Spatiotemporal variation of drought and its influential factors in the Yellow River Basin, China based on vegetation health index Postprint

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Date: 2025-10-22T00:00:00+00:00

Abstract

Drought is a natural disaster that significantly impacts the Earth' s ecological environment, especially in arid and semi-arid areas. However, drought at a large watershed scale, which plays an important role in sustainable environmental development, has received limited attention. In this study, we analyzed the spatial and temporal variations in drought in the Yellow River Basin, China from 2002 to 2022 and its driving factors using a vegetation health index (VHI). Results showed that average VHI in the Yellow River Basin from 2002 to 2022 was 0.581, with the most severe drought occurring in summer and autumn. The basin showed a slow decreasing trend in drought during the study period. Regarding spatial distribution of monthly drought frequency and trend of VHI, the mean of the frequency was 13.00%, and 78.00% had a drought frequency of 10.00%-20.00%, with moderate drought generally prevailing. Regarding land use types, forest land, grassland, agricultural land, construction land, water body, and wasteland showed a descending order for the annual average VHI. VHI of each land use type was the lowest in summer and autumn, with pronounced seasonal characteristics. The uneven distribution of drought in the Yellow River Basin was primarily influenced by annual precipitation, solar-induced chlorophyll fluorescence, and relative humidity. VHI effectively quantified drought conditions at a regional scale and proved to be highly applicable in the Yellow River Basin. The results clarify the effectiveness of VHI for drought monitoring in the Yellow River Basin and can provide a reference for drought monitoring across the basin.

Full Text

Preamble

Spatiotemporal Variation of Drought and Its Influential Factors in the Yellow River Basin, China Based on Vegetation Health Index

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Abstract: Drought is a natural disaster that significantly impacts the Earth' s ecological environment, especially in arid and semi-arid regions. However, drought at large watershed scales, which plays a crucial role in sustainable environmental development, has received limited attention. This study analyzed spatial and temporal variations in drought across the Yellow River Basin, China from 2002 to 2022 and identified its driving factors using the Vegetation Health Index (VHI). Results showed that the average VHI in the Yellow River Basin during this period was 0.581, with the most severe drought occurring in summer and autumn. The basin exhibited a slow decreasing trend in drought severity throughout the study period. Regarding the spatial distribution of monthly drought frequency and VHI trends, the mean frequency was 13.00%, with 78.00% of the area experiencing drought frequencies between 10.00%-20.00%, where moderate drought generally prevailed.

Across different land use types, forest land, grassland, agricultural land, construction land, water bodies, and wasteland showed descending annual average VHI values in that order. VHI for each land use type was lowest in summer and autumn, demonstrating pronounced seasonal characteristics. The uneven distribution of drought in the Yellow River Basin was primarily influenced by annual precipitation, solar-induced chlorophyll fluorescence, and relative humidity. VHI effectively quantified drought conditions at a regional scale and proved highly applicable in the Yellow River Basin. These results clarify the effectiveness of VHI for drought monitoring in the basin and provide a reference for drought monitoring across large watersheds.

Keywords: aridity index; drought frequency; land use; humidity; precipitation; Geodetector

Citation: Haoriwa, Zhalagahu, ZHOU Ruiping. 2025. Spatiotemporal variation of drought and its influential factors in the Yellow River Basin, China based on vegetation health index. *Journal of Arid Land*, 17(10): 1361–1377. doi: 10.1007/s40333-025-0029-3; CSTR: 32276.14.JAL.02500293

1 Introduction

Global average land and sea surface temperatures rose by 0.85°C from 1980 to 2012 (Qin and Stocker, 2014). This warming has intensified extreme weather events that threaten ecosystem sustainability, including extreme heat, cold, precipitation, and drought (Weilnhammer et al., 2021). Extreme drought significantly reduces water body area, increases fragmentation, and enhances landscape heterogeneity (Stewart et al., 2020), resulting in declining water levels, stomatal closure in trees, and rising soil temperatures (Cochard, 2021).

While the World Meteorological Organization (WMO) and China Meteorological Administration (CMA) have proposed different classification standards for drought, these various types essentially represent the transmission and coupling of water deficit across different systems (van Loon, 2015). Early drought detection primarily relied on meteorological monitoring methods using station data for indices such as the Palmer Drought Index (Shen et al., 2017), Standardized Precipitation Index (SPI) (Tigkas et al., 2018), and Palmer Z Index (Noor et al., 2020). However, these methods only monitor meteorological drought and are limited by station distribution. More than 150 indices have been used for drought monitoring across different climatic conditions and regions (Zargar et al., 2011), with commonly utilized indices including SPI, Standardized Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI) (Chikabvumbwa et al., 2023), Normalized Difference Vegetation Index (NDVI) (Sun and Kafatos, 2007), Precipitation Status Index (PCI) (Younis and Jasim, 2024), Vegetation Health Index (VHI) (Kloos et al., 2021), Vegetation Drought Response Index (VDRI) (Tadesse et al., 2017), and Land Surface Temperature (LST) (Hu et al., 2020).

Advances in remote sensing have established satellite-based drought monitoring as the primary method for tracking dry conditions, offering extensive coverage and consistent spatial and temporal data. The remotely sensed Vegetation Condition Index (VCI) reflects changes in vegetation greenness caused by drought and water scarcity, enabling comparison of drought severity across different seasons and regions (Quiring and Ganesh, 2010). Wei et al. (2021) conducted a comparative analysis of drought monitoring indices based on remote sensing data in China and found that VCI and Temperature Condition Index (TCI) better monitor long-term drought conditions under different land use types. Compared with other drought indices, remotely sensed vegetation indices offer continuous data, real-time access, and broad coverage, making them the most promising technical approach for drought monitoring (Liang et al., 2014). To enhance monitoring capabilities, researchers have combined VCI with surface temperature condition indices to form VHI, leveraging the strengths of both to improve remote sensing data utilization (Zuhro et al., 2020). VHI can attenuate or even eliminate effects of geographical location, ecosystem type, and soil conditions on vegetation, thereby effectively characterizing drought (Almeida-Ñauñay et al., 2022). Bento et al. (2020) used VHI to characterize severe drought episodes in arid regions, demonstrating its effectiveness for monitoring drought in terrestrial systems. Masroor et al. (2022) used VHI to analyze the relationship between drought and soil erosion in India, finding it could better describe drought development in the central Godavari River Basin. Javed et al. (2021) compared four indices including SPI and VHI, concluding that VHI better captured changes in soil relative humidity and identified drought occurrence. VHI has been widely applied in drought monitoring and demonstrates strong applicability.

While drought studies have primarily focused on correlations with climate (Berg et al., 2016), greenness (He et al., 2019), soil microorganisms (Neilson et al., 2017), and biomes (Li et al., 2018), drought events as natural hazards are affected by multiple composite factors including urbanization (Hao et al., 2023), plant growth (Doblas-Miranda et al., 2017), and climatic anomalies (Raphael et al., 2017). Currently, most studies lack consideration of the spatial heterogeneity of driving factors and investigation of interactive effects among them. Clarifying both individual and compound influences of these drought-driving factors is particularly significant for drought analysis.

Arid and semi-arid areas cover approximately 56.48% of China' s land area, affecting nearly 6.0×10^{8} people (Prăvălie, 2016). As an important ecological barrier and economic zone in China (Shi et al., 2021), the Yellow River Basin has experienced increasing drought frequency and intensity over the past 50 years. Compared with the mid-20th century, drought events in the middle and lower reaches have increased by 15.00%-20.00%, with extreme drought intensity rising significantly (Wang et al., 2021). Therefore, analyzing drought conditions and their multiple influencing factors in the Yellow River Basin is essential for achieving economic development and environmental sustainability in northern China (Li et al., 2024). This study analyzed drought events in the Yellow River Basin from 2002 to 2022 using TCI, VCI, and VHI indices, revealing the influences of climate, soil, and other factors as well as their interactions to promote ecological recovery in the basin.

2.1 Study Area

The Yellow River Basin is China' s second-largest river basin (32°10 -41°50 N, 95°53 -119°05 E; Fig. 1 [Figure 1: see original paper]). The river originates from the Yoigilanglêb Basin in the northern foothills of the Bayan Har Mountains on the Qinghai-Xizang Plateau. This study divides the basin into four sub-basins: Lanzhou Basin, Lanzhou-Hekou Basin, middle reaches of the Yellow River Basin, and lower reaches of the Yellow River Basin. Terrain decreases from west to east with a relief exceeding 4000 m. The main river channel extends 5464 km, draining a watershed area of 7.95×10^{5} km^2. The climate features significant temperature fluctuations, uneven precipitation distribution, low humidity, and high evaporation rates, making the basin a typical complex transition zone spanning semi-humid, arid, and semi-arid regions. Nine provinces and autonomous regions within the Yellow River Basin comprise approximately 30.20% of the national population and contribute about 25.00% of the country' s gross domestic product.

Fig. 1 Topography (a) and land use cover (b) of the Yellow River Basin, China. The basin figure is based on the standard map (GS(2024)0650) from the National Geomatics Center of China (https://www.ngcc.cn/), with no modifications to the standard map boundary. DEM, digital elevation model.

2.2.1 Remote Sensing-Based Drought Index

VHI is a remote sensing vegetation index that integrates vegetation and temperature data, simultaneously reflecting moisture and temperature changes in an area while monitoring drought variations across different temporal and spatial scales. This study used VHI to characterize drought severity in the Yellow River Basin (Table 1). VHI is calculated as follows:

$$VHI_{i,j,k} = \alpha \times TCI_{i,j,k} + (1-\alpha) \times VCI_{i,j,k}$$

where TCI is the Temperature Condition Index; LST is Local Surface Temperature (°C); VCI is the Vegetation Condition Index; NDVI is the Normalized Difference Vegetation Index; subscripts i, j, and k represent the ith image element, jth month, and kth year, respectively; subscripts max and min denote the multi-year maximum and minimum of corresponding image elements; VHI is the Vegetation Health Index; and α is the weighting factor, typically fixed at 0.5 in practical applications (Zhang and Jia, 2013). Lower VHI values indicate more severe drought, and vice versa.

Table 1 Classification of drought levels based on different indices

Classification of drought	TCI	VCI	VHI
Extreme drought	<10	<10	<10
Severe drought	10–20	10–20	10–20
Moderate drought	20–30	20–30	20–30
Mild drought	30–40	30–40	30–40
General drying	40–60	40–60	40–60
No drought	>60	>60	>60

Note: TCI, temperature condition index; VCI, vegetation condition index; VHI, vegetation health index.

2.2.2 Drought Frequency

Following the methodology of Yuan et al. (2023), we calculated the frequency of moderate and severe droughts in the basin during the 21-year study period using:

$$f = \frac{m}{n} \times 100\%$$

where f is drought frequency (%); m is the number of months with moderate or greater drought; and n is the total number of years from 2002 to 2022.

2.2.3 Trend Analysis

Following Yuan et al. (2023), we used ordinary least squares (OLS) regression and F-statistics to determine drought index trends (Slope):

$$Slope = \frac{n \times \sum_{i=1}^{n} i \times DI_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} DI_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where DI is the mean drought index value in year i. Slope > 0 indicates an increasing drought trend, while slope < 0 indicates a decreasing trend.

2.2.4 Geodetector

Geodetector is a statistical method that identifies spatial element divergence and its driving forces, including factor detection, interaction detection, risk zone analysis, and ecological detection (Wang et al., 2021). This study employed factor and interaction detection to evaluate influences of different factors on regional drought indices. The factor detection metric ranges from 0 to 1, where higher values indicate more significant driver influence on habitat quality, while lower values suggest less influence. The factor detection formula is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where q is the factor detection measure indicating the magnitude of influence of a factor on drought distribution; L is the number of samples of the influencing factor; σ^2 is the discrete variance in stratum h; N is the drought condition in stratum h; N is the drought condition across the entire study area; σ ^{2} is the discrete variance in stratum h; and σ^2 is the discrete variance across the entire study area.

The interaction detector assesses whether influencing factors X_1 and X_2 independently affect drought index Y or interact with each other. If interaction occurs, the test determines whether effects are amplified or diminished. The test involves calculating q-values of factors X_1 and X_2 on drought index Y, followed by the q-value of their interaction. These q-values are compared to categorize relationships into five types (Table 2).

Table 2 Categorization of interactions among factors influencing drought index

Basis of judgement	Interaction
$q(X_1\ X_2) < \min(q(X_1), q(X_2))$	Nonlinear attenuation
$\min(q(X_1), q(X_2)) < q(X_1\ X_2) < \max(q(X_1), q(X_2))$	Single-factor nonlinear attenuation
$q(X_1\ X_2) > \max(q(X_1), q(X_2))$	Two-factor enhancement
$q(X_1\ X_2) < q(X_1) + q(X_2)$	Separate
$q(X_1\ X_2) > q(X_1) + q(X_2)$	Nonlinear enhancement

2.3 Data Analysis

NDVI data from 2002 to 2022 were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS)/061/MOD13Q1 product on the Google Earth Engine (GEE) platform, which included atmospheric correction. The data had a temporal resolution of 16 days and spatial resolution of 250 m. Approximately 966 images were sampled from 483 periods using MODIS/061/MOD11A2 products, which had an 8-day temporal resolution and 1 km spatial resolution. These images were preprocessed through splicing and cropping, with all processes completed on the GEE platform. Table 3 lists data used to examine impact factors, with all data standardized.

Table 3 Description of factor information

Influencing factor	Abbreviation	Data description	Source
Digital elevation model	DEM	Generated based on Latest SRTM v.4.1 data resampling	-
Wind erosion	-	Estimated based on erosion equation and wind erosion equation	https://www.resdc.cn

Influencing factor	Abbreviation	Data description	Source
Water conservation	-	Obtained based on moisture regulation effect equation, modified generalized erosion equation, and modified wind erosion equation model	https://www.resdc.cn
Soil conservation	-	Obtained based on MODIS surface evapotranspiration, ET, and PET (MOD16A2)	https://www.resdc.cn
Wind protection and sand fixation	-	Obtained based on station daily observation and interpolation by ANUSPLIN v.3.2 software	https://www.resdc.cn
Actual evaporation	ET	Obtained by reanalysis based on Orbiting Carbon Observatory-2 discrete GOSIF data and MODIS data, with a resolution of 0.05°	https://globalecology.unh.edu
Potential evaporation	PET	-	https://globalecology.unh.edu
Relative humidity	RH	-	-
Average annual temperature	TEM	-	-
Annual precipitation	PRE	-	-
Solar-induced chlorophyll fluorescence	GOSIF	-	-

Note: SRTM, Shuttle Radar Topography Mission; MODIS, Moderate Resolution Imaging Spectroradiometer.

3.1 Temporal Variation in Aridity Indices

According to established drought classification criteria, higher index values indicate less severe drought, and vice versa. Figure 2 [Figure 2: see original paper] shows seasonal, annual, and monthly changes in TCI, VCI, and VHI in the Yellow River Basin from 2002 to 2022. Seasonally, VHI increased linearly at rates of 0.0044/a, 0.0031/a, 0.0046/a, and 0.0056/a in spring, summer, autumn, and winter, respectively, indicating decreasing aridity across all four seasons. Low VHI values appeared most frequently in summer and autumn, suggesting drought events concentrated in these seasons. At the annual scale, TCI, VCI, and VHI values showed upward trends, with VHI increasing at 0.0040/a, indicating reduced drought conditions. The average VHI was 0.581, peaking at 0.685 in 2012 and reaching a minimum of 0.477 in 2002. At the monthly scale, VHI minima concentrated between May and October, consistent with seasonal clustering characteristics.

Fig. 2 Changes in TCI (Temperature Condition Index), VCI (Vegetation Condition Index), and VHI (Vegetation Health Index) at different time scales in the Yellow River Basin from 2002 to 2022. (a) spring; (b) summer; (c) autumn; (d) winter; (e) annual scale; (f) monthly scale.

Figure 3 [Figure 3: see original paper] illustrates annual variations in TCI, VCI, and VHI across different sub-basins. VHI values increased in all four sub-basins throughout the study period. Linear trend rates for the Lanzhou Basin, Lanzhou-Hekou Basin, middle reaches, and lower reaches were 0.0036/a, 0.0027/a, 0.0060/a, and 0.0026/a, with mean values of 0.5880, 0.5590, 0.5760, and 0.5690, respectively. This indicated improving drought conditions across all sections, with the most significant increase in the middle reaches. However, the Lanzhou-Hekou Basin exhibited higher average drought severity. The highest VHI values occurred in 2019 (Lanzhou Basin), 2012 (Lanzhou-Hekou Basin), and 2011 (middle and lower reaches), with peaks of 0.729, 0.709, 0.723, and 0.728, respectively. The lowest VHI value in the Lanzhou-Hekou Basin was 0.429 in 2006, while the lowest values in the other three basins occurred in 2002, at 0.464, 0.443, and 0.352 for the Lanzhou Basin, middle reaches, and lower reaches, respectively.

Fig. 3 Annual trends of TCI, VCI, and VHI across different sub-basins in the Yellow River Basin from 2002 to 2022. (a) Lanzhou Basin; (b) Lanzhou-Hekou Basin; (c) middle reaches of the Yellow River Basin; (d) lower reaches of the Yellow River Basin.

3.2 Spatial Variation in Aridity Indices

Figure 4 [Figure 4: see original paper] illustrates the spatial distribution of TCI, VCI, and VHI across different seasons. TCI values indicated that 29.34% of the area experienced moderate or greater drought in spring, 35.74% in summer, 31.17% in autumn, and 27.09% in winter, with remaining areas experiencing less than moderate drought. Spatially, spring droughts concentrated in central Qinghai Province within the Lanzhou Basin and the Ningxia Hui Autonomous Region within the Lanzhou-Hekou Basin. Summer droughts were sporadic across all basins, while autumn droughts were prevalent throughout the Lanzhou-Hekou Basin. Winter droughts occurred primarily in Shanxi Province within the middle reaches.

VCI values showed 28.91%, 35.18%, 34.15%, and 21.43% of areas experiencing moderate or greater drought in spring, summer, autumn, and winter, respectively. Spring droughts were mainly distributed in the Ningxia Hui Autonomous Region of the Lanzhou-Hekou Basin and the southern middle reaches, with summer and autumn droughts occurring throughout the entire Lanzhou-Hekou Basin. Winter droughts were sporadic in the Lanzhou Basin and Ningxia Hui Autonomous Region.

VHI values indicated 35.20%, 34.22%, 35.47%, and 32.28% of areas experiencing moderate or greater drought in spring, summer, autumn, and winter, respectively. Spring droughts were sporadic, with significant areas in the Ningxia Hui Autonomous Region of the Lanzhou-Hekou Basin and the southern middle reaches. Summer and autumn droughts were widespread in the Lanzhou-Hekou Basin and Shaanxi Province within the middle reaches. Winter droughts in arid areas were mainly concentrated in the Ningxia Hui Autonomous Region of the Lanzhou-Hekou Basin and Shaanxi Province in the middle reaches.

The Yellow River Basin predominantly experienced moderate drought, with TCI, VCI, and VHI indicating moderate drought across approximately 29.02%–32.16% of the basin. The percentage of drought-affected area was significantly higher in summer and autumn than in spring and winter. Spatial distribution revealed that the Lanzhou-Hekou Basin and Shaanxi Province in the middle reaches were most significantly affected by drought across seasons.

Fig. 4 TCI (a1-a4), VCI (b1-b4), and VHI (c1-c4) distribution in the Yellow River Basin across different seasons from 2002 to 2022.

3.3 Trends and Frequency Characteristics of Drought Indices

Figure 5 [Figure 5: see original paper] shows the variation trend and frequency of annual mean drought index values. We classified drought index trends into six categories based on slope and significance: (1) significant decrease (slope < 0, P < 0.01); (2) moderate decrease (slope < 0, $0.01 \leq$ P ≤ 0.05); (3) no significant decrease (slope < 0, P > 0.05); (4) no significant increase (slope > 0, P > 0.05); (5) moderate increase (slope > 0, $0.01 \leq$ P ≤ 0.05); and (6) significant increase (slope > 0, P < 0.01).

Areas with significant and moderate TCI decreases were negligible. Non-significant decline areas comprised 12.28%, primarily located in the Inner Mongolia Autonomous Region of the Lanzhou-Hekou Basin with scattered occurrences elsewhere. Non-significant increase areas covered 82.31% across the basin, while significantly increased areas accounted for 4.82%. TCI distribution indicated relatively stable surface drought trends with high percentages of non-significantly increasing and decreasing areas.

VCI trend distribution showed a small proportion (9.66%) of non-significantly declining areas, mainly in the Lanzhou and Lanzhou-Hekou basins. Non-significantly increasing areas covered 61.38% of the total area. Significant and moderately significant increases were primarily distributed in Shaanxi, Shanxi, and Shandong provinces within the middle and lower reaches, accounting for 28.90%. VCI trend analysis indicated stable vegetation drought conditions in the middle and lower reaches during the study period.

VHI trend distribution showed 70.17% of the study area exhibited non-significant increases across the entire basin. Non-significant decline areas accounted for 12.93%, mainly in the Lanzhou-Hekou Basin with sporadic distribution in Henan Province. Significantly increased VHI areas comprised 12.76% and were located in the middle reaches, including Shanxi, Shaanxi, and Henan provinces, with concentrations in central Shaanxi and Shanxi. The high proportion of non-significant and moderately significant increases indicated stable drought trends in the middle and lower reaches.

Fig. 5 Drought trends (a–c) and frequency (d–f) distributions of TCI, VCI, and VHI in the Yellow River Basin from 2002 to 2022.

Frequency distribution of drought occurrences, calculated using monthly drought indices, is shown in Figures 5d–5f. Mean monthly drought frequencies using TCI, VCI, and VHI were 27.00%, 23.00%, and 13.00%, respectively. Based on TCI, only 0.33% of the area had drought frequency below 20.00%, while 80.03% had frequencies of 20.00%–30.00% distributed throughout the basin. Approximately 19.64% had frequencies of 30.00%–40.00%, primarily in northwestern Qinghai, Gansu, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region, and southwestern Shaanxi.

According to VCI drought frequency, 20.27% of the area experienced frequencies below 20.00%, mainly in the Lanzhou Basin with scattered occurrences in Inner Mongolia and Shaanxi, Shanxi, and Henan provinces. About 73.36% had frequencies of 20.00%–30.00%, covering large areas in each river basin section. Additionally, 6.14% had frequencies of 30.00%–40.00%, mainly in Gansu Province and Inner Mongolia.

Drought frequency calculated from VHI was lower than TCI and VCI. 19.29% of the area had drought frequency below 10.00%, primarily located in the Lanzhou Basin with sporadic distribution elsewhere. Additionally, 78.00% of the area experienced 10.00%–20.00% drought frequency, while 2.71% had 20.00%–30.00% frequency in the Lanzhou-Hekou Basin.

3.4 VHI Changes in Different Land Use Types

Figure 6a [Figure 6: see original paper] shows that annual average VHI values for each land use type exhibited upward trends similar to overall VHI, though with varying intensities. Forest land showed the highest growth rate and mean VHI value, with a linear trend of 0.0058/a and a study period mean of 0.610, peaking at 0.750 in 2012 and reaching a minimum of 0.430 in 2002. Grassland VHI fluctuated between 0.480–0.700, with a mean of 0.590 and linear trend of 0.0044/a. Highest values occurred in 2011–2012 and 2020–2021 (exceeding 0.650), indicating good drought conditions, while low values below 0.500 appeared in 2002 and 2015. Cropland and bare land showed linear trends of 0.0040/a, with average values of 0.590 and 0.560, respectively. Lower values occurred from 2002–2006, while VHI exceeded 0.650 in 2011 and 2021. Construction land VHI showed a clear upward trend of 0.0032/a, ranging from 0.490–0.670, with lowest values of 0.470 and 0.490 in 2002 and 2013, respectively, indicating significant drought characteristics. VHI exceeded 0.650 in 2011 and 2022. Water body VHI exhibited a slight upward trend of 0.0020/a, with the lowest value of 0.490 in 2002 and higher values concentrated from 2018–2020 (above 0.620).

Monthly average VHI values across land use types showed distinct trends, generally following a "decreasing-increasing-decreasing-increasing" pattern with pronounced seasonal variations (Fig. 6b). From January to April, rising temperatures promoted gradual vegetation growth, but increased evapotranspiration and low precipitation reduced soil water content, causing monthly average VHI values to decline and indicating increasing drought trends. From April to June, further temperature increases aggravated drought due to sparse vegetation distribution in barren land and increased soil moisture evapotranspiration. Monthly average VHI values for other land use types exceeded 0.580, with drought tendency indices increasing and drought trends reversing.

From June to August, increased precipitation and vegetation cover provided sufficient soil moisture, causing VHI values for all land use types except barren land to gradually peak above 0.600, with forest land reaching the highest value (0.650). From August to October, robust vegetation growth and high evapotranspiration combined with declining precipitation gradually decreased VHI values. After October, reduced evapotranspiration, lower surface temperatures, and rainy/snowy weather stabilized soil moisture, resulting in steady VHI values with minimal fluctuations.

Fig. 6 Changes in annual (a) and monthly (b) VHI for each land use type in the Yellow River Basin from 2002 to 2022.

Regarding land use types, bare land experienced varying drought degrees from March to October, primarily due to low vegetation cover and weak soil moisture retention, making it highly susceptible to successive drought conditions. Conversely, grassland, agricultural land, construction land, and water bodies exhibited similar trends due to lower vegetation cover density and greater climate susceptibility. In contrast, forest land' s high vegetation density provided good soil moisture retention, making it more drought-resistant than other land use types.

3.5 Drivers of Drought Indices

Geodetector analysis identified the strength of various factors influencing drought trends (Fig. 7 [Figure 7: see original paper]). Autumn most effectively represented drought distribution characteristics in the study basin, so we further explored drought index drivers based on autumn spatial distribution.

Fig. 7 Factors affecting VHI in the Yellow River Basin. (a) water conservation; (b) wind erosion; (c) soil conservation; (d) wind protection and sand fixation; (e) GOSIF (solar-induced chlorophyll fluorescence); (f) ET (evaporation); (g) PET (potential evaporation); (h) RH (relative humidity); (i) TEM (temperature); (j) PRE (precipitation).

Factor test results (Table 4) showed explanatory power of each influencing factor on drought distribution pattern followed the order: X_{11}, X_6, X_9, X_8, X_2, X_5, X_3, X_7, X_{10}, X_1, and X_4. Average annual precipitation decreases to 150.00 mm when humid oceanic airflow passes the Ordos Plateau and reaches the Lanzhou-Hekou Basin. Mean annual precipitation and relative humidity became the most explanatory climatic factors with q-values of 0.364 and 0.263, respectively. Potential evapotranspiration in northwest China' s inland dry area can reach approximately 80.00% of annual potential evapotranspiration during spring and summer, with seasonal changes primarily controlled by temperature and radiation. From the Qinghai-Xizang Plateau to the North China Plain, altitude gradually decreases and atmospheric influence on solar radiation weakens, representing a main factor causing uneven potential evapotranspiration and drought distribution. The most influential soil factor was solar-induced chlorophyll fluorescence, with highest values in the lower reaches, reflecting plant growth and photosynthetic efficiency. All factor q-values except soil conservation exceeded 0.100, indicating these factors influenced drought distribution.

Table 4 Detection results of factors affecting VHI

Factor code	Factor name	Explanatory power (q-value)
X_1	Water conservation	0.125
X_2	Wind erosion	0.201
X_3	Soil conservation	0.089
X_4	Wind protection and sand fixation	0.098
X_5	GOSIF	0.223
X_6	ET	0.287
X_7	PET	0.156
X_8	RH	0.263
X_9	TEM	0.275

Factor code	Factor name	Explanatory power (q-value)
X_{10}	PRE	0.364
X_{11}	-	-

Factor probing analysis revealed that each of the 11 component factors individually affected autumn VHI magnitude, while high and low drought indices were influenced by multiple factors. Interaction analysis examined how two-factor combinations affected drought index distribution. Table 5 shows interaction detection results. Except for X_1 X_4, X_1 X_6, X_4 X_7, and X_4 X_{11}, which showed two-factor enhancement, all interactions exhibited nonlinear enhancement relationships. Interaction factor X_{11} X_{10} had an explanatory power of 0.415 (Fig. 8 [Figure 8: see original paper]), demonstrating that precipitation and mean annual temperature significantly enhanced impacts on drought index. Interactions of relative humidity and solar-induced chlorophyll fluorescence with other factors exceeded 0.250, indicating that reduced precipitation and rising temperatures elevate atmospheric evaporative demand, intensify drought, and significantly impact vegetation growth. Consequently, vegetation productivity became more sensitive to precipitation changes with increasing atmospheric water demand, highlighting precipitation' s significant effect on the interaction between air temperature and vegetation growth.

Table 5 Interaction detection results

Factor A	Factor B	Interaction between factor A and factor B
X_1	X_2, X_3, X_5, X_7, X_8, X_9, X_{10}, X_{11}	Nonlinear enhancement
X_2	X_4, X_6	Two-factor enhancement
X_3	X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}	Nonlinear enhancement
X_4	X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}	Nonlinear enhancement
X_5	X_7, X_{11}	Two-factor enhancement
X_6	X_7, X_8, X_9, X_{10}, X_{11}	Nonlinear enhancement
X_7	X_8, X_9, X_{10}, X_{11}	Nonlinear enhancement
X_8	X_9, X_{10}, X_{11}	Nonlinear enhancement
X_9	X_{10}, X_{11}	Nonlinear enhancement
X_{10}	X_{11}	Nonlinear enhancement

Fig. 8 Interaction effects of influence factors on VHI in the Yellow River Basin

4.1 Characteristics of Drought in the Yellow River Basin

During the study period, only 2002 showed a significant drought event in the Yellow River Basin, with the remainder being normal, consistent with Qian et al. (2011). The long-term trend shows slightly slowing drought levels, likely related to ecological protection projects implemented in China since 2000. Studies demonstrate that the Returning Farmland to Forest Program (Li and Liu, 2022) and Three-North Protective Forest Program (Li et al., 2012) significantly contributed to regional vegetation recovery. However, large-scale afforestation, while improving surface vegetation cover, has been accompanied by continuous groundwater depletion, potentially impacting basin hydrological balance. This trade-off between ecological restoration and water resource depletion highlights drought monitoring complexity and illustrates limitations of vegetation-perspective monitoring alone.

The Yellow River Basin' s wet-dry cycle exhibits quasi-periodic changes of 30–50 years (Xing et al., 2024). The study period coincided with intensified East Asian summer monsoons over the last 20 years (Liu et al., 2012), potentially leading to over-optimistic estimations of ecological engineering effects.

Spatial analysis revealed 12.93% of the region showed decreasing trends, with the Lanzhou-Hekou Basin most significantly affected. Similarly, Wang et al. (2018) monitored Yellow River Basin drought using SPEI and identified the Lanzhou-Hekou Basin as the most vulnerable region, with drought associated with precipitation and evapotranspiration. Driver analyses confirmed precipitation as the core drought factor. Precipitation distribution was highly consistent with drought gradients because precipitation primarily contributes to soil moisture in the 0.0–1.0 m soil layer (Liu and Shao, 2015). Increased precipitation correlates with increased NDVI and decreased drought (Zhu et al., 2015), highlighting precipitation' s critical role in groundwater supply and vegetation growth.

The Lanzhou-Hekou Basin lies in the East Asian monsoon fringe zone, where rapid southward retreat of the western Pacific subtropical high pressure in autumn causes sudden water vapor transport decreases, resulting in 40.00%–50.00% precipitation reductions compared to summer. Autumn daily average temperatures of 15.00°C–20.00°C and potential evaporation of 80.00–100.00 mm/month (two to three times precipitation) combine with desert grassland dominance and 30.00%–40.00% vegetation cover (significantly lower than other basins) to weaken surface transpiration cooling effects and accelerate soil moisture loss through bare ground evaporation, further exacerbating drought stress (Cochard, 2021).

4.2 Applicability of VHI in the Yellow River Basin

The Yellow River Basin spans arid, semi-arid, and semi-humid climatic zones with diverse vegetation cover, topographic variation, and climatic heterogeneity, making drought monitoring challenging. Remote sensing drought indices are currently the primary regional monitoring tools. Fusion indices such as Temperature Vegetation Dryness Index (TVDI) integrate multi-source remote sensing information, overcoming single-index limitations and improving drought assessment accuracy and stability. TVDI performs well in monitoring arid conditions in cultivated land and high-vegetation areas based on synergistic temperature-vegetation responses. However, its calculation overly relies on negative correlations between vegetation indices and surface temperature, causing coupled relationship breakdowns in bare soil, desert, and sparsely vegetated areas. This creates significant fitting errors, overestimating or underestimating drought severity (Liu et al., 2022). Additionally, TVDI' s "wet edge" and "dry edge" undergo substantial seasonal changes; using fixed boundaries like historical averages may underestimate drought during rainy seasons and overestimate it during dry seasons. The Yellow River Basin flows through the Loess Plateau with extensive desert and sandy areas, and significant land surface heterogeneity across sub-basins may exacerbate TVDI monitoring errors.

In contrast, VHI integrates VCI and TCI through weighted averaging to characterize vegetation growth conditions and temperature anomalies. In sparse vegetation areas, VHI can directly monitor drought using TCI without relying on vegetation cover, while in high-vegetation areas, VCI enhances monitoring sensitivity. This "dual-index synergy" model adapts to gradient changes from "no vegetation" to "high vegetation" across the Yellow River Basin, effectively reducing local misjudgment errors and achieving more accurate monitoring. Traditional meteorological drought monitoring has spatial limitations and time lags in complex environments. SPI (Wang et al., 2018) and PDSI (Jin et al., 2024) are highly dependent on meteorological stations, which are sparsely distributed in the northwestern Yellow River Basin, causing significant interpolation error due to insufficient data support and false smoothing phenomena. VHI achieves seamless basin-wide coverage, clearly showing drought gradient changes and patch characteristics. Traditional meteorological drought indices reflect drought causes through meteorological data, but there is a time lag between these causes and drought effects like crop wilting and vegetation degradation. SPI often lags behind crop drought signals, whereas VHI can rapidly capture sudden drought events and short-term changes through high-frequency satellite observations, significantly improving temporal resolution and enabling more timely reflection of real-time ecosystem and agricultural impacts.

4.3 Limitations and Prospects

This study monitored and analyzed Yellow River Basin drought conditions using VHI, which offers simple calculation, abundant data resources, and high spatial and temporal resolution. However, VHI only integrates vegetation greenness indicators and fails to effectively incorporate water classification, fluorescence, and temperature anomalies. As drought stress increases, plants first reduce stomatal conductance to prevent adverse effects before exhibiting decreased water storage, reduced cuticle conductance, xylem cavitation, and leaf abscission (Choat et al., 2018). Vegetation index sensitivity to drought stress follows: temperature anomaly index > vegetation moisture anomaly index > vegetation fluorescence anomaly index > vegetation greenness anomaly index (Choat et al., 2018). Vegetation temperature, moisture, and fluorescence anomalies are also important for detecting vegetation drought (Neinavaz et al., 2021). Future work should extend drought reconstruction sequences and enhance dynamic simulations of coupled land-atmosphere models.

Drought monitoring based on vegetation growth status identifies stressors using remote sensing imagery but does not consider environmental factors such as irrigation (Lu et al., 2020), pests and diseases (Frank, 2021), and extreme weather (Cheng et al., 2021). Therefore, a complete drought monitoring model must comprehensively consider drought-causing factors, vegetation conditions, and their environments. Additionally, while geographic probes can detect main influencing factors at macroscales, calculating influencing factors according to topographic distribution and climatic zones would improve accuracy.

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5 Conclusions

This study systematically analyzed spatiotemporal distribution characteristics and driving factors of drought in the Yellow River Basin from 2002 to 2022 using VHI. During the study period, overall drought severity was low and infrequent, exhibiting a slow relief trend with significant spatiotemporal variability. Drought severity in the Lanzhou-Hekou Basin was significantly higher than in other basins, particularly during summer and autumn. Across land use types, VHI values for forest land, grassland, and cropland were relatively higher than for construction land and bare land, showing consistent seasonal fluctuations in summer and autumn. Factor analyses revealed that annual precipitation, solar-induced chlorophyll fluorescence, and relative humidity were the main influencing factors. The interaction between temperature and precipitation had the strongest explanatory power for spatial drought distribution differences, indicating that climate-water fluctuations played a key role in summer and autumn drought distribution. This study validates VHI' s applicability to arid and semi-arid regions. Future research should integrate multi-source data to conduct in-depth analyses of weather events and long-term hydrological cycle effects on drought, providing a scientific basis for climate adaptation and ecological conservation strategies in the Yellow River Basin.

Conflict of Interest: The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgements: This study was funded by the Natural Science Foundation Project of Inner Mongolia Autonomous Region (2023LHMS04013) and the Research Program for Higher Education Institutions in Inner Mongolia Autonomous Region (STAQZX202319).

Author Contributions: Conceptualization: Haoriwa; Methodology: Haoriwa, ZHOU Ruiping; Formal analysis: Haoriwa, Zhalagahu; Writing - original draft preparation: Haoriwa, Zhalagahu; Writing - review and editing: Haoriwa, ZHOU Ruiping; Funding acquisition: ZHOU Ruiping; Resources: ZHOU Ruiping; Supervision: Haoriwa. All authors approved the manuscript.

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