

Article

Analysis of Spatiotemporal Characteristics of Drought in Transboundary Watersheds of Northeast Asia Based on Comprehensive Indices

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Abstract: Drought, as an extreme climatic event, is considered one of the most severe natural disasters worldwide. In Northeast Asia, the frequency and intensity of drought have been exacerbated by climate change, causing significant negative impacts on the region's socioeconomic conditions and agricultural production. This study analyzed the spatiotemporal evolution and trends in drought in transboundary river basins in Northeast Asia from 1990 to 2020, using meteorological station data and remote sensing data. The Standardized Precipitation Evapotranspiration Index (SPEI) and Vegetation Condition Index (VCI) were employed to assess drought characteristics, and a comprehensive analysis of the SPEI and VCI indices was conducted to evaluate drought severity under different land cover types. The results indicate that (1) in the past two decades, both the SPEI and VCI indices have shown an increasing trend in the basin, with moderate and mild droughts being predominant. (2) High and extreme droughts mainly occur in forest areas, accounting for 17.91% and 10.76%, respectively, followed by farmland.

Keywords: transboundary river basins in Northeast Asia; drought; SPEI; VCI; spatiotemporal distribution



Academic Editor: Maria Mimikou

Received: 16 December 2024

Revised: 23 January 2025

Accepted: 25 January 2025

Published: 30 January 2025

Citation: Li, J.; Liu, F.; Quan, D.; Zhu, W.; Yu, H.; Jin, R. Analysis of Spatiotemporal Characteristics of Drought in Transboundary Watersheds of Northeast Asia Based on Comprehensive Indices. *Water* **2025**, *17*, 382. <https://doi.org/10.3390/w17030382>

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1. Introduction

Under the influence of global warming and rapid economic development, the global climate has shown a clear warming trend. This change not only leads to polarization of global temperature distribution, but also changes precipitation patterns, making hydrological cycles more complex [1]. The frequency of extreme temperature and precipitation events has significantly increased. Although climate change itself does not directly cause drought, it exacerbates the frequency and intensity of drought occurrence [2,3]. Drought is one of the extreme climate events and one of the most severe natural disasters worldwide [4]. The formation of drought is influenced by a variety of factors, including regional water resource imbalances, exposure, vulnerability, and drought resistance. The imbalance between supply and demand of regional water resources is the fundamental cause of drought, while drought resistance is the ability of ecosystems to maintain their original state under external disturbances [5]. The frequent occurrence, long duration, and wide range of impacts of drought make it a disaster that causes huge losses to human society and ecosystems [6–8]. These characteristics make drought a challenging natural disaster that requires effective prediction, mitigation, and management [9]. Drought not only affects

agricultural production [10,11], but also has profound impacts on various fields such as industry [12], water conservation, and shipping [13–15]. For example, from the late 1960s to the 1980s, Africa experienced a 20-year drought that caused severe famine and affected over 100 million people, earning it the title of “the greatest human disaster in modern African history” from the United Nations [16]. With the intensification of climate change, drought occurrences in Northeast Asia are on the rise, particularly in Northeast China, where it has adversely affected agricultural output and socio-economic development [17–20].

Drought indices are important tools for quantitatively assessing soil moisture conditions and their impact on agriculture, hydrology, and other sectors [21,22]. They serve as a measure of drought severity and can quantify drought at different time scales [23]. Due to the characteristics of drought and the need for more accurate assessments of its spatiotemporal variations, various drought indices have been proposed by researchers. Commonly used meteorological drought indices include the Percentage of Precipitation Anomaly Index (Pa) [24,25], the Z-index [26], and the Standardized Precipitation Index (SPI) [27]. These indices are based on single parameters. Another category of indices incorporates multiple factors, such as the Palmer Drought Severity Index (PDSI) [28], the self-calibrating Palmer Drought Severity Index (Sc-PDSI) [29], and the Standardized Precipitation Evapotranspiration Index (SPEI) [30]. For single-parameter drought indices, Pa directly reflects drought caused by precipitation anomalies and effectively represents surface moisture conditions [31,32]. The Z-index is suitable for large-scale spatiotemporal variation in droughts and floods [33]. SPI is widely used in agricultural and hydrological monitoring to assess the intensity, duration, and frequency of drought events [34,35]. Although these single-parameter drought indices have achieved certain success, drought is influenced by multiple factors, which limits their ability to objectively and accurately characterize drought conditions in many areas. Therefore, combining other indices for drought analysis is necessary. To address the limitations of single-parameter indices, more researchers have turned to the combination of multiple indicators for drought analysis. The PDSI, proposed by Palmer et al. in 1965 [36], integrates factors such as prior precipitation, potential evapotranspiration, and soil moisture to identify the primary cause of drought as the imbalance between actual water supply and demand in the soil. It also considers the effective soil moisture content, and its development is significant for drought monitoring [33,37]. Given the limitations of both the single-meteorological index SPI and the multi-parameter index PDSI [38], Vicente-Serrano et al. in 2010 combined the strengths of SPI and PDSI by incorporating potential evapotranspiration into SPI, thus developing a new drought monitoring index, the SPEI [39,40].

In recent years, with the widespread application of remote sensing technology, drought indicators monitored by remote sensing technology have been widely used in drought monitoring and analysis [41–43]. Compared with station drought indices, remote sensing drought indices have the advantages of simple data acquisition and large-scale macroscopic monitoring. By using remote sensing index information, drought monitoring can be carried out on large areas [44]. At the same time, methods for calculating drought indices using remote sensing technology have been introduced progressively, such as the Normalized Difference Vegetation Index (NDVI), first introduced by Tucker in 1979. The NDVI is the most commonly used vegetation index for monitoring vegetation health, density, and biomass, and is the most widely used remote sensing drought index based on vegetation information [45]. The Enhanced Vegetation Index (EVI), Ratio Vegetation Index (RVI), etc., have also been proposed in subsequent research. Based on these indices, the Vegetation Condition Index (VCI) was proposed in 1990 [46,47]. The VCI is calculated based on the minimum and maximum NDVI values of long-term time series. By eliminating the influence of geographical location and ecosystem on the NDVI [48], the VCI is more suitable

for large-scale drought analysis and has been extensively applied in vegetation and drought surveillance [49,50].

Both remote sensing and meteorological station monitoring have certain limitations. The use of meteorological stations for drought monitoring is constrained by the number and spatial distribution of stations, which results in deviations when monitoring regions are distant from the stations [51]. Remote sensing, on the other hand, is significantly influenced by the underlying surface [52]. Due to the time lag between precipitation and vegetation response, vegetation conditions do not immediately reflect precipitation patterns. Consequently, many researchers combine remote sensing with station-based monitoring for more effective drought assessment. The combination of the VCI and the SPEI allows for a comprehensive monitoring of drought's spatiotemporal dynamics from both climatic and ecological perspectives. While SPEI provides climate-based information on drought, revealing long-term drought trends, VCI captures real-time changes in vegetation health and the impacts of short-term droughts. Together, these indices provide a more precise and comprehensive understanding of drought occurrence, development, and temporal changes [53,54]. Therefore, in this study, drought evaluation is conducted from two perspectives, the meteorological drought index, SPEI, and the remote sensing-based drought index, VCI, to further analyze the drought severity in the transboundary watershed region of Northeast Asia.

In previous research on cross-border watersheds in Northeast Asia, the focus has mainly been on drought analysis of a single watershed, with relatively little analysis of the overall spatiotemporal characteristics of drought in cross-border watersheds. Domestic research mainly focuses on the spatiotemporal distribution characteristics of meteorological drought and vegetation drought. For example, Wang Xiaodan et al. analyzed the drought trend in Northeast China based on SPEI and found that the frequency of drought in the region is increasing, while the intensity and duration of drought are gradually decreasing [55]. In addition, some studies also involve ecological environment changes in cross-border watersheds, such as Zhang et al.'s study on soil cover changes in the border region between China, North Korea, and Russia, which found that land use changes are closely related to changes in vegetation indices (NDVI) [56]; Quan et al. performed a comparative study on the driving factors of forest fires in different countries in the cross-border areas of China, North Korea, and Russia, and found that climate was the most important factor affecting the probability of forest fires in the cross-border areas, followed by terrain and vegetation factors, and human activities had the least impact [57]; Chen et al. studied the fish diversity in a border river between China, North Korea, and Russia, and found that the α diversity value of Hunchun river was the highest, which was attributed to good physical and geographical conditions and effective protection work [58]. Nevertheless, there is still insufficient comprehensive drought analysis for cross-border watersheds in Northeast Asia, especially systematic research on drought severity analysis under different land cover types.

Taking into account the above factors, this study integrates the meteorological drought index SPEI and the remote sensing drought index VCI with equal weights for drought assessment, addressing the limitations of using a single index. The following scientific questions are proposed: What are the spatiotemporal distribution characteristics of the SPEI and VCI indices in the cross-border river basins of Northeast Asia? Under the background of integrated drought indices, what are the drought characteristics across different land cover types? The specific objectives are as follows: To examine the spatiotemporal patterns of meteorological drought in cross-border river basins of Northeast Asia by calculating the SPEI, and to clarify the level, intensity, and frequency of meteorological drought in different regions. By using the VCI, to analyze the spatiotemporal changes in vegetation

drought in cross-border river basins in Northeast Asia, and explore the trends, frequencies, and relationship between vegetation drought and meteorological drought. By using a comprehensive approach with SPEI and VCI indices for drought assessment, analyzing the degree of drought under different land cover types, providing scientific theoretical basis and data support, and offering reference for regional drought management and emergency policy formulation.

2. Materials and Methods

2.1. Study Area

The transboundary region of Northeast Asia includes the basins of the Heilongjiang River, Tumen River, and Yalu River, covering a total area of 576,500 square kilometers (Figure 1). Situated in the northern part of the temperate zone, the region features a typical temperate monsoon climate characterized by distinct seasonal variations: dry and windy springs, warm and rainy summers dominated by warm and humid maritime airflows, cool and dry autumns, and long-lasting cold winters. Annual temperatures typically vary between 2 and 6 °C, with July highs around 25 °C and January lows around −20 °C. Precipitation is concentrated mainly in June, July, and August, accounting for about 60% of the annual total. The vegetation is predominantly deciduous broad-leaved forests and mixed coniferous forests. The study area encompasses secondary tributaries of the three major basins, ranging from an altitude of −50 to 2735 m. Geographically, it spans approximately 117°21'42" to 137°51'15" E and 39°50'17" to 55°7'0" N. Based on the hydrological characteristics, the study area is divided into the Heilongjiang River Basin (HRB), Tumen River Basin (TRB), and Yalu River Basin (YRB). The Ussuri River Basin (URB), one of the major tributaries of the HRB, is analyzed separately, due to its extensive watershed area, in this study.

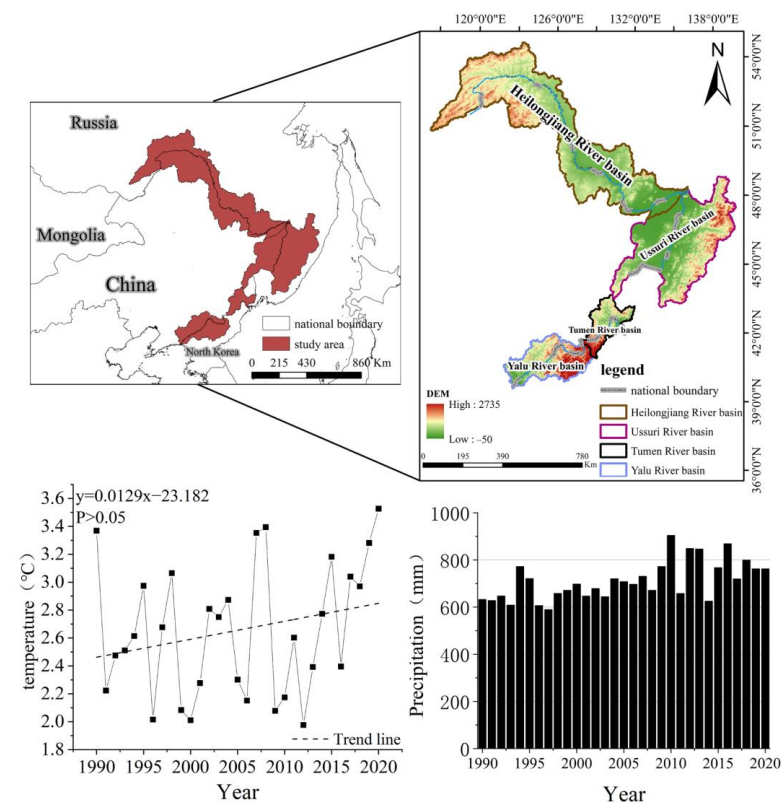


Figure 1. Study area.

2.2. Overarching Study Design

To begin with, meteorological data (1990–2020), MOD13Q1 data, and land use/cover data are obtained. Next, the data undergo preprocessing to derive the VCI and SPEI indices. Subsequently, the VCI and SPEI indices are integrated with equal weights to produce a comprehensive drought index. Finally, the drought levels across different land cover types are calculated and analyzed in greater detail. The technical roadmap is shown in Figure 2.

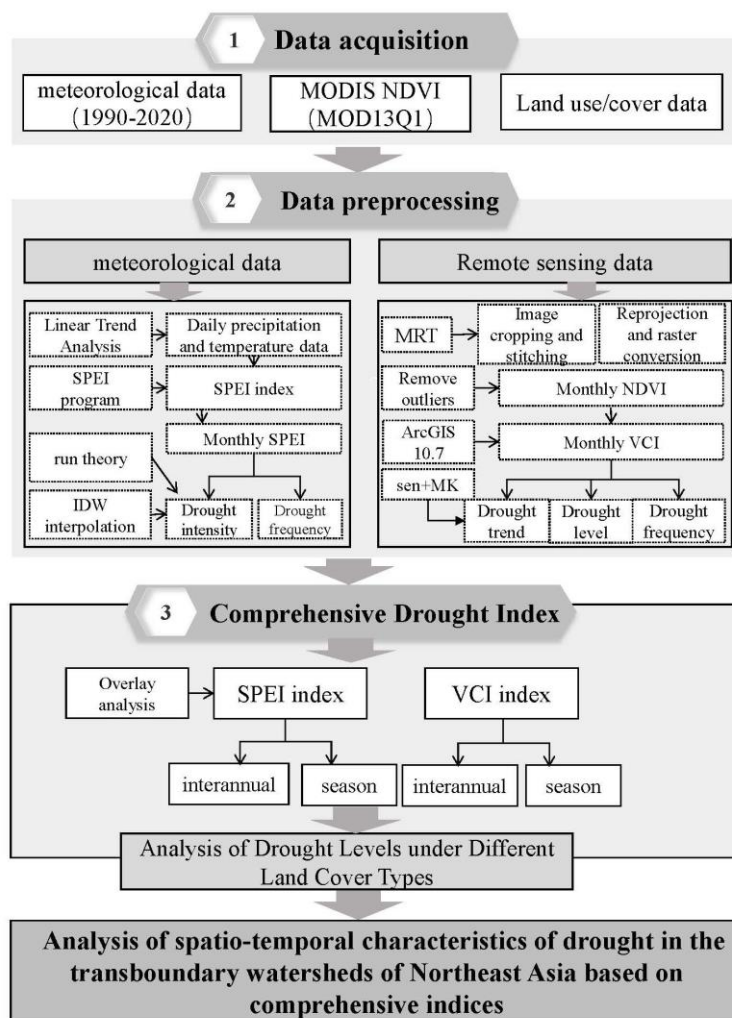


Figure 2. Flowchart of the research approach.

2.3. Data Sources and Preprocessing

2.3.1. Meteorological Data

Meteorological observation data were sourced from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA), available at <https://www.ncei.noaa.gov> (accessed on 20 August 2024), providing daily precipitation and temperature records. Initially, the continuity and quality of historical observation data from meteorological stations across the transboundary North-east Asia region were analyzed and checked. Stations with missing rates exceeding 15% were excluded, while stations with missing rates below 15% were supplemented using the grey relational analysis method. Furthermore, when supplementing the data, missing values were not treated as zero. Instead, interpolation was performed based on valid recorded data to ensure the reliability of the results. Ultimately, a total of 58 meteorological stations with coherent data were selected within the study area and its vicinity (see Supplementary Material Table S1, Figure 3). Among them, several stations are located at a

greater distance, primarily to eliminate boundary effects and thus enhance data accuracy. The data used at these stations were also verified to conform to a gamma distribution. Since the calculation of the SPEI requires more than 30 years of long-term meteorological data, this paper uses the temperature and precipitation data from 1990 to 2020 for the background analysis of climate change and SPEI calculation, collects and sorts the precipitation and temperature data in the region, and establishes the time series of meteorological elements at interannual and seasonal scales.

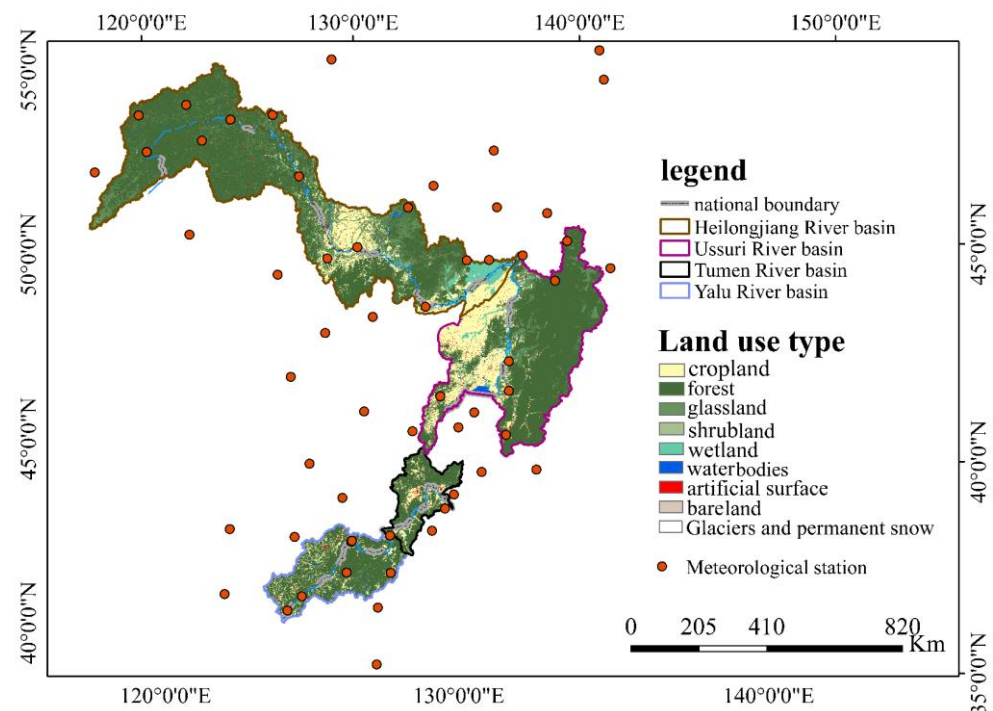


Figure 3. Distribution of meteorological stations in cross-border river basins in Northeast Asia.

2.3.2. Remote Sensing Image Dataset

This study utilized MOD13Q1 product data provided by NASA, obtained from <https://ladsweb.modaps.eosdis.nasa.gov/search/> (accessed on 20 August 2024). A total of 2880 images spanning from 2000 to 2020 were collected. Prior to download, the data underwent preprocessing steps including radiometric calibration. Post-processing yielded 480 monthly remote sensing images (excluding 2000, totaling 20 scenes). As both the VCI and SPEI indices are sensitive to seasonal variations in vegetation growth and meteorological conditions, seasonal analysis is critical to accurately capture the spatiotemporal dynamics of drought. By dividing the data into seasonal categories, we can better assess drought impacts during different stages of the year, providing a more comprehensive understanding of drought severity and its seasonal fluctuations. Seasonal data were categorized into spring (March to May), summer (June to August), autumn (September to November), and winter (December to February of the following year).

2.3.3. Land Use/Land Cover Data

The land use/cover data for the study area were derived from the GlobeLand30 global land cover dataset (<http://www.globallandcover.com/>) (accessed on 20 August 2024). After resampling to a 1 km resolution, the study categorized land cover types into cropland, forest, grassland, shrubland, wetland, water body, artificial surface, bare land, glacier, and permanent snow. Due to the reliance on remote sensing and meteorological data to assess vegetation growth and infer drought conditions, this study does not consider water bodies

and artificial surfaces as land cover types. The primary focus of this research is to evaluate the areal proportions of different land cover types under varying drought severity levels.

2.4. Methodology

2.4.1. Inverse Distance Weighting (IDW)

The IDW interpolation method is widely used in ArcGIS 10.7 [59]. It is a weighted moving average method where the distance between unknown and known points serves as the weighting parameter for interpolation analysis [60]. Samples closer to the interpolation point receive greater weights, making it a deterministic interpolation method, IDW assumes that the influence of data points decreases with increasing distance, making it particularly suitable for environmental research, including drought monitoring, where spatial variability is influenced by local factors such as climate, terrain, and vegetation. The formula for IDW is [61]

$$f(x, y) = \frac{\sum_{j=1}^n \frac{1}{d_i} p_i}{\sum_{j=1}^n \frac{1}{d_i}}, \quad (1)$$

The number of weather stations is denoted by n in the equation, d_i is the distance from the i th meteorological station to another meteorological station, and p_i is the value applied at the i th meteorological station.

2.4.2. Standardized Precipitation Evapotranspiration Index

The SPEI characterizes the drought condition of a certain region by calculating the deviation of precipitation minus potential evapotranspiration (PET) from the average state [62]. The calculation method is as follows: first, calculate the potential evapotranspiration (PET_i) using the TH formula to compute the monthly potential evapotranspiration (PET) (mm).

Calculate the monthly difference between precipitation and potential evapotranspiration D_i :

$$D_i = P_i - PET_i, \quad (2)$$

In the equation, i represents the month, P_i represents the monthly precipitation (unit: mm), and PET_i represents the monthly potential evapotranspiration (unit: mm).

Using the three-parameter log-logistic probability distribution function to calculate the probability density function $f(x)$ of the sequence XK_i and further deriving the cumulative distribution function $F(x)$ [63],

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

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

In the equation, a , β , and γ are, respectively, the scale parameter, shape parameter, and location parameter. By standardizing the cumulative distribution function $F(x)$, the SPEI value can be obtained [39].

Let $p = 1 - F(x)$. When $P \leq 0.5$, the parameter $W = \sqrt{-2 \ln p}$:

$$SPEI = \omega - \frac{c_0 + c_1 \omega + c_2 \omega^2}{1 + d_1 \omega + d_2 \omega^2 + d_3 \omega^3}, \quad (5)$$

When $p > 0.5$, p is replaced by $1 - p$, and the sign of the obtained SPEI is opposite, as follows:

$$SPEI = -\left(\omega - \frac{C_0 + C_1\omega + C_2\omega^2}{1 + d_1\omega + d_2\omega^2 + d_3\omega^3}\right), \quad (6)$$

In the equation, $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

According to the standards issued by the China National Meteorological Center [64], the classification criteria for SPEI drought levels are shown in Table 1.

Table 1. SPEI drought severity levels.

Level	SPEI Value	Grade
1	$-0.5 < \text{SPEI}$	No drought
2	$-1.0 < \text{SPEI} \leq -0.5$	Mild drought
3	$-1.5 < \text{SPEI} \leq -1.0$	Medium drought
4	$-2.0 < \text{SPEI} \leq -1.5$	Severe drought
5	$\text{SPEI} \leq -2.0$	Extreme drought

Drought frequency represents the proportion of years during a certain study period in which drought occurs in a particular region or at a specific site [25]. It can reflect the frequency of drought occurrence. The calculation formula is as follows:

$$P_i = \frac{n_i}{n} \times 100\%, \quad (7)$$

In the equation, P_i represents the drought frequency, where i is the site or region being evaluated for drought, n is the total number of meteorological stations, and n_i represents the frequency of drought occurrences within the i th station or region.

2.4.3. Run-Length Theory

Run-length theory originated in 1967 when Yevjevich applied it to drought research [65]. Firstly, a truncation level K (where K corresponds to the drought level of the SPEI) is assigned to identify drought events. Then, a discrete sequence X_t ($t = 1, 2, \dots, n$), varying with time, is truncated. When the random variable is greater than the truncation level, a positive run occurs; otherwise, a negative run occurs. Drought duration refers to the time from the beginning to the end of a drought event. According to the classification criteria of SPEI drought levels, the drought threshold is set at $R_0 = -0.5$. When the SPEI value at one of the 58 stations in the study area falls below -0.5 for a certain duration, it marks the beginning of a drought event. When the SPEI value is greater than or equal to -0.5 , it marks the end of this drought event. Drought severity is calculated as the total of the SPEI values during a drought event, while drought intensity is determined by dividing the drought severity by the duration of the drought. Choosing -0.5 can more sensitively detect drought events. 0 represents a neutral balance between precipitation and evapotranspiration, while -0.5 indicates that even at lower intensity levels, regions experiencing drought can be clearly distinguished. This provides a more precise representation of the occurrence and severity of drought events, and is also well applicable to the research in this article [66].

2.4.4. Vegetation Condition Index

The NDVI is an indicator of vegetation growth status and vegetation coverage. The calculation formula is [67]

$$NDVI = \frac{DN_{NIR} - DN_R}{DN_{NIR} + DN_R}, \quad (8)$$

In this formula, DN_{NIR} and DN_R , respectively, represent the DN values of the near-infrared and red bands. Since NDVI can only reflect the effects of weather conditions, soil, and moisture on vegetation, it is limited by the conditions of the land cover. Therefore, Kogan et al. [68] derived the VCI in their study, with the calculation formula as

$$VCI = 100 \times \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}, \quad (9)$$

In this formula, $NDVI_i$ represents the NDVI value for the i -th period of a particular year, while $NDVI_{max}$ and $NDVI_{min}$, respectively, denote the maximum and minimum NDVI values for the i th period over multiple years.

The VCI value ranges between 0 and 100, where higher values indicate favorable vegetation conditions, while lower values indicate poor vegetation conditions, indicating more severe drought. The classification criteria for VCI drought levels are shown in Table 2 [69].

Table 2. VCI drought severity levels.

Level	Category	VCI Value
1	No drought	[70, 100)
2	Mild drought	[50, 70)
3	Medium drought	[30, 50)
4	Extreme drought	[0, 30)

Remote sensing drought frequency refers to the frequency of drought occurrence within the study area [70]. By tallying the number of drought occurrences for each pixel, a frequency distribution map of drought occurrence is obtained. Pixels experiencing mild drought or worse are considered as drought pixels. The calculation formula is as follows:

$$f_n = n/N \times 100\%, \quad (10)$$

where n represents the number of drought occurrences for the pixel during the study period, and N represents the study period (21 years).

2.4.5. Theil–Sen Slope Estimation and Mann–Kendall Combined Method

Many researchers employ the Mann–Kendall test to identify trends in climate variables and climate change, especially though examining meteorological and hydrological data series like temperature, precipitation, and runoff [71–73]. With its strong universality, the Mann–Kendall test is a non-parametric statistical technique that is frequently used to identify trend changes in time-series data. It is adequate to handle the majority of trend detection issues in hydrological and meteorological data. The following is its calculation formula:

$$\beta = \text{Median} \left[\frac{(X_j - X_i)}{j - i} \right], \forall j > i, \quad (11)$$

In the formula, β represents the median of all the slopes of corresponding raster data pairs; median denotes the median function; and X_j and X_i represent the values of the j th and i th items in the time series, respectively [74].

A positive or negative value of β indicates whether the raster value trend at that location is increasing or decreasing. $\beta > 0$ indicates an upward trend; otherwise, it indicates a downward trend. The Theil–Sen slope estimation method can effectively detect changes in trends and magnitudes in a time series, but it cannot perform significance testing on the time series itself. Therefore, when conducting significance studies, the Mann–Kendall

method is typically introduced to test the significance of the trend in the time series. Mann–Kendall is a non-parametric test method, also known as a distribution-free test. The specific framework of this method is as follows.

First, determine all the paired values X_j, X_i , where $i < j$. The time series consists of independent samples, and S is the test statistic:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i), i < j \leq n, \quad (12)$$

In the formula, the sgn function is expressed as [75]

$$\text{sgn} = (X_j - X_i) = \begin{cases} 1 & x_j - x_i > 0 \\ 0 & x_j - x_i = 0 \\ -1 & x_j - x_i < 0 \end{cases}, \quad (13)$$

Based on the time series n , different statistical tests are selected using 10 as the boundary. When $n < 10$, the S statistic is used for trend testing, where its positive and negative values indicate upward and downward trends, respectively. When $n > 10$, the S statistic follows a standard normal distribution, and the statistic Z is constructed by standardizing S [76]:

$$Z = \begin{cases} \frac{s-1}{\sqrt{\text{var}(s)}}, & S > 0 \\ 0, & S = 0 \\ \frac{s-1}{\sqrt{\text{var}(s)}}, & S < 0 \end{cases}, \quad (14)$$

In the formula, $\sqrt{\text{var}(s)}$ represents the square root of the variance of S . The formula for the variance of S is [75]

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

In the formula, n represents the number of years in the time series, m represents the number of groups of repeated data in the sequence, and t_i represents the count of repeated data in each group.

If the Z value is positive, it indicates an increase, while if it is negative, it indicates a decrease. At a given significance level α , if the value $|Z| < Z_{\alpha/2}$, the null hypothesis is accepted, indicating that the trend based on the time-series data is not significant. If $|Z| > Z_{\alpha/2}$, the null hypothesis is rejected, suggesting that the trend is significant. Nowadays, due to its ability to predict and evaluate trends in meteorological variables, this indicator is widely used [77,78].

2.4.6. Overlay Analysis

To generate comprehensive drought index evaluation maps for annual and seasonal assessments by adding the extended yearly and quarterly values of SPEI_{ei} and VCI_{ei} , the calculation formula is as follows [54]:

$$\text{DVE} = \sum_{i=2000}^{2020} (\text{SPEI}_{ei} + \text{VCI}_{ei}), \quad (16)$$

In the formula, DVE represents the comprehensive drought index evaluation map, SPEI_{ei} represents the extended SPEI map for the i th year/season, VCI_{ei} represents the extended VCI map for the i th year/season. The comprehensive drought index evaluation maps for different time scales are obtained through equal-weighted aggregation and overlay analysis, followed by reclassification using the natural breaks method. To maintain spatial

resolution uniformity, we adjusted the data to a standard resolution of 250 m and compared it with the original data, ensuring the accuracy and reliability of the analysis.

3. Results

3.1. SPEI Temporal Variation Characteristics

3.1.1. SPEI-12 Temporal Variation Characteristics in Different Regions

The SPEI can be computed at various time scales to reflect drought conditions over different time ranges (Figure 4). Common time scales include SPEI-3, SPEI-6, and SPEI-12, among others. SPEI-3 and SPEI-6 take into account the influence of precipitation and temperature in the early stage, which can reflect the change in water profit and loss in the northeast cross-border basin on a seasonal scale, and are suitable for the study of agricultural drought [79]. SPEI-12 is advantageous for its ability to assess long-term drought, integrate climate elements, capture seasonal variations, and analyze drought trends [80]. It serves as a valuable tool for studying drought, managing water resources, and assessing the impacts of climate change. Therefore, this study utilizes the SPEI-12 index to further analyze the temporal characteristics of SPEI-12 across different regions in the transboundary basins of Northeast Asia.

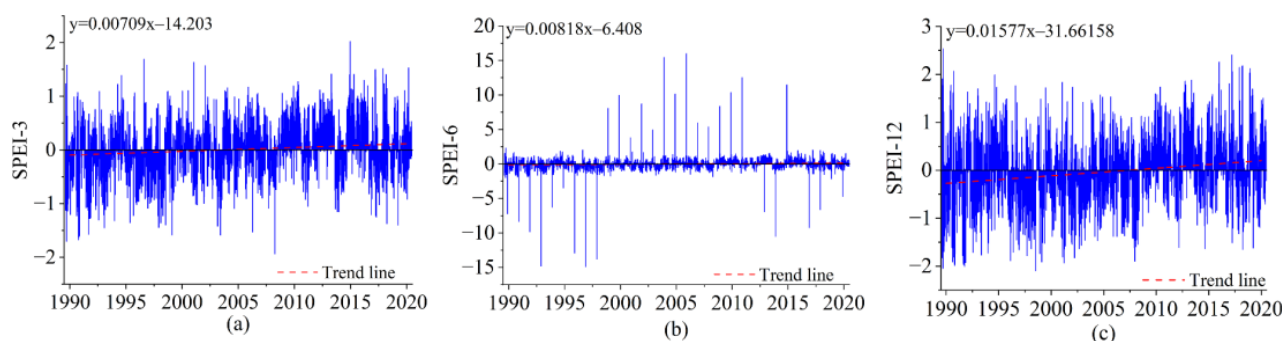


Figure 4. Trend in SPEI at different time scales from 1990 to 2020: (a) SPEI-3; (b) SPEI-6; (c) SPEI-12.

From 1990 to 2020, distinct trends in SPEI-12 indices across different regions (Figure 5) highlight significant variations. The Chinese side of the HRB and the North Korean side of the TRB exhibit declining SPEI indices, while other regions show an upward trend. The decline in the SPEI in these regions may be related to changes in the regional climate model, and may also be affected by land use/cover change and water resource management strategies. Specifically, the Chinese side of the HRB experienced relatively wet conditions from 1990 to 1995, but increased drought from 2000 to 2010. In contrast, the Chinese side of the URB saw increased drought from 1990 to 2005, followed by relatively wetter conditions from 2015 to 2020.

3.1.2. Temporal Variation Characteristics of Drought Intensity

From 2000 to 2020, both interannual and seasonal drought intensities (Figure 6) exhibit similar patterns. Interannual drought intensity ranges between -1.14 and -0.86 , indicating mild to medium drought levels. Looking at seasonal variations, spring drought intensity ranges from -1.28 to -0.82 , summer from -1.24 to -0.82 , autumn from -1.14 to -0.83 , and winter from -1.26 to -0.84 . Across all four seasons, drought intensities consistently fall within the categories of mild and medium drought levels.

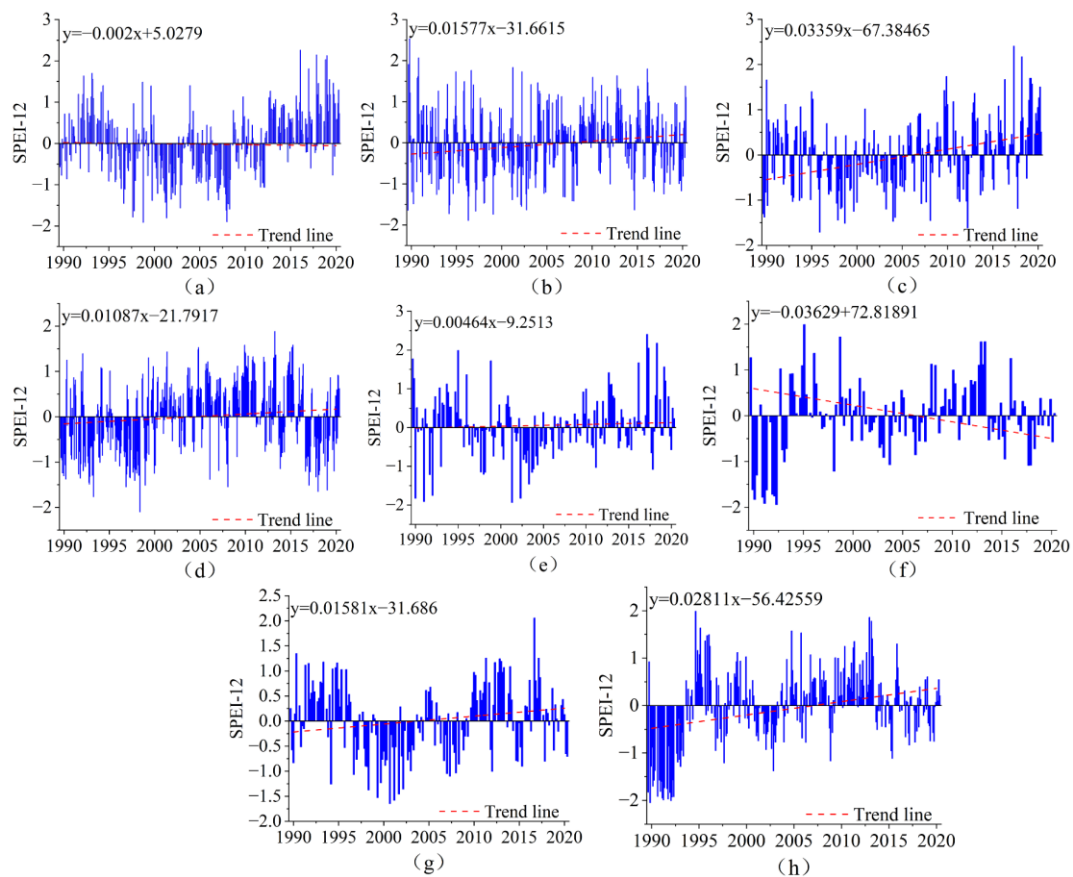


Figure 5. Trends in SPEI-12 indices across different regions from 1990 to 2020. (a) Chinese side of the HRB; (b) Russian side of the HRB; (c) Chinese side of the URB; (d) Russian side of the URB; (e) Chinese side of the TRB; (f) North Korean side of the TRB; (g) Chinese side of the YRB; (h) North Korean side of the YRB.

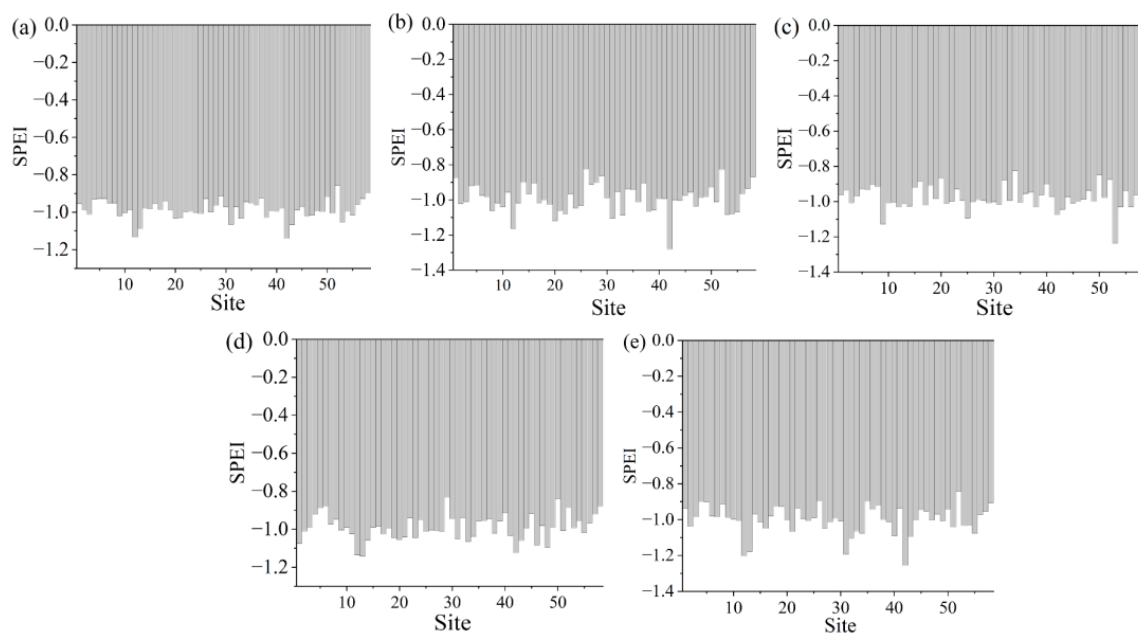


Figure 6. Annual and seasonal drought intensity from 2000 to 2020. (a) Interannual; (b) spring; (c) summer; (d) autumn; (e) winter.

3.2. Spatial Distribution Characteristics of the SPEI

3.2.1. Spatial Distribution of Drought Intensity

Regarding the spatial distribution of drought intensity based on SPEI indices (Figure 7), the overall interannual drought intensity ranges between -1 and -0.5 , indicating mild drought levels. In specific regions such as the Chinese side of the HRB, the Russian side of the HRB, the Russian side of the URB, the Chinese side of the YRB, and the North Korean side of the YRB's southern areas, some regions experience medium drought intensity. In contrast, the TRB generally exhibits characteristics of mild drought.

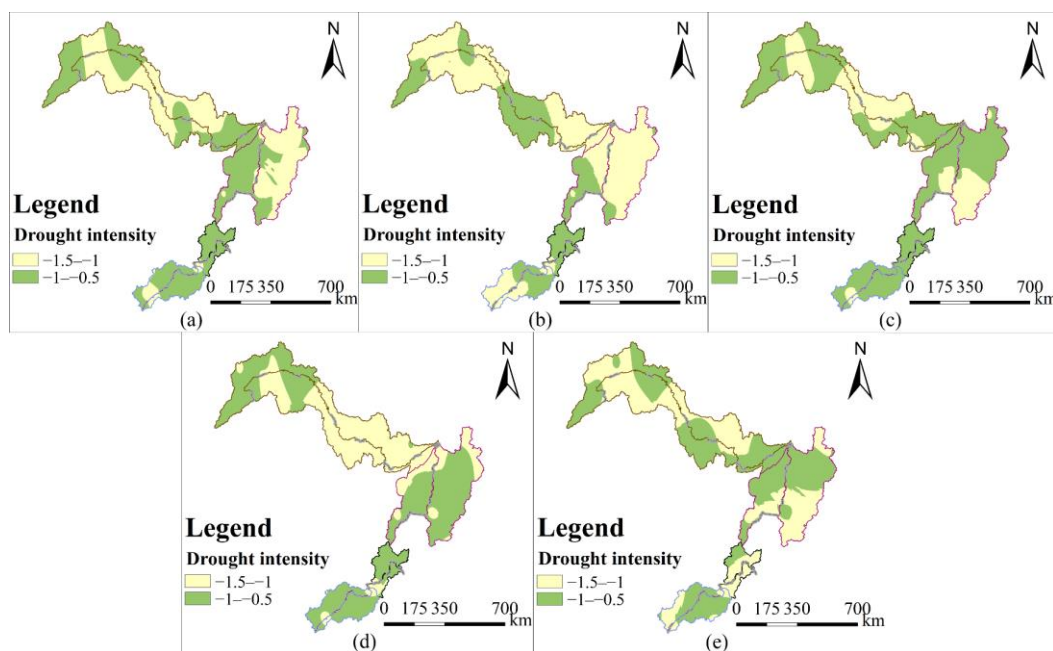


Figure 7. Spatial distribution of drought intensity of SPEI. (a) Interannual; (b) spring; (c) summer; (d) autumn; (e) winter.

The seasonal spatial distribution of drought intensity is mainly mild and moderate drought. In the northwest region of the HRB, medium drought levels are observed across all four seasons. The southwest area of the YRB also shows medium drought throughout the year, with a more extensive distribution in spring. In the TRB, mild drought prevails during spring, summer, and autumn, while medium drought is widespread in winter. In the URB, medium drought is mainly found on the Russian side during spring, with mild drought in summer. In autumn, moderate drought is most common in the central and southern regions of the HRB. During winter, the Russian side of the HRB experiences widespread medium drought, with medium drought mainly on the southern Russian side of the URB and the southwestern Chinese side of the YRB.

3.2.2. Spatial Distribution of Drought Occurrence

Regarding the annual and seasonal spatial distribution of drought frequency based on the SPEI (Figure 8), the region experienced annual drought occurrences primarily ranging from 4 to 16 times, with most areas experiencing droughts between 8 and 12 times. The drought frequency is divided into five grades according to the equal spacing. The northern part of the HRB, the southern Russian side of the URB, and most areas of the TRB experienced more frequent droughts, ranging from 12 to 16 occurrences. In terms of seasonal drought frequency, spring saw drought occurrences mainly between 4 and 8 times, with higher frequencies of 8 to 12 times on the southern Russian side of the URB and the northern Chinese side of the YRB. Summer droughts occurred mainly

between 4 and 12 times, with most of the TRB experiencing between 8 and 12 occurrences. The frequency distribution of droughts in autumn and winter was similar, primarily ranging from 4 to 8 times. This indicates that the region experienced relatively frequent annual droughts, especially in summer.

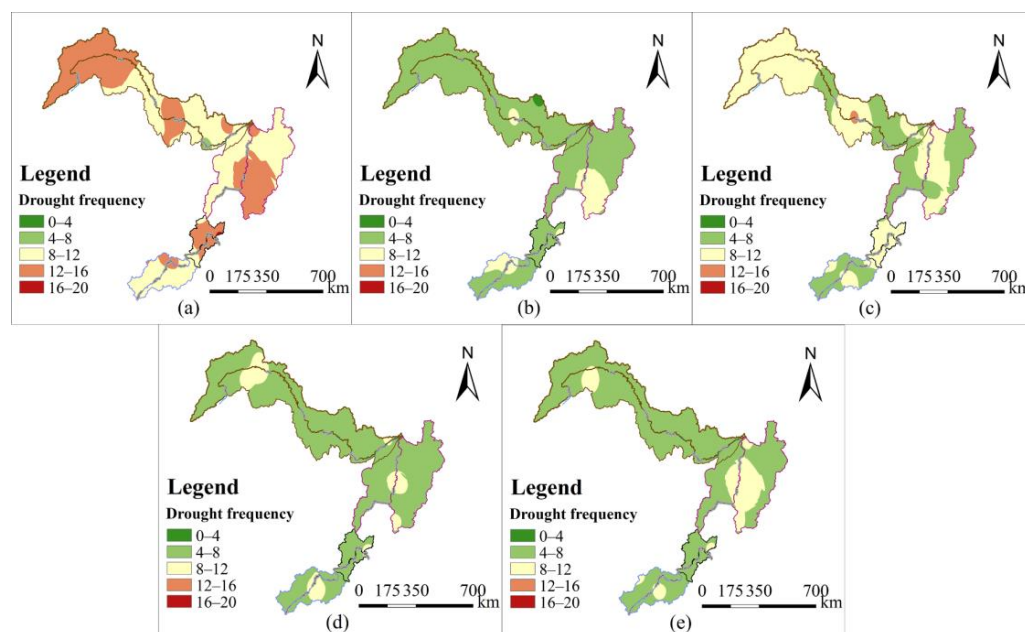


Figure 8. Spatial distribution of annual and seasonal drought frequency based on the SPEI. (a) Inter-annual; (b) spring; (c) summer; (d) autumn; (e) winter.

3.3. Temporal Variation Trend in the VCI

The interannual variation in the VCI shows an overall upward trend, with a notable increase since 2015 ($p < 0.05$). However, there were declines observed from 2002 to 2004 and a sharp decrease from 2008 to 2009 (Figure 9).

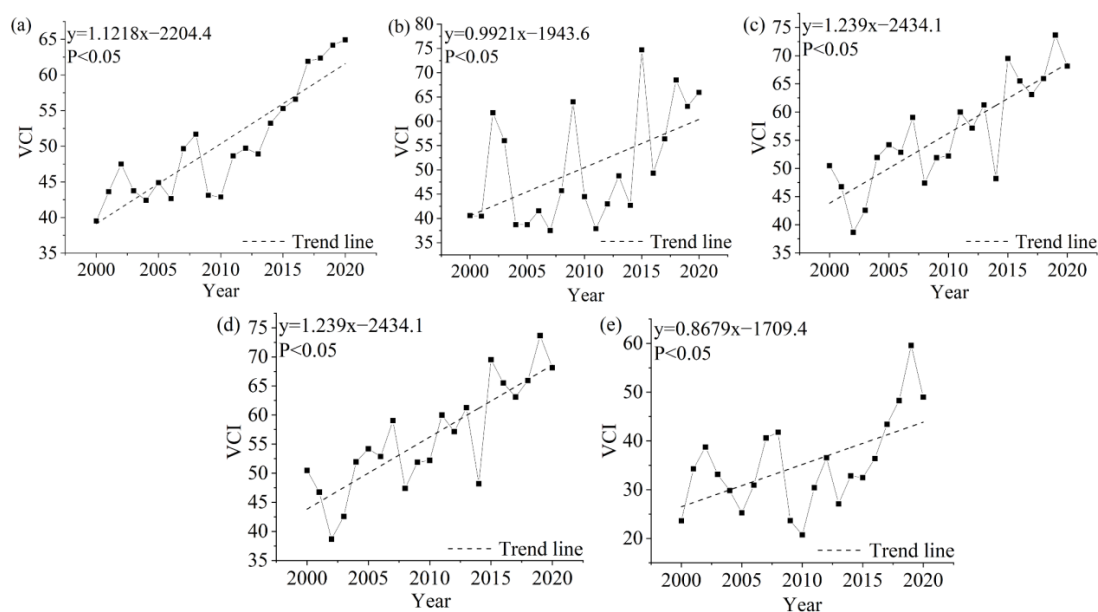


Figure 9. Depicts the annual and seasonal trends in the VCI. (a) Inter-annual; (b) spring; (c) summer; (d) autumn; (e) winter.

Seasonally, the VCI decreased during spring from 2003 to 2005, 2009 to 2011, and 2016 to 2017 ($p < 0.05$), with a peak in 2014–2015. The summer season exhibited relatively minor changes, with the VCI reaching its highest in 2020. In autumn, the VCI peaked in 2019 and was at its lowest in 2002 ($p < 0.05$). During winter, there was a significant rise from 2016 to 2019, with 2019 marking the highest point and 2010 the lowest.

3.4. VCI Spatial Variation Characteristics

3.4.1. Spatial Trend Analysis of VCI

Using Theil–Sen slope estimation and the Mann–Kendall test, we conducted spatial trend analysis on the VCI in the Northeast Asian cross-border river basin region. Regarding the interannual and seasonal spatial variation trends in the VCI (Figure 10) from 2000 to 2020, the overall trend in the interannual VCI spatial variation predominantly shows a significant increase, with areas of significant decrease being minimal. Significant increases are most prominent on the Chinese side of the HRB, the Russian side of the URB, the Chinese side of the TRB, and the Chinese side of the YRB. In contrast, the Russian side of the HRB and parts of the Chinese side of the URB exhibit areas with significant decreases. These interannual variations are further influenced by seasonal trends, with spring and summer exhibiting mild drought conditions, while autumn and winter are characterized by more severe droughts, particularly in forested areas.

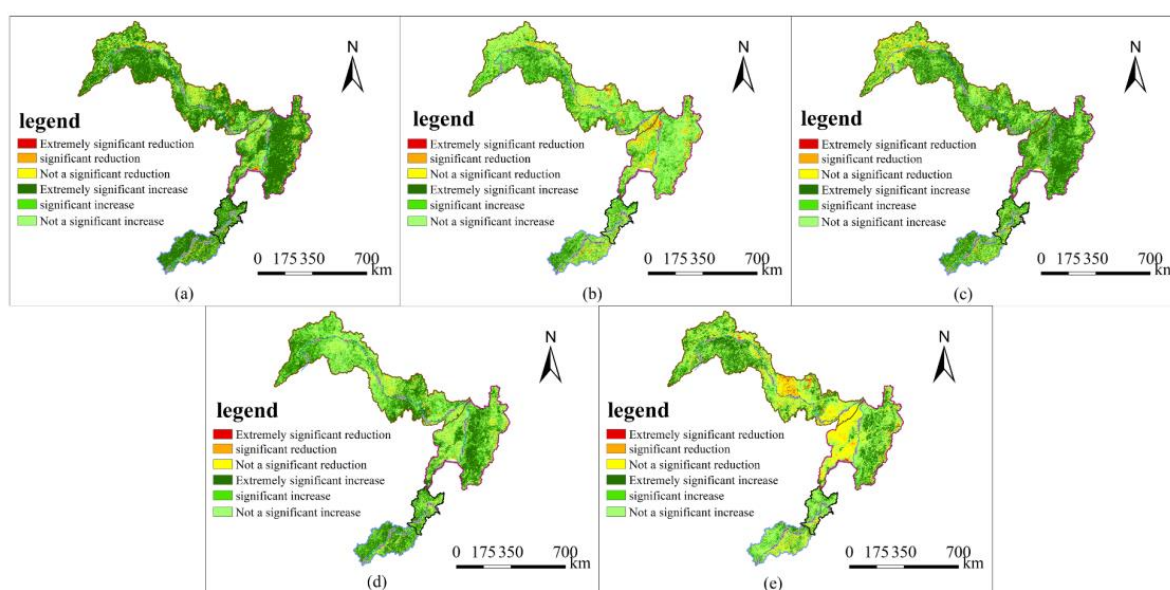


Figure 10. Spatial variation trends in the VCI on annual and seasonal scales. (a) Interannual; (b) spring; (c) summer; (d) autumn; (e) winter.

3.4.2. Spatial Distribution of Drought Levels

(1) Annual Scale

Based on the spatial distribution characteristics of the interannual VCI from 2000 to 2020 (Figure 11), the region predominantly experienced mild and medium droughts, covering 53.87% and 46.1% of the total area, respectively. The northern part of the HRB had a larger area of medium drought, the Chinese side of the URB primarily experienced medium drought, while the Russian side experienced mild drought. The TRB and the YRB were mainly characterized by mild drought conditions. The annual-scale drought distribution results provide an overall framework, while seasonal variations highlight significant differences in drought patterns, which warrant further investigation.

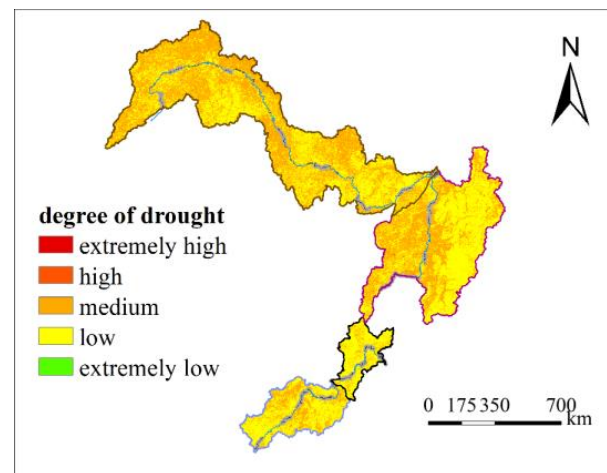


Figure 11. Spatial distribution of annual VCI drought levels.

(2) Seasonal

According to Figure 12 and Table 3, it can be seen that the drought conditions in the study area show significant differences in different seasons. Mild drought is dominant in spring and summer, accounting for 62.93% and 78.74% of the area, respectively, while mild drought (80.64%) and moderate drought (62.92%) are dominant in autumn and winter, respectively. In terms of space, the Russian side of the URB, the HRB, and the YRB have varying degrees of drought distribution in different seasons. In addition, due to the influence of vegetation status, the reported SPEI of the VCI for dry materials is relatively high, which is related to seasonal vegetation wilting and a small vegetation coverage area, and therefore not discussed in detail in the analysis.

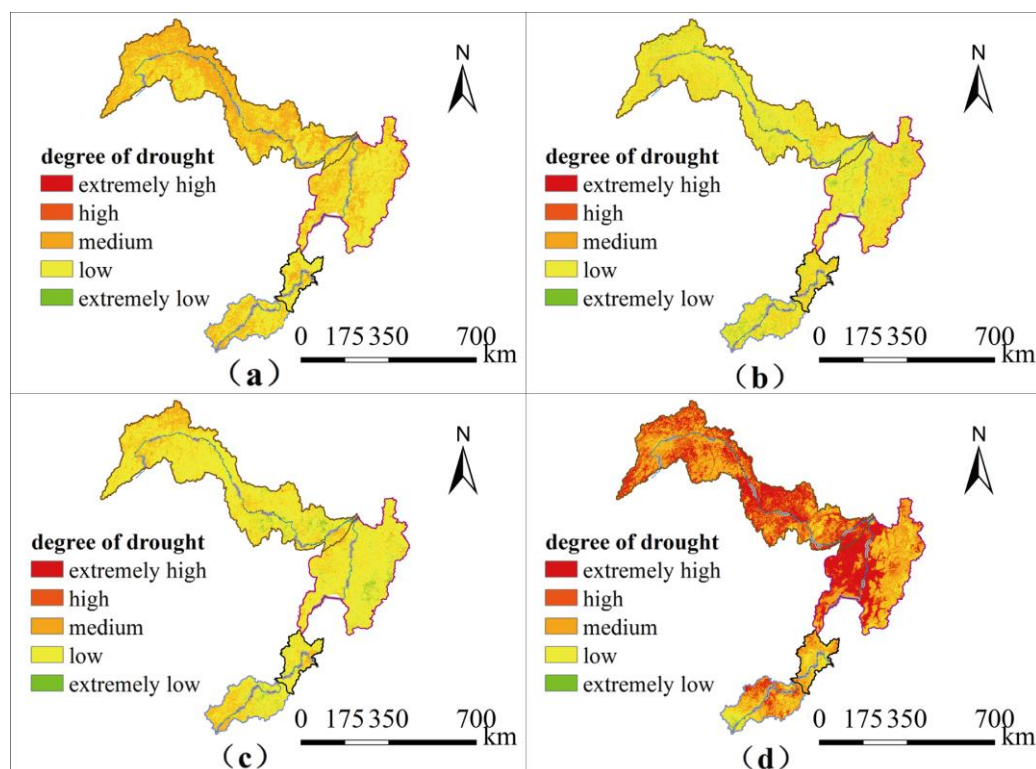


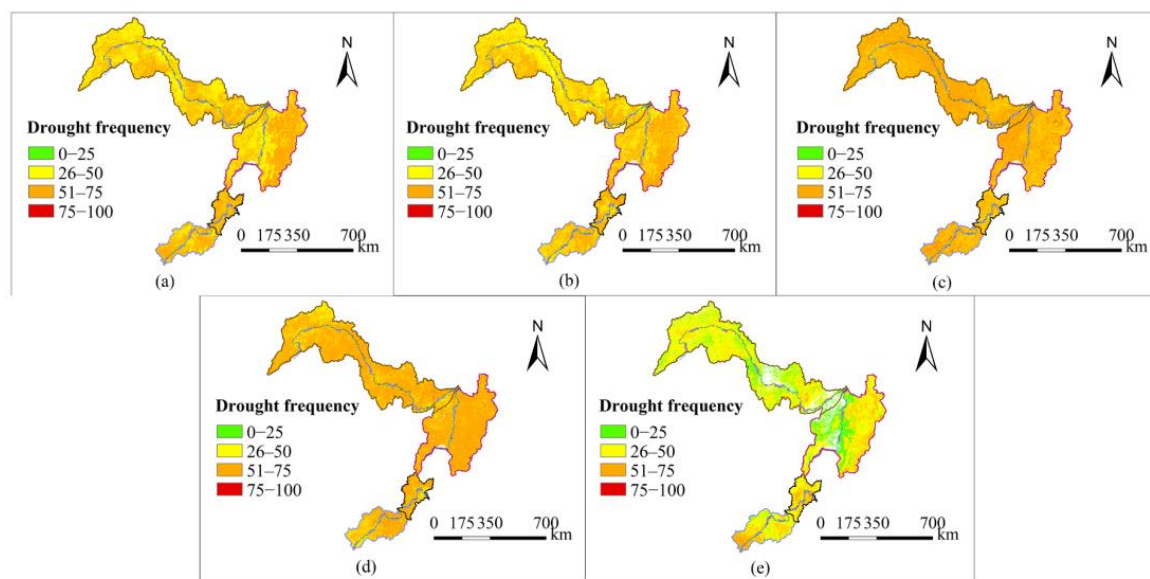
Figure 12. Spatial distribution of VCI drought levels by season. (a) Spring; (b) summer; (c) autumn; (d) winter.

Table 3. The seasonal area statistics of drought severity in transboundary river basins of Northeast Asia (km²).

Season	Severe Drought	Medium Drought	Mild Drought	No Drought
Spring	680	212,098	362,764	925
Summer	381	96,213	453,924	25,950
Autumn	614	98,897	464,891	12,063
Winter	210,565	302,981	61,681	1240

3.4.3. Spatial Distribution of Drought Frequency

Regarding the interannual and seasonal spatial distribution of drought frequency based on the VCI (Figure 13), the interannual drought frequency mainly ranged from 51% to 75%, covering an area of 310,491 km² (Table 4), which accounts for 54% of the total region, indicating frequent droughts in the Northeast Asian transboundary river basins. Seasonally, the drought frequency during spring, summer, and autumn was concentrated between 51% and 75%, suggesting that droughts were more common in these three seasons. In contrast, the drought frequency in winter was mainly between 26% and 50%, indicating a relatively lower frequency. Spatially, summer and autumn exhibited high drought frequency over large areas of the study region, whereas winter showed a lower drought frequency, particularly in the central URB.

**Figure 13.** Spatial distribution of annual and seasonal drought frequency based on the VCI. (a) Inter-annual; (b) spring; (c) summer; (d) autumn; (e) winter.**Table 4.** Interannual and seasonal area statistics of drought frequency in transboundary river basins of Northeast Asia (km²).

Frequency (%)	Annual	Spring	Summer	Autumn	Winter
0–25	11	22	4	6	91,849
26–50	264,477	262,328	94,979	96,581	366,478
51–75	310,491	310,997	473,845	474,317	62,474
75–100	1	10	5442	923	134

3.5. Annual Integrated Drought Index Spatial Distribution

Regarding the interannual spatial distribution of the integrated drought index (Figure 14), areas of “extremely high”, “high”, and “medium” drought levels are mainly located in the

central western part of the HRB and the Chinese side of the URB. These regions experience prolonged and severe drought conditions, which can have significant impacts on local ecosystems, agricultural productivity, and water resources. There are regions of high drought levels in the central part of the YRB, but their area is relatively small. This localized nature of droughts may still have concentrated impacts, particularly on specific agricultural regions or vulnerable communities. The TRB predominantly exhibits “extremely low” and “low” drought levels, with fewer occurrences of “medium” and “high” drought levels. An analysis of the area of different drought levels under various land cover types (Table 5) reveals the following.

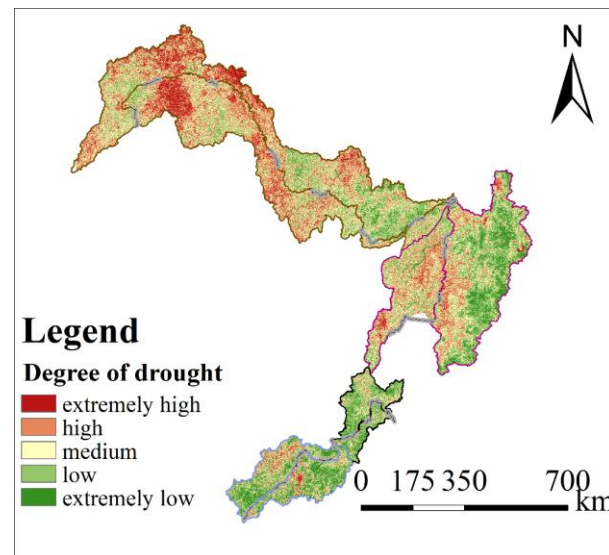


Figure 14. Spatial distribution of annual integrated drought index.

Table 5. Percentage of land cover types under different drought levels.

Land Cover Types	Drought Level (%)					Total
	Extremely Low	Low	Medium	High	Extremely High	
Cropland	1.21	3.98	5.64	4.44	1.31	16.58
Forest	6.49	15.53	20.56	17.91	10.76	71.25
Grassland	1.66	3.72	3.80	2.26	0.73	12.17
Shrubland	0.00	0.00	0.00	0.00	0.00	0.00
Bare land	0.00	0.00	0.00	0.00	0.00	0.00
Total	9.36	23.23	30.00	24.61	12.80	100

Overall, “medium” drought levels are the most common across different land cover types, suggesting a widespread moderate drought condition across the region. Forested areas, which constitute 71.25% of the total region, are most affected by drought. These forested regions are particularly vulnerable to “high” and “extremely high” drought levels, which can exacerbate ecological risks such as reduced carbon sequestration, increased fire hazards, and biodiversity loss. In the entire study area, “high” and “extremely high” drought levels are primarily found in forested regions. Croplands, accounting for 16.58% of the total area, are mostly affected by “medium” drought levels, comprising 5.64% of the total area. The proportions of shrublands and barren lands are very small, almost negligible. The proportion of “high” and “extremely high” drought levels across the entire study area is 37.41%.

Regarding the distribution of drought level across different land cover types (Figure 15), the areas with “medium” drought levels predominated in 2003, likely due to moderate climatic

conditions and varying water retention across land types. Generally, both 2003 and 2008 exhibited a higher level of drought distribution, whereas after 2014, there was an increase in the area covered by “extremely low” drought levels, primarily due to changes in precipitation patterns, with a decline in rainfall after 2014. In 2019, grasslands showed the largest area covered by “medium” drought levels. Drought levels in grasslands primarily remained at “low” and “extremely low” levels; after 2014, except for 2019, the area covered by “extremely low” drought levels in grasslands was highest, with “low” drought levels dominating in other years. In 2002, there was a small area covered by “extremely high” drought levels, while the highest proportion of high-level drought occurred in 2008. Cropland experienced predominantly “low” and “extremely low” drought levels; in 2003, the area covered by “medium” drought levels was largest at 19%, with “high” drought levels primarily appearing in 2008 at 8%. The occurrence of the strong El Niño event in 2008 likely contributed to the extreme drought conditions in that year, exacerbating the dry conditions in the region. Over the past two decades, forest drought levels have mainly been at “low” and “extremely low” levels, with the largest area covered by “medium” drought levels in 2003 at 19%, and the highest area covered by “high” drought levels in 2008, at 8%. After 2014, the area covered by “extremely low” drought levels was largest.

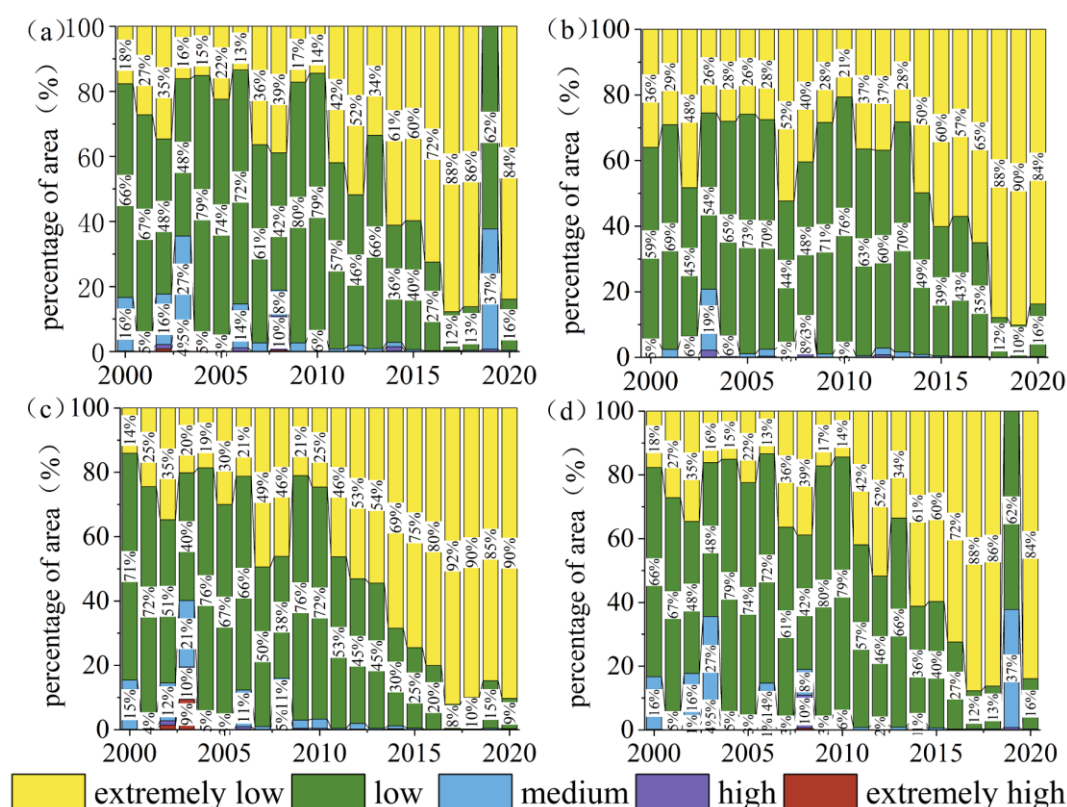


Figure 15. Annual proportion of drought level area under different land cover types. (a) Interannual; (b) cropland; (c) forest; (d) grassland.

In relation to the distribution of drought severity across different land use types in various regions (Figure 16 and Supplementary Table S2), on the Chinese side of the HRB the predominant land cover type is forest, with drought levels primarily categorized as “medium”, and “extremely high” drought levels concentrated in forest areas. In the URB, cropland is predominant on the Chinese side, while forest is more prevalent on the Russian side, with both regions mostly exhibiting “medium” drought severity. Similarly, in the TRB and YRB, forest is the dominant land cover type, and drought levels generally range

from “low” to “extremely low”, with occasional high drought severity observed in specific forested areas.

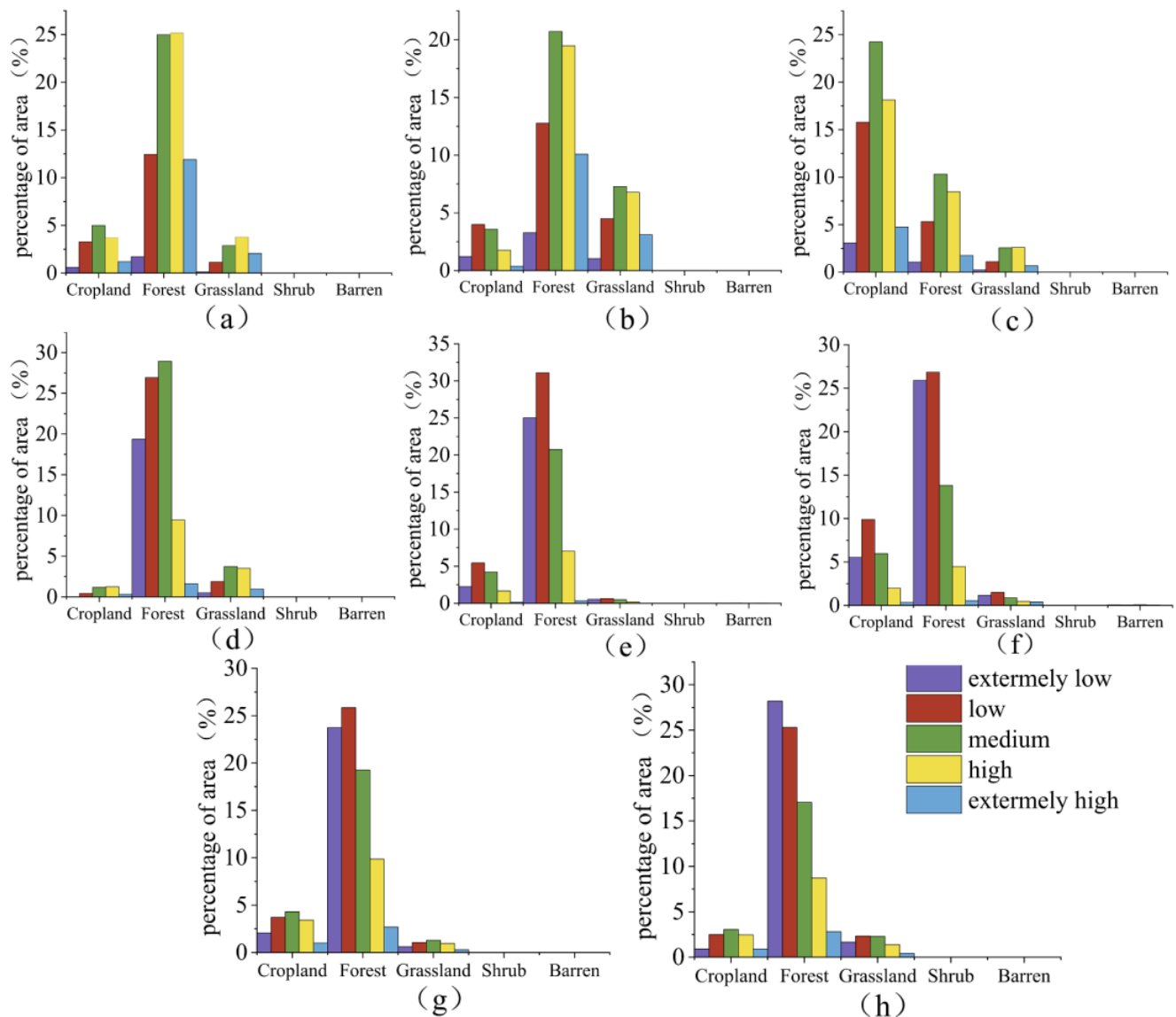


Figure 16. Area statistics of drought levels under different land cover types in different regions. (a) Chinese side of the HRB; (b) Russian side of the HRB; (c) Chinese side of the URB; (d) Russian side of the URB; (e) Chinese side of the TRB; (f) North Korean side of the TRB; (g) Chinese side of the YRB; (h) North Korean side of the YRB.

3.6. Spatial Distribution of Seasonal Comprehensive Drought Index

Regarding the seasonal and geographic distribution of the comprehensive drought index (Figure 17), various degrees of drought are observed across all basins in spring, with the HRB showing more pronounced drought conditions. In summer and autumn, the predominant drought levels are categorized as “extremely low”, while winter primarily experiences “medium” drought levels.

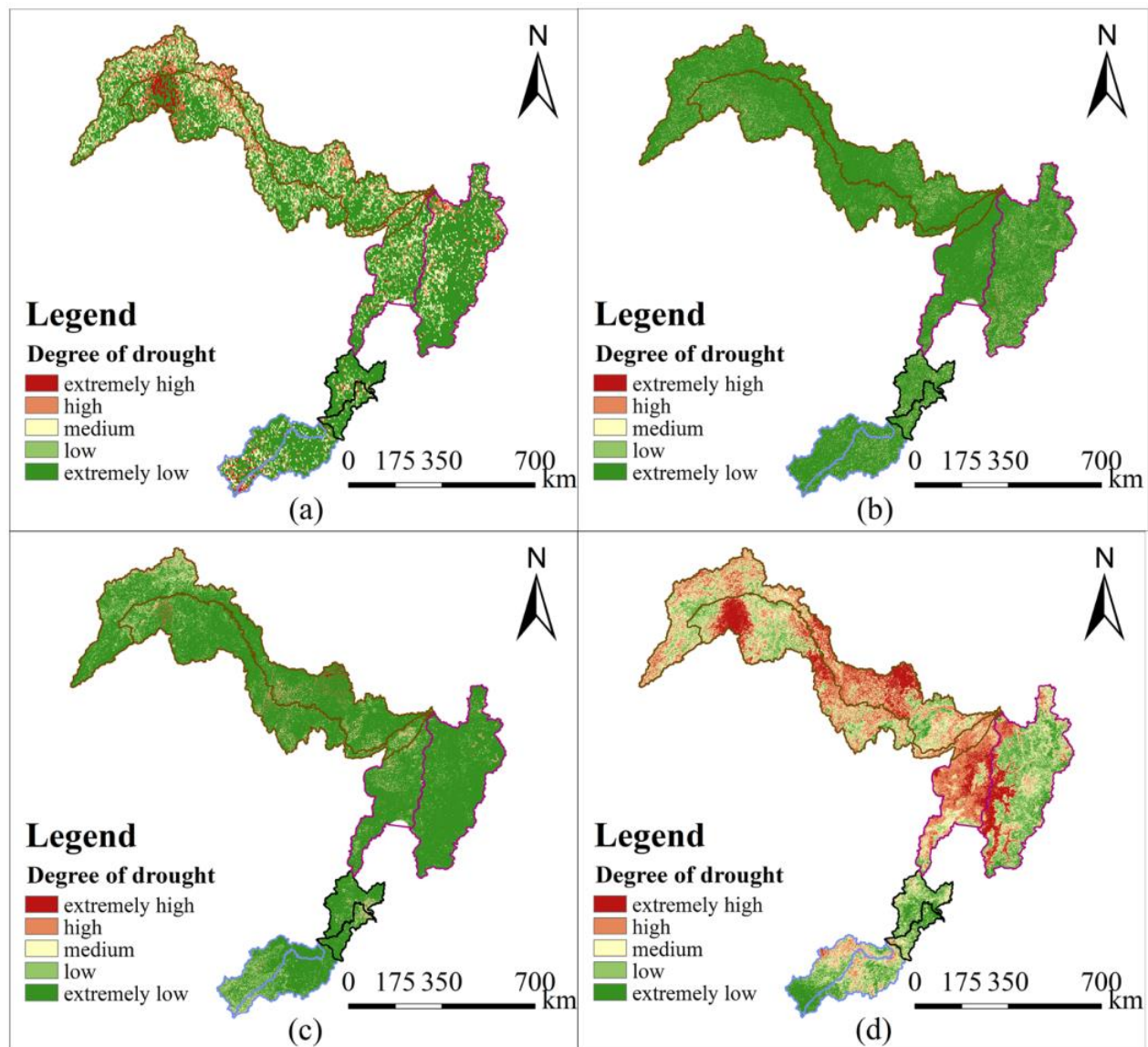


Figure 17. Spatial distribution of seasonal comprehensive drought index. (a) Spring; (b) summer; (c) autumn; (d) winter.

During spring, northern parts of the Chinese side of the HRB exhibit “extremely high” drought levels, whereas the northern parts of the Russian side primarily experience “low” and “medium” drought levels. Southern regions of the YRB show higher levels of drought. In summer, the Russian side of the URB is predominantly categorized under “low” and “medium” drought levels. During autumn, the northern Russian side of the HRB, northwestern parts of the Chinese side of the URB, northeastern parts of the TRB, and southern regions of the YRB mainly exhibit “low” and “medium” drought levels. Winter shows significant drought levels influenced by the VCI, with vegetation in a withered state. The Heilongjiang and URB are notably drier during this season.

Regarding the area statistics of drought levels under different land cover types across seasons (Figure 18), except for winter, most regions predominantly experience “extremely low” drought levels. Forest generally exhibits “high” drought levels, particularly in spring and winter when drought conditions are more severe.

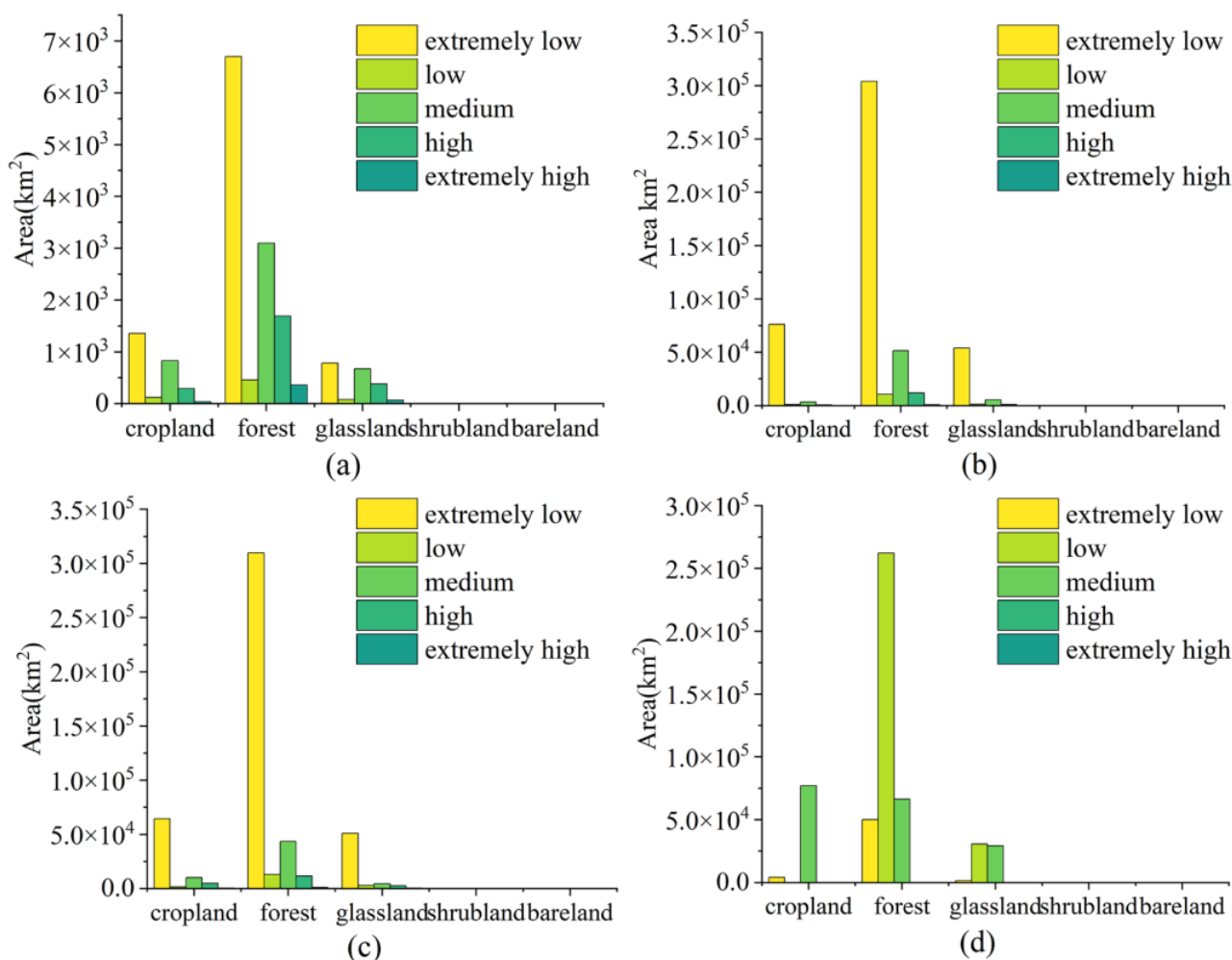


Figure 18. Area statistics of drought levels under different land cover types in each season. (a) Spring; (b) summer; (c) autumn; (d) winter.

In spring, “extremely low” drought levels are most common, followed by “medium” levels, with “high” drought levels primarily concentrated in forest. In summer and autumn, drought conditions are mostly “extremely low”.

In winter, bare land and grassland show a larger area of “low” drought levels, while forest is mainly affected by “medium” drought levels.

4. Discussion

4.1. Analysis of Spatiotemporal Characteristics of the SPEI

Based on analysis of the SPEI, there is significant interannual variability, showing an overall upward trend, indicating a tendency towards wetter conditions in recent years [55]. This is consistent with the findings of He et al. [62]. In terms of drought intensity, moderate and mild droughts are predominant. Areas experiencing stronger drought intensities are mainly located in the northwestern and northern parts of the HRB. These regions are geographically remote, inland, and less influenced by moist air currents, resulting in insufficient precipitation and dry climatic conditions. Some areas consist of deserts and arid lands with predominantly grassland cover, making them more susceptible to drought impacts [81]. Additionally, on the Russian side of the URB, drought intensity is also significant due to the influences of the Western Pacific High and the Siberian Low [82]. These atmospheric systems interact with local geographical features, such as the lack of significant mountain ranges or water bodies, which could otherwise help regulate the

climate. Regarding the seasonal distribution of drought, many regions experience moderate drought conditions during summer. Regarding the frequency of drought occurrences, drought events are concentrated mainly between 8 and 16 occurrences, indicating relatively frequent drought events across the region. However, a statistical analysis of drought frequency is essential to ascertain whether these variations are significant or part of a larger cyclical pattern. Future analyses could benefit from examining the statistical significance of these trends, using long-term climate data to assess the role of regional climate change in driving the observed drought trends.

4.2. Analysis of Spatiotemporal Characteristics of the VCI

Based on analysis of the VCI over the past two decades, there has been an overall upward trend in annual variations, particularly marked by significant increases. This is consistent with the findings of Liang et al. [83]. This trend suggests a mitigation of drought conditions and a tendency towards wetter conditions in Northeast Asia's transboundary river basins [84], which aligns with findings from the SPEI. The VCI over the past 20 years shows an upward trend, with a significant increase after 2015, likely related to climate change, precipitation patterns, and vegetation recovery. The declines in 2002–2004 and 2008–2009 are associated with drought events or reduced precipitation. Seasonal increases indicate overall vegetation recovery in spring, summer, autumn, and winter, with faster growth in spring and autumn, likely linked to changes in seasonal precipitation, temperature, and the growing cycle. The decline in the spring VCI (2003–2005, 2009–2011, 2016–2017) is related to drought and seasonal wilting, while the summer VCI remains stable, reaching its peak in 2020, indicating good vegetation growth. Significant changes in the autumn and winter VCI, especially in 2019, reflect improved climate conditions and vegetation recovery. In terms of drought frequency, drought events are concentrated between 51% and 75%. Seasonally, during spring, summer, and autumn, mild droughts are predominant, followed by moderate droughts, with drought occurrence frequencies also centered between 51% and 75%.

However, there is a discrepancy in the depiction of winter drought conditions between the VCI and SPEI. The SPEI indicates predominantly mild and moderate drought intensities during winter. In contrast, the VCI suggests higher drought severity during winter, which correlates with the vegetative status of the region. Harsh winter conditions such as low temperatures and sparse precipitation lead to vegetation wilting, contributing to higher drought severity as observed by remote sensing compared to meteorological drought indices [85]. It is important to note that the winter drought severity observed based on the VCI does not necessarily represent actual drought conditions. It reflects the impact of seasonal changes on vegetation, particularly in winter when vegetation naturally enters dormancy and wilts. This is a limitation of the study, as the VCI may not fully capture meteorological drought conditions during winter. In addition, to ensure the reliability of spatial drought, we selected six sampling points on the Chinese side of the Tumen River Basin and conducted a ten-day field validation from 10 August to 20 August 2024 (Figure 19).

4.3. Combined Analysis of Drought Severity Under Different Land Cover Types Using SPEI and VCI Indices

In different land use types, the area covered by “medium” drought levels is the largest. “High” and “extremely high” drought levels, primarily observed in the Heilongjiang and RUB, account for 37.41% of the entire study area. These drought levels are predominantly found in forest areas. This distribution is attributed to the composition of forest and cropland in the Heilongjiang and URB, where a significant portion of the land is covered by dense vegetation. Forested areas with dense vegetation cover are more sensitive to

water shortages, thus making them more susceptible to drought impacts during periods of water scarcity [86]. Although farmland is relatively less extensive, there are substantial agricultural areas on the Chinese side of the URB. Human activities such as agriculture and irrigation practices can affect soil moisture conditions, thereby increasing the susceptibility of these areas to drought [82]. Improper land management or inefficient water resource utilization can exacerbate the vulnerability of farmland to drought. It is recommended to promote sustainable land management practices, particularly on the Chinese side of the Heilongjiang and URB regions, and improve water resource efficiency to mitigate land degradation and soil erosion. Measures such as afforestation, soil conservation practices, and conservation tillage can help maintain soil moisture and nutrient balance in agricultural lands. Additionally, the extension of irrigated land in these areas contributes to enhancing water use efficiency and mitigating drought conditions.

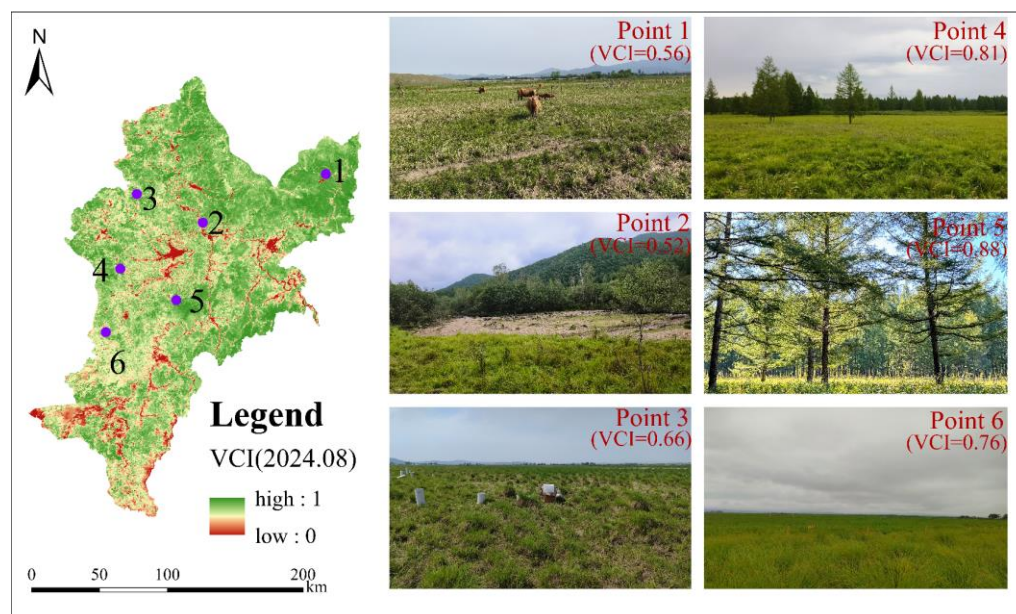


Figure 19. Field investigation of VCI in the Tumen River cross-border watershed (visited in August 2024).

Different regions exhibit varying levels of drought severity, which are more effectively explained by the spatial variation in geographical factors and land use distribution across the basin. The Heilongjiang and URB predominantly experience “medium” drought levels due to their location in Northeast Asia, characterized by an inland continental climate. These areas are far from the ocean, resulting in dry climatic conditions exacerbated by seasonal climate fluctuations such as dry winters and insufficient summer rainfall [81]. These climatic characteristics, together with the specific land use patterns in these regions, contribute to the overall “medium” drought status in these river basins. In contrast, the Tumen and YRB mainly experience “low” and “extremely low” drought levels. This can be attributed to their relatively humid geographical locations and the maritime climate influence from the nearby East Sea [87], and the favorable spatial distribution of land use. These regions benefit from higher humidity levels and sufficient precipitation resources, which are evenly distributed throughout the year. Additionally, favorable groundwater distribution and hydrological cycles reduce the frequency and severity of drought events. Based on these observations, it is recommended to enhance ecosystem protection and restoration efforts, particularly focusing on vegetation conservation. Measures such as afforestation, wetland protection, and grassland restoration can help maintain vegetation cover, reduce water evaporation, and preserve water conservation areas. Furthermore,

implementing climate adaptation strategies, such as establishing early warning systems, improving drought resilience through adaptive agricultural practices, and promoting sustainable water management, is crucial.

In analyzing drought levels across different seasons, several patterns emerge. Spring sees varying degrees of drought, with the most severe conditions occurring in the HRB. This is largely due to irregular precipitation distribution during early spring, which leads to insufficient replenishment of soil moisture. Moreover, increased evaporation rates before the onset of rainfall exacerbate drought conditions. In summer and autumn, the predominant drought level is “extremely low”. This is attributed to relatively higher and more evenly distributed precipitation during these seasons, which adequately meets the water needs of vegetation and soil moisture, thereby maintaining low drought levels. Winter predominantly experiences “medium” drought levels. This season is characterized by insufficient precipitation, particularly during specific drought periods, leading to inadequate soil moisture that can impact vegetation conditions during winter. Overall, the variations in drought levels across different seasons are influenced by factors such as precipitation amount, climate variability, vegetation water demands, and soil conditions. These factors interact differently across seasons, affecting soil moisture and vegetation growth states, thereby creating seasonal differences in drought severity. To address these challenges, it is recommended to strengthen water resource management. Water storage can be achieved through the construction of reservoirs and rainwater harvesting systems, while irrigation efficiency should be improved, such as using drip irrigation. Protecting wetlands and groundwater recharge areas is essential for mitigating drought. Funds for wetland restoration can be obtained through transboundary cooperation projects or support from international environmental foundations. During summer and autumn, soil moisture monitoring and irrigation adjustments should be implemented to avoid overuse of water. It is recommended to strengthen water resource cooperation among China, Russia, and North Korea by establishing a transboundary drought monitoring system and a data-sharing platform to jointly address the challenges posed by drought.

4.4. This Study's Limitations and Goals for Further Research

This work clearly outlines the spatial layout and shifting trends of drought in Northeast Asia by integrating the SPEI and VCI to examine the spatiotemporal evolution characteristics of drought events in cross-border watersheds. The integration of remote sensing technologies and meteorological observation data makes this research distinctive when compared to earlier studies since it offers a more thorough and three-dimensional perspective for drought evaluation. This study, however, has a number of drawbacks. First, the uncertainty concerns surrounding the SPEI and VCI indices have not been adequately addressed in the present research, which restricts a thorough understanding of the dependability of drought assessment findings. Second, this study's investigation of how various vegetation types respond to drought in various seasons is limited, which results in an inadequately detailed and thorough trend analysis of drought consequences and their spatial distribution. Addressing these uncertainties and investigating the drought response of various vegetation types in various seasons will be the main goals of future research. To increase the precision of drought monitoring and the capacity to anticipate extreme drought episodes, future studies should also incorporate a wider range of drought indices, sophisticated climate models, and comprehensive land use change data. In addition to improving our comprehension of the dynamic changes in drought, this thorough analysis approach offers stronger theoretical justification for ecological preservation and water resource management. Additionally, future research could explore the integration of advanced models, such as the Integrated Geographically Weighted Dryness Index (IGWDI), to

enhance the spatiotemporal analysis of drought and provide more comprehensive insights into drought dynamics across diverse land cover types [88].

5. Conclusions

This study explored the spatiotemporal characteristics of drought in cross-border watersheds in Northeast Asia by using meteorological station data and remote sensing data to calculate the Standardized Precipitation Evapotranspiration Index (SPEI) and Vegetation Condition Index (VCI). The study found that (1) an increase in the SPEI indicates a trend towards more mild drought conditions, with mild and moderate drought conditions being predominant. In terms of space, most areas experience mild drought early, while some watershed regions experience moderate drought. (2) The VCI has significantly increased, indicating an improvement in vegetation conditions, a reduction in drought, and an increase in drought-free areas. The spatial distribution of VCI is mainly characterized by mild and moderate drought, and in recent years, the early drying condition has gradually weakened. (3) Based on the SPEI and VCI indices, the study area is mainly characterized by moderate drought levels, while high and extremely high drought levels are mainly distributed in forests, accounting for 17.91% and 10.76% of the total area, respectively. There are differences in drought levels among different seasons and land cover types. This study provides scientific support for regional water resource management and ecological protection.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w17030382/s1>, Table S1. Transboundary river basins in Northeast Asia and surrounding meteorological stations; Table S2. Land cover type area proportions under different drought levels in various regions.

Author Contributions: Conceptualization, F.L. and J.L.; methodology, D.Q.; software, H.Y.; validation, D.Q., J.L. and R.J.; formal analysis, F.L.; investigation, H.Y.; resources, W.Z.; data curation, F.L.; writing—original draft preparation, J.L.; writing—review and editing, D.Q.; visualization, F.L.; supervision, R.J.; project administration, W.Z.; funding acquisition, R.J., W.Z. and H.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Jilin Provincial Department of Science and Technology project (20210101106JC, 20200403030SF), the National Natural Science Foundation of China (42471093, U24A20585, 42461017) and the Ministry of Science and Technology project (2019FY101703).

Data Availability Statement: The raw data supporting the conclusions of this article can be obtained from the authors upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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