Multi-scale Response of Vegetation Dynamics to SPEI Meteorological Drought Index in North China (2001-2014): Postprint

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Abstract

In recent years, reduced precipitation and the impacts of global climate warming have intensified drought severity in the North China region, affecting vegetation growth conditions and deteriorating the regional ecological environment. Based on TRMM and MODIS data from 2001-2014 for North China, this study evaluates the spatiotemporal variations of meteorological drought and vegetation conditions in recent years, and analyzes the multi-scale responses of vegetation to drought, using the Normalized Difference Vegetation Index (NDVI), Net Primary Productivity (NPP), and Vegetation Condition Index (VCI) as vegetation condition indicators, and the Standardized Precipitation Evapotranspiration Index (SPEI) as a meteorological drought indicator. The results show that: (1) Drought in North China exhibits a significant intensifying trend in the southwestern region, while drought conditions in the northeastern region have improved; analyzing drought variation trends using SPEI at different temporal scales reveals that monthly-scale drought demonstrates alternating wet and dry characteristics, and longer SPEI temporal scales show more pronounced trends toward aridification; (2) The spatial distribution of vegetation growth status reflected by NDVI and NPP shows slight differences; overall, vegetation conditions in most areas of North China show an improving trend, but vegetation conditions have deteriorated in some parts of the central study area and some coastal regions; (3) Vegetation condition indices and SPEI are positively correlated in most areas, with the correlation between NPP and SPEI being stronger than that between NDVI and SPEI, and the degree of correlation is highest in grassland areas and mid- to high-altitude regions, while forestland shows the weakest sensitivity to drought; various vegetation types respond most significantly to SPEI-3 during most months of the vegetation growing season, with the highest correlation occurring in summer, and seasonal-scale drought during summer and its preceding period more easily affects vegetation growth

conditions, while the impact of SPEI-12 on vegetation is mainly manifested in affecting vegetation status during the early growing season.

Full Text

Preamble

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Multi-scale responses of vegetation changes relative to the SPEI meteorological drought index in North China in 2001–2014

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Abstract

In recent years, decreasing precipitation and global warming have intensified drought conditions in North China, affecting vegetation growth and deteriorating the regional ecological environment. Based on TRMM (Tropical Rainfall Measuring Mission) and MODIS (Moderate-resolution Imaging Spectroradiometer) data for North China, this study used the Standardized Precipitation Evapotranspiration Index (SPEI) to characterize meteorological drought and the Normalized Difference Vegetation Index (NDVI), Net Primary Production (NPP), and Vegetation Condition Index (VCI) to characterize vegetation status. We examined the spatiotemporal variation of meteorological drought and vegetation, as well as the multi-scale response of vegetation changes to drought. Results indicated that drought showed an increasing trend in the southwestern region, whereas a decreasing trend was observed in the northeastern region of North China. Month-scale SPEI exhibited alternating drought and wet characteristics, and with increasing time scales, more obvious drought trends were observed. The spatial distribution trends of NDVI and NPP in North China were slightly different, but generally, vegetation conditions improved across most of North China, while deteriorating in central and coastal areas. The vegetation condition index was positively correlated with SPEI in most areas of North China, with higher correlation degrees in grassland areas and middle-high altitude regions, whereas forest land response to drought was relatively insensitive.

The response of each vegetation type to SPEI-3 was most obvious during the vegetation growing season, especially in summer, while SPEI-12 mainly affected the early growth stage. These findings would assist drought research in North China.

Keywords: North China; drought; SPEI; vegetation changes; multi-scale

Introduction

Vegetation is a crucial component of global land cover, and vegetation response to climatic and environmental changes constitutes an important aspect of land cover change research. Vegetation serves as an indicator of ecological environmental changes and provides important feedback on drought impacts. Drought is a meteorological disaster caused by water deficit, leading to water shortages. It is characterized by long duration and wide impact range, with persistent drought causing serious socioeconomic problems and large-scale crop yield reductions. Compared to other natural disasters, drought affects people's lives and production, and its scope and severity have been increasing annually in China [1-2]. Reduced precipitation and rising temperatures are important factors intensifying drought, particularly in water-scarce northern regions. North China, a semi-humid region with complex and diverse underlying surfaces, sparse surface vegetation, and sensitive response to climate change, is one of the areas most significantly affected by global climate change [3]. Drought impacts on vegetation vary across different vegetation types and regions [4], and water requirements differ among seasons [5]. Therefore, associations between vegetation and drought must be studied at finer spatiotemporal scales.

Drought severity is typically evaluated quantitatively through drought indices. Previous studies predominantly used meteorological station data to calculate indices such as the Standardized Precipitation Index (SPI) [6], Palmer Drought Severity Index (PDSI) [7], and Standardized Precipitation Evapotranspiration Index (SPEI) [8]. Recent research applying station-based SPEI to evaluate meteorological drought trends across China has revealed widespread aridification [9-10]. Studies have also verified correlations with temperature and precipitation elements and temporal lag effects [11-12]. However, comprehensive vegetation responses to drought environments require consideration. Previous research on drought-vegetation responses has been based either on individual drought events, meteorological stations, or annual scales [13-15]. Since meteorological stations have limited coverage and uneven spatiotemporal distribution, and considering the advantages of remote sensing data—easy acquisition, large-scale observation, and minimal human interference—this study adopted MODIS data as the data source. For the drought index, we selected SPEI with multiple time scales integrating precipitation and potential evapotranspiration to analyze the spatial distribution and temporal evolution of drought during 2001–2014. This approach facilitates subsequent scientific research in North China and provides reference for drought monitoring studies based on remote sensing data in other regions.

Regarding vegetation response to climate and environment, previous studies have often considered single meteorological factors. However, vegetation changes and their drought responses should be examined from perspectives of different vegetation differences and multi-temporal scales. This study selected annual-scale vegetation indicators (NDVI and NPP) and monthly-scale vegetation indicator (VCI) to evaluate vegetation responses to drought across multiple SPEI time scales through correlation coefficient analysis, and to analyze responses of different vegetation cover types to different temporal scale droughts.

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1 Study Area Overview

Definitions of North China vary across literature. Based on administrative divisions and precipitation distribution characteristics, this study selected a region including Beijing, Tianjin, Hebei, Shanxi, and Henan provinces. North China is a semi-humid area with uneven intra-annual precipitation distribution (400–800 mm annually, concentrated in summer). Located among the Yellow, Huai, and Hai River basins, it features a semi-humid continental climate. The northern and western parts are mountainous with forest and grassland vegetation, while the central and eastern areas have large plains that constitute China' s major crop production region.

[Figure 1: see original paper] General situation of study area

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2 Methods

2.1 Drought Monitoring Indicator–SPEI

This study selected the Standardized Precipitation Evapotranspiration Index (SPEI) as the drought monitoring indicator. Single precipitation or temperature factors cannot comprehensively describe climatic dry/wet conditions. SPEI incorporates both precipitation and potential evapotranspiration effects while maintaining multi-time scale characteristics of SPI. Previous studies have analyzed SPEI applicability in China [16-17], confirming its reliability for this research region.

The calculation method follows Vicente-Serrano: monthly precipitation minus potential evapotranspiration (Di = Pi - PETi) is computed to establish water balance accumulation series at different time scales. The three-parameter Log-logistic probability density function is used:

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x-\gamma}{\alpha} \right)^{\beta-1} \left[1 + \left(\frac{x-\gamma}{\alpha} \right)^{\beta} \right]^{-2}$$

where , , and are scale, shape, and origin parameters, respectively. Parameters are estimated using the linear moment method. The cumulative probability distribution F(x) is then standardized to obtain SPEI.

In this study, k values of 1, 3, 6, 9, and 12 months were used. Longer time steps can weaken monthly water balance differences while highlighting seasonal and annual characteristics: SPEI-1 reflects short-term surface water anomalies; SPEI-3 reflects seasonal drought variation; SPEI-12 reflects interannual drought variation.

SPEI grade standard of drought [18]

SPEI range	Drought level
0 < SPEI	Normal
-1 < SPEI 0	Mild drought
-1.5 < SPEI -1	Moderate drought
-2 < SPEI -1.5	Severe drought
SPEI -2	Extreme drought

2.2 Data Sources

Most previous SPEI studies used meteorological station data, which suffers from low distribution density and uneven spatiotemporal distribution. Observation data density and its spatiotemporal distribution rationality affect drought monitoring accuracy. Therefore, this study used MODIS data as the data source to calculate SPEI, obtaining more uniform spatial distribution.

Precipitation data: TRMM3B43 monthly precipitation dataset (http://trmm.gsfc.nasa.gov/), with 0.25° × 0.25° spatial resolution, covering global latitudes. The data fuses multiple microwave remote sensing observations and has good applicability in China, showing significant linear correlation with measured station data. Data units were converted to mm/h through preprocessing.

Potential evapotranspiration data: MOD16A2 product (http://www.ntsg.umt.edu/project/mod16) based on the Penman-Monteith algorithm. Data were resampled to 0.25° × 0.25° using bilinear interpolation to match TRMM resolution. These datasets served as input for SPEI calculation covering 2001–2014.

2.3 Vegetation Indices

Normalized Difference Vegetation Index (NDVI): NDVI is the most widely used vegetation index, reflecting vegetation coverage and basic growth status. Since drought impacts are most evident during the growing season

(April–October in North China when vegetation shows obvious greenness), we selected data from this period. Data came from MOD13A3 Version 6 (https://ladsweb.nascom.nasa.gov/data/search.html) with 1 km × 1 km spatial resolution. The study area required four image tiles: h26v04, h26v05, h27v04, h27v05.

Net Primary Production (NPP): NPP refers to the remaining organic matter after autotrophic respiration is deducted from total photosynthetic production per unit time and area. As the foundation of material and energy transfer in vegetation ecosystems, NPP directly reflects vegetation productivity under natural conditions and effectively responds to climate and environmental changes [21]. MOD17A3 dataset (http://www.ntsg.umt.edu/project/mod17) with 1 km × 1 km resolution was used. Based on the BIOME-BGC model and light use efficiency model, this dataset uses more parameters and refined estimation methods, offering higher accuracy than traditional regression models [22].

Vegetation Condition Index (VCI): VCI [23] is obtained by normalizing NDVI values for a given month and year against the maximum and minimum NDVI values for that month across all years in the study period. The normalized VCI serves as an indicator of vegetation stress from environmental factors and is widely used in agricultural drought monitoring:

$$VCI = \frac{NDVI_{ijk} - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

where NDVI_max and NDVI_min are the monthly maximum and minimum values, respectively, calculated by month to eliminate seasonal effects; i, j, k represent pixel, month, and year, respectively.

2.4 Linear Trend Analysis

Linear trends in NDVI, NPP, and VCI were calculated using simple linear regression:

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

where n is the total number of months and i is the month number.

2.5 Correlation Analysis

Correlation coefficients were used to analyze vegetation growth responses to drought:

$$R = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

where x_i and y_i represent SPEI and vegetation indices (NDVI, NPP, VCI), respectively.

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3 Results

3.1 Spatiotemporal Variation of Drought in North China

Leveraging SPEI' s multi-time scale advantage, we calculated 1-, 3-, 6-, 9-, and 12-month SPEI values and analyzed their temporal trends across North China from 2001–2014. Different time-scale SPEI values all indicated gradually intensifying drought trends in North China. Longer time scales showed smoother time series curves, longer drought-wetness alternation cycles, and more significant aridification trends. From the regional mean perspective, SPEI-6, SPEI-9, and SPEI-12 trends passed significance tests at = 0.05, while SPEI-1 and SPEI-3 passed at = 0.01. Although different time scales don' t change original data or fitting methods, longer time steps weaken monthly water balance differences while highlighting seasonal and annual characteristics.

Linear trend analysis revealed different dry/wet changes across regions. With increasing time scales, drought or wetting degrees in different regions intensified. From the perspective of aridification area proportion and trend significance: SPEI-1, SPEI-3, SPEI-6, SPEI-9, and SPEI-12 showed linear slopes < 0 (indicating aridification) in 44%, 51%, 64%, 69%, and 71% of the area, respectively. Within these aridification areas, 96%, 83%, 78%, 72%, and 71% reached significance at = 0.05. Taking SPEI-6 as an example, drought severity gradually weakened from southwest to northeast, with the most severe aridification in Henan Province. Wetted areas were located in northeastern Hebei.

[Figure 2: see original paper] Spatial distribution of SPEI-6 variation trend (Significant arid region)

Based on SPEI classification standards, we counted drought occurrence frequency and spatial distribution across different grades and time scales within the 14-year period. One-month scale severe drought (SPEI -1.5) mainly occurred in southern Shanxi and eastern coastal areas of North China. Southern Shanxi experienced high-frequency but short-duration drought events, resulting in low drought frequency at medium-long time scales. Eastern coastal areas showed high severe drought frequency at medium-long time scales, indicating long-term drought persistence. Most areas in Henan had moderate single-month drought but easily formed severe drought across consecutive months at medium time scales (SPEI-3/6/9/12).

[Figure 3: see original paper] Spatial distribution of severe drought frequency in multi-scale SPEI

3.2 Spatiotemporal Variation of Vegetation in North China

Using annual growing season data, NDVI and NPP both showed increasing trends from 2001–2014, indicating overall improvement in vegetation conditions in North China. Spatially, 88% of the area had slope > 0 (improved vegetation), mainly in western high-altitude areas and Shanxi. However, vegetation conditions deteriorated in most areas of southern Henan, coastal regions, and small parts of Shandong—preliminarily associated with high medium-long term drought frequency. The Taihang Mountain area showed obvious declining trends, mainly in crop planting regions. In northern forest and grassland areas, NDVI showed relative improvement while NPP showed deterioration.

[Figure 4: see original paper] Spatial distribution of NDVI and NPP annual variation trend

Since vegetation growth varies significantly across months in North China, VCI was used as a monthly vegetation status indicator for inter-month comparability and to analyze differences in drought impact across months. Results showed overall vegetation improvement during 2001–2014, consistent with NDVI and NPP trends. Monthly trends were consistent with overall trends, showing improvement. However, spring and autumn precipitation is low while potential evaporation is high, easily causing spring and autumn droughts. Monthly mean SPEI-3 values were below -1 in these seasons. Although drought frequency didn' t differ much across seasons, drought severity was greater in spring/autumn than summer, affecting vegetation growth.

[Figure 5: see original paper] Temporal variation trend of VCI index of vegetation growing season in North China

3.3 Annual Vegetation Response to Annual Drought

Annual growing season means of NDVI and NPP were composited and resampled to 1 km × 1 km resolution. SPEI-12 was used as the annual drought indicator. Correlation analysis showed positive correlations between NDVI/NPP and SPEI-12 across most regions, with mean correlation coefficients of 0.28 (significant at = 0.05) and 0.37 (significant at = 0.1), respectively. Higher correlations occurred in northern and western Hebei, Shanxi border areas, and central Henan and central Shandong high-altitude regions.

Considering different vegetation types using the MCD12Q1 land cover classification reclassified into five types (Table 2), mean positive correlation coefficients between NDVI/NPP and SPEI-12 varied by type: grassland showed highest sensitivity (0.30), followed by shrubland (0.27), farmland (0.26), and forest (0.25). Forest response to drought was relatively insensitive. Grassland showed strongest drought sensitivity, while forest responded more slowly.

Land cover/Land use classification

3.4 Monthly Vegetation Response to Multi-scale Drought

To study temporal lag effects of drought on vegetation, we analyzed monthly VCI responses to multi-scale SPEI. Correlation analysis between VCI and SPEI-1/3/6/9/12 showed similar spatial patterns to annual-scale results, with higher correlations in high-altitude northern regions. Positive correlation areas accounted for 86%, 90%, 78%, 71%, and 71% of total area, respectively. Areas significant at = 0.01 accounted for 6%, 33%, 19%, 22%, and 24%.

All vegetation types showed maximum correlation with SPEI-3, indicating that 3-month cumulative drought most affects current month vegetation status. However, different vegetation types show varying response time scales and degrees across growing season months. Calculating correlations between VCI and SPEI across five time scales for each month revealed that grassland responded most strongly to SPEI-3 in most months (April–October), with correlation coefficients reaching 0.43. This pattern was more universal in summer months. Longer time scale droughts (SPEI-12) mainly affected early growing season vegetation status.

The maximum time scale of the response degree of VCI to SPEI in different vegetation types and different months (correlation coefficient in brackets)

From monthly wet/dry conditions, correlations between SPEI-3/SPEI-12 and VCI were weak (0.21), indicating monthly drought degree is one factor affecting vegetation drought response. Correlations peaked in summer months, showing seasonal effects on drought response. The correlation between SPEI-12 and VCI was larger in summer, indicating that drought environment from the past year more significantly affects current vegetation.

To distinguish effects of elevation and vegetation type, we divided the region into plain (DEM < 200m), mountain (200m < DEM < 1000m), and high mountain (DEM > 1000m) types, randomly sampling 1000 points per type to avoid sample size effects. Mountain and high mountain areas showed better correlations than plains. High-altitude areas dominated by natural forest and grassland with minimal human interference were more sensitive to climate change. Grassland correlations were better than forest and farmland. In short time scales, spring farmland correlations were higher than forest, while in long time scales, forest correlations exceeded farmland. This reflects deeper root systems in forest vegetation providing better drought tolerance, while farmland in plains experiences more human intervention affecting drought response.

[Figure 6: see original paper] Land cover/Land use map of the study area
[Figure 7: see original paper] Spatial distribution of correlation coefficient of NDVI and NPP to SPEI-12 in North China
[Figure 8: see original paper] Mean values of correlation coefficients of Vegetation Condition Index to SPEI-3/SPEI-12 in different elevation and land cover types

4 Conclusions

(1) From 2001-2014, multi-scale SPEI showed drought intensification trends across North China, with trends passing = 0.05 significance tests. Spatially, the most severe aridification occurred in southern Henan and surrounding areas, while wetting areas were distributed in northeastern Hebei. Spring drought intensification was stronger than other seasons.

(2) The three vegetation indicators (NDVI, NPP, VCI) showed overall increasing trends, with 88% of the region improving. However, vegetation conditions deteriorated in central Hebei, eastern coastal areas, and most of Henan. Spatial distribution of vegetation changes showed some consistency with drought patterns.

(3) NDVI, NPP, and VCI were positively correlated with SPEI across most regions. Grassland showed the highest drought sensitivity, followed by shrubland, farmland, and forest. At annual scale, SPEI-12 showed strongest correlation with vegetation status. At monthly scale, vegetation was most sensitive to SPEI-3, with correlations peaking in summer. Mountain and high mountain vegetation showed better correlations than plain areas, indicating that high-altitude vegetation with less human disturbance better represents natural vegetation response characteristics.

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5 Discussion

This study evaluated multi-scale meteorological drought and vegetation condition changes in North China during 2001-2014 using MODIS data, focusing on multi-scale vegetation drought responses and differences among vegetation types. The uniform spatial distribution of gridded drought indices facilitates detailed analysis of vegetation drought responses and regional comparisons.

Correlation coefficients calculated for NDVI, NPP, and VCI were positive but relatively low, affected by mean value statistics and monthly variations across vegetation types. In forest types, broadleaf and coniferous forests showed different SPEI correlations across time scales. Farmland showed relatively low correlations with monthly drought indices, related to irrigation activities and different crop growth cycles (e.g., wheat, corn, soybeans) that require differentiated consideration in future research.

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