SPEI-Based Analysis of Drought Evolution Characteristics in the Xilin River Basin (Postprint)

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Abstract

Based on daily meteorological observation data from 13 national meteorological stations within and around the Xilin River basin, and employing the Standardized Precipitation Evapotranspiration Index (SPEI), this study utilizes Mann-Kendall and Mann-Whitney Pettitt change point tests, non-parametric statistical tests, and rescaled range R/S analysis to conduct an in-depth investigation of long-term drought evolution trends and future drought predictions in the Xilin River region. The results indicate that the drought regime shift in the Xilin River region began in the 1990s; over the past 60 years, SPEI has exhibited a significant decreasing trend, with the decreasing trend being less pronounced in the upper reaches than in the middle and lower reaches; the middle and lower reaches constitute a drought-prone zone; and the northwestern end of the lower reaches represents a high-risk area for drought occurrence. In the future, drought conditions in the basin will be alleviated to some extent, but there is a possibility of continuous intensification of winter drought. Drought monitoring should be strengthened.

Full Text

Preamble

Analysis of Drought Evolution Characteristics in the Xilin River Basin Based on SPEI

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Abstract

Based on daily meteorological observation data from 13 national meteorological stations within and surrounding the Xilin River Basin, this study employs the Standardized Precipitation Evapotranspiration Index (SPEI) combined with Mann-Kendall and Mann-Whitney Pettitt mutation tests, nonparametric statistical tests, and rescaled range (R/S) analysis to investigate the long-term drought evolution trends and future drought predictions in the Xilin River region. The results indicate that drought mutation in the Xilin River region began in the 1990s. Over the past 60 years, SPEI has shown a significant decreasing trend, with a smaller decline in the upstream region compared to the middle and lower reaches. The middle and lower reaches represent drought-prone zones, while the northwestern end of the downstream area constitutes a critical drought hazard zone. In the future, drought conditions in the basin are expected to alleviate somewhat, though winter drought may intensify, necessitating enhanced drought monitoring efforts.

Keywords: SPEI; SPI; drought variation; Mann-Kendall; Xilin River Basin

Introduction

Against the backdrop of global warming and drying, extreme climate events such as droughts and floods have become increasingly normalized, with rising frequency and intensity [1-2]. In recent years, due to climate change and unsustainable grazing practices, the ecological environment of arid and semi-arid grassland watersheds has suffered severe degradation, leading to reduced forage yields, accelerating land desertification, and frequent drought events that pose significant challenges to sustainable socio-economic development in pastoral regions [3-6].

Drought monitoring serves as a crucial tool for addressing drought variation. Given the extensive impacts of drought events, utilizing drought indices to effectively monitor and assess regional drought conditions at specific temporal scales can mitigate the effects of natural disasters on human life [7]. Climate change may alter precipitation patterns, with temperature, precipitation, and potential evapotranspiration representing the primary climatic factors affecting arid and semi-arid grassland regions and serving as direct indicators of drought [8]. Early drought indices employed single precipitation elements to characterize drought [9], offering broad applicability but neglecting the influence of other factors. Through continuous exploration, researchers have combined precipitation and temperature for drought characterization, and with gradual optimization of potential evapotranspiration calculation methods, standardized drought indices have gained increasing acceptance among scholars [3,10]. The SPEI, for instance, accurately characterizes drought features with strong applicability [11]. Applications of SPEI to study drought evolution characteristics in northeastern and southwestern China have yielded results highly consistent with actual conditions [12-14], and research demonstrates that integrated application of SPEI and SPI at different temporal scales enables comprehensive climate change assessment [8,11,15]. While SPI has been used to evaluate drought in the Xilin River Basin and analyze seasonal drought-flood disaster frequencies to delineate timing and intensity of such events [16], analysis of spatial and long-term temporal drought evolution trends remains insufficient. Therefore, to improve drought monitoring and evaluation accuracy, this study selects SPEI and SPI for spatiotemporal drought evolution trend analysis in the basin and compares the regional applicability of the two indices, aiming to provide support for watershed ecological protection, drought evolution characteristic assessment, and future drought disaster prevention.

1.1 Study Area Overview

The Xilin River originates in Keshiketeng Banner, Chifeng City, and is an inland river (43°26 -44°39 N, 115°32 -117°12 E) with a total length of 198 km and a drainage area of 6,263 km^2. The river is demarcated at Kunisuman, with the upstream section flowing through hilly terrain with exceptionally meandering channels and intermittent marshlands. The region features a typical temperate arid/semi-arid continental climate with distinct seasonal variations. The multi-year average precipitation is 276.3 mm (ranging from 121.1 mm to 511.7 mm), characterized by dryness and frequent winds. Potential evapotranspiration in the Xilin River Basin, calculated using the Penman-Monteith formula recommended by the Food and Agriculture Organization (FAO) [17], averages 1,105.6 mm annually (ranging from 978.2 mm to 1,243.5 mm).

[Figure 1: see original paper] Distribution map of meteorological stations

1.2 Data Sources

Since only one national meteorological station (Xilinhot) exists within the Xilin River Basin, this study downloaded and compiled daily meteorological data from 13 national stations within and surrounding the basin for the period 1960–2018, including precipitation, mean temperature, maximum temperature, minimum temperature, mean relative humidity, sunshine duration, and mean wind speed (see Figure 1). Meteorological data were obtained from the China Meteorological Data Sharing Service Network (http://data.cma.cn) China Surface Climate Data Daily Dataset (V3.0) [18-19], with missing data rates $ $10%. To ensure temporal series completeness, missing data for each station from 1960–2018 were interpolated and extended using partial least squares regression, and data reliability, consistency, and representativeness were verified and corrected.

2.1 SPEI and SPI

The SPI calculation considers only precipitation factors, offering simplicity and multi-temporal scale applicability, and has been widely used in meteorological drought monitoring [14,20]. SPEI was proposed by Vicente-Serrano in 2010 to address SPI' s limitation in adequately expressing temperature indicators [21].

SPEI calculates the difference between potential evapotranspiration and precipitation, followed by normalization, thereby incorporating temperature effects on drought and more objectively describing surface moisture variations, making it suitable for drought characteristic analysis under climate warming [22].

This study calculates potential evapotranspiration (PET) based on the Penman-Monteith formula and computes the climatic water balance (BAL) as:

$$BAL_i = P_i - PET_i$$

where BAL_i is the difference between precipitation and evapotranspiration (mm), P_i is precipitation (mm), and PET_i is potential evapotranspiration (mm).

The BAL_i data series is normalized. Since negative values may exist in the original data series, SPEI employs a three-parameter log-logistic probability distribution with the probability distribution function:

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

where parameters α, β, and γ are fitted using the linear moment estimation method:

$$\beta = \frac{\omega_0 - 2\omega_1}{\Gamma(1+1/\alpha)\Gamma(1-1/\alpha)}$$

$$\gamma = \omega_0 - \alpha\beta\left[\Gamma(1+1/\alpha)\Gamma(1-1/\alpha)\right]$$

where Γ is the factorial function and ω_s represents probability-weighted moments of the original data series BAL_i, calculated as:

$$\omega_s = \frac{1}{N}\sum_{i=1}^{N}(1-F_i)^s \cdot BAL_i$$

where $F_i = \frac{i-0.35}{N}$ and N is the number of months included in the calculation.

The cumulative probability distribution $F(x)$ is then standardized. When cumulative probability $P \leq 0.5$:

$$SPEI = -\left(\omega - \frac{c_0 + c_1\omega + c_2\omega^2}{1 + d_1\omega + d_2\omega^2 + d_3\omega^3}\right)$$

When $P > 0.5$:

$$SPEI = + \left(\omega - \frac{c_0 + c_1\omega + c_2\omega^2}{1 + d_1\omega + d_2\omega^2 + d_3\omega^3} \right)$$

where $\omega = \sqrt{-2\ln(P)}$.

2.2.1 Mutation Test

The Mann-Kendall mutation test is a method for detecting mutations in long-term sequences, widely used in recent hydrometeorological research due to its operational simplicity and precise results [23]. For a time series $\{x_1, x_2, ..., x_n\}$ of length n, assuming no trend exists, a statistical variable is established based on statistical principles.

The calculated sequence forms a random order series following a normal distribution, from which its expected value and variance can be computed. The variable UF_k is defined as:

$$UF_k = \frac{d_k - E(d_k)}{\sqrt{Var(d_k)}}$$

where $d_k = \sum_{i=1}^{k} r_i$ and r_i is determined by comparing sequential values. The inverse sequence of time series X is then processed similarly to obtain the trend sequence UB_k for the inverse series, where $UB_k = -UF_k'$.

By plotting the corresponding trend curves, mutation points can be identified. If the two curves intersect within the confidence interval, that intersection represents the mutation point in the time series [24-26].

2.2.2 Mann-Kendall Nonparametric Statistical Test

The Mann-Kendall nonparametric statistical method, recommended by the World Meteorological Organization and widely applied, can effectively distinguish whether a natural process represents normal fluctuation or a definitive trend. It is minimally disturbed by outliers and unaffected by data distribution characteristics, making it extensively used for trend detection in precipitation and drought frequency under climate change.

For a time series $\{x_1, x_2, ..., x_n\}$ of length n, the null hypothesis H_0 states that the series consists of independent, identically distributed random variables. The alternative hypothesis H_1 is a two-sided test: for all $i \leq n$ and $j \leq n$ where $i \neq j$, the distributions of x_i and x_j differ. The test statistic s is calculated as:

$$s = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i)$$

where sgn is the sign function. When $n \geq 8$, the random sequence approximately follows a normal distribution. The Mann-Kendall statistical test value Z_{mk} is then obtained:

$$Z_{mk} = \begin{cases} \frac{s-1}{\sqrt{Var(s)}} & s > 0 \\ 0 & s = 0 \\ \frac{s+1}{\sqrt{Var(s)}} & s < 0 \end{cases}$$

where $Var(s) = \frac{n(n-1)(2n+5)}{18}$. At significance level $\alpha = 0.05$ (critical value ≥ 1.96) and $\alpha = 0.01$ (critical value ≥ 2.58), detected trends can be categorized into six regions: (1) $s < -0.02$, significantly decreasing; (2) $-0.02 \leq s < -0.01$, decreasing; (3) $-0.01 \leq s < -0.004$, insignificantly decreasing; (4) $-0.004 \leq s < 0.01$, no significant increase; (5) $0.01 \leq s < 0.02$, weak increase; (6) $s \geq 0.02$, significantly increasing.

Autocorrelation was found negligible in SPEI and SPI time series at different temporal scales. Kendall' s τ from Mann-Kendall trend tests for SPEI and SPI series was spatially interpolated using inverse distance weighting to analyze spatiotemporal drought evolution characteristics in the Xilin River Basin.

2.2.3 Mann Whitney Pettitt Mutation Test

The Mann-Whitney Pettitt mutation test (Pettitt method) is a nonparametric test originally developed by Pettitt for detecting change-points [27]. For a climate series of sample size n, the method constructs a rank sequence and statistical measures. If a mutation occurs in a particular year, that year serves as a dividing point, splitting the climate series into pre- and post-mutation segments.

2.2.4 Rescaled Range R/S Analysis

R/S analysis (Hurst coefficient method) is commonly used to analyze fractal characteristics and long-term memory processes in time series. Named after British hydrologist Harold Hurst, it is widely applied in hydrometeorological element variation analysis.

3.1 Temperature and Precipitation Characteristics

Polynomial and linear regression analyses of annual precipitation and temperature reveal that over the past 60 years, mean annual temperature in the Xilin River Basin has exhibited an increasing trend at a rate of $0.390°C \cdot (10a)^{-1}$. Daniel' s test results show $r = 0.686$ with $p < 0.05$, indicating a significant upward trend. Seasonal analysis shows temperature increase rates of $0.483°C \cdot (10a)^{-1}$, $0.383°C \cdot (10a)^{-1}$, $0.344°C \cdot (10a)^{-1}$, and $0.348°C \cdot (10a)^{-1}$ for spring, summer, autumn, and winter, respectively, with r values around 0.50 and $p < 0.05$, confirming significant seasonal temperature variations. Spring and summer show the largest increases, contributing substantially to basin-wide warming.

From 1960–2018, mean annual precipitation showed a linear decreasing trend [Figure 2: see original paper] at a rate of -1.811 mm · $(10a)^{-1}$. Daniel' s test yields $r = -0.079$ with $p > 0.05$, indicating an insignificant decreasing trend. Seasonal precipitation changes varied: spring, autumn, and winter showed increasing trends of 0.368 mm · $(10a)^{-1}$, 0.537 mm · $(10a)^{-1}$, and 0.327 mm · $(10a)^{-1}$, respectively, while summer showed a decreasing trend of -1.860 mm · $10a^{-1}$. However, seasonal precipitation changes were not significant ($p > 0.05$). Since summer precipitation accounts for 66.97% of annual totals, its reduction drives the overall decreasing trend, while spring, autumn, and winter contributions are relatively small. Sixth-order polynomial curves for temperature and precipitation indicate that post-1990s variations have been more pronounced with clear periodic changes.

3.2 SPEI and SPI Analysis

3.2.1 SPEI and SPI Trend Variations

SPEI and SPI at different temporal scales exhibit distinct fluctuation patterns [Figure 3: see original paper]. As temporal scale increases, wet-dry variations become smoother; conversely, smaller scales show more dramatic fluctuations. Monthly scale reflects meteorological drought from short-term precipitation deficits with the most volatile changes. Seasonal scale reflects agricultural drought conditions with reduced fluctuation frequency, while interannual variations reflect hydrological drought including groundwater and river systems. SPEI shows a persistent decreasing trend, reaching minimum values in the 2000s–2010s, with a slight recovery around 2010 but recent decreasing signs. In contrast, SPI shows alternating low-high-low and high-low-high patterns, with notable decreasing trends during the 1960s–1970s, 1980s–1990s, and 2000s–2010s.

3.2.2 Comparative Analysis of Drought Grades Characterized by SPEI and SPI

To further investigate differences between SPEI and SPI in describing drought severity, drought occurrence frequencies at different levels were statistically analyzed for 1960–2018 at monthly scale [Figure 4: see original paper]. Over the past 60 years, SPEI recorded 123, 76, 33, and 14 occurrences of light, moderate, severe, and extreme drought, respectively (total 246 events). SPI recorded 109, 65, 31, and 7 occurrences (total 212 events). SPEI provides finer characterization of light and severe drought than SPI, demonstrating stronger drought identification capability. Decadal variations show 40–60 drought events in the 1980s and 2000s, approximately 30 events in the 1990s, and 26–38 events in other decades. Notably, drought frequency increased significantly from the 1990s to 2000s, peaking in the 2000s before stabilizing in the 2010s.

3.2.3 Mann-Kendall Mutation Test for SPEI and SPI

Mann-Kendall mutation tests for SPI-12 at different stations in the Xilin River Basin (1960–2018) reveal a single mutation point in 1999 within the confidence interval [Figure 5: see original paper]. Pettitt test results are consistent and significant. SPEI shows multiple intersection points (1962, 1996, 1998, 1999), but further verification using Pettitt testing identifies 1998 as the mutation year, though not significant. This indicates SPI is more strongly influenced by precipitation fluctuations, making mutation points less detectable. Results demonstrate that representative drought mutations in the Xilin River Basin began in the 1990s.

3.3 Spatiotemporal Comparison of SPEI and SPI Trend Changes

3.3.1 Monthly Trend Variations

Spatial patterns of monthly SPEI trends [Figure 6: see original paper] show no significant increase in January, with weaker increasing trends in upstream and northwestern downstream areas compared to other middle and lower reaches. February SPEI shows decreasing trends in the northwestern downstream, though insignificant. March exhibits nonsignificant decreasing trends in upstream and northwestern downstream areas. April shows decreasing SPEI in the middle and lower reaches, easing by May, closely related to spring being the season with the most pronounced temperature increases. The variation intensity gradually weakens from northwestern downstream to southeastern upstream to middle reaches. June–August SPEI reflects combined temperature and precipitation effects, decreasing from June–July to significantly decreasing in August, demonstrating SPEI' s capacity to capture integrated temperature-precipitation impacts on drought. September–October SPEI continues decreasing, particularly in the downstream, with increases only beginning in November–December, stronger in downstream and middle reaches than upstream. SPEI shows high sensitivity to temperature and precipitation changes as temperatures drop significantly from October.

Inverse distance weighting interpolation of Mann-Kendall tests for SPI (1960–2018) [Figure 7: see original paper] shows weak increasing trends in upstream January SPI, more pronounced increases from middle to upper downstream, with the downstream end approaching monthly mean values. February SPI shows upward trends across most of the basin, except for weak decreasing trends in western downstream areas. March shows decreasing SPI in upstream and downstream areas with weak increases in the middle reaches. April shows stronger increasing trends basin-wide, closely related to increased spring precipitation. Rising temperatures enhance evaporation, weakening SPI' s upward trend in May and resulting in weak growth in June. July–August SPI shows persistent significant decreases related to decreasing summer precipitation and increasing temperatures, with maximum decrease zones shifting from upstream to middle to downstream, closely correlating with runoff variations. September–November SPI shows increasing trends, first in downstream then extending to middle and lower reaches, with significant basin-wide increases in November associated with recovered autumn precipitation and decreased temperatures. December' s increasing trend diminishes as temperatures drop, continuing through February.

3.3.2 Interannual Trend Variations

SPEI-characterized drought trends [FIGURE:8, left] show overall decreasing SPEI across the basin, with severe drought intensification in middle and lower reaches, particularly at the northwestern end. SPI-characterized trends [FIGURE:8, right] show insignificant increasing trends basin-wide, with drought intensification only in the middle reaches, failing to identify more severe trends or drought conditions in other downstream areas. Research by Du Bobo et al. [28] identified drought phenomena in southwestern, central, and north-central Xilingol League with high severe drought frequency. Comparative spatiotemporal evolution demonstrates that SPEI can predict droughts better and earlier than SPI, encompassing drought patterns identified by SPI and showing better applicability in the Xilin River Basin.

3.4 Future Drought Prediction

Based on R/S analysis principles, the Hurst exponent for SPEI series in the Xilin River Basin over the past 59 years was calculated using least squares method. When $H > 0.50$, the correlation between past and future increments is positive, indicating persistent effects; otherwise, anti-persistence occurs. Table 2 shows the annual Hurst exponent is 0.4178, suggesting possible future SPEI mitigation but with low probability. Spring, summer, and autumn SPEI show greater potential for mitigation. Winter SPEI Hurst exponent exceeds 0.50, indicating possible persistent winter drought intensification requiring focused attention, particularly in middle and lower reaches.

Statistics of R/S analysis results

4 Conclusions and Discussion

(1) Comparative analysis of SPEI and SPI differences reveals that SPEI better captures extreme, severe, and moderate drought events during 1960–2018. SPEI-characterized drought durations are longer and more frequent than SPI. While precipitation shows no significant long-term change, temperature exhibits significant annual and seasonal variations, indicating temperature' s more pronounced role in Xilin River Basin drought. Consequently, SPEI provides better and earlier drought predictions than SPI, demonstrating superior applicability.

(2) SPEI in the Xilin River Basin shows an overall decreasing trend, with

drought mutation beginning in the 1990s. Monthly-scale Kendall' s τ variations indicate the northwestern downstream area as a severe drought zone requiring enhanced monitoring. Future drought conditions may gradually alleviate, though winter drought shows potential for persistent intensification.

(3) Meteorological drought provides the earliest warning for regional drought conditions, with annual drought resulting from coupling of multiple land surface and atmospheric factors. Further research is needed on drought disaster mechanisms in grassland watersheds, particularly regarding drought disasters formed by superimposed multiple disaster-causing factors during different forage growth stages. Temperature, precipitation, and potential evapotranspiration from multiple single points can only roughly estimate regional drought trends, necessitating future optimization of regional applicability and integrated use of drought indices.

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Note: Figure translations are in progress. See original paper for figures.