

Article

Characteristics of Dry and Wet Changes and Future Trends in the Tarim River Basin Based on the Standardized Precipitation Evapotranspiration Index

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Abstract: Global changes in drought and wetness and their future trends in arid regions have recently become a major focus of research attention. The Tarim River Basin (TRB) in Xinjiang, China, is among the most climate-sensitive regions in the world. This study uses data from the past 60 years (1962–2021) to analyze the spatial and temporal features of drought and wetness conditions in the TRB, calculating the Standardized Precipitation Evapotranspiration Index (SPEI). Trend detection for SPEI is performed using the BEAST mutation test, identification of drought events using the theory of operations, and spatial and temporal analyses of dry and wet changes using Empirical Orthogonal Function (EOF) decomposition. Additionally, the CMIP6 dataset is used to estimate future changes. The study results indicate the following: (1) From 1962 to 1998, the TRB exhibited a “warm and wet” trend that suddenly shifted from “wet-to-dry” in 1998 and subsequently transitioned to a pronounced “warm and dry” trend. (2) After the “wet-to-dry” shift, the frequency of drought events noticeably increased. The northern section of the basin witnessed more frequent drought events, albeit with lower severity, while the southern part had fewer occurrences but with higher severity. The spatial distribution of drought event frequency and severity is inconsistent. (3) The EOF decomposition results for SPEI-variable fields at 1-, 3-, and 6-month time scales show that the cumulative variance contribution rate of the first three principal spatial modal feature vectors exceeds 70%. The spatial distribution of the modes includes a consistent pattern across the entire basin, a north–south opposite pattern, and an east–west opposite pattern. (4) The future trend of drought in the TRB is expected to intensify, manifesting a spatial pattern characterized by dryness in the middle of the basin and wetness around the periphery. These research findings can provide support for decisions addressing regional drought risks.



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1. Introduction

Drought is among the world’s most significant climatic phenomena, due to the extensive harm and losses it causes [1,2]. Moreover, droughts are becoming more frequent and complex [3]. According to relevant organizations, drought is a meteorological phenomenon marked by an extended period of dry weather within the natural climate cycle, leading to water shortages [4,5]. It is important to underscore that unlike other natural disasters such as floods and wildfires, it is a slow-onset threat that becomes apparent as societies and ecosystems begin to feel its impacts. Additionally, drought has non-structural and widespread geographical ramifications [6,7]. Projections for the next 70 years show that drought-prone areas around the world may continue to expand, leading to an escalating negative impact of drought [8]. In China, the repercussions of drought are already severe,

making it one of the nation's most critical natural disasters. Drought affects not only the ecological environment and agricultural production but also wide-ranging economic and social aspects [9]. Statistics reveal that annual agricultural economic losses due to drought in China may reach as high as CNY 27.2 billion [10].

The Tarim River Basin (TRB) exemplifies the challenges faced by arid regions worldwide, making it an important case study for understanding drought dynamics. Against the backdrop of global climate warming, drought events in arid zones are steadily increasing in frequency and intensity [11–13]. The TRB, which is situated in the heart of Central Asia's arid region [14], exemplifies a characteristic continental arid climate. It is an environmentally fragile area whose ecosystems are extremely vulnerable to worldwide climate change. Climate variations within the basin can result in the onset of numerous extreme weather events. The TRB experiences a temperate continental climate characterized by low precipitation, high temperatures, and intense evaporation. Drought is among the most frequent and predominant natural disasters in the basin, and extreme drought events have had significant impacts on both the basin's ecological environment and human life [15]. Hence, monitoring drought and researching related mechanisms have become pressing priorities for development and disaster mitigation efforts in the TRB.

In its simplest form, drought manifests as a relative deficiency of water over a specific period compared to normal conditions. Water deficiency could refer to a severe imbalance in the surface water budget caused by significantly reduced precipitation or other abnormally dry climate conditions. This type of drought is often associated with meteorological conditions, such as changes in high-pressure systems or rainfall patterns, and is characterized by a wide-reaching impact and prolonged duration [16]. Meteorological drought typically manifests first and serves as a precursor to other drought types. It usually initiates with insufficient precipitation and accompanies the entire drought event [17].

The extent and intensity of meteorological drought largely determine the duration and intensity of other forms of drought events [18]. Since meteorological drought (like other forms) can be challenging to define, various indices are commonly used in meteorological drought-related research for quantitative analysis and monitoring of drought severity [19]. Currently, there is no optimal indicator to describe drought characteristics, as the complex relationships between evaporation, infiltration, groundwater, and surface water mean that different indices assess drought characteristics differently [20]. For instance, the PDSI considers temperature, precipitation, and groundwater factors, rendering it suitable for agricultural drought, but it has limitations in terms of its ability to capture multi-scale variability and cannot distinguish between different types of drought [21]. The SPI is simple to calculate and flexible in terms of time scale, but it only focuses on precipitation, overlooking the other important factors [22,23]. In comparison, the SPEI represents an improvement over both the PSDI and SPI, as it considers factors that are relevant to drought, such as temperature and precipitation. Furthermore, due to its temporal flexibility and spatial continuity, the SPEI can detect different types of drought occurrences across various temporal scales, making it well suited for reflecting regional drought characteristics [24].

Accordingly, the SPEI has become a crucial tool for assessing dry and wet conditions and is now widely applied in various fields of drought research [25–27]. In previous studies, this tool was extensively used in climate change investigations for analyzing drought variability and identifying drought impacts on agriculture and ecosystems [24,28]. Recent research has shown that temporal variations in Standardized Precipitation Evapotranspiration Indices (SPEIs) demonstrate differing reactions across various time scales. Specifically, it has been observed that shorter time scales, such as SPEI-3 and SPI-6, are characterized by a heightened frequency of drought occurrences coupled with shorter durations. At the end of the 1980s, some scholars suggested that there was a trend of “warm-drying” to “warm-wetting” climate change in the arid areas of Northwest China, and the amount of glacier ablation and precipitation showed a continuous increase, while the runoff volume also increased [29]. However, some scholars have questioned this statement [30,31], and since the 21st century, Xinjiang has witnessed a steady rise in temperature alongside a

slight decline in precipitation, which is expected to influence the wet and dry climate patterns in the TRB [32]. Some scholars have used SPI to analyze droughts in Xinjiang, China, from 1957 to 2009, and found that the severity and duration of droughts have been increasing [33].

Currently, there has been minimal focus on the trends of wet and dry changes in small watersheds over extended time periods, particularly within the context of transitioning from warm–wet to warm–dry conditions in the arid regions of Northwest China [34], whether there is a wet and dry transition in the watersheds, and there is a deficiency in predictions of future spatial and temporal changes in wet and dry changes in the watersheds as a whole, which is crucial for drought risk assessment in the TRB. This study utilizes temperature, precipitation, and the SPEI from the TRB spanning the last 60 years (1962–2021). This research systematically analyzes the spatiotemporal characteristics of drought and wetness in the region, and the run theory is employed to identify the frequency and severity of drought events. This comprehensive analysis aims to offer insights into the frequency, severity, and spatial distribution of meteorological drought events. This study employs advanced statistical methods and climate model projections to enhance understanding and preparedness for meteorological drought risks in the TRB, serving as a valuable reference for drought warning research and strategies to mitigate meteorological drought risks in the drought-prone region.

2. Data and Methods

2.1. Study Area

The Tarim River Basin is situated in the hinterland of the arid zone of Central Asia, and it is China's largest inland river basin. The main stream of the Tarim River is 1321 km long, with a total basin area of 1.02×10^6 km². The TRB comprises a network of 144 rivers, the most notable being the Yarkand River, the Kashgar River, the Hotan River, the Aksu River, the Kaidu–Kongque River, the Weigan–Kuqa River, the Dina River, the Keriya River, and the Cherchen River [35]. The water sources in the basin are diverse, consisting of meltwater from high-altitude snow and ice, precipitation from mid-mountain forested areas, and fractured rock water from low-mountain areas [36]. The Tarim River's four major tributaries are the Yarkand, Hotan, Aksu, and Kaidu–Kongque Rivers. Although the main stem of the Tarim River itself does not generate flow, the ecological environment of the basin is sustained by replenishment from these four tributaries. Consequently, the basin follows a supply pattern known as the “four sources and one main stem” [37]. Furthermore, due to its considerable distance from the ocean and the influence of high mountain barriers, the TRB has developed a typical mid-latitude continental arid climate characterized by low precipitation, high evaporation rates, and significant temperature fluctuations (Figure 1).

2.2. Data Sources and Methods

2.2.1. Data Sources

The meteorological data utilized in this research span from 1 January 1962, to 31 December 2021, and were gathered from 41 meteorological stations within the TRB. The dataset includes daily climate data. These data were sourced from the China Meteorological Administration's China Ground Climate Daily Dataset (V3.0) and underwent rigorous quality control. Thirty-seven meteorological stations were selected based on criteria such as complete data time series, typical representativeness, and relatively uniform distribution within the basin. The data from these 37 stations were subsequently employed to analyze climate and drought characteristics in the TRB (Figure 2).

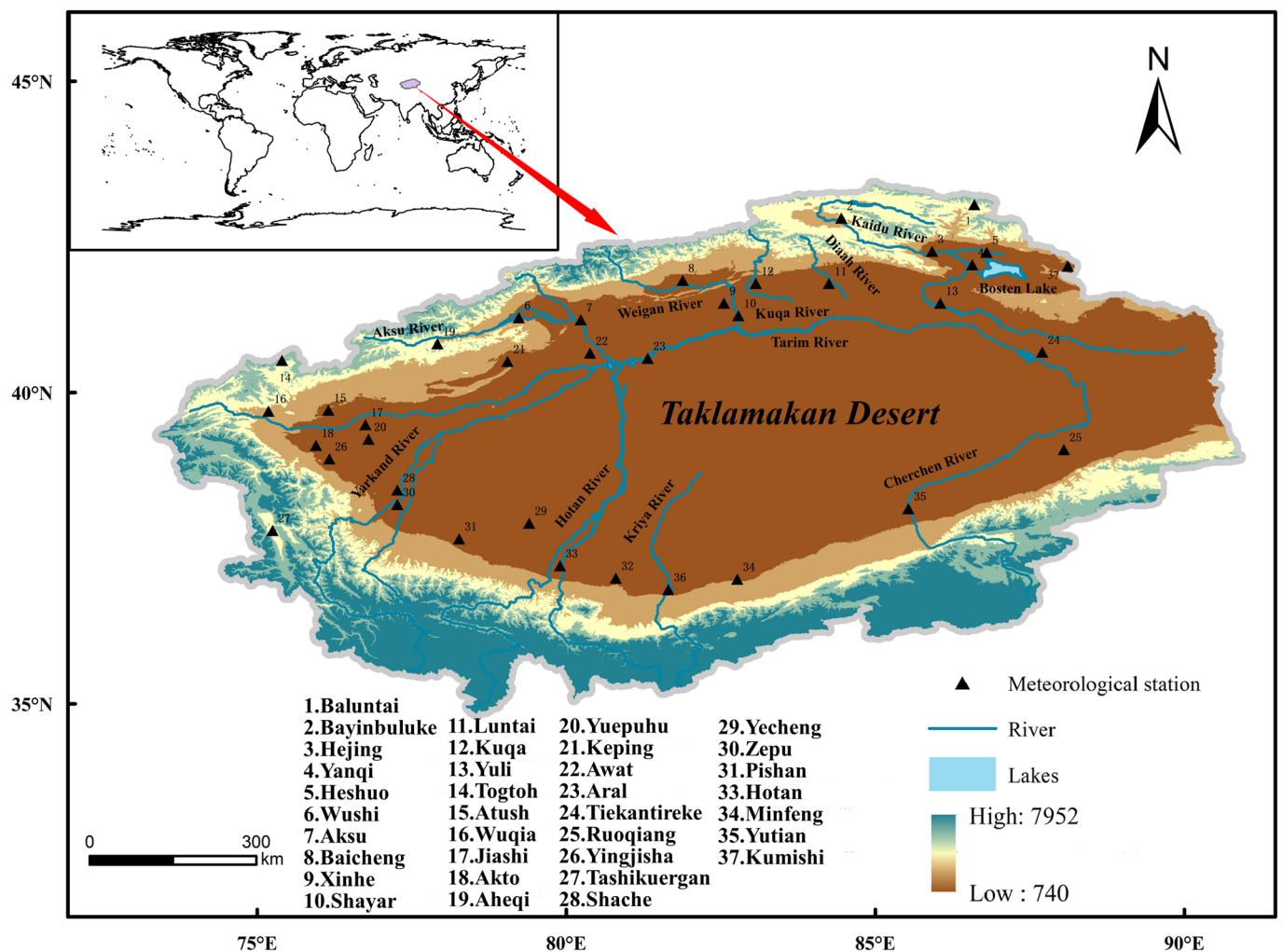


Figure 1. Geographical location and topographic map of the TRB.

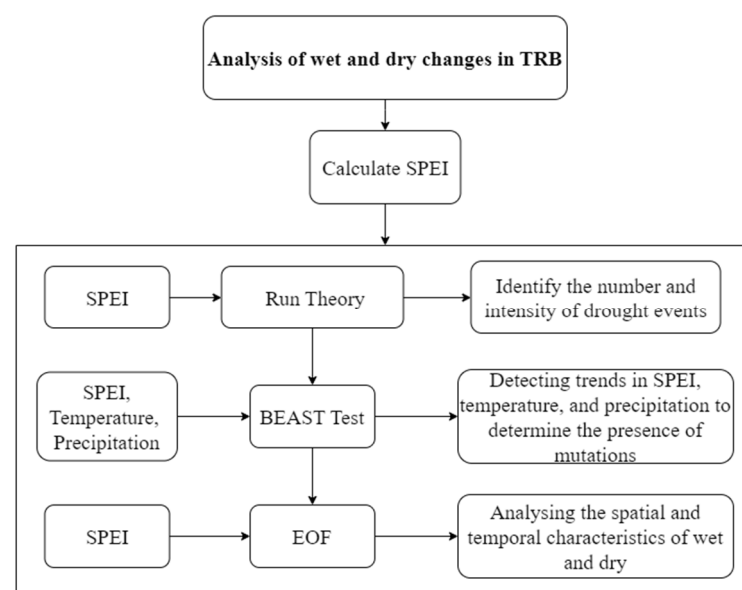


Figure 2. Technology roadmap.

Additionally, ten representative CMIP6 models were chosen to analyze future climate conditions for the period of 2022–2100. The selected models are shown in Table 1. Our analysis focused on the SSP126 scenario. The same running model control indicators under the AMIP plan were selected, using r1i1p1f1 for each CMIP6 model. Meteorological data predictions for each CMIP6 model included datasets for precipitation and temperature (<https://nex-gddp-cmip6> (accessed on 27 August 2023)). Employing such a comprehensive approach ensures that the selected data sources and methodologies contribute to a robust analysis of climate and drought characteristics in the TRB, as well as reliable projections of future climate conditions.

Table 1. A list of CMIP6 models utilized in this study.

Model	Resolution	Nation
ACCESS-CM2	0.25° × 0.25°	Australian
CanESM5	0.25° × 0.25°	Canada
EC-Earth3	0.25° × 0.25°	Europe
FGOALS-g3	0.25° × 0.25°	USA
GFDL-ESM4	0.25° × 0.25°	USA
INM-CM4-8	0.25° × 0.25°	Russia
IPSL-CM6A-LR	0.25° × 0.25°	France
MIROC6	0.25° × 0.25°	Japan
MPI-ESM1-2-LR	0.25° × 0.25°	Germany
NorESM2-MM	0.25° × 0.25°	Norway

2.2.2. SPEI Calculation Method

The SPEI is calculated by assuming that the cumulative moisture deficit sequence in the same month of history obeys a three-parameter log-logistic distribution. The process has the following four main steps: (1) compute evapotranspiration and water deficit, (2) fit the log-logistic probability density function to the water deficit sequence, (3) calculate cumulative probabilities using the distribution function, and (4) standardize the results into a normal distribution [24].

Potential evapotranspiration (PET) is computed utilizing the Thornthwaite classification method, as follows:

$$PET = \begin{cases} 0 & T < 0 \\ 16 \times \frac{N}{12} \times \frac{NDM}{30} \times \left(\frac{10T}{I}\right)^m & 0 \leq T < 26.5 \\ -415.85 + 32.24T - 0.43T^2 & T \geq 26.5 \end{cases} \quad (1)$$

where T represents the monthly average temperature, N denotes the maximum daylight hours, NDM stands for the number of days in the month, and I is the heat index for the year.

SPEIs for 1-, 3-, 6-, 12-, and 24-month time scales represent wet and dry conditions on monthly, seasonal, semiannual, annual, and biennial time scales, respectively. In this paper, these representative SPEI time scales are selected and analyzed for different time scales using the BEAST test, running theory, EOF, etc.

2.2.3. Drought Identification Using Run Theory

In recent years, run theory has been widely adopted as a method for analyzing time series of variables, particularly for extracting and distinguishing drought events. Compared to traditional methods that solely rely on comparing drought indicators, run theory offers higher accuracy in identifying regional droughts and enhances overall comprehension of drought events. A “run” refers to the segment of all values within a time series that fall either below or above a truncation threshold. A positive run occurs when values exceed the truncation threshold, while a negative run occurs when values fall below it. The SPEI sequence values were computed using run theory to detect drought occurrences. According to the drought classification criteria (refer to Table 2), drought is identified only when the SPEI value is below −0.5. In this study, three thresholds were established for identifying

drought events: $X_0 = 0.5$, $X_1 = -0.5$, and $X_2 = -1.5$. The implementation rules are outlined in Figure 3.

Table 2. SPEI classification.

Category	SPEI Value
Extremely wet	$\text{SPEI} \geq 2$
Moderately wet	$1.5 \leq \text{SPEI} < 2$
Slightly wet	$1 \leq \text{SPEI} < 1.5$
Normal	$-0.5 < \text{SPEI} < 0.5$
Mild dry	$-0.5 < \text{SPEI} \leq -1$
Moderate dry	$-1 < \text{SPEI} \leq -1.5$
Extreme dry	$\text{SPEI} \leq -2$

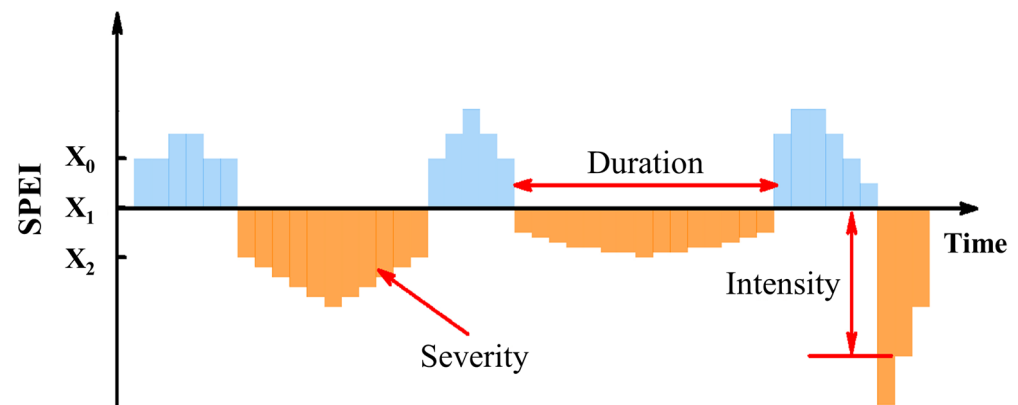


Figure 3. Schematic representation of run theory.

The implementation rules of run theory are grounded in the classification criteria of drought severity based on the SPEI. Three pre-set cut-off thresholds are established: 0.5, −0.5, and −1.5. When the SPEI for a certain month is less than X_1 , it is considered a drought. If the drought persists for at least one month and the SPEI falls below X_2 , it is labeled as a drought event; otherwise, it is deemed a minor drought event and disregarded. For adjacent drought events with a one-month interval, if the SPEI for the interval event falls within $X_1 < \text{SPEI} < X_0$, it is considered a minor drought [38].

2.2.4. BEAST Mutation Test

The BEAST (Bayesian Evolutionary Analysis Sampling Trees) program not only detects when mutations occur in time series but also quantifies the likelihood of mutations. Additionally, the software can detect segmented linear trends and identify arbitrary non-linear ones. In the present study, BEAST is employed to identify trends in temperature, precipitation, and SPEI time series [39].

This method adjusts the time series through BEAST linear regression:

$$y = \sum_{i=1}^m \beta_i X_i + \varepsilon \quad (2)$$

where y denotes the trend test value, β denotes the original time series data, ε denotes the stochastic error term, and X_i denotes the i th predictor variable, which contains a total of m predictor variables.

The BEAST method involves three key steps in computing mutation points:

- (1) Calculate the probability density function of the observed time series.
- (2) Utilize dynamic programming for forward recursion.

- (3) Employ Bayesian rules for stochastic backtracking, considering the quantity and positioning of change points.

2.2.5. Empirical Orthogonal Function Decomposition (EOF)

EOF decomposes the meteorological element field that varies with time in spatial and temporal components, with these two parts being orthogonal to each other. The basic principles and implementation steps are as follows [34]:

- (1) Convert the SPEI calculated for various meteorological stations into a data matrix describing the meteorological field of the region. Assume there are a total of m meteorological stations, each with n sample values, denoted as X_{ij} , $i = 1, 2, 3, \dots, m$, $j = 1, 2, \dots, n$:

$$X_{m \times n} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} \quad (3)$$

The Empirical Orthogonal Function decomposition aims to break down X into a spatial function V and a temporal function Z :

$$X_{m \times n} = V_{m \times n} Z_{m \times n} \quad (4)$$

3. Results and Analysis

3.1. Characteristics of Dry and Wet Changes in the TRB

The overall trend of the annual average SPEI in the TRB for 1-, 3-, 6-, 12-, and 24-month time scales from 1962 to 2021 is generally similar. Changes at shorter time scales are quite frequent, with dramatic alternations between dry and wet periods, though the overall trend of dry and wet changes is not significant. However, as the time scale increases, the numerical changes in the SPEI gradually stabilize, resulting in a longer persistence of drought and wetness periods and a more pronounced overall trend of dry and wet changes (Figure 4a–e).

As evident in the time series plot of the 24-month time scale SPEI changes, from 1962 to 1987, the SPEI alternated between positive and negative values. From 1987 to 1998, the index was predominantly positive, indicating a relatively humid period, whereas after 1998, a cyclic pattern of positive and negative values again emerged. From 2005 to 2021, there was a noticeable increase in negative SPEI values, revealing an intensification of drought conditions and a drought trend that became steadily more pronounced (Figure 4e). This trend aligns with the overarching trend in the multi-time scale SPEI evolution in the TRB (Figure 4f). It is worth mentioning that the SPEI was relatively low in 1997, 1999, 2006–2009, 2017, and 2019, which means that these years were particularly drought-prone. Looking at the changes in the SPEI time series at different scales, the values show a decreasing trend at an average reduction rate of 0.048/year ($p < 0.05$). Both the duration and severity of the droughts are on the rise.

We conducted a BEAST mutation test to examine the shifting trends of the SPEI in the TRB. The test outcomes reveal an overall decreasing trend in the index during the past 60 years. However, a significant wet-to-dry transition was observed from 1997 to 1998, with a mutation test probability close to 80%. Using 1998 as the dividing point, the basin's hydroclimate variations exhibit two distinct phases. From 1960 to 1997, the SPEI indicated a rising trend, with a growth rate of 0.008/year ($p < 0.05$). Overall, the region demonstrated a gradually wetter trend. In contrast, from 1998 to 2021, the SPEI displayed a decreasing trend, with a decline rate of 0.027/year ($p < 0.05$), indicating a transition towards a drier climate (Figure 5a).

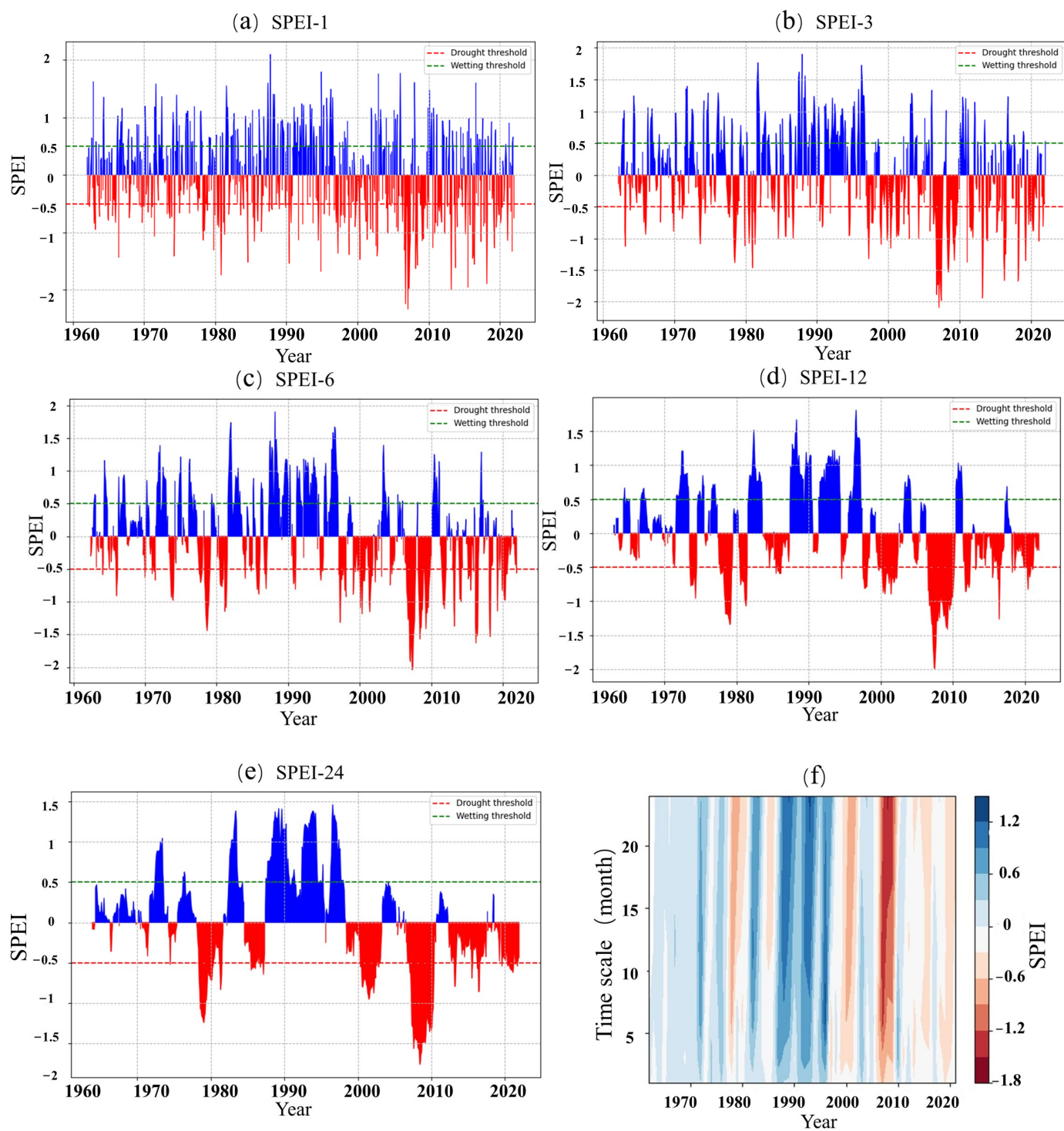


Figure 4. Temporal variability of SPEI (a–e) and SPEI at different time scales (1 to 24 months) for the period 1962–2021 (f) in the TRB.

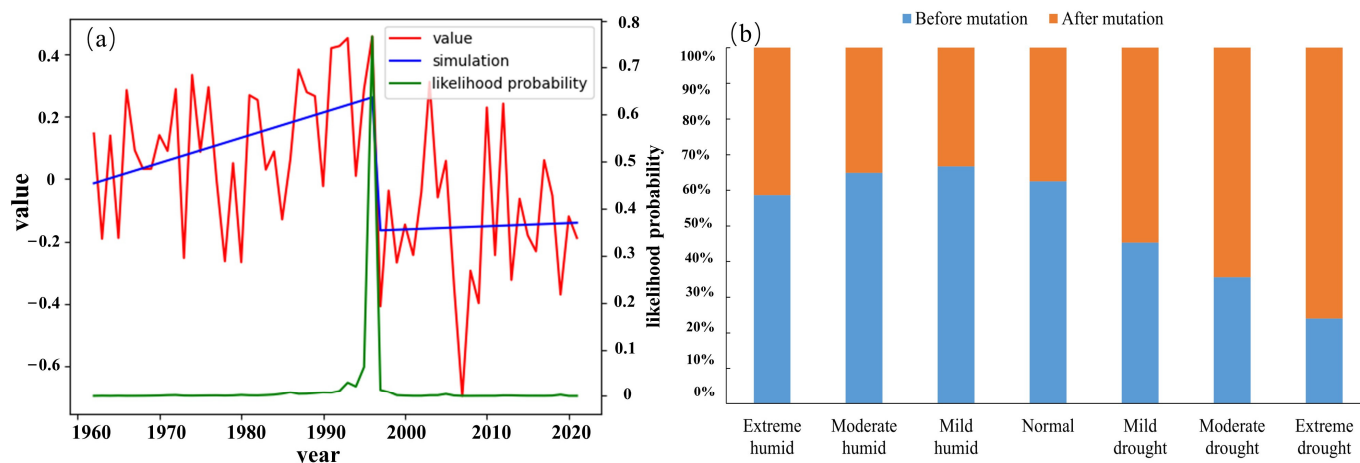


Figure 5. BEAST test for SPEI (a) and changes in the frequency of drought and wetness before and after 1998 (b) in the TRB.

In examining the proportion of wet and dry events over the years, Our investigation revealed that before the wet-to-dry transition, the highest proportions in the 37 meteorological stations in the basin were for mild and moderate wet conditions. After the mutation, the highest proportions shifted to moderate and extreme drought, with an overall increase in the proportions of mild, moderate, and extreme severity. Further, in analyzing the evolution of wet and dry events at different time scales, we observed a clear transition from wet to dry conditions both before and after the mutation. As the time scale increased, this transition became more pronounced (Figure 5b), suggesting that drought is expected to become a fundamental climatic characteristic of the TRB in the future.

Next, using run theory, we extracted and identified drought event frequency and intensity for the stations. In terms of drought frequency, there were 5286 drought events from 1962 to 2021, averaging 147 drought events per station. The stations with the highest drought event frequency were Aheqi/Kumishi/Baicheng (164), Kuqa (158), and Yuli (155), while the station with the lowest frequency was Zepu (133) (Figure 6a). Spatially, the northern part of the basin emerged as a high-frequency center of drought events, while the southern part experienced relatively fewer events. The high-frequency centers in the north were concentrated in the Aksu, Weigan, and Kaidu river basins, whereas in the south, the high-frequency centers were in the Hetian and Keriya river basins. The main stem portion of the Tarim River Basin, along with the Carleton, Yarkant, and Kashgar river basins, experienced relatively fewer and more dispersed drought events (Figure 6b).

Additionally, we found that the three stations with the peak intensity of drought events in the basin are Wuqia, Ruoqiang, and Zepu, with average intensities of -1.85 , -1.84 , and -1.83 , respectively (Figure 6c). The geographic spread of drought event severity in the basin generally exhibits a pattern of higher intensity in the south and lower intensity in the north. Higher levels of drought intensity are concentrated in the southern region of the TRB, while the northern part generally experiences lower drought intensity with sporadic high-intensity values. Specifically, the Aksu, Weigan, and Dina river basins in the north show lower drought event intensities, while the Kashgar and Kaidu river basins, which are also in the north, exhibit higher drought event intensities. In the south, the overall drought intensity is higher in the Hetian, Keriya, and Carleton river basins. This suggests that drought event intensity is typically greater in the southern areas compared to the northern ones (Figure 6d).

We compared the spatial distribution characteristics of the frequency and intensity of drought events in the basin. In the northern region, drought events occur relatively more frequently, but their intensity is lower. In contrast, the southern region has fewer occurrences of drought events, but their intensity is higher (Figure 6b,d). These findings

reveal a lack of consistency between the spatial distribution characteristics of the frequency and intensity of drought events within the study area.

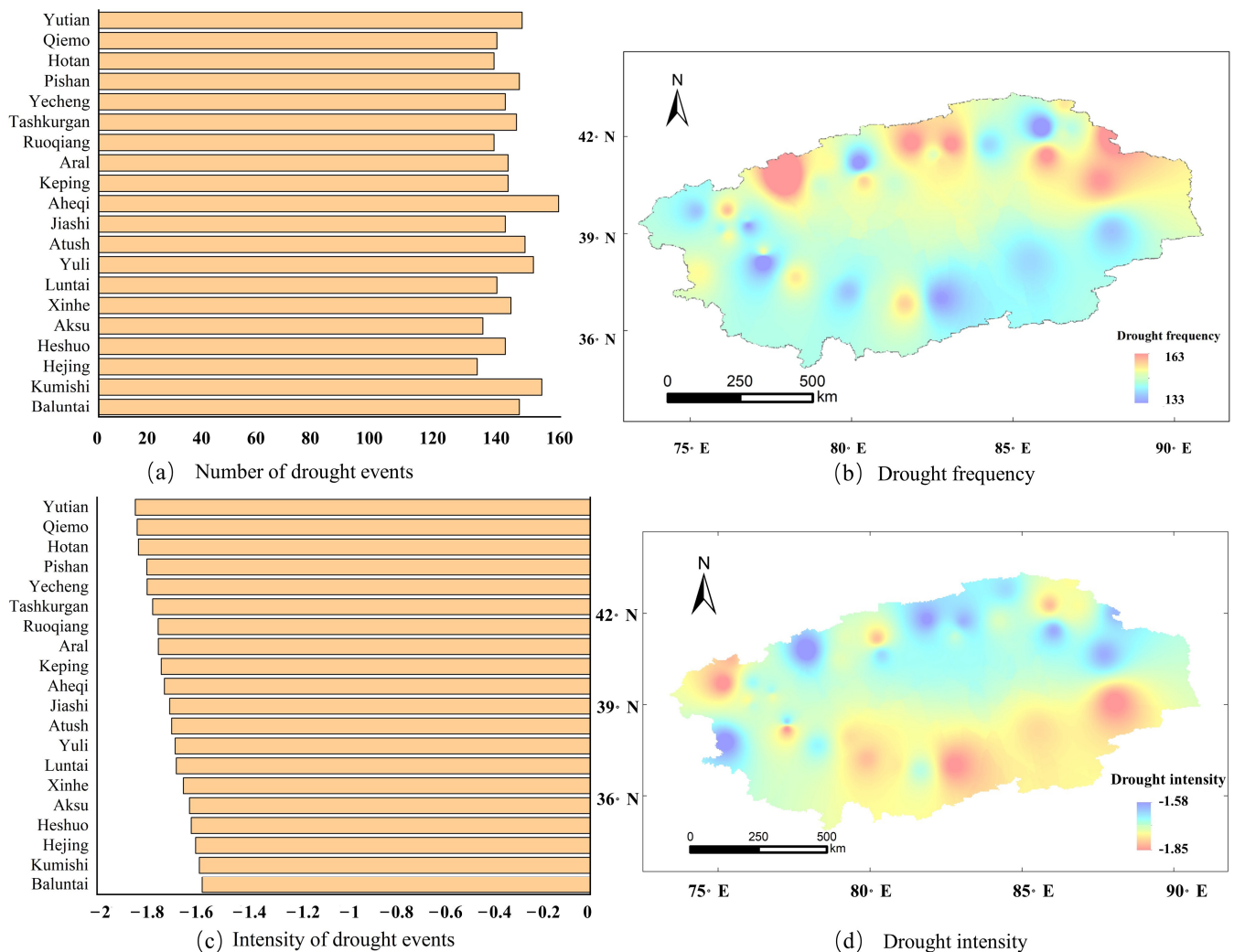


Figure 6. Number, intensity, and corresponding spatial distribution of drought events in the TRB.

3.2. Spatial Patterns of Drought and Wetness Variability in the TRB

To delve deeper into the spatial distribution characteristics of drought and wetness variability in the basin, this study applied EOF analysis to the SPEI at different time scales. The results show that the cumulative variance contribution rates of the first three EOF modes of the indices are 75.54%, 74.94%, and 75.19%, respectively, and that the rates at different time scales all exceed 70% (Table 3). This indicates that the EOF is suitable for spatially analyzing the climate variability of drought and wetness in the TRB and that it is related to the main spatial and temporal distribution characteristics of climate variability in the TRB.

Table 3. Explained variance of the leading EOFs of multi-scale averaged SPEI.

Mode	Explained Variance (Cumulative Explained Variance) (%)		
	SPEI-1	SPEI-3	SPEI-6
1	56.196 (56.196)	55.225 (55.225)	54.083 (54.083)
2	12.348 (68.544)	12.888 (68.113)	14.357 (68.440)
3	7.001 (75.544)	6.827 (74.940)	6.754 (75.194)

Furthermore, the modal decomposition results of SPEI-1, SPEI-3, and SPEI-6 show that the characteristic vectors of the first mode at different time scales are all positive and that the intervals from low to high values are generally consistent (Figure 7a). The cumulative variance contribution rates of the first mode at these three time scales are 56.19%, 55.22%, and 54.08%, respectively (Table 3). These rates indicate that the geographical distribution of climate variability regarding drought and wetness is highly consistent across the TRB, i.e., the entire basin experiences simultaneous periods of dryness or wetness.

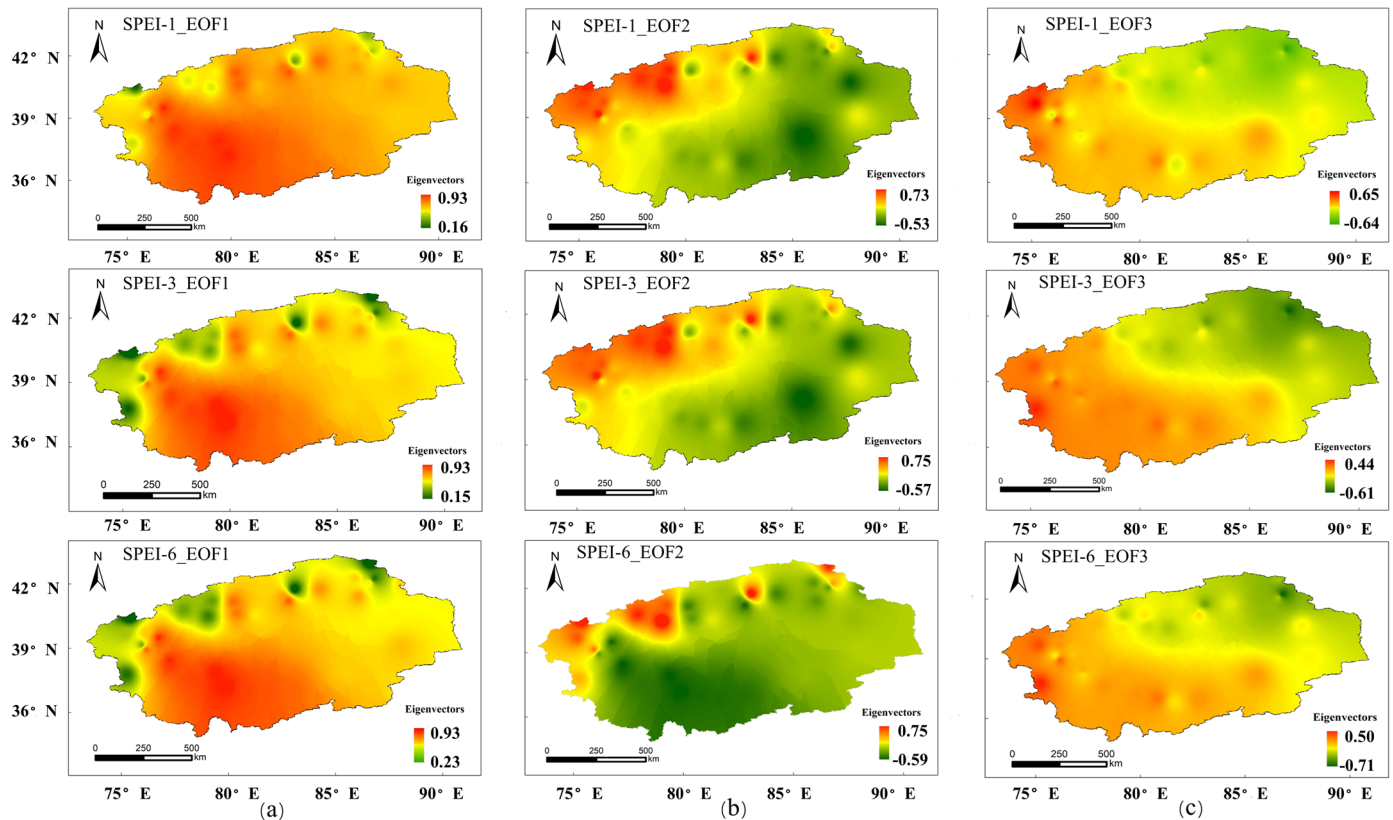


Figure 7. The first three feature vectors of the averaged SPEI ((a–c) are the spatial distributions of the first, second, and third modal eigenvectors on 1-, 3-, and 6-month time scales, respectively).

Nonetheless, there are still some notable variations. The center of high values of EOF decomposition at different time scales is in the southwestern part of the TRB, with scattered distribution in the north, specifically in the Yarkand, Weihegan, and Dina river basins (Figure 7a). This suggests that these areas exhibit high sensitivity to changes and are susceptible to drought events. Moreover, the range of modal characteristic vector values for SPEI-3 in the first mode is greater than that for SPEI-6, and the time coefficients correspond to the temporal trends of drought and wetness across the TRB. From 1962 to 1986, the time coefficients show an increasing trend, indicating an increase in humidity and a gradually wetter climate. From 1987 to 1998, the time coefficients show continuous fluctuations and most are positive, denoting an overall wetter period. After 1998, the time coefficients reveal a decreasing trend that points to a weakening of the basin-wide consistency in climate variability, and a trend towards drought emerges (Figure 8a). This is closely related to the wet–dry transition that occurred in 1998.

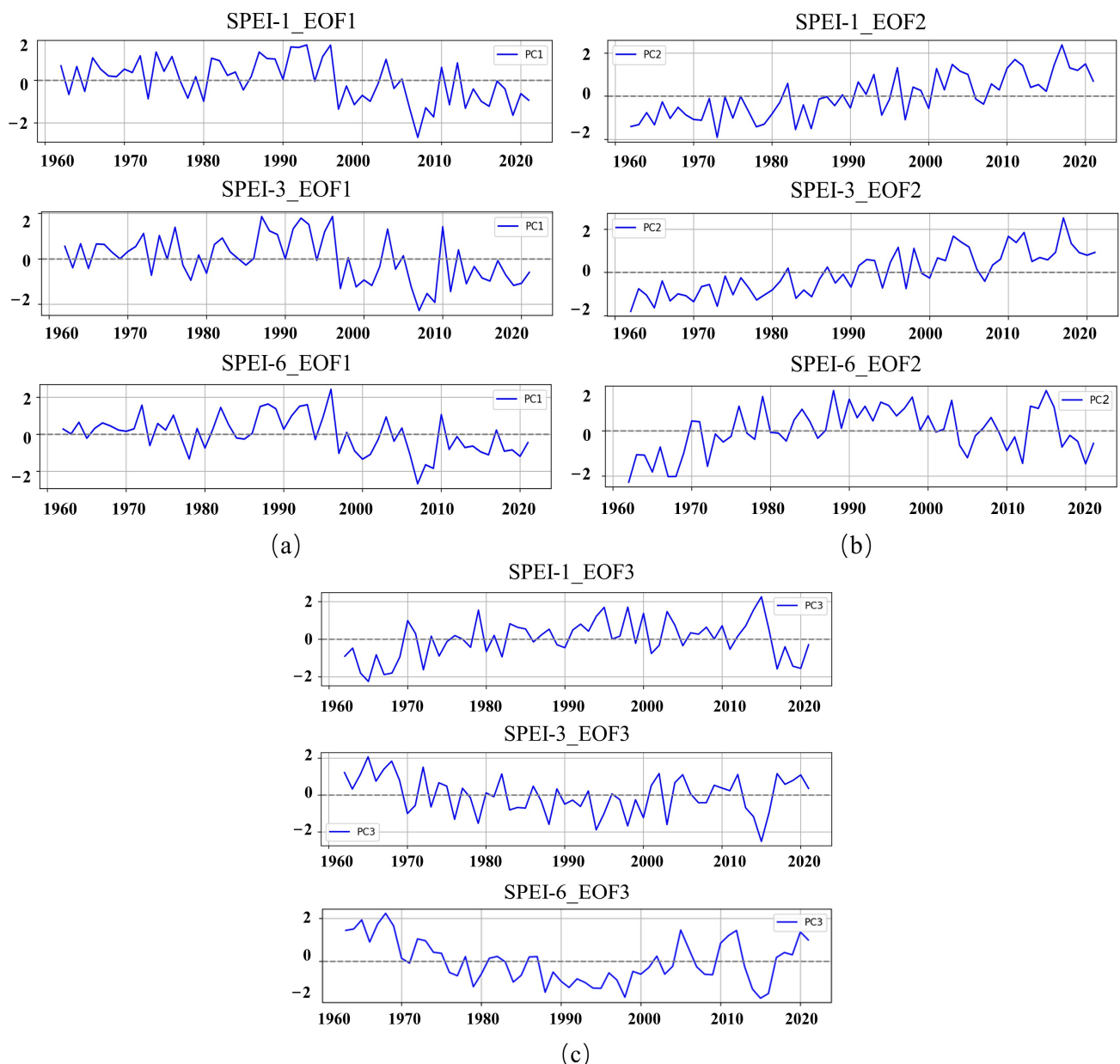


Figure 8. Time coefficients of the first three feature vectors ((a–c) are the time series of the first, second, and third modal eigenvectors on 1-, 3-, and 6-month time scales, respectively).

The contribution rates of the second-mode characteristic vectors of EOF decomposition for SPEI-1, SPEI-3, and SPEI-6 to the variance are 12.35%, 12.89%, and 14.36%, respectively (Table 2). As shown in the table, the spatial distribution pattern of the second mode exhibits notable differences compared to that of the first mode, with the second mode exhibiting a “north-south opposite” spatial dynamic distribution pattern. The spatial distribution patterns of the second mode for SPEI-1, SPEI-3, and SPEI-6 are similar, although there are some variations in local ranges. The spectrum of low to high values for SPEI-3 is greater than that for SPEI-1, indicating regional complexity in the second mode of drought (Figure 7b).

The trend of change in the second-mode time coefficients can be roughly categorized into three stages: negative, alternating, and positive. Prior to 1986, the time coefficients were mostly negative, but between 1986 and 1998, the time coefficients alternated between positive and negative. After 1998, the time coefficients were mostly positive (Figure 8b).

This also indicates that the study region experienced a significant “wet-dry transition” in 1998.

By integrating the spatial distribution maps of the second mode across various time scales, it becomes apparent that the northern region of the TRB underwent a shift from dry to wet conditions, whereas the southern region witnessed the opposite trend. Over the past decade, certain areas in the northern part of the basin have experienced a partial alleviation of drought, whereas the majority of areas in the southern part have seen a worsening of drought conditions. Nonetheless, considering the regional distribution of the modal spatial pattern, the predominant trend across the basin indicates an escalation of drought (Figure 7b).

The contribution rates of the third-mode characteristic vectors of EOF decomposition for SPEI-1, SPEI-3, and SPEI-6 to the variance are 7.00%, 6.83%, and 6.75%, respectively. This represents the third important mode of drought characteristics in the TRB. Analyzing the spatial distribution characteristics of this mode at various time scales, we observe contrasting patterns in the western and eastern regions, with a relatively pronounced and complex distribution. Overall, the western part has high values, while the eastern part has low values. The high-value center is situated in the western portion, including the Kashgar and Yarkand river basins, while the low-value center is positioned in the Weigan, Dina, and Kaidu river basins (Figure 7c).

By combining the time coefficients of the third-mode characteristic vectors, we can see that the 1960s to the 1970s were typical years of western drought and eastern wetness. In contrast, 2005, 2012, 2016, and 2020 were typical years of western wetness and eastern drought. The overall trend of the time coefficients infers that in the last 30 years, the drought trend in western TRB has weakened, indicating an increase in humidity in this region. Conversely, the climate trend in eastern TRB is the opposite (Figure 8c), showing a trend towards increased aridity.

3.3. Analysis of the Causes of Wet and Dry Changes in the TRB

Over the historical period (1962 to 2021), the average SPEI trend at the 1-, 3-, 6-, 12-, and 24-month time scales in the TRB is $-0.0166/a$ ($p < 0.05$), denoting a tendency towards aridification. However, the magnitude of the change is not pronounced. Examining the aridity and wetness characteristics at different time scales, apart from the notable “wet-dry transition” in 1998, the aridity indices have shown an overall decrease post-1998, and this feature exhibits a relatively regular interannual variation (Figure 2).

The temperature trend across the study area reveals temperature fluctuations from 1962 to 1996. In 1997, there was a significant jump in temperature, and since then, it has maintained a high and oscillating pattern (Figure 9a). This trend is validated by the BEAST mutation test, with a mutation probability exceeding 80% (Figure 9b). In other words, the temperature in the TRB underwent a mutation in 1997, followed by a significant upward trend. Similarly, the precipitation trend showed fluctuations from 1962 to 1985. This feature aligns closely with the multi-time scale SPEI changes in the basin, exhibiting a high correlation during this period. However, in 1986, there was a sudden increase in precipitation (Figure 9c), a result confirmed by the BEAST mutation test (mutation probability exceeding 50%). Since that time, precipitation has maintained a generally high and oscillating pattern (Figure 9d).

The period from 1962 to 1986 exhibited a cyclic pattern of alternating positive and negative values in the drought index. Climatically, this period showed a fluctuating pattern of dry and wet conditions with no apparent trend towards increased dryness or wetness. Then, from 1986 to 1998, there was a noticeable trend towards increased wetness due to a sudden increase in precipitation. At the same time, temperatures in the basin consistently rose during this period, resulting in warm and humid characteristics. However, with the continued rise in temperatures, the PET also intensified. The extent of temperature rise surpassed the growth in precipitation, causing the drying effect induced by the temperature rise to offset the wetting effect of the precipitation. Since 1998, the TRB has therefore

experienced a pronounced shift from wet to dry conditions, with the climate shifting from a warm and humid pattern to a warm and dry one. Subsequently, there has been an increased frequency and intensity of drought events at all levels of the basin.

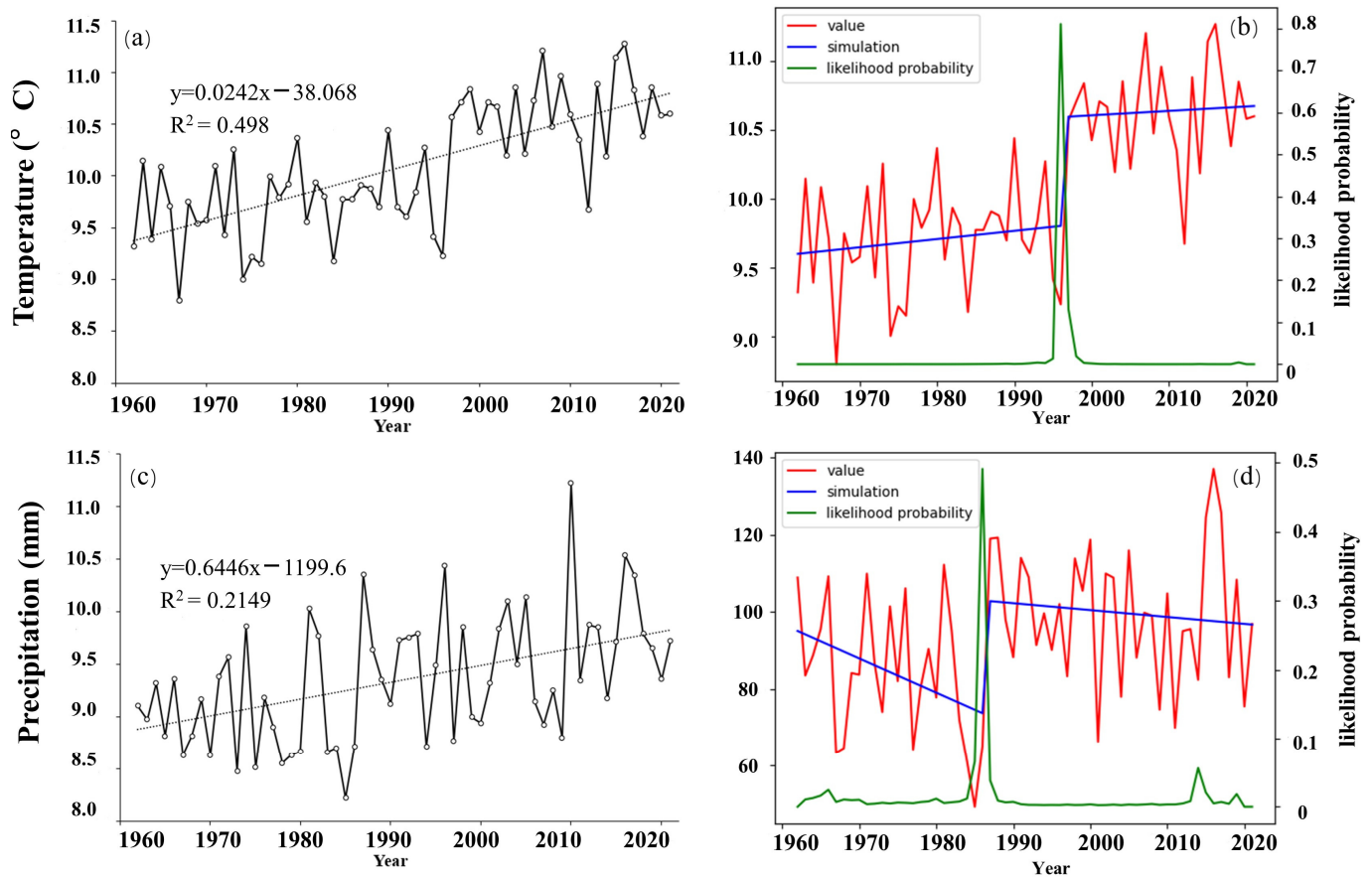


Figure 9. Temperature and precipitation trends and BEAST test in the TRB ((a) is the trend in temperature, (b) is the test for abrupt changes in temperature, (c) is the trend in precipitation, and (d) is the test for abrupt changes in precipitation).

3.4. Future Trends of Wet and Dry Changes in the TRB

We utilized the CMIP6 dataset under the SSP126 scenario to analyze temperature and precipitation data for the period 2022–2100, calculating the SPEI within the basin. The results indicate that, when examining the changing characteristics of SPEI trends at short time scales, there is pronounced variability in future dry and wet conditions. The overall trend in dryness and wetness is not apparent, but as the time scale increases, the future climate gradually shifts towards becoming drier (Figure 10a–e). By analyzing the trends in the 12- and 24-month time scales for SPEI, we can see that the indices are mostly positive during 2022–2040 and then mostly become negative during 2041–2100 (Figure 10d,e). Further, the changes in dry and wet events at different time scales reveal an overall trend of increasing aridity. During 2022–2040, the basin is generally more humid, but after 2041, it starts transitioning towards increased aridity. This trend becomes more pronounced with increases in SPEI time scales (Figure 10f).

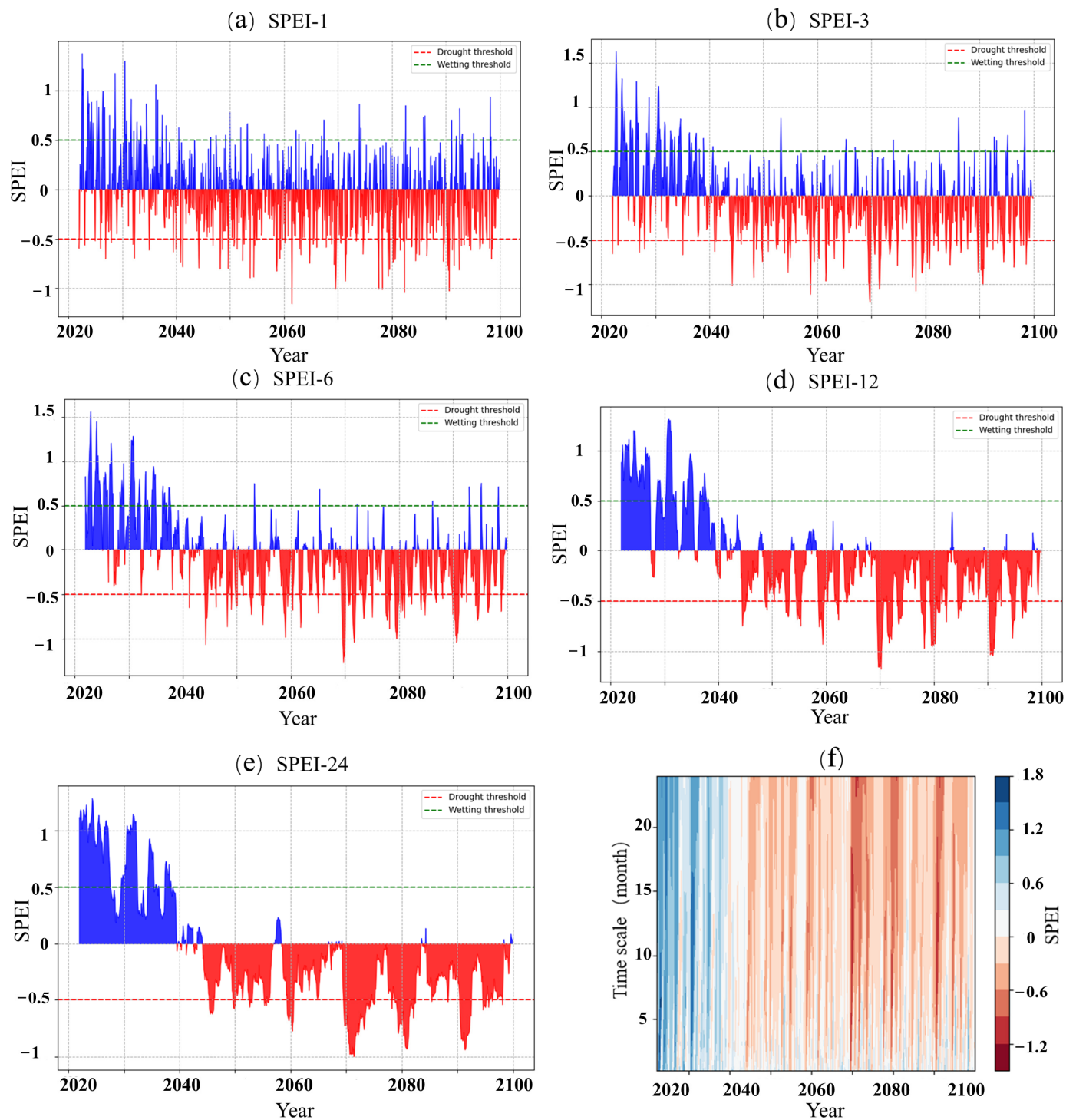


Figure 10. Temporal variability of SPEI (a–e) and SPEI at different time scales (1 to 24 months) for the period 2022–2100 (f) in the TRB.

Using the SSP126 scenario, we examined the spatial distribution characteristics of future trends in dry and wet conditions using the Sen's slope of the basin's SPEI and the Mann–Kendall (M-K) test, with a significance level of 0.05. The spatial distribution features showed that the proportion of areas within the TRB underwent major changes and that the 0.05 significance level exceeded 75.4%. Moreover, future dry and wet trends in the basin were predominantly concentrated in the central and eastern regions of the TRB, with 72.1% of the region exhibiting a significant increase in drought trends. Meanwhile,

27.9% of the TRB showed a significant decrease in drought trends, with most of these areas situated in the northern, western, and southern peripheral regions of the basin. Overall, the distribution features exhibit a pattern of intensified drought in the central area surrounded by areas where drought trends are alleviated.

4. Discussion

Global warming has contributed to significant changes in the TRB, shifting the region's climate from "warm-wet" to "warm-dry". Tang QiuHong et al. discovered that the rise in temperature, decline in relative humidity, and increase in wind speed in Northwest China over the last 60 years offset the wetting trend brought about by the increase in precipitation, which is an important reason for the change from wet to dry [40]. Wan et al. suggested that the dominant factor for the drought characteristics of recent years in China is the increase in the PET [41], and some studies have shown that the Indian Ocean Basin-wide Modal (IOBM) and the Pacific Ocean Basin-wide Modal are the same. Additionally, they discovered that the IOBM and the Pacific Interdecadal Oscillation may serve as the primary drivers of climate change in Northwest China, whereas in Xinjiang, the Arctic Oscillation and North Atlantic Oscillation concurrently play crucial roles in drought evolution, particularly from January to March. In related work, Tao Hui et al. analyzed the wet and dry variations in the TRB and found that atmospheric circulation significantly influences changes in dry and wet conditions and that the effects of water vapor transport and atmospheric structure changes on the basin cannot be ignored [42]. Furthermore, under the scenario of continuously increasing temperature without a substantial rise in precipitation, the influence of a potential increase in evapotranspiration has gradually exceeded that of precipitation, and this region has been reversed from a humid trend to an arid one [43]. Despite the increasing precipitation in NW China, the primary cause of the escalating drought in Northwest China remains the increase in evapotranspiration due to rising temperatures [31].

Additionally, we found that the EOF decomposition of basin drought showed three main modes: the first mode exhibited consistency across the basin, while the second mode showed a north–south opposition, and the third mode displayed an east–west opposition, which was closer to the results of Zhao et al. [44]. The first mode shows the overall convergence of wet and dry conditions in the TRB, exhibiting obvious polycentricity, with the center of high values situated in the southwest part of the basin. The time coefficients corresponding to this mode indicate a transition from wet to dry, echoing the results of related studies on climate change in the northwestern region [29,45,46]. As the time scale increases, the time coefficients and spatial modes of wet and dry changes are inclined to show global rather than local trends, and generality rather than details [47]. Therefore, the SPEI benefits from multiple time scales and can be used as an important tool to analyze the characteristics of short-, medium- and long-term drought temporal changes as well as spatial distribution characteristics. Meanwhile, the EOF decomposition method was able to extract mutually orthogonal spatiotemporal modes from the complex drought variable field, accurately reflecting the spatiotemporal changes of drought, which is a key method for analyzing drought characteristics [48]. The dry and wet spatiotemporal change characteristics obtained from the analysis have strong regularity and identifiability.

Our analysis of future trends of wet and dry changes in the TRB found that drought levels will likely increase and that the area of drought intensification is concentrated in the central region of the basin. For the past several years, global warming and the increase in evapotranspiration have had a rising impact on the Northwestern Arid Zone. This factor is the primary driver behind the intensification of drought in this region [45]. Some scholars have also studied the drought characteristics of the TRB through four different scenarios of CMIP6 and the VIC distributed hydrological model. Their results show that under the different scenarios, the future drought trend intensifies in the basin's central region but is somewhat weaker in the mountainous areas on the periphery of the basin, which aligns well with the findings of the current study [49]. Meanwhile, in the Taklamakan Desert in

the central part of the TRB, the future drought trend increases sharply, demonstrating that the desert amplifies the impact of global warming within the context of a warmer climate in the future, making the whole area more sensitive to climate change. This sensitivity causes the arid and water-scarce land mass to become even more arid so that the risk of drought intensification within the basin is higher in the future [50].

Research indicates that climate warming amplifies the dynamic alterations of vegetation in the Northern Hemisphere [51]. Against the backdrop of climate warming, vegetation coverage in Xinjiang exhibits a declining trend [52]. Recent studies have demonstrated that extreme temperatures and intense precipitation in Xinjiang play a crucial role in influencing changes in vegetation coverage. Hence, the poor state of vegetation degradation may be caused by the combination of climate “wet-dry transition” and frequent recurrence of extreme climate events. Climate change will affect glacier melting. This, in turn, affects the generation of meltwater runoff and makes a significant contribution to the total volume of water resources. The runoff of TRB is heavily dependent on glacier melting [35]. Over the past few decades, many glaciers have experienced a complete retreat; the ongoing decrease in runoff since the 21st century is intimately associated with the diminishing glacier area, the thinning of glacier thickness, and the elevation of the equilibrium line in the basin [53]. The present study also found that the trends of the SPEI were not significant at short time scales but showed a significant downward trend at long time scales. Moreover, the frequency of changes in the SPEI gradually weakened, while the magnitude of changes gradually increased with the expansion of the time scale. This indicates that the index’s response to climate slows down for long time scales, reflecting the general trend of wet and dry changes [54].

In this paper, a limited amount of station data within the watershed is extended to the entire study area by inverse distance weight interpolation. The findings vary depending on the interpolation methods. The inverse distance weight method is simple and flexible, but it only considers the influence of distance and ignores the spatial variability between variables. The inverse distance weight interpolation method used in this paper has the advantage of simplicity, but the effect of terrain factors on drought may be underestimated, especially since some areas in southern TRB are located in the hinterland of the Taklamakan Desert and lack meteorological stations. Therefore, because the results of our analyses may be subject to certain limitations and uncertainties, the potential advantages of surface source data in the in-depth study of drought need to be further explored.

5. Conclusions

This study employed data from 37 meteorological stations and the CMIP6 dataset to compute the SPEI at various time scales in the TRB. Empirical orthogonal decomposition of the indices was carried out to make a detailed analysis of the climate dry and wet changes during a historical interval (1962–2021) and the forthcoming interval (2022–2100), along with their characteristics of spatiotemporal distributions. The main conclusions of this study include the following:

- (1) From the latter part of the 1980s to the conclusion of the 1990s, the TRB showed a clear trend of warming and humidification, but from 1998 onwards, the basin as a whole began to change from wetness to dryness, and the proportion of mild drought, moderate drought, and extreme drought notably expanded at all measured sites. Since then, the proportion of mild drought, moderate drought, and extreme drought has increased significantly.
- (2) The salient features of the spatial distribution of drought in the TRB are “more in the north and less in the south”, but drought severity characteristics are “less in the north and more in the south”. Overall, the drought severity and the spatial distribution of the number of droughts have little consistency, and droughts are frequent in the north, whereas they are severe in the south. In other words, the severity and frequency of drought events do not exhibit spatial consistency, with frequent but less severe droughts in the north and fewer but more severe droughts in the south.

- (3) There were three main types of spatial modes in the TRB: regionally consistent, north–south opposite, and east–west opposite. About 75% of the cumulative variance contribution was attributed to the first three modes, with the first mode primarily characterizing the basin.
- (4) Anticipated future climate change will elevate drought risk in the TRB, exacerbating the drought trend and concentrating the spatial distribution more in the basin’s center and less at its periphery.

The climate warming of TRB leads to the acceleration of glacier melting, which increases the water resources within the basin during a specific time interval. However, in the long run, as the temperature continues to rise, the glaciers will face depletion, which is very unfavorable to the development of the already arid TRB. Therefore, the government should take energy conservation, emission reduction, and consumption reduction as important starting points for economic development; develop and utilize new renewable energy sources; strengthen water resource management and optimal allocation; and coordinate ecological environment and economic and social development. These results are consistent with the drying trend in Central Asia that started in 2004. This paper uses EOF and integrates the CMIP6 dataset for future dry and wet prediction, providing a reference for promoting climate modeling and future climate prediction methods.

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