 2 °C global warming background. Significant drought aggravation trends were observed in southern XJ, northern QTP, and northern Northwest. In contrast, a small but significant drought-weakening trend was observed in southwestern south China. The results of this study provide a reference for society and government departments to make decisions in response to future drought events.

Keywords: drought event; CMIP6 models; standardized precipitation–evapotranspiration index; intensity–area–duration; spatial dynamics; climate scenarios

1. Introduction

The Sixth Assessment Report of the Intergovernmental Panel on Climate Change concluded that there is global climate system warming [1]. To reduce the risks and impacts

of climate warming, the Paris Agreement recommends limiting the increase in the global average temperature to well below 2.0 °C above pre-industrial levels and working to limit the warming to 1.5 °C [2]. As the global climate warms, the intensity, duration, and the range of impacts due to the resulting high temperatures, heavy precipitation, droughts, extreme weather, and climatic events will intensify [3]. Among these extreme climate events, drought is one of the most widespread and serious natural disasters worldwide and is characterized by a high frequency, large area of influence, and long duration [4]. It has been reported that droughts have caused more than 11 million deaths and affected 2 billion people since 1900 [5], with direct or indirect impacts on human agricultural production [6], water resources [7], ecological environment [8,9], and socioeconomic development [10]. The studies of Wilhite and Buda showed that the global economic losses caused by drought averaged USD 17.33 billion per year from 1980 to 2009, while the economic losses increased to USD 23.125 billion per year from 2010 to 2017, which was much faster than the growth rate of losses from other meteorological disasters [11,12].

China is seriously affected by drought, and it has already caused huge socioeconomic losses in recent decades [13]. For example, a severe drought in northern China in 1997 resulted in zero flow for the Yellow River for 222 days [14]. A 100-year drought struck southwestern China from the fall of 2009 to the spring of 2010 [15], and caused nearly USD 30 billion in economic losses, and more than 16 million people and 11 million livestock lacked adequate drinking water supplies during this time [16]. The summer drought in the middle and lower reaches of the Yangtze River in 2011 affected 30 million people along the river basin in China, with losses of approximately USD 2.4 billion [17]. Over the past 50 years, agricultural losses due to droughts have increased by approximately 0.5% per decade [18]. Furthermore, the drought area in China has increased by approximately 3.72% per decade since the late 1990s [13], a trend that is likely to continue until 2100 [18]. With further warming, droughts have become increasingly frequent and severe and will further threaten the country's food security and economic development [19,20]. The characteristics of droughts in China and the expected changes under different climate change scenarios must be analyzed to provide climate change mitigation and adaptation information for disaster prevention and mitigation strategies [21].

Droughts are caused by a complex set of factors [22], making drought identification and evaluation difficult [23]. Many drought indices have been developed in recent decades [24]. The three commonly used drought indices are the Palmer drought severity index (PDSI) [24], the standardized precipitation index (SPI) [25], and the standardized precipitation evapotranspiration index (SPEI) [26]. However, each drought index has its advantages and limitations, as the PDSI combines the amount and duration of water deficit with soil moisture modeling to comprehensively consider the impact of drought and is the most suitable index for assessing the impact of global warming on drought [27]; however, it does not consider multi-scale drought characteristics and requires high soil moisture data. This index is relatively fixed in time scale, requires multiple empirical parameters, and is cumbersome and complex to calculate. Its applicability to short time scales and humid regions has not yet been verified, reducing spatiotemporal consistency and comparability [28]. The SPI standardizes regional climatic precipitation, eliminates differences in the spatial and temporal distributions of precipitation, and provides simple, multi-scale, and stable calculation results. The World Meteorological Organization recommends the SPI for drought monitoring and analysis due to its simplicity, stability at multiple scales, and easy data access. However, it only considers changes in precipitation and ignores changes in evapotranspiration caused by temperature changes [29]. SPI values are also based on long-term precipitation, which may change, resulting in inaccurate results or long-term time scales [30], and consequently, this method is limited with respect to its ability to truly reflect the evolution of drought in the context of climate warming [31]. The SPEI adds surface evaporation changes to drought based on the SPI, compensating for SPI shortcomings [32]. The SPEI has both the multi-scale characteristics of the SPI and the sensitivity of the PDSI to atmospheric water demand. The recently introduced SPEI

is superior to other methods because it accurately assesses drought conditions in various regions, time frames, and severity levels. It is also more sensitive in drought regions [33] and performs better in the humid and semi-humid regions of China [26,34–36].

Global climate models (GCMs) help study climate responses to forcings and make projections and prognoses. The Coupled Model Intercomparison Project (CMIP) is presently regarded as one of the most reliable and comprehensive sources of data. It has been utilized to examine the influence of climate change on forthcoming droughts [29,37]. The latest version, CMIP6, is more accurate at reproducing spatial pattern changes in large-scale average surface temperature and precipitation than CMIP5 [38,39]. We selected five models in CMIP6 to assess the duration, impact area, and severity of future drought events in mainland China under the (1.5° and 2°) shared socioeconomic pathway (SSP) scenarios in the context of global climate warming.

At present, in the identification methods of extreme climate (drought and extreme rainfall) events, a variety of mature methods have emerged to identify extreme climate (drought or extreme rainfall) events from different angles. The most common of them are based on the Copula conditional probability model method and the intensity–area–duration (IAD) algorithm. The Copula function method constructs the multi-dimensional joint distribution by fitting the edge distribution function and the correlation structure. Therefore, it has been widely used in extreme precipitation, drought characteristics analysis, and drought prediction [40,41]. Drought characteristics are highly sensitive to time, and the Copula function needs to be time-dependent when applied to drought problems. When dealing with high-dimensional data, the parameter estimation of the Copula function becomes complicated and not accurate enough. Therefore, a relatively simple intensity–area–duration algorithm (IAD) was selected to identify and analyze drought events.

This study investigates regional drought events in mainland China and analyzes their spatiotemporal variations on three aspects: (1) the IAD (intensity–area–duration) algorithm identifies regional drought events using temporal continuity and spatial dynamics, (2) the intensity, impact area, and duration of regional droughts are described, and (3) illustrating the spatiotemporal dynamic evolution of drought events through a typical one. The main innovation of this study is the identification of drought evolution patterns on a regional scale. This study can help us understand drought in specific geographic regions and identify climate change's effects on drought and its future. The results can help the public reduce drought damage and its effects.

2. Materials and Methods

2.1. Study Area

This study focuses on mainland China (excluding the Hong Kong, Macao, and Taiwan provinces) with a land area of 9.6 million km² and a complex and diverse topography leading to different climate zones (18–54° N, 73–135° E). China's climate is in the monsoon climate zone of East Asia and is largely influenced by changes in winter and summer winds. Different climate types and unique geographic locations have led to large spatiotemporal variations in drought characteristics. To better understand the drought characteristics of different regions in China, the geographical zoning method adopted in our previous study [42] is used to classify the area according to the precipitation gradient and comprehensive temperate zone as follows (Figure 1): (1) northwest China (NW) with an arid and semi-arid climate; (2) Xinjiang (XJ) with a temperate continental climate; (3) southwest (SW) and (4) south China (SC) with humid climates; (5) northeast China (NE) with a humid and semi-humid climate; (6) the Qinghai–Tibet Plateau (QTP) with a sub-frigid climate; and (7) north China (NC) with a semi-humid climate.

China has a population of 1412 million as of 2022, approximately 18% of the global population, and a cultivated land area of 1,278,619 km², which is 7% of the world's total cultivated land area. The country is highly susceptible to drought, which is the most important factor constraining China's sustainable socioeconomic development. According to statistics, the average area of croplands affected by drought in China ranges from

$2.09 \times 10^5 \text{ km}^2$ per year to $4.09 \times 10^5 \text{ km}^2$. The occurrence of drought leads to a decrease in grain production by more than 30 million tons each year, resulting in direct economic losses amounting to CNY 44 billion [12,43].

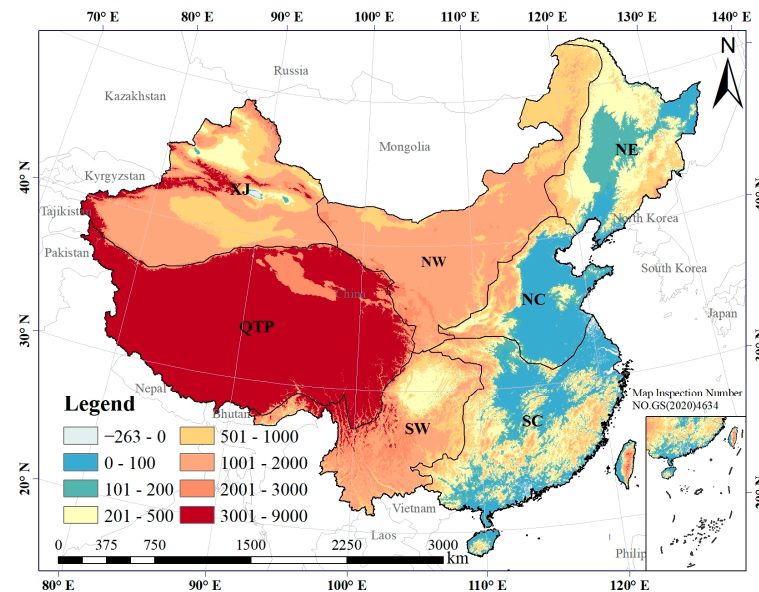


Figure 1. Map of China showing the seven geographic regions, northwest (NW), Xinjiang (XJ), southwest (SW), south China (SC), northeast (NE), Tibetan Plateau (QTP), and north China (NC).

2.2. Datasets

2.2.1. Observation Data

The data used in this study are the gridded observation dataset CN05.1 from more than 2400 ground-based meteorological stations in China interpolated by the “distance-approximation” [44] method, with a $0.25^\circ \times 0.25^\circ$ resolution. The uneven distribution of ground observation stations, especially in places with large topography and few or no observation stations, such as the northern Tibetan Plateau to the western Kunlun Mountains, leads to the uncertainty of grid data in these areas. Compared with the reanalysis data, the data of CN05.1 have greater reliability. They can represent the changes in various meteorological elements relatively accurately and are the most accurate dataset of the grid near-surface meteorological field in China at present. In this dataset, daily maximum and minimum temperatures and precipitation were selected to construct the SPEI. The study period was from 1961 to 2015. The dataset excludes Hong Kong, the Macao Special Administrative Region, and Taiwan because of the data limitations [45]. The dataset was converted to a monthly series of maximum and minimum temperatures as well as precipitation. We used the bilinear interpolation method to convert the spatial resolution of the monthly data series to $1^\circ \times 1^\circ$. This will ensure a consistent spatial resolution with that of the climate model. Compared to the previous studies [46–48], the time period of 1984–2014 was chosen as the reference period for the revision of the observed data [49].

2.2.2. Climate Model Data

In this study, historical and future drought characteristics in China were simulated using five CMIP6 models (Table 1) we selected that are commonly used by researchers, popular enough, take into account climate sensitivity, and are the result of the reliability assessment of a large number of GCMs [44,46,48,50–52], including GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL with scenario data from the Earth System Grid Federation (<https://esgf-node.llnl.gov/projects/cmip6/>, accessed on 1 June 2023). There is no single generalized ideal climate model, and there have been many studies [50,51] confirming that the CMIP6 multi-model ensemble median is superior

to individual models in characterizing extreme precipitation and temperature [52]. We downloaded the data for monthly maximum/minimum near-surface temperature (tas-max/tasmin) and monthly precipitation (pr) for our purpose. For the future period, two different SSPs were selected considering data availability, namely the medium-emission scenario, SSP245, and the highest-emission scenario, SSP585, which are the most commonly used scenarios for possible future scenarios [53] with a possible increase of 1.5 °C and 2.0 °C.

Table 1. Summary data for the five CMIP6 models used in this study.

No.	Model	Nationality	Institution	Realization	Resolution (Lon × Lat)
1	MPI-ESM1-2-HR	Germany	DKRZ	r1i1p1f1	0.938° × 0.938°
2	GFDL-ESM4	America	NOAA-GFDL	r1i1p1f1	1.250° × 1.000°
3	IPSL-CM6A-LR	France	IPSL	r1i1p1f1	2.500° × 1.259°
4	MRI-ESM2-0	Japanese	MRI	r1i1p1f1	1.125° × 1.125°
5	UKESM1-0-LL	Britain	NCAS	r1i1p1f2	1.875° × 1.250°

To facilitate a comparison with observations and references to previous studies, these variables were interpolated to a 1.0° × 1.0° resolution grid using a bilinear approach. The ensemble averaging method was used to average each model variable into an integrated dataset for the selected climate model data. The selected climate model data were bias-corrected using the quartile mapping method [54] to construct the SPEI datasets for SSP245 and SSP585 scenarios. Before the variables were used to construct the SPEI dataset, the precipitation values in the integrated dataset after model averaging were converted into mm, and the maximum and minimum temperatures were converted from Kelvin to centigrade.

Referring to the current studies [48,55–58], for the SSP245 scenario, the years 2017–2066 and 2036–2066 were used for future projections under 1.5 °C and 2.0 °C warmings, respectively. The corresponding timeframes for the SSP585 were 2015–2045 and 2027–2057.

2.3. Methodology

2.3.1. SPEI and Drought Levels

SPEI was calculated as follows:

- (a) ET_{OH} (mm) was estimated according to the method of Hargreaves [59].

$$ET_{OH} = 0.0023R_a(T + 17.8)\sqrt{T_{max} - T_{min}} \quad (1)$$

where ET_{OH} is the potential evapotranspiration, T , T_{max} , and T_{min} are the monthly maximum, minimum, and mean temperature (°C), R_a is the water equivalent of the extraterrestrial radiation ($\text{mm} \cdot \text{d}^{-1}$) computed according to the monthly total solar radiation [60], with T calculated as the average of T_{max} and T_{min} . The value 0.0023 is the original empirical coefficient proposed by Hargreaves and Samani [54].

- (b) The calculation of the climate–water balance (precipitation–evapotranspiration) deficit or surplus, which is the difference between monthly precipitation and evapotranspiration, was conducted as [61]

$$D_i = P_i - ET_i \quad (2)$$

where D_i is the moisture deficit (mm), P_i is the precipitation (mm), and PET_i is the potential evapotranspiration (mm) for the i th month. The water gain or loss for a month is determined by adding up the accumulated water gain or loss from the previous $n - 1$ months and the current month.

- (c) A three-parameter probability density distribution was utilized, and the D series was standardized using a log-logistic distribution, $f(x)$, expressed as

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x - \gamma}{\alpha} \right)^{\beta-1} \left[1 + \left(\frac{x - \gamma}{\alpha} \right)^{\beta} \right]^{-2} \quad (3)$$

where D is in the range of $\gamma < D < \infty$. Thus, the probability distribution function of D series $F(x)$ is given by Equation (4) as

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

where α , β , and γ are the scale, shape, and origin parameters, respectively, obtained from

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \quad (5)$$

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma\left(1 + \frac{1}{\beta}\right)\Gamma\left(1 - \frac{1}{\beta}\right)} \quad (6)$$

$$\gamma = w_0 - \alpha\Gamma\left(1 + \frac{1}{\beta}\right)\Gamma\left(1 - \frac{1}{\beta}\right) \quad (7)$$

where the k -th probability-weighted moment can be estimated as

$$W_k = \frac{1}{n} \sum_{i=1}^n X_i \left(1 - \frac{i - 0.35}{n} \right)^k, \quad k = 0, 1, 2 \quad (8)$$

where X_i is an ordered random sample $x_1 \leq x_2 \leq \dots \leq x_n$ and n is the sample size.

Next, the probability distribution function $F(x)$ was normalized. We defined P as the SPEI occurrence probability because the standardized values $F(x)$ can be easily calculated [62].

$$P = 1 - F(x) \quad (9)$$

when the cumulative probability $P \leq 0.5$

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \quad (10)$$

when the cumulative probability $P \geq 0.5$

$$P = 1 - P \quad (11)$$

$$SPEI = - \left(W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \right) \quad (12)$$

where $W = \sqrt{-2 \ln(P)}$ for $P < 0.5$, $W = \sqrt{-2 \ln(1 - P)}$ for $P > 0.5$, and P is the probability of D overestimation. $C_0 = 2.515517$; $C_1 = 0.802853$; $C_2 = 0.010328$; $d_1 = 1.432788$; $d_2 = 0.189269$; $d_3 = 0.001308$.

- (d) The SPEI was derived from the standardized values of $F(x)$. A typical classification of the drought index is presented in Table 2 [63].

Table 2. Drought classifications based on the SPEI.

Level	Type	SPEI
1	No drought	$SPEI > -0.5$
2	Mild drought	$-1.0 < SPEI \leq -0.5$
3	Moderate drought	$-1.5 < SPEI \leq -1.0$
4	Severe drought	$-2 < SPEI \leq -1.5$
5	Extreme drought	$SPEI \leq -2$

The monthly SPEI values for each station were computed using an SPEI calculator. In this study, a drought event was identified for $SPEI < -1.0$.

2.3.2. IAD Method

The intensity–area–duration (IAD) method considers both the temporal and spatial aspects of droughts. For drought detection, the IAD method spatially connects regions (clusters) under similar drought conditions [64,65]. Clusters are created from the lowest SPEI center, which is then connected to adjacent grids with lower values until all grids with SPEI values ≤ -1 are combined into a single drought event. Then, the area of consecutive grids is accumulated as the area coverage of the drought event, and the average SPEI value of the grids is defined as the intensity of the drought event [66,67]. To analyze the drought events and their characteristics, we utilized an existing IAD algorithm framework that takes into account the temporal continuity and spatial dynamics of the drought events. The IAD framework is fully described below [68].

(1) To find the strongest center of potential drought events in the monthly SPEI dataset, the highest SPEI value within the threshold range is chosen. Alternatively, the month was assumed to be drought-free.

(2) After identifying all drought events from the monthly SPEI datasets, we repeated the steps (Figure 2b,c) until no point in the region had an average SPEI above the threshold for that month. After finding all regional drought events in the month, we repeated the steps (Figure 2b–d) to find all SPEI dataset drought events for each month. Each drought received a unique number for each year.

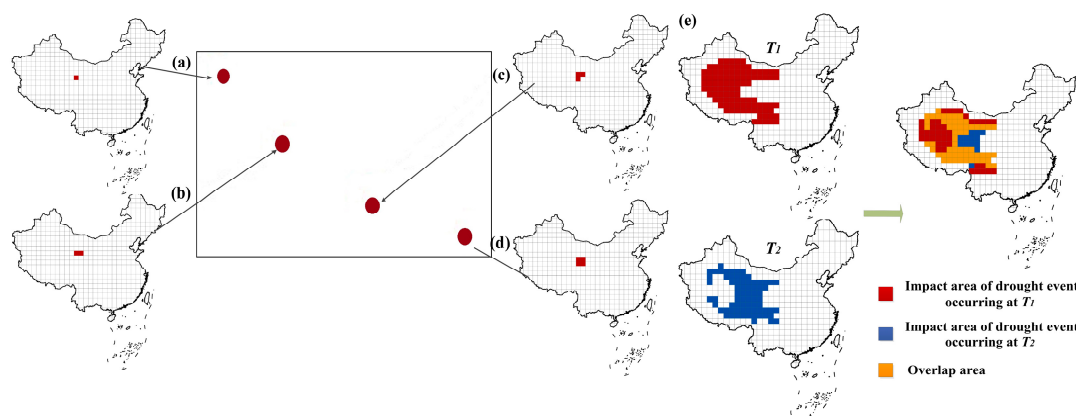


Figure 2. Schematic representation of the analysis. (a) The highest SPEI values from the monthly datasets are identified, and the intensity and area of the starting points are recorded (b,c). (d) The sum of the average intensity of the existing grid points that have been merged into the event range and the area of the established grid points are recorded. (e) The steps are repeated until no grid point in the continuous space exceeds the threshold. Two drought events are considered the same if the overlapping areas in continuous time exceed the area threshold.

(3) Area thresholds were used to establish event temporal consistency. Only events above a certain area threshold were considered. Two consecutive drought events were considered the same if their overlapping areas exceeded the area threshold (Figure 2e). In this study, drought events were considered the same if they occurred within two consecutive time periods and overlapped by more than three pixels within the defined range of influence. Based on this principle, successive instances were compared, and all were connected in space and time and given numerical values.

(4) Three key parameters, including intensity, duration, and impact area, were used to characterize drought events. Intensity is the average SPEI at all grid points within the event, duration is the number of months from the onset to termination, and area of influence is the event's maximum influence.

2.3.3. Theil–Sen Median Trend and Mann–Kendall (MK) Method

The Theil–Sen median trend and Mann–Kendall (MK) method are robust non-parametric statistical trend calculation methods. If there are outliers or non-normal distribution in the data, Theil–Sen trend analysis may be more reliable; this method has high computational efficiency and is suitable for the trend analysis of long time series data. The Mann–Kendall test is a common choice for the statistical test of trend significance. In this study, we used the Theil–Sen median trend and MK tests to analyze the significance of factors associated with drought events. The null hypothesis of the test (H_0) is that there is no trend, and that the data are randomly and independently ordered. The alternative hypothesis (H_1) assumes the presence of a trend [66]. The MK test is dimensionless, and the trend test statistic S was calculated using Equation (13).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (13)$$

in which

$$\text{sgn}(x_j - x_i) = \begin{cases} 1 & \text{if}(x_j - x_i) > 0 \\ 0 & \text{if}(x_j - x_i) = 0 \\ -1 & \text{if}(x_j - x_i) < 0 \end{cases} \quad (14)$$

where S is a normal distribution with a mean value of zero and a variance of

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18} \quad (15)$$

where m denotes the number of tied groups, and t_i represents the number of ties of the extent i . A tied group is a set of data samples with identical values. Finally, the MK rank trend test statistic Z value was calculated using Equation (16).

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if}(S > 0) \\ 0 & \text{if}(S = 0) \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if}(S < 0) \end{cases} \quad (16)$$

where a positive or negative value of Z shows an upward or downward trend. Specifically, at the 95% significance level, the null hypothesis (H_0) is rejected if $|Z| > 1.96$; similarly, at the 90% significance level, the null hypothesis is rejected if $|Z| > 1.64$.

3. Results

3.1. Variation in the Drought Event Characteristics

3.1.1. Drought Event Intensity

A drought event's intensity is the average drought index SPEI at its impact grid points. However, the average intensity does not fully reflect the drought severity. Thus, this study examined the drought event intensity from two angles: annual average and strongest center intensity. The annual average intensity and strongest center expressions differ from the drought intensity expression. A smaller negative value indicates greater intensity, while a larger negative value indicates lower intensity. Unlike the traditional expression, the change trend slope is interpreted differently. Positive value slopes indicate strength decreases, and larger positive numbers indicate a more significant decrease. According to Figure 3a, the annual average intensity and strongest center showed a non-significant increasing trend of -0.002 and -0.04 per decade, respectively, from 1984 to 2014. The annual average minimum was -1.24 in 2002, peaking at -1.34 in 2003, fluctuating frequently during this period. The strongest annual center was -3.09 in 1986, while the weakest was -2.03 in 1989. The annual strongest center fluctuated more than the average intensity. The annual

mean center and strongest center increased during this period, according to decade-specific interannual statistics.

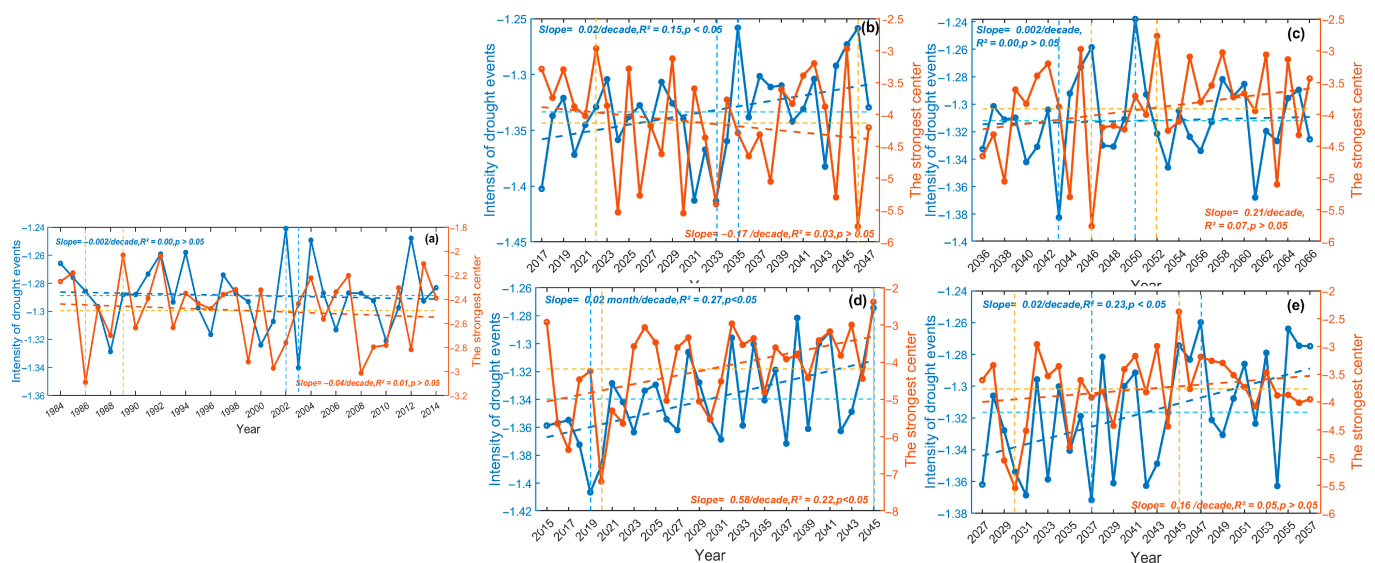


Figure 3. Variations in the intensity and strongest central intensity for drought events. The average annual intensity data are shown for (a) 1984–2014, (b) 2017–2047~SSP245 1.5, (c) 2036–2066~SSP245 2 °C, (d) 2015–2045~SSP585 1.5 °C, and (e) 2027–2057~SSP585 2 °C. Blue and brown solid lines indicate the annual average intensity and the strongest central intensity, respectively; Blue and brown horizontal dashed lines indicate the annual average intensity and the strongest central intensity, respectively; vertical sky blue and light brown dashed lines indicate the minimum and maximum values each year for intensity and the strongest central intensity, respectively.

Under the SSP245~1.5 °C scenario, the average annual intensity during 2017–2047 showed a significant weakening trend of 0.016 per decade (Figure 3b), while the annual center of maximum showed a non-significant upward trend of −0.167 per decade. This suggests that the average intensity of drought events was greater, and the strongest center weakened under this scenario. In 2033, the greatest annual mean intensity is −1.41, and the lowest is −1.26 in 2035. The minimum annual strongest center is −2.97 in 2022, while the maximum is −5.76 in 2046. Figure 3c shows the annual mean intensity and strongest center statistics for 2036–2066 under the SSP245~2 °C scenario. The annual average intensity peaks at −1.38 in 2043 and decreases to −1.24 in 2050. The strongest center has a projected value of −5.76 in 2046 and a smaller value of −2.76 in 2052. The annual average intensity and the strongest center show a non-significant weakening trend of 0.002 per decade and 0.21 per decade, respectively, and the strongest center weakens more than the annual average intensity, indicating that the strongest center for drought events is weakening in this projection period, which matches the slower rate in the annual average intensity. Figure 3c shows that drought events have the highest fluctuation amplitude and a lower annual average intensity. Figure 3d shows that the annual average intensity and strongest center change significantly, with a decreasing trend of 0.018 and 0.58 per decade, respectively, during 2015–2045 under the SSP585~1.5 °C scenario. In 2019, the greatest annual average intensity is −1.41, and the lowest is −1.27 in 2045. The minimum annual strongest center is −2.38 in 2045, while the maximum is −7.2 in 2020. The SSP585~2 °C scenario predicts a significant decreasing trend of 0.018 per decade and a non-significant decreasing trend of 0.16 per decade (Figure 3e). The projected annual average intensity ranges from −1.37 in 2037 to −1.26 in 2047, −5.54 in 2030, and −2.38 in 2045.

Figure 4a shows that the drought intensity increased with the duration from 1984–2014, with a trend of −0.17 per decade. However, the strongest center was the opposite, with a slope of 0.74 per decade. A trend of −0.59 per decade indicates an increase in the

mean intensity with the duration, while the strongest center shows an opposite trend to the reference time period. The average intensity of drought events increased with the duration during the forecast time period of 2036–2066 (Figure 4c), while the strongest center followed the reference time period. The strongest centers showed an overall weakening trend. During January–May, it showed a weakening trend, while during June–November, it showed a significant increase. The projected time period of 2015–2045 and the average intensity of drought events from 2027–2057 both increase (Figure 4d,e), while the strongest center of intensity weakens.

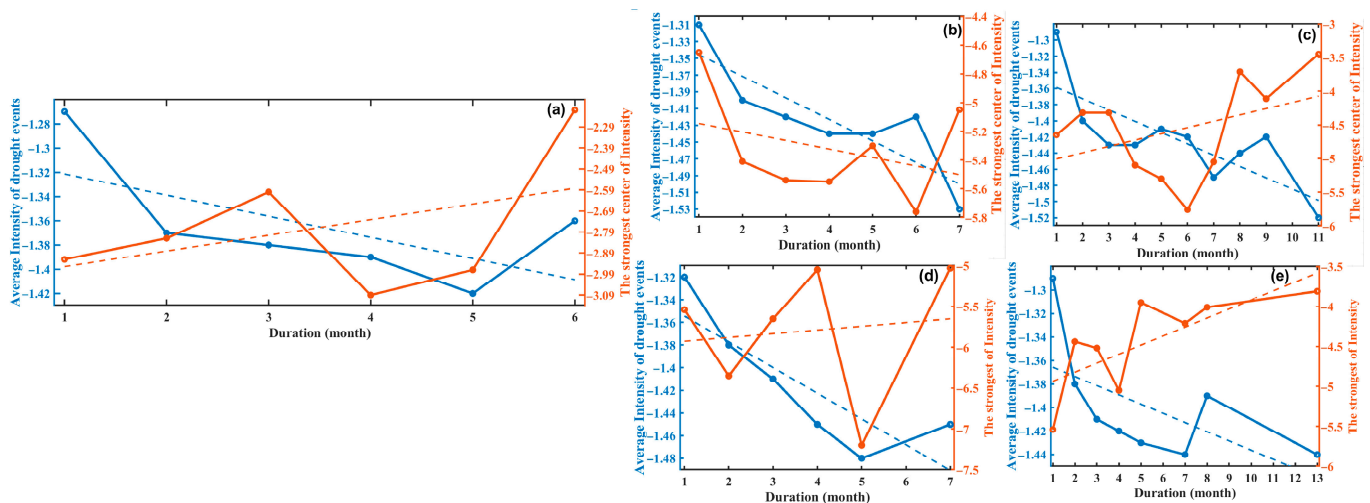


Figure 4. Trends for the average intensity and strongest centers for drought events with increased duration. Trends in the average intensity and strongest center changes for drought events with duration increase for (a) 1984–2014, (b) 2017–2047 for the SSP245 ~ 1.5 °C, (c) 2036–2066 for the SSP245~1.5 °C, (d) 2015–2045 for the SSP585~1.5 °C, and (e) 2027–2057 for the SSP585~2 °C. The blue and brown solid lines indicate the changes in mean intensity and strongest center for drought events under different duration conditions, and the blue and brown dashed lines indicate the slopes of the changes in the mean and strongest center intensities, respectively, during each study period.

Figure 5a depicts the reference time drought intensity spatial distribution. Larger drought mean intensity distributions were found in northern XJ and southwestern and central QTP. Drought intensity clustering in SC and SW was stronger, with 5.73% of the study area having an intensity >-1.4 . In the north of XJ and QTP, the western part of NW has a weaker drought intensity. About 1.7% of the study area had intensity values greater and less than -1.2 . Figure 5f shows a weakening trend in central QTP, northern NC, and southeastern NW (8.48% of the study area) and an increasing trend in northern SC, northeastern SW, and northwestern NE (-0.33 per decade), with the highest value in the eastern SW. Figure 5j reveals a significantly enhanced clustering area for the MK test in the northwestern part of SC and central and western parts of SW, covering 13.31×10^5 km², or 11.66% of the Chinese mainland. Similarly, 14.64×10^5 km² ($p < 0.05$) exhibited a distribution pattern centered at the SC/NC junction and northern NE, while 13.31×10^5 km² showed a minimally significant trend focusing on aggregation and scattered distribution in northwestern NE. A significant weakening trend is observed in the southwestern part of QTP and central NC, covering 13.31×10^4 km².

Based on the SSP245~1.5 °C scenario, Figure 5b shows that the drought temporal intensity during 2017–2047 was mostly in the southwest of SW and southwest of QTP. Northern XJ had a higher intensity aggregation. About 62.67% of the study area had a drought intensity ≥ 1.4 , with an average intensity of -1.43 . The intensity value and spatial distribution were higher in western SW, southwestern QTP, northern XJ, central SC, NC, southwestern NW, and southern NE. Weaker droughts were detected in western QTP, southern XJ, and eastern NW. Figure 5g,l show that the drought intensity increased over

time in southwest QTP, north and south XJ, the middle and west NE, and northeast NW, which accounted for 23.97% of the Chinese mainland. The drought's intensity gradually decreased over time, with signs of weakening in northwestern XJ. Southern XJ had a strong and significant enhancement trend, and approximately 20.25% of regions were significant ($p < 0.05$) in the MK test.

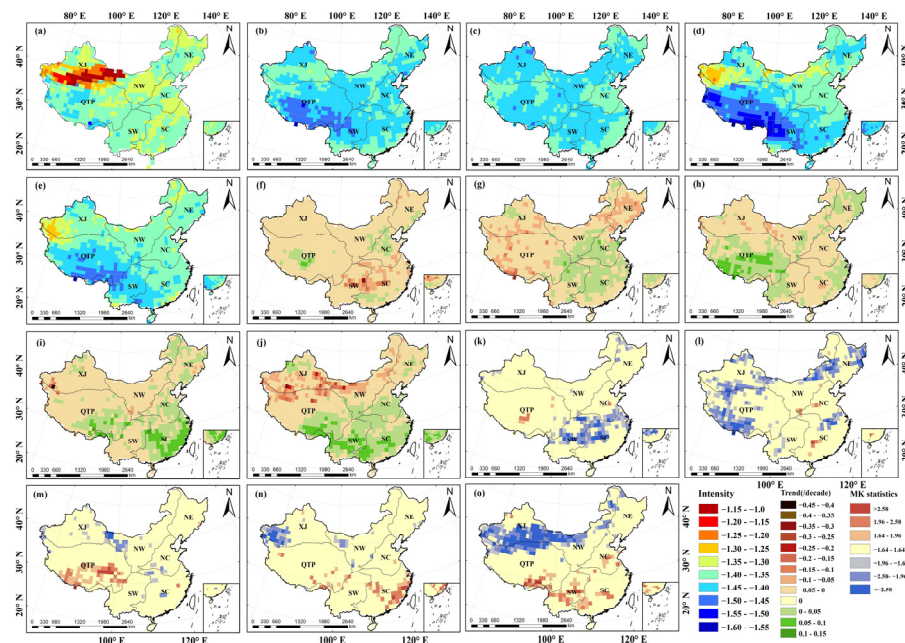


Figure 5. Spatial distributions for the intensity (a–e), change trend (f–j), and Mann–Kendall statistics (k–o).

In the SSP245~2 °C scenario, drought events had a maximum intensity of -1.46 during 2036–2066, covering $77.8 \times 10^5 \text{ km}^2$ (68.19% of the study area). It was mostly found in SW, northwestern SC, QTP, NW, XJ, the NE southeastern, and northern ranges of SC (Figure 5c). The changing trend created a drought enhancement zone in most of SW, NW SC, and southern NC. Over time, the drought intensity decreased in central QTP, southwestern SC, and central NC (Figure 5h,m), but increased in northwestern NW, southwestern NC, central SC, and northwestern NW, with 12.2% of the area showing a significant enhancement ($p < 0.05$).

The drought intensity in the SSP585~1.5 °C scenario during 2015–2045 clustered in southwestern QTP, southern SW, and northern XJ, covering $6.9 \times 10^5 \text{ km}^2$ (Figure 5d). In southwestern XJ, the drought intensity was more widespread, with a considerable value of < -1.3 aggregation range and an area of $2.78 \times 10^5 \text{ km}^2$. The drought intensity decreased significantly over time in SC, southeast QTP, eastern NE, NC, and northeast NW regions, covering 46.13% of the study area (~11.3% of the total). At the junction of northwestern QTP and southwestern XJ, the drought intensity increased over an area of $6.53 \times 10^5 \text{ km}^2$, comprising 5.73% of the study area.

Drought events exceeding -1.4 intensity in the SSP585~2 °C scenario during 2027–2057 were concentrated in southwestern QTP and western SW, with a few high-intensity regions in southwestern SC and northern XJ, covering 31.71% of the study area. Northern QTP and southern XJ show low drought intensity aggregation, covering an area of about $1.82 \times 10^5 \text{ km}^2$. The study found that drought intensity increased in northern QTP, southern XJ, and northwestern NW, covering $4.48 \times 10^5 \text{ km}^2$, while southeastern QTP, central SW, and southcentral SC showed a weakening trend, affecting 6.26% of the study area. According to the MK test, the significant drought intensity trend ($p < 0.05$) covered about 29.59% of the study area. An enhanced drought intensity of $24.68 \times 10^5 \text{ km}^2$ was observed in northern QTP, southern XJ, and northern NW, forming a band-like large-scale aggregated

area. Only 7.85% of southeastern QTP, southern SW, and western SC showed a significant weakening trend.

3.1.2. Variations in Area Influenced by the Drought Events

The cumulative effect area averaged $98.28 \times 10^5 \text{ km}^2$ from 1984–2014, peaking at $17.08 \times 10^6 \text{ km}^2$ in 2010, 1.6 times the total study area (Figure 6a). The lowest annual average drought impact area was $4.86 \times 10^5 \text{ km}^2$ in 1984. Over the 31-year reference period, the cumulative area increased by up to $13.59 \times 10^5 \text{ km}^2$ per decade. Figure 6b displays the sustained warming in the SSP245~1.5 °C scenario during 2017–2047. The annual average cumulative area was $19.88 \times 10^5 \text{ km}^2$, 1.8 times the study area. The cumulative area affected by drought events was approximately 3.2 times the study area. Currently, the cumulative area is growing at $32.92 \times 10^5 \text{ km}^2$ per decade. Using the SSP245 scenario, the cumulative impact area from 2036 to 2066 averaged $25.11 \times 10^6 \text{ km}^2$, an increasing trend.

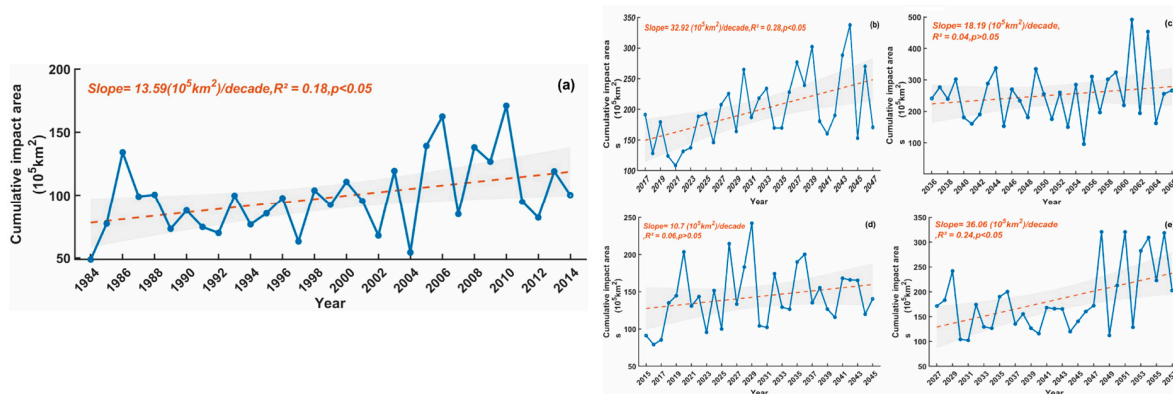


Figure 6. Statistics for the cumulative area affected by drought events during (a) 1984–2014, (b) 2017–2047 for the SSP245 ~ 1.5 °C, (c) 2036–2066 for the SSP245 ~ 2 °C, (d) 2015–2045 for the SSP585~1.5 °C, and (e) 2027–2057 for the SSP585 ~ 2 °C continuous warming period model. The brown dashed line indicates the slope of the cumulative impact area change in the corresponding time period, and the shaded area is the range of significance statistics of the 95% confidence interval for each slope.

Using the SSP585~1.5 °C scenario, Figure 6d shows a sustained warming period with an average cumulative impact area of $14.37 \times 10^6 \text{ km}^2$, indicating a non-significant increasing trend. Figure 6e depicts the results for the SSP585~2 °C scenario. The cumulative impact area averaged $18.32 \times 10^6 \text{ km}^2$ annually, 1.7 times the study area, with the minimum in 2031. In 2054, the cumulative impact area reached $30.93 \times 10^6 \text{ km}^2$, which is 3.1 times the total Chinese mainland. The cumulative impact area increased by $36.06 \times 10^5 \text{ km}^2$ per decade during this period.

During the reference period, SC had the largest cumulative effect area (31.02%) of $94.51 \times 10^6 \text{ km}^2$ and the largest increasing trend ($61.53 \times 10^4 \text{ km}^2$ per decade). Table A1 shows that the cumulative effect area in XJ was the smallest at 4.32%, while in NC, the annual cumulative area decreased by $8.13 \times 10^4 \text{ km}^2$ per decade. Regional trends showed varying increases, except for NW, where the annual cumulative area decreased by $-1.28 \times 10^4 \text{ km}^2$ per decade.

In the SSP245~1.5 °C scenario during 2017–2047, the QTP has the largest cumulative effect area at $222.24 \times 10^7 \text{ km}^2$, followed by NE at $117.48 \times 10^6 \text{ km}^2$ (36.06% and 19.06%, respectively). Meanwhile, the QTP had a maximum annual cumulative area increase of $35.6 \times 10^5 \text{ km}^2$ per decade, while SC had a maximum decrease of $-72.93 \times 10^4 \text{ km}^2$ per decade. In the SSP245~2 °C scenario during 2036–2066, the QTP had the largest cumulative effect area ($37.01 \times 10^7 \text{ km}^2$) and the largest increase in the annual cumulative influence area ($17.15 \times 10^5 \text{ km}^2$ per decade), accounting for 47.54% of the total cumulative area. The

increasing trends for SC and SW were $41.0 \times 10^4 \text{ km}^2$ per decade and $6.27 \times 10^4 \text{ km}^2$ per decade, respectively. Other regions showed different decreasing trends.

In the SSP585~1.5 °C scenario from 2015 to 2045, the QTP and SC cumulative impact areas accounted for 27.98% and 20.52% of sustained warming. The annual cumulative effect areas increased by $130 \times 10^4 \text{ km}^2$ per decade in NE and $35.6 \times 10^4 \text{ km}^2$ in SC. The QTP was the only region with a non-significant decreasing trend. Using the SSP585 ~ 2 °C scenario during 2027–2057, the cumulative drought effect area was balanced across regions, with the largest area in NE. During the projection period, the annual cumulative effect area showed significant changes, with NE increasing by $202.85 \times 10^4 \text{ km}^2$ per decade and SC decreasing by $-58.37 \times 10^4 \text{ km}^2$ per decade.

3.1.3. Variation in Drought Event Duration

The average annual duration of drought events from 1984 to 2014 was 1.29 months, with a maximum of 1.75 months (Figure 7a). This period saw a non-significant increase in drought event duration, reaching 0.08 months per decade. The duration averaged 3.26 months annually, and the longest was 6 months. The SSP245~2 °C scenario during 2017–2047 showed a non-significant increasing trend of 0.07 months per decade (Figure 7b). The longest annual average drought duration was 1.42 months, increasing by 0.59 months per decade, and averaged 4.77 months. During 2036–2066, the maximum annual mean duration of drought events was 1.84 months in 2056, with an average of 1.46 months. The trend for the annual average duration of drought events was not significant. The longest annual duration of drought events was 11 months in 2061, and the average annual maximum duration was 6.1 months. The tendency for the longest annual duration increased non-significantly over time.

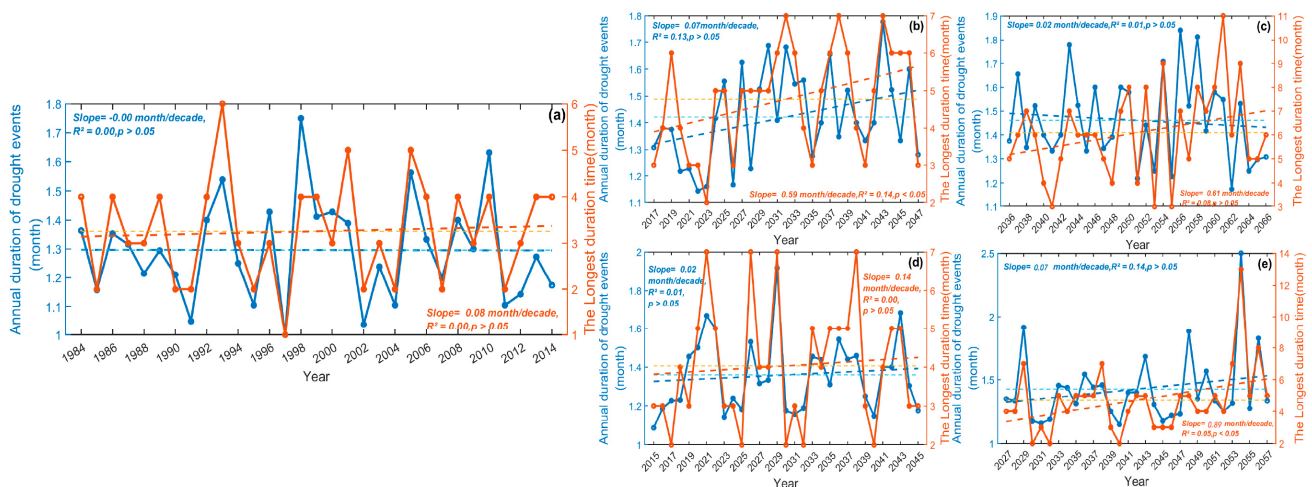


Figure 7. Duration statistics for drought events. The changes in annual average duration and annual longest duration in (a) 1984–2014, (b) 2017–2047 for the SSP245~1.5 °C, (c) 2036–2066 for the SSP245~2 °C, (d) 2015–2045 for the SSP585~1.5 °C, and (e) 2027–2057 for the SSP585~2 °C. The blue lines indicate the annual mean duration changes, and the brown lines indicate the annual longest durations for the drought events. The dashed lines with the corresponding colors indicate the slope of the trend. The labels in each panel correspond to the lines of the same color.

Figure 7d shows that the SSP585~1.5 °C scenario during 2015–2045 had a maximum annual average duration of 1.91 months in 2029, with an average of 1.36 months. The annual average duration increased by 0.02 months per decade, the average annual maximum duration was 4.03 months, and the maximum annual duration was 7 months, increasing by 0.14 months per decade. The SSP585~2 °C scenario during 2027–2057 (Figure 7e) showed a non-significant increasing trend of 0.07 months per decade, a maximum annual mean duration of 2.5 months in 2054, an average of 1.42 months, and a projected longest duration

of 13 months in 2054, with an average of 4.71 months. The longest duration increased non-significantly by 0.89 months per decade.

Based on the analysis results of the accumulated impact area characteristics of drought events in Section 3.1.2, it can be observed from the accumulated statistics of impact areas for drought events of the same duration (Figure 8) that the longer the duration of a drought event, the smaller the accumulated impact area. Conversely, the average impact area tends to be larger for drought events of longer duration. However, this pattern is not entirely consistent; for instance, during the periods 2036–2066 under SSP245 with a 2 °C increase (Figure 8b) and 2015–2045 under SSP585 with a 1.5 °C increase (Figure 8c), the accumulated impact areas for drought events lasting 4–6 months exhibit anomalous behavior.

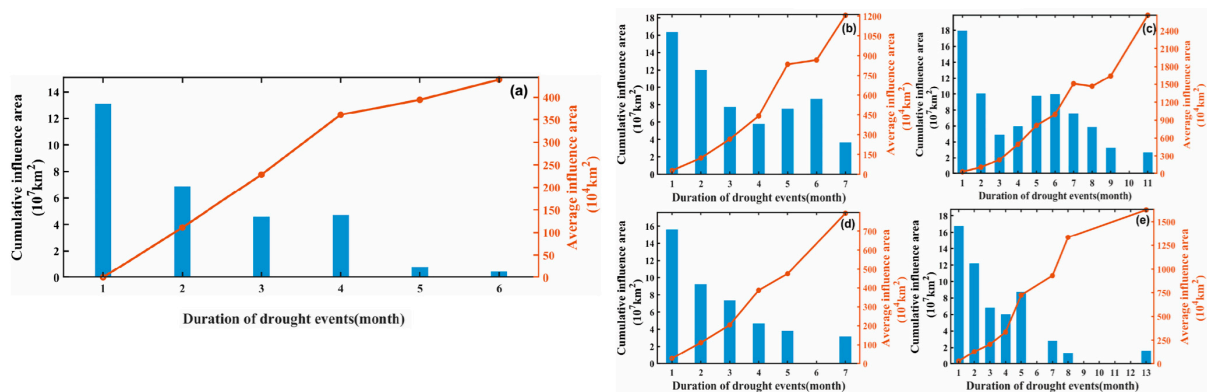


Figure 8. Trends in the cumulative and average impact areas corresponding to the increased duration of the drought events in (a) 1984–2014, (b) 2017–2047 for the SSP245~1.5 °C, (c) 2036–2066 for the SSP245~2 °C, (d) 2015–2045 for the SSP585~1.5 °C, and (e) 2027–2057 for the SSP585~2 °C. Blue bars indicate the cumulative impact area for the drought events of the same duration, and the brown line indicates the change in the mean impact area for the drought events with different durations.

Figure 9a depicts the average drought duration spatially during the reference period. Northern QTP has the longest duration of 4.1 months, covering an area of only $1.21 \times 10^4 \text{ km}^2$. Longer droughts occur in northern QTP, southern XJ, and a small area in western NW, covering $5.32 \times 10^5 \text{ km}^2$ (4.66% of the study area) and lasting 3–4 months. South SC, south SW, southwestern QTP, most of NE, northwestern NW, and northern XJ have areas with 1–2-month durations, covering $38.84 \times 10^5 \text{ km}^2$. Drought events in western SC and eastern SW have a small but significant increase in duration, covering $8.95 \times 10^5 \text{ km}^2$. The weakening trend is limited to $1.21 \times 10^4 \text{ km}^2$ in northern SC. According to the MK test, 20.78% of the area was significant ($p < 0.05$). Figure 9k shows a significant increase in drought duration in western SC, northern SW, southern NC, and a small clustering in northern NE, covering $16.7 \times 10^5 \text{ km}^2$. However, only $7.26 \times 10^4 \text{ km}^2$ of the area exhibits significant weakening, which is scattered in the QTP.

Figure 9b shows the distribution of the drought duration in 2017–2047 under the SSP245~1.5 °C scenario. Northern SW and southern XJ have longer drought durations. A few 3–4-month regions are scattered in northern NC and northwestern NW, with an average duration of 3.25 months. Areas with 1-month duration were mostly found in northern NE, northeastern NW, southern QTP, northern XJ, and a few areas in southern SC. The southern part of XJ had a larger area with an increasing trend, accounting for 37.22% of the study area (Figure 9g). Only $4.84 \times 10^4 \text{ km}^2$ of SC shows a significant weakening trend. Figure 9k reveals that 28.42% of the study area had a significant ($p < 0.05$) increasing trend in western SC, northern SW, and northern NE, covering $31.34 \times 10^5 \text{ km}^2$ or 27.47% of the study area. Only $1.21 \times 10^4 \text{ km}^2$ of the area showed significant weakening.

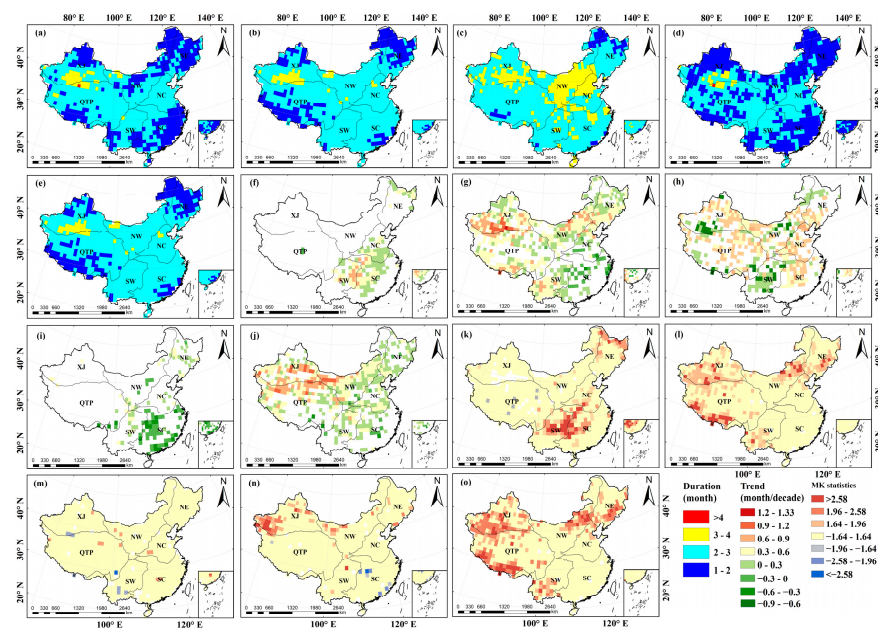


Figure 9. Spatial distribution of the duration (a–e), change trend (f–j), and MK statistics (k–o).

3.2. Analysis of the Spatiotemporal Evolution of Drought Events

Based on the drought event identification results, the longest-lasting drought event between 2027 and 2057 was chosen to study its evolutionary process. The longest drought event's intensity and affected area decreased over time, peaking in September 2063. In October of 2063, the drought depth reached its peak. Figure 10 shows that in September and October of 2063, the drought intensity and area are high.

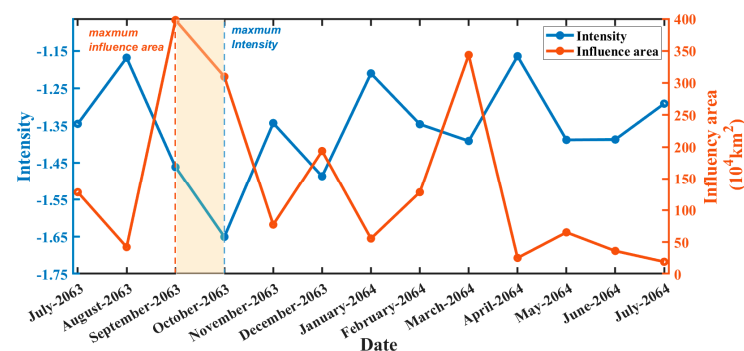


Figure 10. Evolution process for the drought event with the longest duration and comparison between the event's intensity and influence area. The light brown shaded area indicates the most severe moment of the drought event, when both the affected area and the intensity of the drought are at their maximum at the same time.

To show the drought intensity changes more clearly, we plotted the location with the highest intensity throughout the event (Figure 11). We also showed the event duration's spatial distribution (Figure 12). The drought event's temporal and spatial fluctuations reveal its evolution.

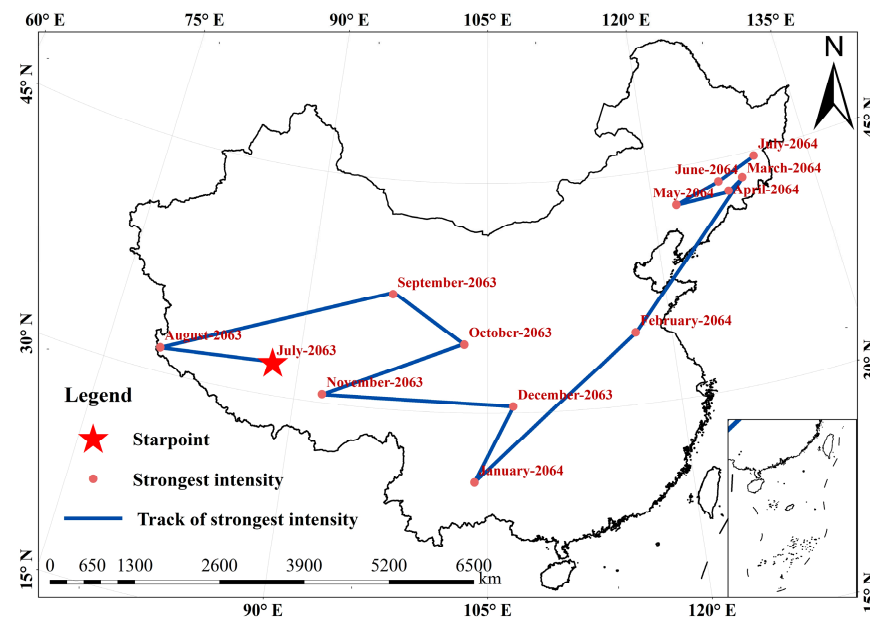


Figure 11. Dynamic variations in the strongest intensity location of the drought event with the longest duration.

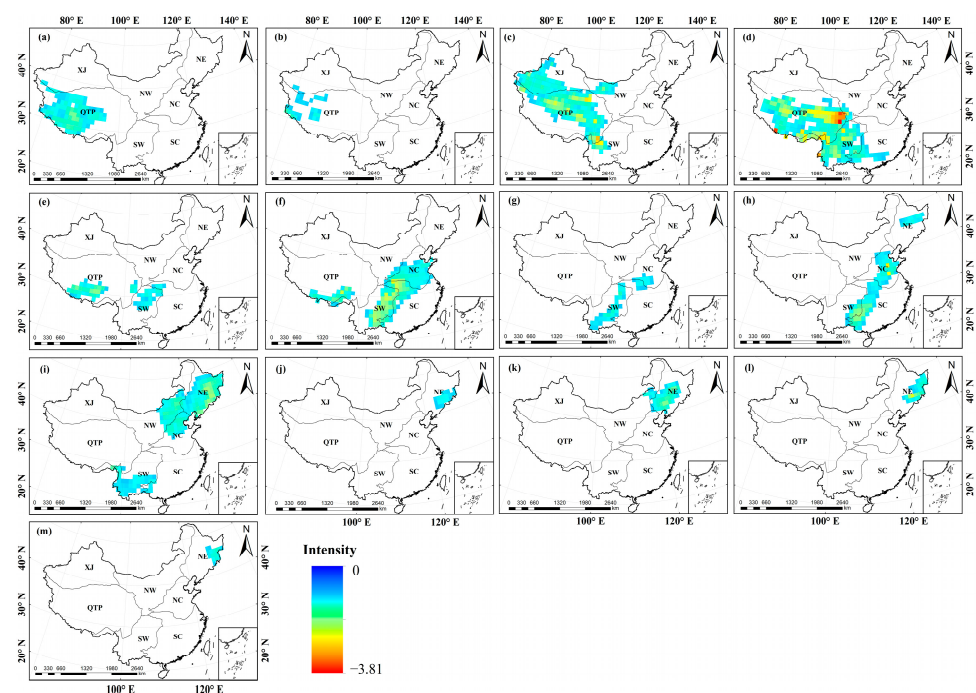


Figure 12. The spatiotemporal evolution process of the drought event with the longest duration (a–m).

The drought began in July 2063 in central QTP (Figure 11), affecting southern areas such as Geer County, Shigatse, Lhasa, Naqu County, Geermu, Zhiduo County, and Hotan City. It covered $13.83 \times 10^5 \text{ km}^2$ and spread northwest to the west of Naqu County, southwest and north of Gar County, south of Hotan City, and south of Korla in the QTP area, covering $4.24 \times 10^5 \text{ km}^2$. In September 2063, the drought impacted a large area of $29.52 \times 10^5 \text{ km}^2$ in southwest XJ, the QTP, and part of west NW, with the strongest center intensity moving from Zada County to Wulan County in the QTP (Figure 12c). In SW, Naqu, Seda, and Yanyuan counties had several intensity extremes. Nagqu County had the strongest center. With an area of $30.98 \times 10^5 \text{ km}^2$, it covered the entire SW, most of

the QTP, and the southern part of NW, accounting for 27.15% of the study area. It then moved towards southeastern QTP and almost reached SW and southwestern SC. The intensity peaked at -3.81 in Zhuoni County. The impact area was significantly reduced to $5.57 \times 10^5 \text{ km}^2$ in November of the same year. Two regions are presented: one in the southwest of the QTP (approximately $3.87 \times 10^5 \text{ km}^2$) and the other in the northern part of SW and northwest of SC (approximately $3.87 \times 10^5 \text{ km}^2$). Southwest QTP's drought is stronger than the latter, with Lhasa and Shigatse being the strongest centers. During December, the drought impact range moved north of SC and covered $16.98 \times 10^5 \text{ km}^2$ in the south of NC. SW had high-intensity values, forming a dry-intensity drought belt from southwest to northeast.

In January 2064, the drought weakened and shifted southwest-to-northeast (Figure 12g), with an impact area of $5.58 \times 10^5 \text{ km}^2$. The intensity was concentrated in two areas with very high values, with central Qujing City having the highest values. As the drought moved northwest, its impact area grew. The drought area was expanded from the January banded area and connected to form a wider unit. Jinan and the borders of Xuzhou, Zaozhuang, and Jining had the worst droughts. In addition to the banded drought area, a low-value drought area of $2.3 \times 10^5 \text{ km}^2$ appeared in northern NE. The drought expanded northward in March, covering the entire NE and western NW. In NC and other areas, the drought covered $19.84 \times 10^5 \text{ km}^2$, while in SW, it was smaller at $4.84 \times 10^5 \text{ km}^2$. A high-intensity aggregation band formed in eastern NE, with Mudanjiang City experiencing the worst drought. The drought impact area decreased to $2.54 \times 10^5 \text{ km}^2$ in April 2064, with the strongest center in Jilin city in NE, with minimum migration. In May 2064, the drought moved southwest, affecting southern NE and NW, peaking in Fuxin City. Finally, the drought moved northwest near the NW NE border. The affected area shrank to $3.63 \times 10^5 \text{ km}^2$, with the highest intensity in Jilin City. Over time, the drought shifted northwest and weakened, with the highest intensity in Mudanjiang City (Figure 12m). The intensity value also decreased significantly compared to the previous period.

4. Discussion

Based on CMIP6 model data, different scenario models (SSP245, SSP585) for China and its seven geographic subregions were examined to characterize the intensity, projected impact area, and projected durations of future drought projections. The future drought intensity, impact area, and duration were examined. Using the IAD method and monthly SPEI dataset, the spatiotemporal characteristics of drought events were examined. The medium- and high-emission scenarios (SSP245 and SSP585) showed that the 2°C global warming scenario would increase the drought intensity, cumulative impact area, and average duration in China compared to 1.5°C . Additionally, the cumulative impact area of droughts may increase by 1.4 to $16.2 \times 10^7 \text{ km}^2$, equivalent to 14.2 times the Chinese mainland. Our results showed that the severity and cumulative impact area increased to various degrees. The cumulative impact area increased by $12.25 \times 10^7 \text{ km}^2$, 10.74 times the Chinese mainland, similar to the findings of Chen [68].

In the SSP245~ 2°C scenario, compared to SSP245~ 1.5°C (Figure 13a), the drought intensity shows a larger distribution of the annual mean drought intensity with an enhancement in southwestern QTP, the western part of SW, northern QTP, southern XJ, and northwestern NW. Moreover, there is an area with weakened drought intensity in northern SW, northwestern and southwestern SC, and southwestern NC. The northwest and northeast of China's major territory tend to have more intense droughts in relation to the features of drought intensity, which increase with global warming, which is consistent with the results of existing studies [61,69,70]. Regarding the drought duration (Figure 13c), there is an upward trend in northern XJ, central NW, and most regions in NC and southwestern NE. Conversely, there is a weakening trend in southern XJ and southwestern SW. This suggests that as temperatures continue to rise, the duration of droughts is shifting towards the northwestern and northeastern regions of the Chinese mainland.

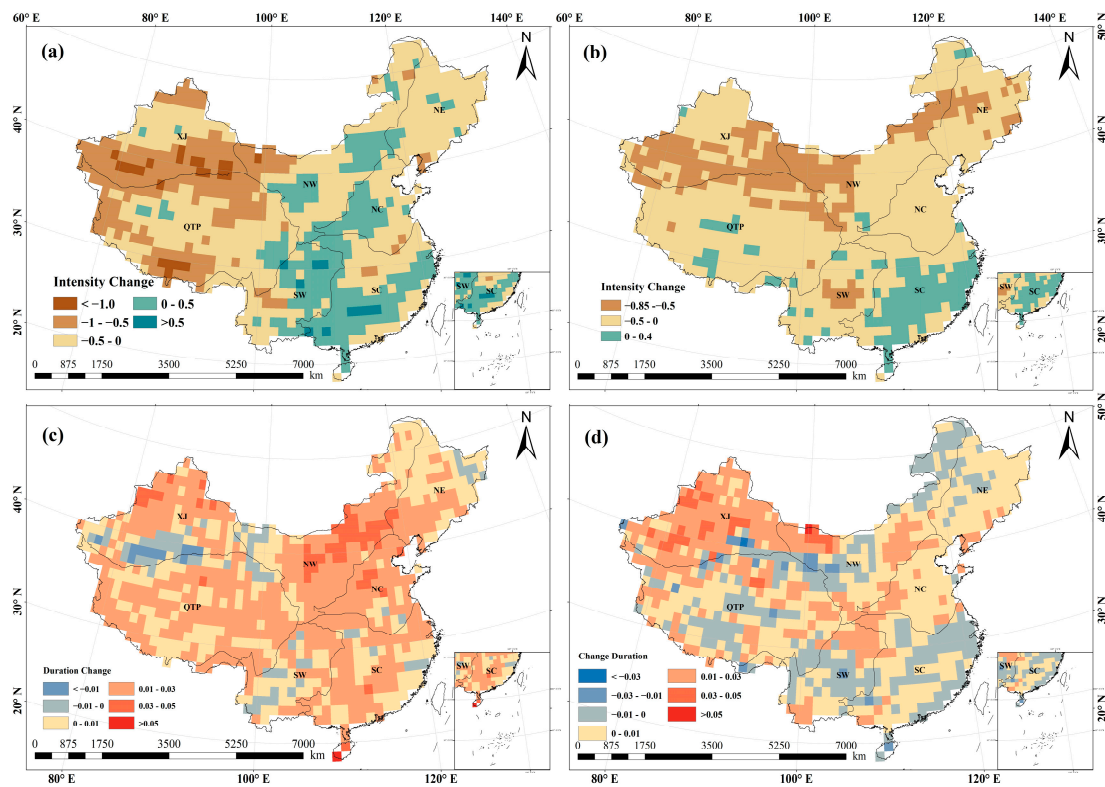


Figure 13. For the medium-emission scenario model SSP245, the change trends in drought intensity, duration of (a) intensity, and (c) duration. For the high-emission scenario model SSP585, the change trends of (b) intensity and (d) duration. This figure shows the annual average change in drought characteristics (severity and duration) over time, not variations in the warming contexts of the scenarios for the same time period in the same year.

Under the SSP585~2 °C scenario, compared with the SSP585~1.5 °C scenario (Figure 13b), there are larger bands of significantly enhanced drought intensity in northern QTP, XJ, and western NW, western NE, and northeastern NW. There is a large band with weakening drought intensity in central SC, and a small trend of weakening drought intensity in southwestern QTP and southeastern SW. With this scenario, the drought intensity tends to shift towards the northwest and northeast of the Chinese mainland. In terms of the drought duration (Figure 13d), there is an increasing drought duration trend in most parts of XJ and northwestern NW, while there is a clustering trend with shorter durations in central QTP, eastern SC, and central SW, as well as in western and northeastern NW. This suggests that the drought duration characteristics are associated with the persistent increase in temperature. Furthermore, there is a noticeable trend towards longer periods of drought in the northwestern region of mainland China.

This study's global warming analysis under two medium- and high-emission scenarios, SSP245 and SSP585, matches existing reports [61,68,70]. Additionally, this study found that the drought intensity in southwestern China decreased with incremental 1.5 °C increases to reach the upper limit of 2 °C (Figure 5h,m). Further analysis found that the scPDSI algorithm for identifying drought events and the Penman–Monteith method for assessing PET are different from the algorithms used to identify droughts in this study. This also shows that the choice of drought indices and the method for calculating the evapotranspiration process affect drought uncertainty.

4.1. Uncertainty in the GCM Model Data and Drought Identification Methods

Both scenario-based future studies may be uncertain due to GCM model internal variability, parameterization, and emission pathways. This study selected monthly scenario

product data from the CMIP6 model for MPI-ESM1-2-HR, GFDL-ESM4, IPSL-CM6A-LR, MRI-ESM2-0, and UKESM1-0-LL. In this study, $1^\circ \times 1^\circ$ data were used. The regional meteorological dataset in China describes the real surface situation, which may affect the SPEI calculated in this study and the identification and spatiotemporal analysis of drought events. Since the drought has no authoritative definition, most current studies set parameters empirically and artificially, such as the drought intensity and minimum event area. Ren et al. [69] examined the sensitivity of the minimum overlap area of drought events in adjacent times and found that different overlap area settings would increase the drought number, intensity, and duration, which would affect drought identification and spatiotemporal analyses.

4.2. Detection of Correlations between Drought Event Characteristics (Intensity, Impact Area, and Duration)

Table A2 shows a simple Pearson correlation analysis of the drought intensity, impact area, and duration. Note that these scenarios only summarize interannual averages of characteristics over each period. The intensity of drought events was negatively correlated with the cumulative area and duration within the historical reference time. The drought duration and cumulative area had a significant positive correlation. This finding suggests that in the historical reference time, drought events with a larger area of influence may be longer and more intense.

In the SSP245~1.5 °C scenario during 2017–2047, the duration of drought events showed positive and negative correlations with the cumulative impact area and drought intensity, respectively, which were consistent with the historical reference time analysis, while the intensity and the cumulative impact area correlations showed large differences. In the SSP245~2 °C scenario during 2036–2066, the drought cumulative impact area showed a significant negative and positive correlation with the intensity and duration, respectively, which was consistent with the historical reference time analysis, while the intensity and duration correlations showed large differences, suggesting that a larger impact area may be associated with a longer duration of severe drought events. The duration of drought events showed negative and positive correlations with the intensity and cumulative impact area under the high-emission scenarios, which were consistent with the historical reference time analysis, while the intensity and cumulative impact area correlations showed the exact opposite.

In the medium- and high-emission scenarios, only the correlation between the duration of the drought event and cumulative impact area is consistent with the historical reference time analysis results, and the correlation between other features is significantly different from the historical reference analysis results, in which drought events occur with greater volatility and lack statistical regularity, confirming that GCM data are also uncertain.

5. Conclusions

The findings in this study can be concluded as follows:

Shorter drought events were more frequent. The CMIP6 model accurately simulates historical drought events. The medium- and high-emission scenarios showed an enhanced drought event intensity and duration. In the SSP245-1.5 °C scenario, the drought intensity increase was mainly distributed in southern XJ, southwest and northern QTP and southwest SW, and in southwest QTP, NE, and southern XJ, there is a significant trend of enhancement. With the increase in global warming, the drought intensity shifts to the northwest and southeast China. In this scenario, drought events of greater duration occurred mainly in northern QTP, southern XJ, northwestern and southwestern NW, and northern NC. There is a significant increasing trend in southern XJ, southern QTP, southwestern SW, and eastern NW. With continued global warming, it shows that the center of drought events with a longer duration of drought mainly shifts to the northwest and northeast China.

In the SSP585~1.5 °C scenario, an event of greater drought intensity mainly occurred in the QTP, southwest SW, and southern SC. Over time, in southern XJ, southern QTP,

southwestern SW, and eastern NW, there is a significant trend of enhancement but this decreased in the QTP and southeastern SC. And drought intensity to the northwest and southeast China, and drought duration to the northwest and northeast China. With the increase in global warming, the distribution center of drought events with a higher drought duration gradually shifted to northwest and northeast China. In this scenario, the drought events with a longer duration were mainly distributed in southeast XJ and north QTP. With the passage of time, the drought duration showed a decreasing trend in SC. In SSP585-2 °C, the increasing duration of drought mainly occurred in southern XJ, northern NW, and northern NC. Over time, the characteristics of drought increased significantly in XJ, northern QTP, and northwestern NW. Under the condition of continuous global warming, the center of drought events with greater a drought duration tends to shift towards northwestern and northeastern China. The findings are important for understanding the drought situation in the future of China and the related water resources management and climate change adaptation.

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Appendix A

Table A1. Cumulative effect area (CEA) of the drought events in seven regions of China during the study periods.

Period	Region	NW	XJ	SW	SC	NE	QTP	NC
Historical 1984–2014	CEA (10 ⁶ km ²)	20.75	13.16	14.40	94.51	46.83	57.68	57.34
	Percentage (%)	6.81	4.32	4.73	31.02	15.37	18.93	18.82
	Slope (10 ⁴ km ² per decade)	−1.28	10.55	12.85	61.53	33.09	27.34	−8.13
SS24-5 1.5 °C 2017–2047	CEA (10 ⁶ km ²)	45.54	47.71	29.29	85.12	117.48	222.24	68.99
	Percentage (%)	7.39	7.74	4.75	13.81	19.06	36.06	11.19
	Slope (10 ⁴ km ² per decade)	−15.48	−10.84	6.23	−72.93	55.98	356 **	10.19
SS24-5 2 °C 2036–2066	CEA (10 ⁶ km ²)	39.25	57.71	23.23	78.76	116.44	370.09	92.93
	Percentage (%)	5.04	7.41	2.98	10.12	14.96	47.54	11.94
	Slope (10 ⁴ km ² per decade)	−0.89	−4.11	6.27	41.10	−30.01	171.52	−1.95
SS58-5 1.5 °C 2015–2045	CEA (10 ⁶ km ²)	41.53	31.38	16.87	91.38	77.75	124.64	61.86
	Percentage (%)	9.32	7.04	3.79	20.52	17.46	27.98	13.89
	Slope (10 ⁴ km ² per decade)	19.66	34.42	0.56	35.60	130	−43.58	15.94
SS58-5 2 °C 2027–2057	CEA (10 ⁶ km ²)	50.46	50.01	18.75	92.61	143.48	143.08	69.55
	Percentage (%)	8.88	8.81	3.30	16.31	25.26	25.19	12.25
	Slope (10 ⁴ km ² per decade)	17.06	54.09	8.11	−58.37	202.85	143.12	−6.27

Note: “***” denotes that the corresponding change rates are statistically significant at 99%, and bold numbers indicate a decreasing trend.

Table A2. Correlations between the intensity, influence area, and duration.

Period	Characteristic	Intensity	Area	Duration
Historical 1984–2014	Intensity	1	−0.61 **	−0.36 *
	Area	−0.61 **	1	0.53 **
	Duration	−0.36 *	0.53 **	1
SSP245-1.5 °C 2017–2047	Intensity	1	0.11	−0.16
	Area	0.11	1	0.69 **
	Duration	−0.16	0.69 **	1
SSP245-2 °C 2036–2066	Intensity	1	−0.14	0.03
	Area	−0.14	1	0.57 **
	Duration	0.03	0.57 **	1
SSP585-1.5 °C 2015–2045	Intensity	1	0.16	−0.01
	Area	0.16	1	0.67 **
	Duration	−0.01	0.67 **	1
SSP585-2 °C 2027–2057	Intensity	1	0.29	−0.22
	Area	0.29	1	0.63 **
	Duration	−0.22	0.63 **	1

Note: * and ** indicate significance at 0.05 and 0.01, respectively.

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