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Characteristics and Causes of Meteorological Drought in Zhejiang Province (1971–2020): Insights from Comprehensive Discrimination Indices

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Abstract: This study examines the multi-scale spatio-temporal evolution of drought characteristics in Zhejiang Province. We propose a comprehensive index to identify drought days and events by incorporating three widely used monitoring indices: the precipitation anomaly percentage, relative humidity index, and standardized precipitation index. The analysis reveals a significant long-term decreasing trend in the frequency of drought days across Zhejiang Province from 1971 to 2020, with a total of 170 drought events being identified. An Empirical Orthogonal Function (EOF) analysis of precipitation anomalies during these events reveals a dominant province-wide monopole mode, alongside a secondary north-south inverse dipole, a third tripole, and a fourth southwest-northeast inverse dipole. Furthermore, a composite analysis of the drought events demonstrates a widespread increase in temperature across all stations, with a strong spatial correspondence between the temperature anomalies and their associated frequency. The study identifies 21 extreme drought events, characterized by spatially inconsistent precipitation patterns across the entire province.

Key words: drought; comprehensive drought index; climate influence; combined climate impact index; agricultural effects

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1 INTRODUCTION

Drought is a persistent water scarcity in the atmosphere-land system resulting from an imbalance between water supply and demand (Wilhite 1991). It has a significant impact on various socio-economic aspects including agricultural production, irrigation, plant protection, inland navigation, and energy supply, posing a serious threat to human well-being. Statistics from the World Meteorological Organization (WMO) indicate that 70% of natural disasters are meteorological disasters, with approximately 50% of these disasters being related to drought (Vicente-Serrano et al. 2012). Therefore, drought has long been a central scientific issue in climatology research (Zhang et al. 2019; Ari et al. 2021). Drought can generally be categorized into two types. Firstly, it refers to a long-term climatic phenomenon (arid climate)

characterized by deficient precipitation. Secondly, it corresponds to a discrete meteorological event (drought disaster) where precipitation in a specific location and period is significantly below the climatological mean. Such events can lead to challenges in water resource supply and management, severely impacting societal functions, economic production, and daily life (Zhao et al. 2024). Drought event is of particular interest to meteorologists (Wu et al. 2018; Ibebuchi 2021). In terms of its occurrence and development, drought exhibits four major climatic features. First is its ubiquity. Drought disasters are not limited to arid or semi-arid regions but can affect various land areas around the globe, and even some humid areas frequently experience them (Sheffield et al. 2012). Second is its cumulative nature. It gradually develops under reduced precipitation in the early stages. Therefore, the onset of drought often follows a critical transition from a quantitative precipitation deficit to a qualitative state (Li et al. 2014). Third is its sustainability. a drought can either terminate abruptly (forming a “flash drought”) or persist for extended periods (manifesting as a “lasting drought”) (Qing et al. 2022). Studies have demonstrated that the severity of drought’s impacts is directly linked to its duration (Zhang and Liang 2010). In other words, longer-lasting droughts result in more severe impacts and greater losses. Last is its variability. Research indicates that drought often demonstrates multi-time scale variations, ranging from interannual to interdecadal, a characteristic observed in regions worldwide (Yang et al.

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2020). This variability poses significant challenges for drought prediction.

In the field of drought research, extensive work has been conducted on the synoptic and climatological characteristics of drought (Lyu et al. 2023), as well as the formation and evolution mechanisms (Dong et al. 2023). Research has also been carried out on risk assessment methods and models of agricultural and ecological effects (Chen et al. 2014; Edgar et al. 2019), and the impact of global warming on regional drought, sparking interest among scholars from different fields (Nguvava et al. 2019). However, a fundamental concern persists in the field of drought research, namely the identification and delineation of drought. Unlike conventional meteorological elements such as temperature and precipitation, drought cannot be directly observed. As a result, meteorologists have developed a series of indices to characterize drought from different perspectives, such as the Palmer Drought Severity Index (PDSI), precipitation anomaly index, Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010). It has been observed that drought indices established based on different backgrounds possess differ in monitoring capabilities. The main factors causing drought differ in various regions, resulting in differences in the applicability of these indices. Currently, dozens of drought indices are commonly used internationally and meteorologists employ them to compare different indicators when evaluating applicability, leading to conflicting results and even contradictory conclusions. For instance, in China, numerous studies assessing the applicability of various indices have reached disparate conclusions regarding their suitability for regional drought monitoring (Wu et al. 2001; Yuan and Zhou 2004; Lin et al. 2015; Huang et al. 2017). Another significant issue is that the existing indicators are designed to identify the “drought state,” which means determining whether there is a drought at a specific time. The national standard “Meteorological Drought Grade” (GB/T 20481-2017) formulated by the China Meteorological Administration provides reference indicators such as Percentage of Accumulated Precipitation (PA), Moisture Index (MI), SPI, SPEI, and PDSI for monitoring drought in a “specific period” and a composite index called the meteorological drought composite index (MCI) for monitoring “drought days” (Zhang et al. 2017). However, the former indicators, such as PA, are limited by an inability to facilitate daily rolling monitoring, making them impractical for operational use. The latter index MCI involves multiple parameters, subjective judgments, and complex calculations, leading to controversy in drought monitoring and failing to capture the entire drought process (Heim 2002). Besides, large-scale or regional drought events exhibit multi-scale variations rather than remaining constant, making the implementation of drought monitoring a formidable challenge. In addition, the role of

different meteorological elements in forming drought events is still elusive. Therefore, the unsolved scientific challenge lies in developing appropriate indicators that can extract and elucidate the dynamics of the drought process, as well as exploring the role of various meteorological elements (such as temperature and precipitation) in the initiation and progression of drought events.

Zhejiang Province, situated in the eastern part of China, is considered a humid area, but it has also experienced several severe drought disasters in recent years. For example, since 2000, Zhejiang has underwent three severe drought events, forming a long and narrow northeast-southwest “drought corridor” (Fan et al. 2006). While scholars have used different indicators for drought monitoring in Zhejiang, a consensus on which index is the most suitable one remains controversial (Xu et al. 2013; Ding et al. 2011). Indeed, a growing body of research pointed out that single-index-based approaches for drought identification and diagnosis are loose and risky, underscoring the critical need to evaluate different indices and develop comprehensive monitoring indicators that can improve the objective identification of regional drought. To achieve this goal, it is necessary to establishing a robust strategy for identifying regional individual drought days, developing a methodology to aggregate these days into coherent drought events, and subsequently extracting their characteristics and analyzing their spatio-temporal patterns. Additionally, it is important to understand the respective contributions of temperature and precipitation to the formation and development of drought in the region (Kew et al. 2021). Although in Zhejiang, the impact of mild and moderate droughts on agricultural production is limited, in some cases even boost certain crops (Huang 1992), severe and extreme droughts often lead to heavy crop disasters, yield reductions, or even complete crop failures. The extent of such impacts is commonly used as direct evidence to validate drought monitoring indices (Behrang et al. 2019). In this paper, we aim to construct a comprehensive monitoring indicator capable of identifying drought days in Zhejiang by selecting and integrating several widely used and operationally feasible drought indices. We also intends to propose a technical method for aggregating drought days into drought events and establish criteria for identifying extreme drought events. Furthermore, the study will analyze the multi-scale spatial and temporal variations of drought events in Zhejiang and examine the relative contributions of temperature and precipitation to the formation of these events. The research will also explore the relationship between identified drought events and recorded agricultural disasters in Zhejiang. The ultimate goal is to comprehend the climatic characteristics of drought events in Zhejiang and provide a scientific basis for enhancing the effectiveness of drought monitoring, early warning systems, and risk management in the region.

2 MATERIALS AND METHODS

2.1 Sources of information

Daily averaged temperature and daily accumulated precipitation are collected from 66 conventional meteorological stations in Zhejiang Province, spanning from 1 January, 1971, to 31 December, 2020. The spatial distribution of these stations can be seen in Fig. 1. In addition, agricultural data, including crop cultivation areas and drought disaster statistics, are extracted from the China Agricultural and Rural Statistical Yearbook. The crop area data provides different crop information in Zhejiang cultivated areas, and the drought disaster statistics encompass various aspects such as disaster-affected area, severely damaged area, and total crop failure area due to drought.

2.2 Selection of indicators

Although there are many drought indicators proposed by different scientists, not all are suitable for drought monitoring in operational meteorological departments. This is because some meteorological drought indicators, such as runoff, depend on variables that has not yet been included in routine meteorological observations. To address this problem, China's national standard, "Meteorological Drought Levels" (2017), provides six drought indicators with potential for operational drought monitoring (Zhang et al. 2017). Among these indicators, the SPEI is primarily applied in semi-arid and semi-humid regions. Calculation of the PDSI requires variables that are currently beyond the scope of usual meteorological observation. The MCI incorporates the MI and SPI in its calculation process and is suited for monitoring long-lasting drought events. Considering these factors, we have selected three fundamental indicators for drought monitoring: the PA, MI, and SPI. These indices were chosen due to their suitability for monitoring meteorological drought in moist regions and the

observation data needed during the calculating process can be easily obtained. Definitions and calculation formulas for these three indicators are as follows.

PA reflects the deviation of precipitation at a specific time from the average conditions during the same period. It can be calculated with the following equation:

$$PA = \frac{P - \bar{P}}{\bar{P}} \times 100\% \quad (1)$$

where PA indicates the percentage of precipitation distance level at a certain period (%). P and $\bar{P}$ represent the accumulated precipitation and its climatological mean over a certain period (mm), respectively. The climatological baseline is derived from the 1971–2020 period.

MI represents the relative wetness at a given time and can be calculated as the difference between precipitation and potential evapotranspiration during a drought event. The detailed formula is given as follows:

$$MI = \frac{P - PET}{PET} \quad (2)$$

where MI and P indicate relative wetness (%) and precipitation (mm) at a given time, respectively. PET represents potential evapotranspiration (mm) for the same period, which is calculated using the FAO Penman-Monteith method (Allen et al. 1998).

SPI is widely used in drought monitoring. The calculation procedure can be summarized as follows: First, the probability of T distribution for precipitation during a certain period should be calculated; Then, the probability curve needs to be normalized; Finally, the drought grads can be divided by the accumulated frequency distribution of normalized precipitation series. The calculation formula for SPI is expressed as follows:

$$SPI = S \left\{ t - \frac{(c_2 t + c_1)t + c_0}{((d_3 t + d_2)t + d_1)t + 1.0} \right\} \quad (3)$$

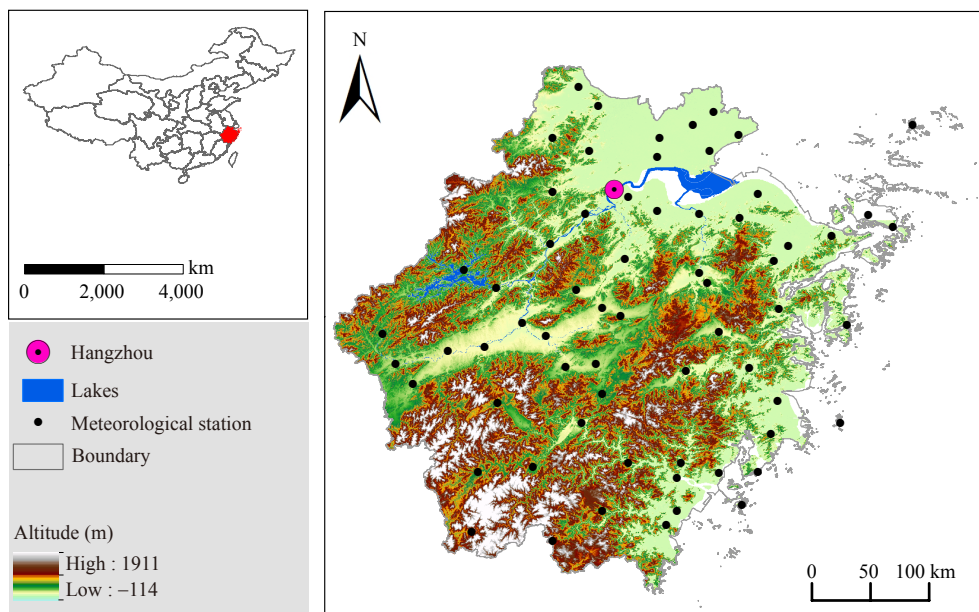


Figure 1. Spatial distribution of conventional meteorological stations in Zhejiang Province.

where SPI represents the standardized precipitation index; t is a function of $G(x)$ and can be expressed by

$$t = \sqrt{\ln \frac{1}{G(x)^2}}; G(x) \text{ is the probability distribution}$$

associated with the Γ function; S is the positive and negative probability coefficients. When $G(x) > 0.5$, then $G(x) = 1.0 - G(x)$, $S = 1$; when $G(x) \leq 0.5$, then $S = -1$. The integral formula for the probability density of the distribution function is obtained from the following equation:

$$G(x) = \frac{1}{\beta^\gamma \Gamma(\gamma)} \int_0^x t^{\gamma-1} e^{-t/\beta} dt, x > 0 \quad (4)$$

where γ and β are the shape and scale parameters of the Γ distribution function, respectively; c_0, c_1, c_2 , and d_1, d_2, d_3 are computational parameters for converting Γ distribution function to a simplified approximation of the cumulative frequency solution formula. The empirical coefficient values used are: $c_0 = 2.0515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

2.3 Establishment of comprehensive drought index and identification of drought days

To establish a comprehensive drought index for identifying drought days, we systematically evaluate meteorological conditions over the past period. In this study, a 30-day running calculation strategy was chosen, and daily PA, MI, and SPI can be obtained using a 30-day sliding window (referred to as the 30d PA, MI, and SPI indices) (Zhang et al. 2017). Table 1 presents the drought discrimination thresholds for these indices. Besides, to account for the inherent limitations of any single drought index and thereby enhance the reliability of our results, we aim to minimize the potential identification errors by merging multiple indices. If all three indices reach the drought level (moderate drought or higher), a certain day will be classified as a drought day. Conversely, if only one or two indices reach the drought level, it will not be considered as a drought day. For instance, the day on 20 September, 1974 is identified as a drought day because the 30d PA index (63.9%), SPI index (0.75), and MI index (0.52) all surpassed their respective moderate drought thresholds. However, the preceding day (19 September) is not classified as a drought day. Although the 30d PA index reached the threshold for light drought (51.8%), neither the SPI index (0.38) nor the MI index (0.35) reached the drought level.

2.4 Identification and extraction of drought events

To identify and extract drought events, a suitable index for a drought event is generally defined as a consecutive series of drought days from a start date (N_1) to an end date (N_2) ($N_1 \leq N_2$). The duration of the drought event is calculated as $(N_2 - N_1 + 1)$ days. During each drought event, the days on which each of the three indicators (PA, MI, and SPI) reaches the thresholds for light, moderate, severe, and excessive drought are recorded as D1, D2, D3, and D4, respectively. When drought events span multiple seasons, the seasonal classification is dependent on the main period of drought occurrence. For example, if a drought process occurs from 20 November to 20 December, it is classified as occurring in the winter season because the number of drought days in winter (20 d) is more than that in autumn (10 d).

2.5 Agricultural disaster assessment methods

In terms of agricultural disaster assessment, data on drought damage in Zhejiang from 1971 to 2020 are obtained from the *China Agricultural and Rural Statistical Yearbook* and the *Zhejiang Provincial Statistical Yearbook*. According to the statistical regulations of the China's Ministry of Civil Affairs, the disaster-affected area, severely damaged area, and total crop failure area are determined based on the percentage of yield reduction. If the yield reduction exceeds 10%, 30%, and 80% in drought years, the area is marked as an affected area, disaster area, and crop failure area, respectively. The following equation is used to calculate the loss of crops due to disasters in drought years.

$$L_i = a_1 \times Y_i \times (AS_i - AC_i) + a_2 \times Y_i \times (AC_i - AJ_i) + a_3 \times Y_i \times AJ_i \quad (5)$$

where L_i represents the agricultural loss due to drought in the i^{th} year; AS_i , AC_i , AJ_i denote the affected area, disaster area, and crop failure area in the i^{th} year, respectively; Y_i represents the unit crop yield in the i^{th} year; a_1 , a_2 , a_3 are mean losses of crop-affected areas, disaster areas, and crop failure areas, respectively. In this study, the median values are taken as 0.2, 0.55, and 0.9, respectively. TA_i represents the planted area of crops in the i^{th} year. Therefore, the agricultural yield reduction rate (LR_i) in the i^{th} year can be calculated using the following equation:

$$LR_i = \frac{L_i}{TA_i \times Y_i} = \frac{a_1 \times (AS_i - AC_i) + a_2 \times (AC_i - AJ_i) + a_3 \times AJ_i}{TA_i} \quad (6)$$

Table 1. Classification of drought types based on PA, MI, and SPI indices.

Grade	Type	PA	MI	SPI
1	No drought	$-40 < PA$	$-0.40 < MI$	$-0.5 < SPI$
2	Light drought	$-60 < PA \leq -40$	$-0.60 < MI \leq -0.40$	$-1.0 < SPI \leq -0.5$
3	Moderate drought	$-80 < PA \leq -60$	$-0.80 < MI \leq -0.60$	$-1.5 < SPI \leq -1.0$
4	Severe drought	$-95 < PA \leq -80$	$-0.95 < MI \leq -0.80$	$-2.0 < SPI \leq -1.5$
5	Excessive drought	$PA \leq -95$	$MI \leq -0.95$	$SPI \leq -2.0$

2.6 Extraction and assessment of extreme drought events

Nowadays, extreme drought events are of particular interest in drought research because of their long duration, severe impact, and significant consequences for various industries. In this study, we focus on identifying and analyzing extreme drought events, which are defined as persistent drought events with an occurrence probability of less than 10% among all drought events. Additionally, these events must contain moderate or more serious drought days in the entire process. In this paper, we extract the extreme drought events and analyze the spatiotemporal characteristics and their association with crop disaster losses.

2.7 Trend analysis

In climatic trend analysis, we employ the least squares method to calculate the linear regression coefficient for time series. The relationship between variable and time can be expressed using a first-order linear equation, as shown in the following equation (Wei 2007):

$$y = a \cdot x + b \quad (7)$$

where y is the climate variable, x is time, a is the regression coefficient representing the rate of change, and b is the intercept. The decadal trend rate is denoted by $10 \times a$. By analyzing the trend rate, we can identify whether climate variables are increasing, decreasing, or remaining relatively stable with the evolution of time.

2.8 EOF analysis

Empirical Orthogonal Function (EOF) analysis, also known as eigenvector analysis or principal component analysis, is widely used in climate research. This method is used to analyze the structural characteristics of matrix data and extract principal features. The eigenvectors correspond to spatial samples, known as spatial feature vectors or spatial modes, which reflect the spatial distribution characteristics of the field variables. The principal components correspond to temporal variations, also known as time coefficients, which reflect the weight changes of the corresponding spatial modes over time. EOF analysis decomposes a climate variable field into a product of spatial modes and time coefficients (Wei 2007).

2.9 Analysis of the relative contributions of temperature and precipitation on the formation of drought events

Previous research has highlighted the significant roles of temperature and precipitation in drought formation. High temperatures contribute to drought by increasing evaporation rates and reducing plant water availability, while insufficient precipitation directly leads to drought occurrence (Grotjahn et al. 2016; Barlow et al. 2019). However, the detailed contributions of temperature and precipitation to drought events are often examined through case studies, and a statistical understanding of their relative importance is still limited.

This study aims to reveal the spatiotemporal characteristics of temperature and precipitation corresponding to drought events in Zhejiang province using a synthetic analysis approach, thereby gaining a

climate-based understanding of the separate roles of temperature and precipitation in triggering drought. The specific steps are as follows: (1) Calculating temperature and precipitation anomalies. Temperature anomalies and the percentage of precipitation anomalies are calculated for all drought events. This process involves comparing the observational values with their climatological counterparts to extract deviations from normal conditions. (2) Conducting composite analysis. By averaging temperature anomalies and the percentage of precipitation anomalies for each separate drought event, we can obtain the composite results, which represent the overall characteristics of temperature anomalies and the percentage of precipitation anomalies associated with drought events. (3) Revealing the comprehensive climatic impact of temperature and precipitation. Here, we define a climatic comprehensive impact index (CCII) as the product of the temperature anomalies and the percentage of the precipitation anomalies. Generally, higher temperatures and less precipitation are favorable conditions for drought development. Therefore, a smaller CCII (typically a negative value) indicates a more distinct combined effect of temperature and precipitation in triggering drought.

3 RESULTS

3.1 Number of drought days

Figure 2a provides an overview of the annual number of drought days in Zhejiang Province from 1971 to 2020. On average, Zhejiang experiences 41.9 drought days per year, which accounts for approximately 11.5% of the total days in a year. This indicates that drought can be seen as a frequent meteorological disaster in Zhejiang Province. Notably, the annual number of drought days exhibits a clear long-term declining trend, with a decreasing rate of approximately 4.0 days per decade ($p > 0.1$). The year with the highest number of drought days is 1971, with 116 drought days recorded. This includes 10 days of extreme drought, 14 days of severe drought, 24 days of moderate drought, and 68 days of mild drought. According to the historical records, in 1971, Zhejiang initially experienced a spring drought, followed by 70 to 90 days of continuous drought during the summer and autumn. Domestic water supplies in the regions of Ningbo, Shaoxing, and Wenzhou faced significant challenges, leading to the temporary suspension of water service in numerous cities. Many factories halted production, and agricultural land suffered greatly from the drought. In response, the State Council dispatched three aircraft to carry out cloud seeding operations. In terms of drought severity, light-moderate drought, light-severe drought, light-severe drought, and light-excessive drought occurred in 5 yr, 15 yr, 14 yr, 15 yr, respectively. Overall, drought reaches at least a moderate level in 44 years, accounting for 88% of all years, which indicates that drought events in Zhejiang Province not only occur frequently but also possess the potential to evolve into severe disasters.

In terms of monthly distribution (Fig. 2b), January and October–December are the main periods of drought in Zhejiang Province. The number of drought days in these months account for 59.8%, 80.3%, 97.8%, and 100% of the total number of light, moderate, severe, and excessive drought days, respectively. Almost all severe and excessive drought days happen during this period. Furthermore, the seasonal variation of drought days was investigated (Fig. 3). It is evident that the number of drought days in autumn and winter is higher compared to that in spring and summer. Also, an upward trend is observed for the number of drought days in spring and autumn, with a linear trend of approximately 0.5 and 0.1 days per decade, respectively.

However, in summer and winter, the number of drought days exhibits a downward trend, with a linear trend of -1.5 and -3.2 days per decade, respectively. The reduction in the total annual number of drought days is primarily driven by the decrease in winter. Since 2000, the number of winter drought days has been consistently less than 30 days, and in 15 of those years, the number is even less than 20 days. This is quite different from the situation observed during the 1970s–1990s.

3.2 Spatiotemporal variations of drought events

As discussed above, drought events can be acquired by merging continuous drought days. A total of 170 drought events occurred in Zhejiang from 1971 to 2020,

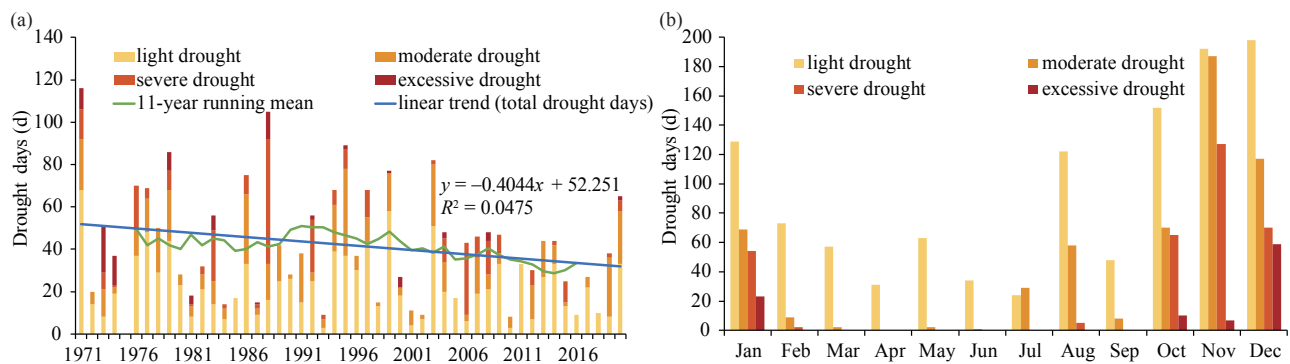


Figure 2. Yearly evolution and inter-monthly distribution of the number of drought days at different levels in Zhejiang Province from 1971 to 2020 (units: d).

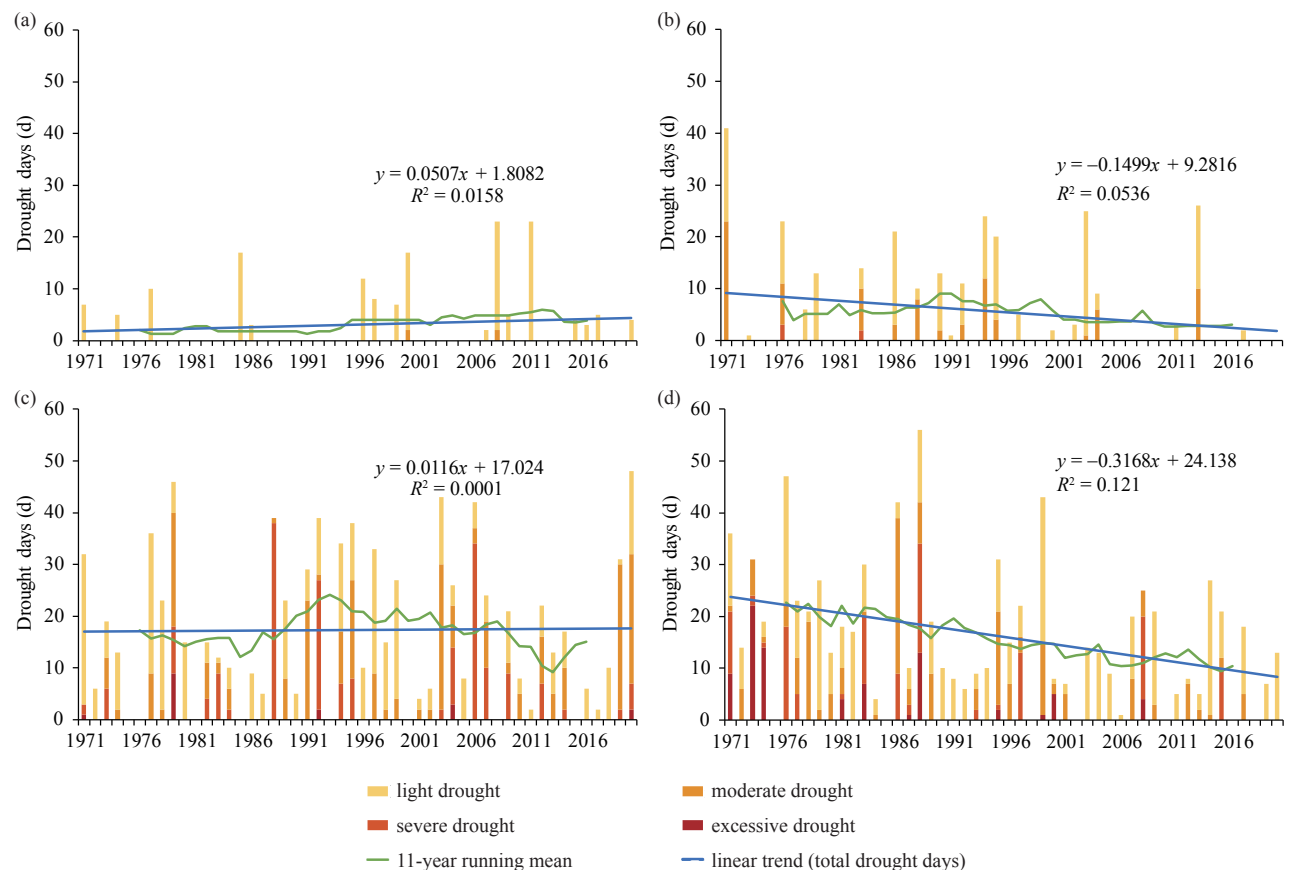


Figure 3. Yearly evolution of the number of drought days at different levels in (a) spring, (b) summer, (c) autumn, and (d) winter in Zhejiang Province from 1971 to 2020 (units: d).

averaging 3.4 events per year. No drought events were recorded for the year 1975, while the maximum number of annual drought events (8) were observed in 1994 and 2003. Besides, 7 drought events took place in 1997. Before 1993, the number of drought events remained relatively stable with slight fluctuations. However, after that year, a notable increasing trend appeared, indicating a notable rise in drought events. During this period, years characterized by extreme drought—defined as those with at least seven annual drought events—began to emerge (e.g., 1994, 1997, and 2003; Fig. 4). Moreover, the annual number of drought days exhibits strong interannual variability, ranging from 0 in 1975 to a maximum of 75 in 1988. Among these drought events, 60 lasted for more than 10 days, with an average value of 1.20 events each year. Additionally, 31 drought events persisted for over 20 days with a mean value of 0.62 per year, 18 drought events lasting more than 30 days (0.36 per year on average), and 13 drought events lasting more than 40 days (0.26 per year on average) (Table 2). For the 31 droughts exceeding 20 days, there were 1 light, 7 light–moderate, 11 light–severe, and 12 light–excessive drought events. These statistical findings indicate that short-term droughts lasting less than 10 days were primarily of light intensity. As the duration of droughts increased, the proportion of moderate, severe, and excessive drought also escalated accordingly. During persistent droughts lasting more than 20 days, the number of severe and excessive drought surpassed that of light and moderate droughts.

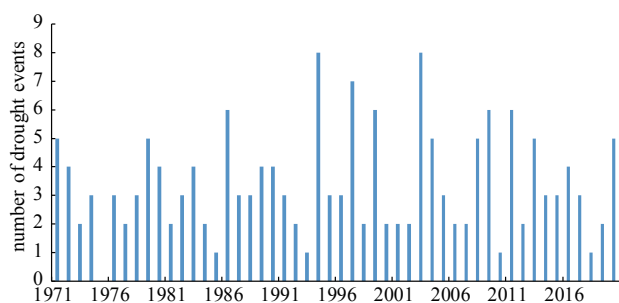


Figure 4. Annual number of drought events occurred in Zhejiang Province from 1971 to 2020 (units: times).

To better understand spatial distribution characteristics of drought occurrences, an Empirical Orthogonal Function (EOF) decomposition was applied to the precipitation percentage anomalies corresponding to the 170 drought events. At this point, the temporal coefficients become meaningless, but the spatial modes can reflect the main distribution characteristics of precipitation anomalies during drought events (Fig. 5). The calculation results show that the cumulative variance contribution of the first four modes reaches 82%, exceeding 80%. Therefore, the main analysis focuses on the spatial characteristics of these leading four modes. The first mode is the “uniform pattern”, with a variance contribution of 58.9%, indicating the dominant mode of precipitation anomalies across all drought events. The second mode, the “north-south anti-phase” mode, accounts for 12.4% of the variance and reflects opposite fluctuations of drought and flood in northern Zhejiang and southern central Zhejiang regions. The third mode is a “triple-mode structure”, with a variance contribution of 5.8%, showing a spatial distribution pattern with stronger anomalies at both ends or weaker anomalies in the central region. The fourth mode, the “southwestern Zhejiang” pattern, accounts for 5.0% of the variance, displaying an inverse relationship in precipitation anomalies between southwestern Zhejiang and other regions.

3.3 Relative contributions of temperature and precipitation

(1) Temperature

The synthetic analysis of temperature anomalies for all drought events (Fig. 6a) reveals that all stations exhibit positive anomalies, ranging from 0.7 to 1.4 °C. This suggests that droughts are often accompanied by high temperatures, with some regions in southwestern Zhejiang exhibiting temperature anomalies even higher than 1 °C. According to the operational regulations of the China Meteorological Administration, the scenario temperature anomalies ≥ 2 °C are classified as abnormally high. Although the observed temperature anomalies do not achieve this threshold, it is evident that high temperatures are a common characteristic during drought events. The frequency of positive anomalies varies between 34 and 63

Table 2. Statistics on the occurrence of different levels of drought events in Zhejiang Province from 1971 to 2020 (units: times).

Number of days of persistent drought/(d)	Different levels of drought events and their frequencies of occurrence				
	Number of times	Light drought	Light–moderate drought	Light–severe drought	Light–excessive drought
(70, +∞)	1	0	0	0	1
(60, 70]	2	0	0	0	2
(50, 60]	3	0	0	1	2
(40, 50]	7	0	1	3	3
(30, 40]	5	0	1	2	2
(20, 30]	13	1	5	5	2
(10, 20]	29	9	13	6	1
[1, 2]	110	91	17	2	0
Total number	170	101	37	19	13

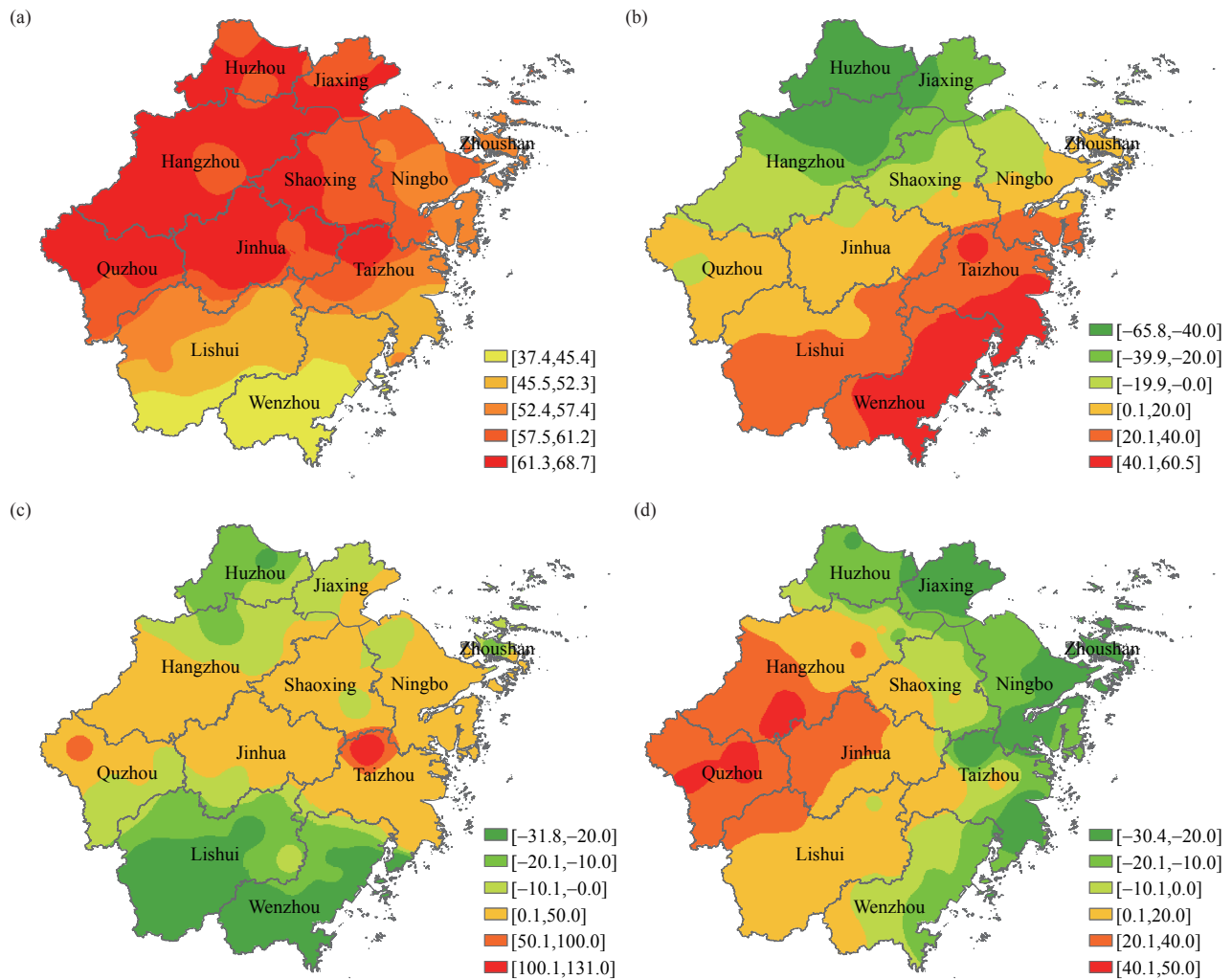


Figure 5. Spatial distribution of the first 4 modes of EOF analysis for precipitation anomaly percentages corresponding to drought events in Zhejiang Province from 1971 to 2020.

occurrences across all stations, with southwest Zhejiang experiencing a notably higher frequency (Fig. 6b). Moreover, the spatial distribution of temperature magnitude and the frequency of temperature anomalies align well, with areas of strong positive anomalies predominantly located in southwest Zhejiang. This indicates that high-temperature anomalies are a significant factor in the formation of drought events in southwest Zhejiang.

When considering seasonal changes (Figs. 7–8), spring temperature exhibits much larger positive anomalies, exceeding 1°C at all stations and surpassing 1.5°C in most areas (Fig. 7a). However, the frequency of these positive anomalies is relatively low, with a range of 10–16 times at each station (Fig. 9a), which suggests that, during spring droughts, while extreme high-temperature events are infrequent, the overall positive anomalies are significant, playing a key role in their formation. In summer, most areas of the province experience positive anomalies below 1°C (Fig. 7b), and the frequency of positive anomalies is also below 10 days (Fig. 8b). Thus, the positive anomalies in summer are the weakest positive

anomalies along with the lowest frequency. In autumn, most areas show positive anomalies below 1°C (Fig. 7c), but the frequency of positive anomalies is high, with 14–18 times for each station (Fig. 8c). In winter, the frequency of positive anomalies reaches the highest, ranging from 16–22, with corresponding positive anomalies of 1.0 to 1.4°C at all stations. Winter temperatures in Zhejiang have exhibited an upward trend and frequent warm winters under the global warming background, providing favorable temperature conditions for the formation of droughts.

(2) Precipitation

The composite analysis of precipitation anomaly percentages for all drought events (Fig. 9a) reveals a consistently insufficient precipitation at all stations, with negative anomaly percentages exceeding 20% and even more than 50% in some areas (ranging from -33.9% to -61.9%). The frequency of negative anomaly percentages range from 83 to 104 occurrences, with almost all stations experiencing negative anomaly percentages exceeding 50%. This indicates that anomalous less precipitation is an important meteorological condition for drought

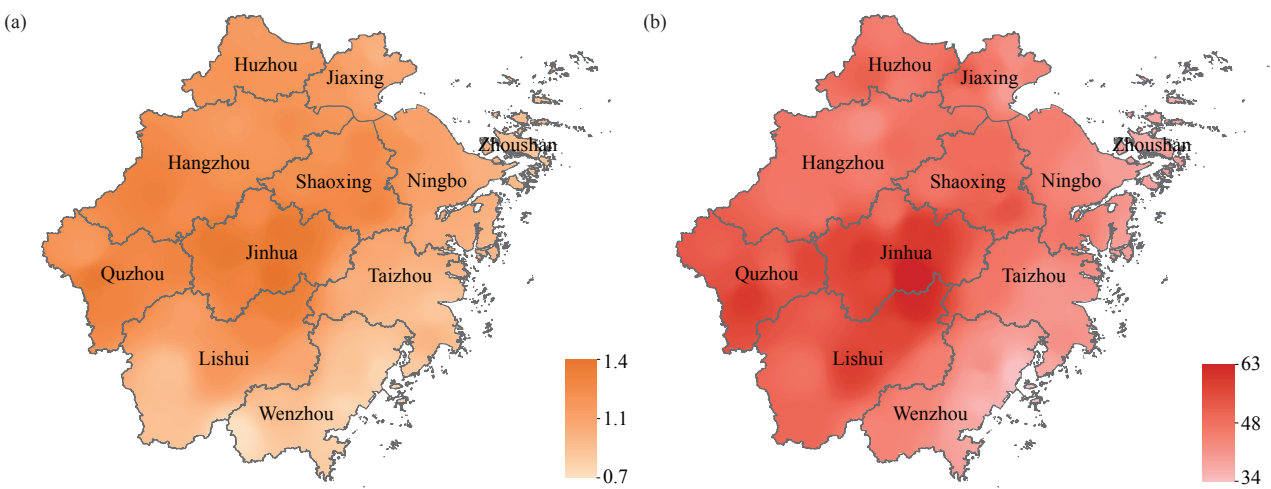


Figure 6. Spatial distribution of composite (a) temperature anomalies (units: $^{\circ}\text{C}$) and (b) frequency of positive anomalies (units: times) for all drought events in Zhejiang Province.

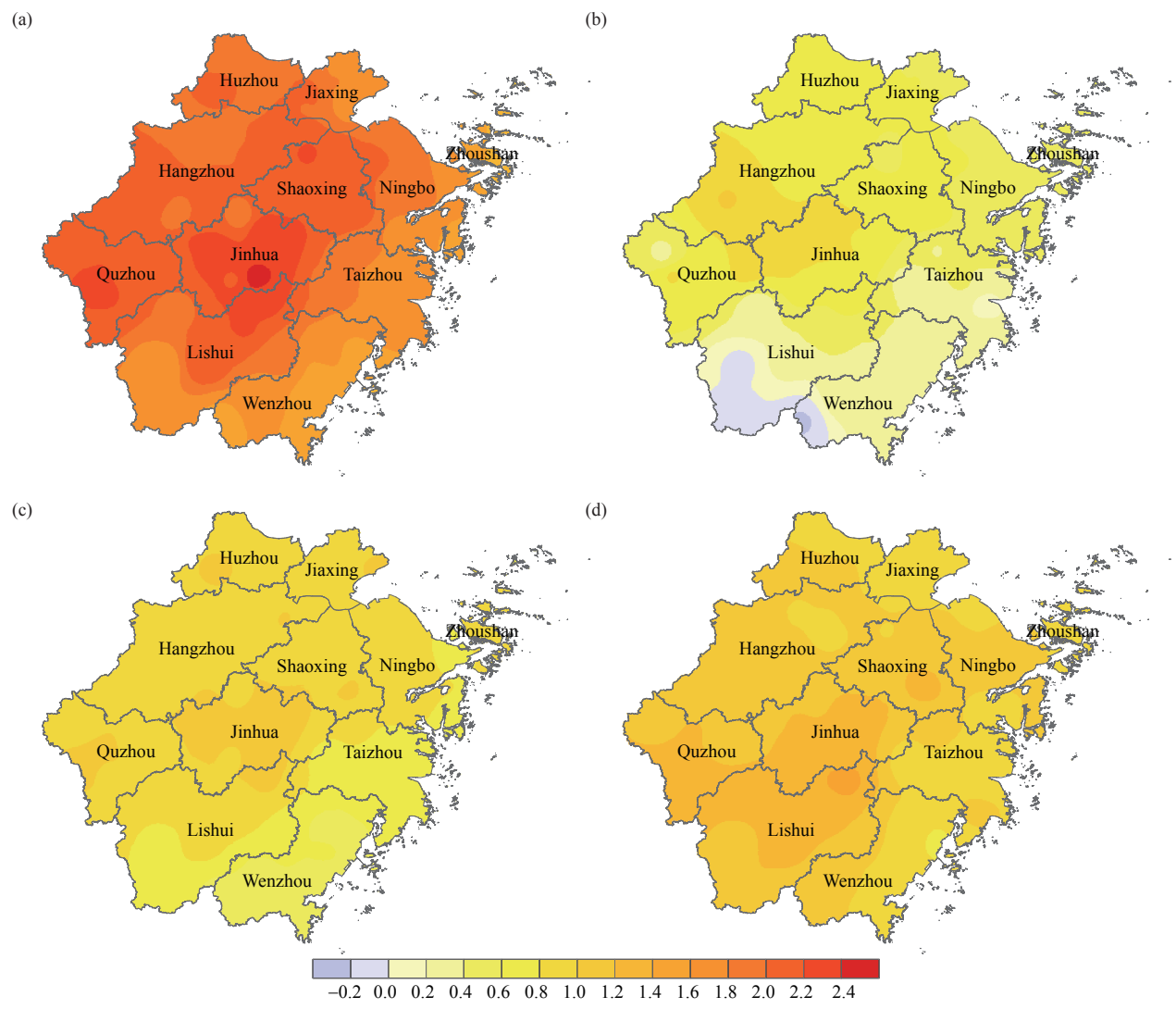


Figure 7. Spatial distribution of composite temperature anomalies for drought events in (a) spring, (b) summer, (c) autumn, and (d) winter over Zhejiang Province (units: $^{\circ}\text{C}$).

formation. The areas with a high frequency of negative anomalies are located in northeast and southwest Zhejiang

and the southeast coastal areas, which align with the areas of inadequate precipitation (Fig. 9b).

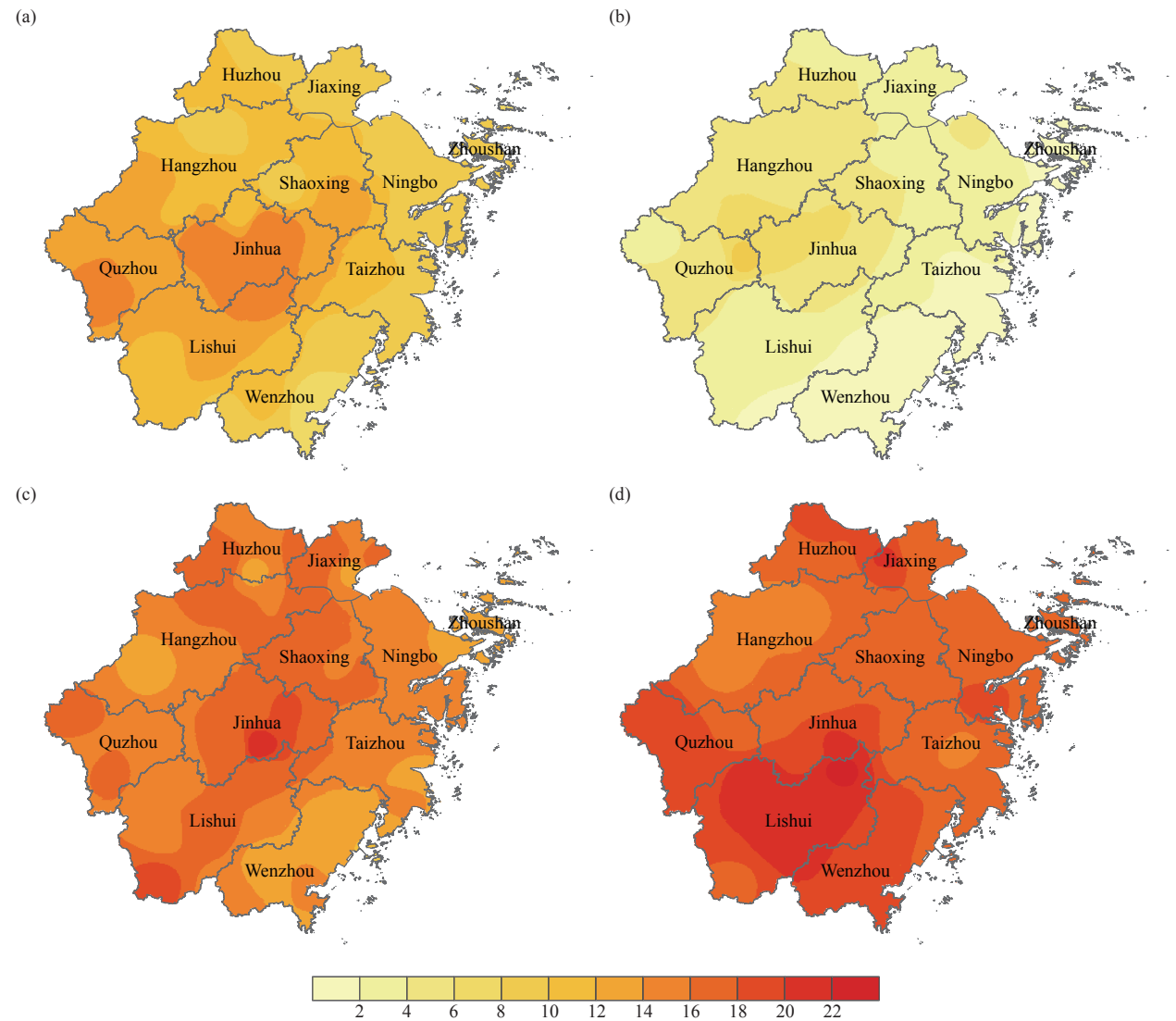


Figure 8. Spatial distribution of the frequency of positive temperature anomalies for all the drought events in (a) spring, (b) summer, (c) autumn, and (d) winter in Zhejiang (units: times).

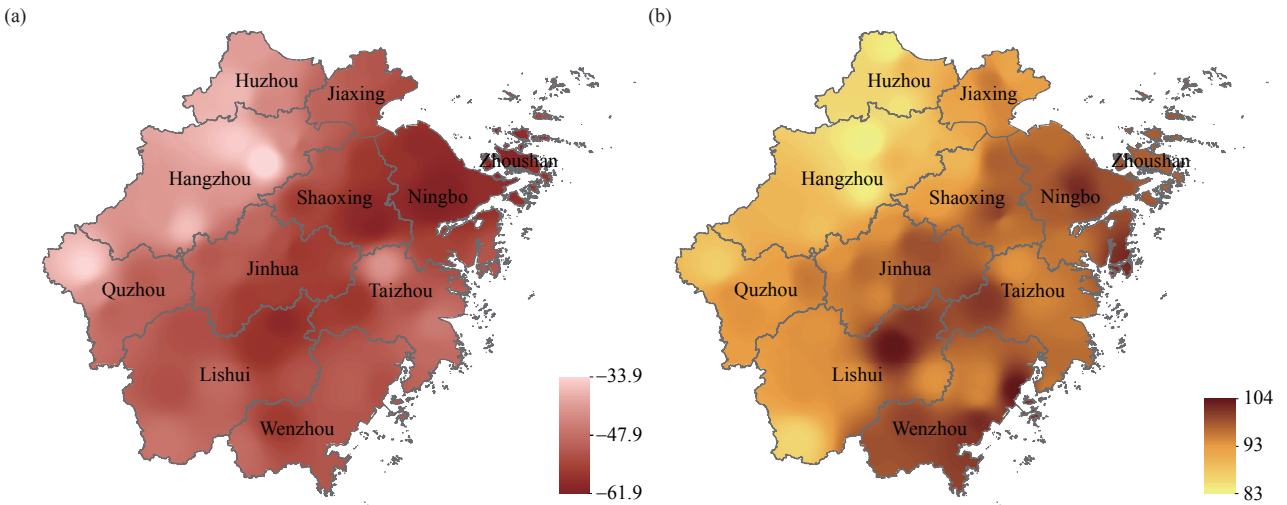


Figure 9. Spatial distribution of composite (a) precipitation anomaly percentages (units: %) and (b) frequency of negative anomaly percentages (units: times) for all drought events in Zhejiang Province.

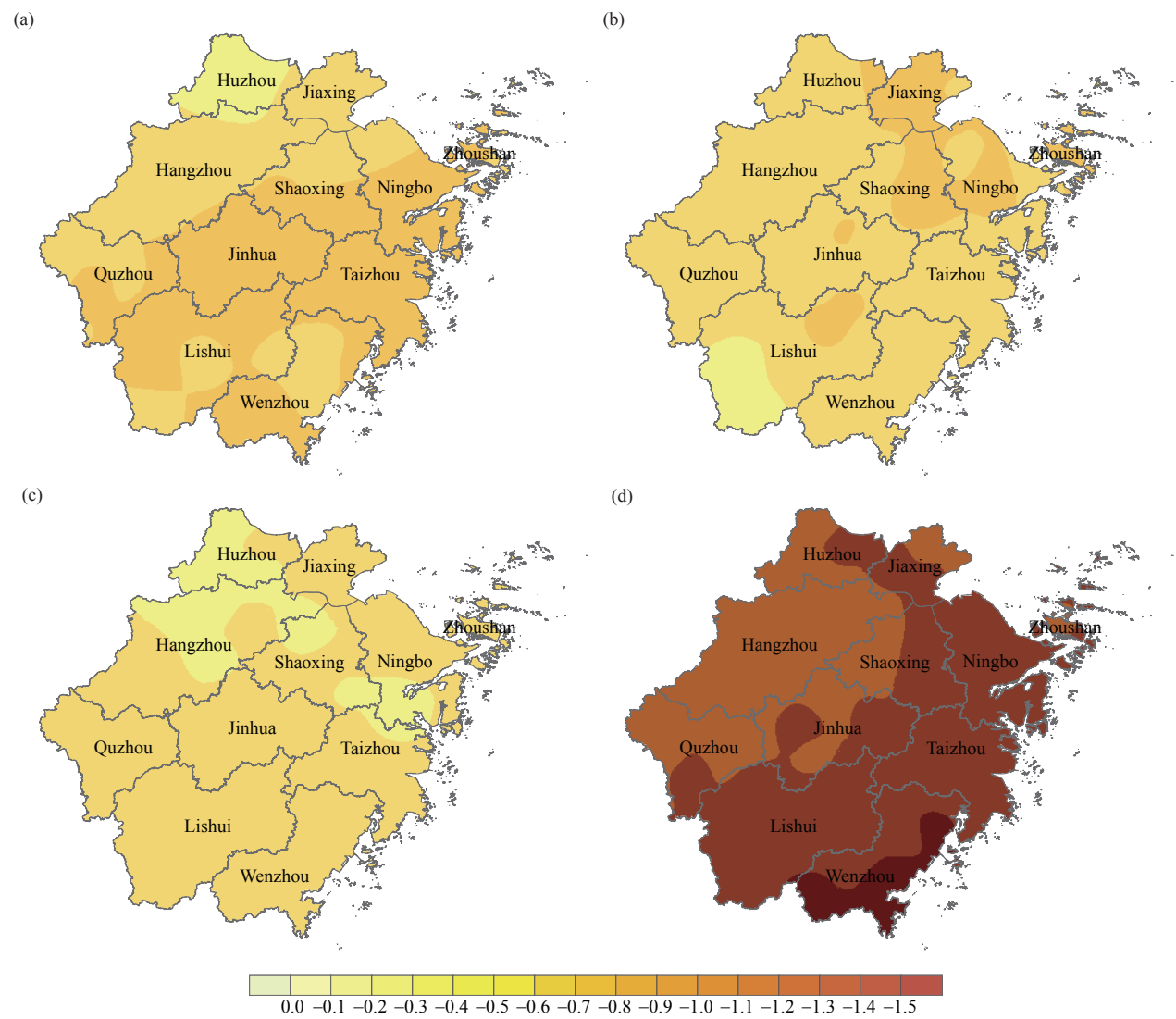


Figure 11. Spatial distribution of the frequency of negative precipitation anomaly percentages for all the drought events over Zhejiang in (a) spring, (b) summer, (c) autumn, and (d) winter (units: times).



Figure 12. Spatial distribution of composite CCII for all drought events in Zhejiang (units: °C).

precipitation (Fig. 9a) becomes more pronounced. In other words, the more severe the drought, the larger the impact

of a synergy of temperature and precipitation. Regarding the seasonal distribution (Fig. 13), spring exhibits the strongest combined effects compared to the other three seasons. During spring droughts, CCII is lower than -0.5 at all stations, with most areas lower than -0.8 . The physical explanation behind this phenomenon is as follows: during summer, the baseline temperature is already very high, making it less susceptible to promoting abnormally high-temperature events. In autumn and winter, the frequent incursion of cold air acts as a suppressant against sharp temperature increases. However, in spring, the joint effect of quickly increased temperature and limited rainfall is favorable for the formation and development of drought. As a result, the drought events may correspond to both “cold dry” and “warm dry” conditions.

3.4 Extreme drought events

3.4.1 IDENTIFICATION OF EXTREME DROUGHT EVENTS AND THEIR IMPACTS

According to the identification criteria for extreme

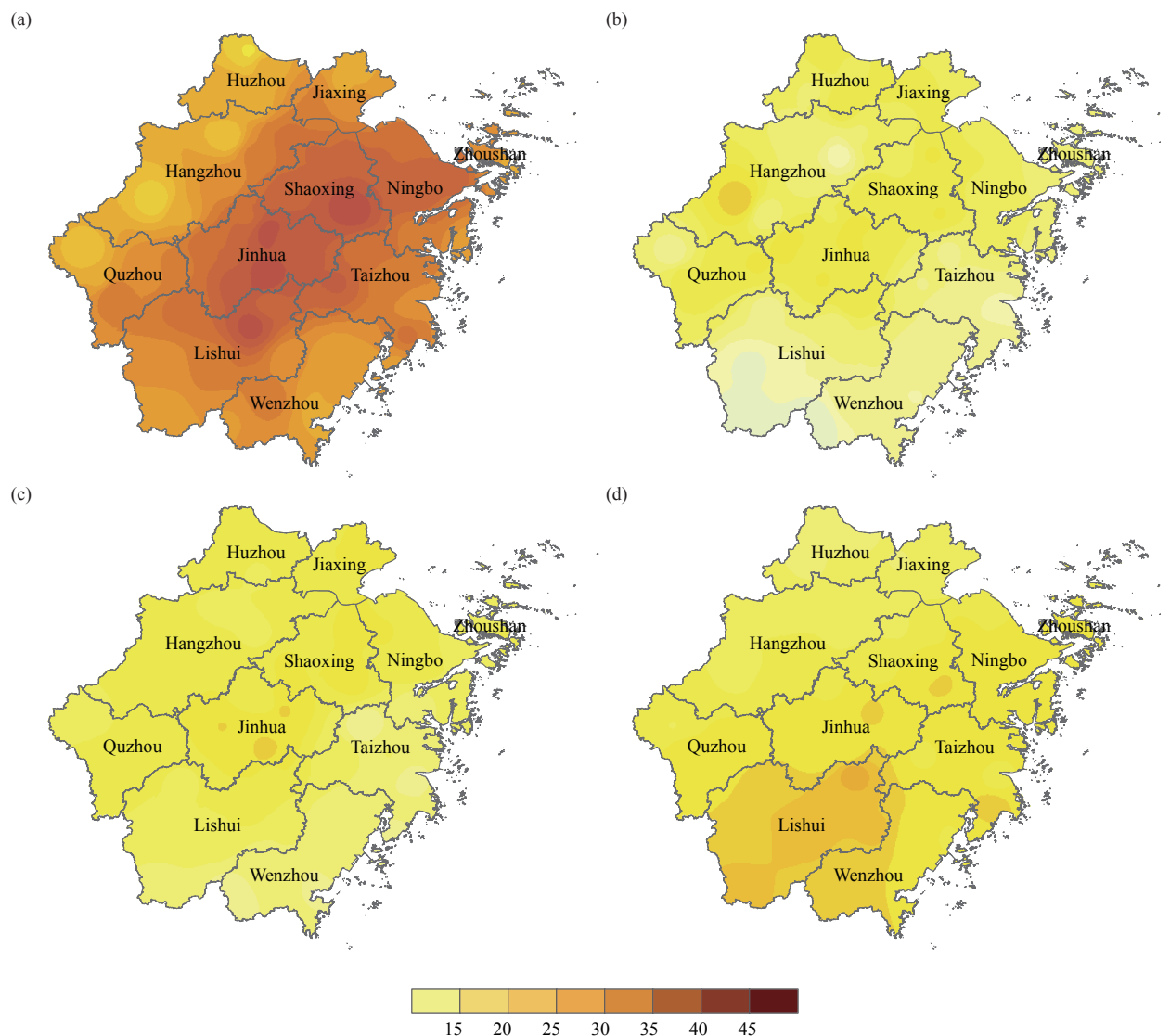


Figure 13. Spatial distribution of CCII for all the drought events over Zhejiang in (a) spring, (b) summer, (c) autumn, and (d) winter (units: $^{\circ}\text{C}$).

climate events, a total of 21 extreme drought events were identified in Zhejiang Province, which occurred in 1971, 1973, 1976, 1977, 1979, 1983, 1988, 1991, 1992, 1995, 1999, 2003, 2004, 2006, 2007, 2008, 2013, 2019, and 2020. Among them, both 1971 and 1988 experienced two extreme drought events. The frequency of extreme drought events is approximately one event every 2 to 3 years, and there were consecutive extreme drought events in the years 1976–1977, 1991–1992, 2003–2004, 2006–2008, and 2019–2020. When examining the meteorological conditions triggering extreme drought events, it is found that these events are primarily caused by significantly reduced precipitation. The percentage anomalies of precipitation in all events were less than -40% . Additionally, when these deficits are combined with remarkable positive temperature anomalies, the impact of extreme drought events can be further exacerbated (Fig. 14).

3.4.2 SPATIAL CHARACTERISTICS OF EXTREME DROUGHT EVENTS

With EOF analysis, the dominant spatial modes of

extreme drought events over Zhejiang can be acquired (Fig. 15). The first mode, which accounts for 91.2% of the total variance, indicates that long-lasting and widespread extreme drought events are characterized by consistently insufficient precipitation across the province (Fig. 15a). Areas with very little precipitation are primarily located in southern-central Zhejiang and the southern part of North Zhejiang. Compared to the first mode, the variance contribution of the second mode (3.9%), third (1.5%), and fourth (0.5%) modes is very limited. Spatially, the second mode displays a coastal-inland inversion pattern (Fig. 15b); The third mode shows a meridional tripole structure (Fig. 15c), and the fourth mode exhibits a southwest-northeast inversion pattern (Fig. 15d). Comparing these results with the EOF analysis for total drought events (Fig. 4), the spatial characteristics of the first four modes are broadly similar. However, there are still some differences in the location of large-value areas of the first mode. Drought events mainly occur in central and northern Zhejiang, while extreme drought events occur

predominantly in central and southern Zhejiang. This suggests that province-wide drought events in Zhejiang generally correspond to continuous precipitation deficits in the central and northern parts of the province, while

province-wide extreme drought events are typically associated with significantly less precipitation in central and southern Zhejiang.

To further analyze the impact of extreme drought

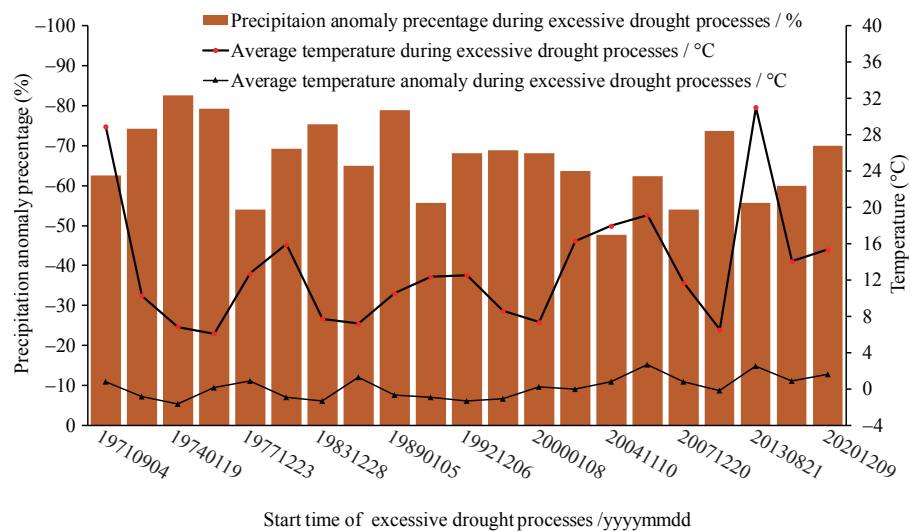


Figure 14. Characteristics of temperature and precipitation for extreme drought events in Zhejiang Province from 1971 to 2020.

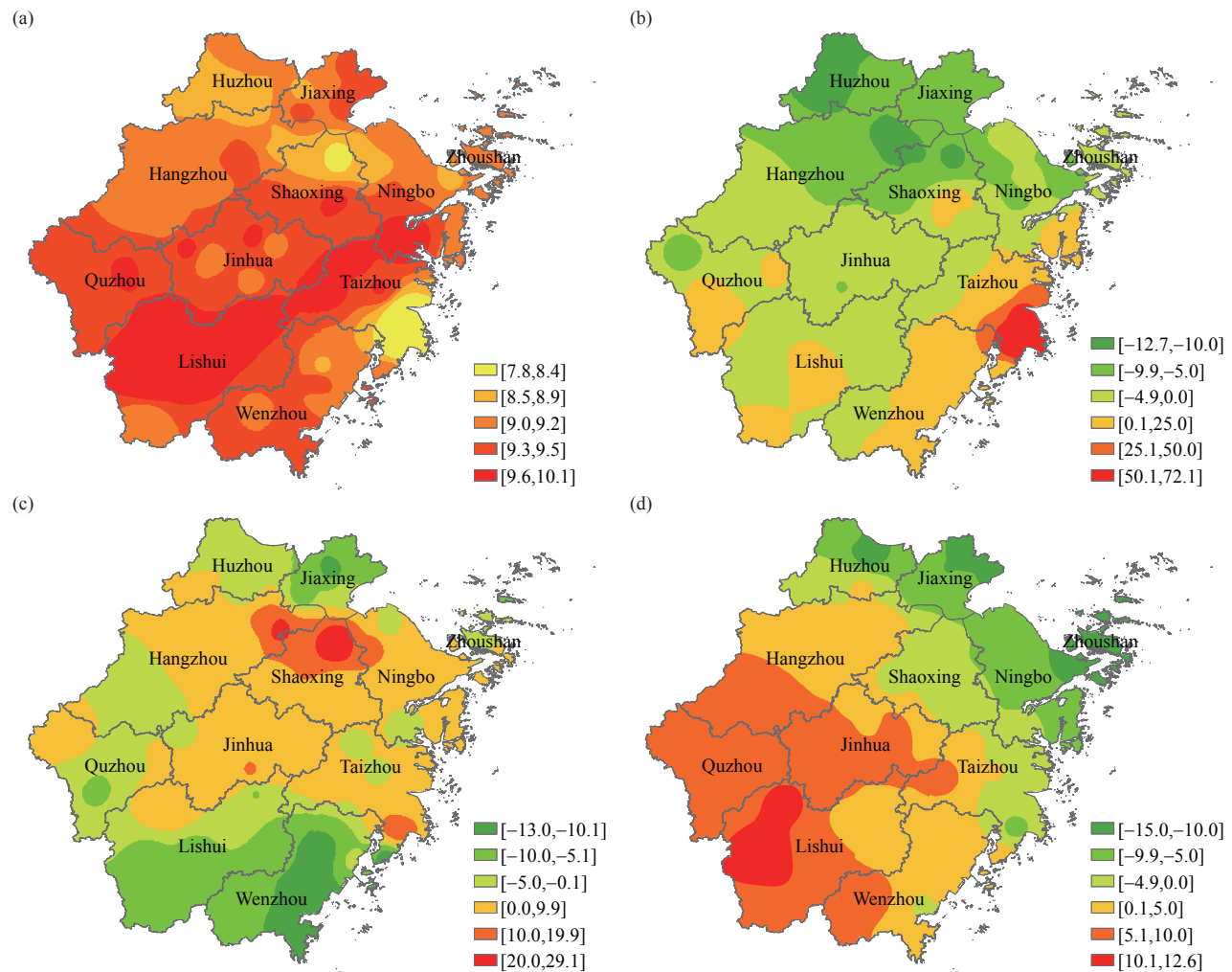


Figure 15. The spatial distribution of the (a) first, (b) second, (c) third, and (d) fourth EOF modes for the precipitation anomaly percentage (%) in all the extreme drought events over Zhejiang Province.

events on agriculture, we examined the relationship between agricultural losses and extreme drought events since 1971 (Table 3). The results show that extreme drought events are typically long-lasting and often result in agricultural damage. However, the relationship between drought severity and crop damage is not linear due to various factors. One primary factor is the occurrence time of drought events. Droughts can occur at any time of the year, but the resulting crop damage is not solely caused by drought but can also be influenced by other factors such as heat, cold air, wind, and other synoptic processes. For example, the drought event from 11 November 1973 to 19 January 1974 lasted for 69 days, including 9 days of severe drought and 36 days of extreme drought. Nevertheless, the event occurring in autumn-winter, a period of minimal soil evaporation and high water-holding capacity, is able to mitigate agricultural losses. Consequently, there were no severely damaged areas or total crop-failure areas. An affected area of 266.7 ha coincided with a yield reduction of 1.1%. Human activities also play a significant role in determining the extent of agricultural damage. When droughts occur, industries and sectors actively engage in irrigation, diversion, and carrying out artificial rainfall to mitigate the adverse effects. Therefore, the occurrence of extreme droughts serves as an important indicator of potential agricultural losses, but the actual damage depends on multiple factors. For instance, the drought event in 2013 from 27 July to 27 August, although not reaching historical extremes in terms of the number and

severity of drought days (27 days of light drought and 17 days of moderate drought), caused significant agricultural losses. Disaster-affected area reached approximately 6.356×10^5 ha, severely damaged area amounted to 2.471×10^5 ha, and total crop failure area was recorded as 5.84×10^4 ha. These statistics accounted for 28.9%, 11.24%, and 2.66% of the total crops planted that year, respectively. The yield reduction rate reached 10.6%. This was due to the occurrence of a rare heat wave affecting Zhejiang in summer. The province experienced a quantity of high-temperature days (34 d, daily maximum temperature $\geq 35^\circ\text{C}$), hazardous high-temperature days (17 d, daily maximum temperature $\geq 38^\circ\text{C}$), and extremely hot days (6 d, daily maximum temperature $\geq 40^\circ\text{C}$), respectively. The highest recorded temperature reached 44.1°C at the Xinchang Station, achieving a return period of approximately once-in-a-century. The heat wave, combined with the effect of drought, resulted in severe crop damage, including scorching and plant mortality. Furthermore, four additional extreme drought events were observed from 26 October to 23 December 1977, from 28 December 1987 to 25 January 1988, from 6 December 1999 to 8 January 2000, and from 7 December 2008 to 20 January 2009. However, statistical information indicates that these events did not significantly affect crops. This can be attributed, in part, to the fact that all four events occurred in the autumn and winter seasons, which are not critical periods for crop growth. Additionally, during the periods of 7 September to 18 October 1977 and 30 October

Table 3. Identification of extreme drought events in Zhejiang province from 1971 to 2020.

Start date	End date	Different levels of drought (light/medium/severe/excessive drought) days (d)	Crop area (10^3 hm^2)	Disaster-affected area (10^3 hm^2)	Severely damaged area (10^3 hm^2)	Total crop failure area (10^3 hm^2)	Yield reduction rate (%)
19710722	19710904	45 (22/23/0/0)	-	-	-	-	-
19711103	19711224	52 (27/1/14/10)	-	-	-	-	-
19731112	19740119	69 (10/14/9/36)	4780.8	266.7	0	0	1.1
19760107	19760216	41 (19/4/18/0)	4680.6	333.3	0	0	1.4
19771026	19771223	59 (38/16/5/0)	7086.2	-	-	-	-
19791007	19791121	46 (6/22/9/9)	4731.6	189.3	76.7	6.7	1.4
19831119	19831228	40 (8/3/22/7)	4578.1	276.7	106	3.3	2
19871228	19880125	29 (13/9/6/1)	6450.8	-	-	-	-
19881023	19890105	75 (6/1/55/13)	4300.5	578	133.3	13.3	3.9
19911102	19911202	31 (8/23/0/0)	4379.5	302.7	86.7	23.3	2.3
19921023	19921206	45 (17/1/25/2)	4275.1	421	213	28	3.9
19951104	19960112	70 (20/39/9/2)	3923	500.7	238	59.3	5.2
19991206	20000108	34 (22/6/0/6)	5849.2	-	-	-	-
20031015	20031119	36 (6/28/2/0)	2834.4	542	311	92	8.8
20041016	20041110	26 (4/8/11/3)	2778.4	276.1	184	21	4.6
20061011	20061121	42 (5/3/34/0)	2516.2	87.3	72.8	6	1.8
20071107	20071220	44 (17/17/10/0)	2491.6	83	33.7	3	1.2
20081207	20090120	45 (17/8/16/4)	3757.2	-	-	-	-
20130727	20130821	26 (16/10/0/0)	2199.0	635.6	247.1	58.4	10.6
20191031	20191205	36 (6/28/2/0)	2161.5	12	5	0	0.1
20201020	20201209	51 (19/25/5/2)	-	-	-	-	-

to 1 December 2008, the provincial accumulated precipitation reached 226 mm and 111 mm, respectively, which were 50% and 40% more than the climatological values. The resulting abundant reservoirs and moist soil provided sufficient water reserves for drought defense.

4 CONCLUSION

By merging three widely applicable drought indexes, PA, MI, and SPI, this study introduces a comprehensive discrimination index for identifying and diagnosing drought days and drought events in Zhejiang Province. The main findings can be summarized as follows:

(1) The time series of the annual number of drought days in Zhejiang Province between 1971 and 2020 displays a clear long-term downward trend, with an average value of 41.9 days per year. The most severe and excessive drought days occurred in January and during the October–December period. Drought days are substantially more frequent in autumn and winter than in spring and summer. Regarding seasonal trends, the number of drought days exhibits an upward trend in spring and autumn and a downward trend in summer and winter.

(2) Zhejiang Province experienced a total of 170 drought events between 1971 and 2020, and the annual frequency of these events shows distinct interannual variability. As the duration of drought events increased, the proportion of moderate, severe, and excessive drought days also increased. Drought events lasting more than 20 days are more likely to develop into severe and extreme droughts. The primary EOF mode of the precipitation anomaly percentage for all the drought events was characterized as the province-wide consistent pattern. The second, third, and fourth modes were classified as a north-south inverse type, a meridional triode type, and a southwest-northeast inverse type, respectively.

(3) A composite analysis of temperature anomalies revealed that all the stations suffering drought events exhibited higher temperatures, particularly in southwestern Zhejiang. In spring, positive temperature anomalies were more significant, while the frequency of positive anomalies in autumn and winter made a decisive contribution to the total frequency of positive anomalies. The composite precipitation anomaly percentage was lower than –20% in all the stations, with significantly less precipitation situated in northeastern and southwestern Zhejiang. Prominent negative precipitation anomalies were observed across all seasons, with the frequency of negative anomalies being much higher in autumn and winter. The combined effect of temperature and precipitation was the most influential in the development of drought events in spring.

(4) Zhejiang Province experienced 21 extreme drought events during 1971–2020, with an occurrence rate of approximately one event every 2 to 3 years. These extreme drought events were characterized by strongly reduced precipitation across the entire province. The relationship between extreme drought and agricultural

losses was found to be complex and nonlinear.

5 DISCUSSION

The identification and analysis of drought events are influenced by various uncertainties, primarily arising from factors such as data quality and the selection of drought indices. First and foremost, data quality is a critical factor affecting the calculation of drought indices. The meteorological data used in this study are sourced from multiple weather stations, and the spatial distribution and data continuity of these stations may lead to inaccuracies in identifying local drought events. An uneven distribution of meteorological stations can result in the underestimation or overestimation of drought conditions in certain areas. Additionally, some meteorological stations may experience inconsistencies in data uniformity due to relocation, which can further impact the calculation of drought indices. Secondly, the selection of drought indices introduces additional uncertainty. Different drought indices exhibit varying sensitivities to meteorological variables, potentially leading to different identification outcomes for the same drought event. For instance, the SPI is primarily based on precipitation, while the MI also incorporates the effects of potential evapotranspiration. Furthermore, the calculation methodology of drought indices may also affect the reliability of the results. For example, the calculation of the SPI relies on the assumption of a normal distribution of precipitation, which may not hold in some instances, thus impacting the accuracy of the SPI. Finally, the conclusions of this paper are based on stringent threshold values for three drought indicators: PA, MI, and SPA. While this approach may help avoid “false alarms” from a forecasting perspective, it cannot eliminate the risk of “missed alarms.” As a result, it may not fully capture drought conditions characterized by high temperatures and specific humidity types, which could contribute to discrepancies between the conclusions of this paper and those of prior studies.

Our study found a significant decrease in the annual number of drought days in Zhejiang Province from 1971 to 2020, which is inconsistent with the conclusions of some earlier research. For example, Zou et al. (2010) indicated that the change in drought areas in the middle and lower reaches of the Yangtze River was not significant, while Cao et al. (2012) believed that drought in Zhejiang was gradually intensifying. However, recent numerical simulations support the hypothesis that the decrease in drought days may be a result of global warming (Xin et al. 2013) which has accelerated the water cycle and increased precipitation frequency (Held et al. 2006; Xie et al. 2010). It is also possible that the inconsistencies are due to differences in the analyzed time periods.

The spatial distribution of drought events in Zhejiang exhibits different patterns. The EOF analysis of precipitation anomaly percentages during drought events identifies four dominant modes: a province-wide

consistent pattern, a north-south inversion pattern, east-west tripoles, and a southwest-northeast inversion configuration. Among these, the primary mode is the province-wide consistent pattern. This is mainly attributed to the relatively small geographical scope of Zhejiang, which makes it prone to a province-wide deficit of precipitation under the influence of persistent large-scale circulation systems such as the Western Pacific Subtropical High and the Siberian High. From a climate dynamics perspective, the northern part of Zhejiang is primarily influenced by precipitation from the westerlies, while the central and southern regions are predominantly affected by the southwest warm and moist airflow and tropical systems. Droughts occur in the northern part of Zhejiang when the westerlies-induced precipitation is weakened, and droughts in the central and southern regions are often associated with the weakening of the southwest moisture transport or a reduced influence of tropical systems such as typhoons. This corresponds to the north-south inversion pattern. If different precipitation systems affect the northern and southern parts of Zhejiang separately and with limited intensity, drought usually occurs in the central region, or when the precipitation system has a smaller scale and mainly affects the central part of Zhejiang, a meridional tripole structure appears. Precipitation in southwestern Zhejiang is strongly influenced by the India-Burma trough. When the southwest moisture transport is weakened, drought is likely to occur in this region. Additionally, due to its lower insusceptibility to typhoon impacts, when typhoons affect Zhejiang, a pattern emerges where southwestern Zhejiang experiences relatively less rainfall while other areas receive more, resulting in the “southwest Zhejiang type” drought pattern. Although this mode contributes less to the overall variance, it is worth noting that in recent years, drought has frequently occurred in southwestern Zhejiang, and even persistent droughts have been observed multiple times (Wang et al. 2023). This new scenario has significantly impacted the orderly regulation of water resources, necessitating considerable attention to such drought patterns.

The temporal and spatial characteristics of drought occurrence in Zhejiang Province are investigated. In terms of inter-month change, January and October–December are the two main periods for the formation of drought days in Zhejiang, with over 95% of severe and extreme drought days also occurring during this period. On the seasonal scale, drought days are more frequent in autumn and winter than in spring and summer. The number of drought days shows an upward trend in spring and autumn, while a downward trend is observed in summer and winter. The decreasing trend in winter has made a decisive contribution to the overall reduction in annual drought days. This is contrary to previous studies, which suggested that drought disasters in Zhejiang mainly occur in summer and autumn. This shift can be attributed to global warming, Zhejiang Province frequently experiences

“warm autumn” and “warm winter”, seasons that are already characterized by less precipitation. In the absence of continuous rainy days, higher temperatures and less precipitation can accelerate soil evaporation and increase crop water consumption, leading to drought formation. In Zhejiang, although there are frequent heatwaves in summer, the occurrence of heavy precipitation events, including the Mei-yu and typhoon rainfall, mitigates the risk of drought. It should be noted that in August, Zhejiang’s precipitation is mainly influenced by typhoon rainfall, which primarily affects coastal and southern areas, making the inland regions such as southwestern Zhejiang still prone to drought (Ma et al. 2021). Extreme drought occurs approximately once every 2 to 3 years in Zhejiang, which is consistent with the conclusion drawn by Fan et al. (2008) that severe drought in Zhejiang often occurs consecutively for two years. On spatial distribution, drought in Zhejiang is concentrated in the northeastern and southwestern regions, where precipitation during drought periods is significantly below normal. Additionally, the combined effects of temperature and precipitation are more pronounced in these areas, which corresponds well to the traditional concept of the “drought corridor” location.

This study proposes a new perspective on defining regional drought events. The comprehensive discrimination index, which merges three common indices (i.e. PA, MI, and SPI), can be used to identify and classify drought events, providing convenience for operational drought assessment and services. It should be noted that this method is only applicable to a fixed region, and the spatial resolution and applicability of the selected indicators need to be considered when studying regional drought with such a strategy. Besides, due to the simultaneous consideration of the intersection of three indices, the identification standard is relatively strict, which may result in relatively fewer drought-duration days. Furthermore, although the PA, MI, and SPI indices are commonly used drought indicators, they may not comprehensively and accurately describe the nature and severity of drought. For example, these three indices mainly rely on precipitation data and overlook the impacts of other meteorological factors such as temperature, wind speed, and humidity on drought. Moreover, these indices are often calculated based on large-scale observational data and cannot provide regional or small-scale drought information. In the calculation process of drought indices, data reliability, and completeness are important issues. Many studies have indicated that problems exist with the quality and spatial distribution of meteorological data due to limitations in data collection, transmission, and uneven distribution of observation stations. This may lead to inaccuracies and limitations in drought monitoring results. Thus, when conducting drought monitoring and early warning, it is important to carefully consider data reliability and spatial distribution to improve the accuracy of results (Wilhite 1991; Mishra et al. 2010).

Besides, the impacts and consequences of drought nowadays are influenced by many factors such as human activities and land use changes. Massive studies have pointed out that these factors can alter the sensitivity and vulnerability of drought, and hence affect drought monitoring and assessment results (Vicente-Serrano et al. 2012). When conducting drought monitoring and early warning, it is necessary to consider the impacts of multiple factors comprehensively to make a more accurate assessment. In the development process of a drought event, its spatial patterns are determined and modified by some dynamic and thermodynamic processes (Sundararajan et al. 2021). A key next step is to further integrate artificial intelligence methods with the comprehensive discrimination index to dynamically monitor the spatial scope of drought events.

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