Postprint: Monitoring and Analysis of Influencing Factors of Vegetation Drought Resistance in the Loess Plateau

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Abstract

With the intensification of climate change and human activities, droughts on the Loess Plateau have become more frequent and increasingly severe, imposing serious constraints on regional vegetation growth. Based on the standardized precipitation evapotranspiration index, normalized difference vegetation index, and gross primary productivity data for 2000–2022, three vegetation drought resistance indicators—lag time, impact intensity, and vegetation resilience—were established using the maximum correlation coefficient method. A comprehensive vegetation drought resistance monitoring approach was then constructed to investigate vegetation responses under drought conditions and the magnitude of vegetation drought resistance. The results show that: (1) The lag effect is most pronounced at a lag of 1 month on the Loess Plateau, with 73% of the area exhibiting a maximum correlation coefficient above 0.4. As lag time increases, the correlation coefficient shows a decreasing trend from south to north. (2) Vegetation drought resistance in the southern and eastern parts of the southern temperate zone of the Loess Plateau and in the northern part of the plateau climatic region is mainly in the range of 0.0–0.2, while in the central part of the mid-temperate zone it reaches 0.2–0.4. Overall, the general pattern of vegetation drought resistance is: shrubs exhibit the highest drought resistance, followed by forests and croplands, and grasslands have the lowest. (3) Among the linear relationships, the three factors with the highest correlations are land surface temperature, precipitation, and pH, which are broadly consistent with the primary influencing factors identified by the optimal-parameter geographical detector across the different climatic zones. Research on comprehensive monitoring methods of plant drought resistance helps to elucidate the patterns of vegetation drought resistance and provides a useful reference for reducing disaster risk.

Full Text

Monitoring and Analysis of Influencing Factors of Vegetation Drought Resistance on the Loess Plateau

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Abstract

With intensifying climate change and human activities, drought events on the Loess Plateau have become increasingly frequent and severe, severely constraining regional vegetation growth. Based on 2000–2022 standardized precipitation evapotranspiration index (SPEI), normalized difference vegetation index (NDVI), and gross primary productivity (GPP) data, this study established three vegetation drought resistance indices—lag time, impact degree, and vegetation resilience—using the maximum correlation coefficient method. A comprehensive monitoring framework was constructed to investigate vegetation responses under drought conditions and quantify drought resistance magnitude. Results revealed: (1) A 1-month lag time was most pronounced across the Loess Plateau, with maximum correlation coefficients exceeding 0.4 in 73% of the region; correlation coefficients exhibited a decreasing trend from south to north as lag time increased. (2) Vegetation drought resistance ranged from 0.0–0.2 in the southern and eastern parts of the southern temperate zone and northern plateau climate zone, and reached 0.2–0.4 in the central mid-temperate zone. Overall, drought resistance was highest in shrubs, followed by forest and farmland, and lowest in grassland. (3) Land surface temperature, rainfall, and soil pH showed the strongest linear correlations with vegetation drought resistance, consistent with the main influencing factors identified by optimal parameter geographic detector analyses across climate zones. This comprehensive monitoring approach enhances understanding of vegetation drought resistance patterns and provides valuable guidance for reducing disaster risks.

Keywords: correlation coefficient; vegetation drought resistance; drought index; remote sensing; Loess Plateau

1. Data and Methods

1.1 Study Area Overview

The Loess Plateau (33°43′-41°16′N, 102°54′-114°33′E) is located in the middle reaches of the Yellow River basin and represents one of China' s four major plateaus, covering a total area of 6.4$×10^{5}$ km^2. Characterized by a semi-arid continental monsoon climate, the plateau exhibits elevations ranging from 75 to 5149 m, with mean annual temperatures increasing gradually from northwest to southeast (3.6-14.3°C). Annual precipitation averages 300-600 mm, concentrated primarily in summer and autumn. The landscape is dominated by farmland, forest, and grassland, which collectively account for 87% of the total area. The plateau encompasses three primary climate zones (mid-temperate, southern temperate, and plateau climate zones), where variations in elevation, climate, and soil conditions produce differential vegetation responses to drought.

1.2 Data Sources

Land use type data (2020) were obtained from the land cover dataset released by Wuhan University at 30 m resolution. The study focused on four vegetation types: grassland, farmland, forest, and shrubland.

Remote sensing products including rainfall, potential evapotranspiration (PET), land surface temperature (LST), and gross primary productivity (GPP) (2000-2022) were sourced from the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/) and Google Earth Engine (https://code.earthengine.google.com/), with monthly temporal resolution and spatial resolutions of 500 m and 1 km.

A digital elevation model (DEM) (2020) was obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/) at 250 m resolution. Soil data (2020) were derived from the World Soil Database (https://www.fao.org/), including soil type, pH, effective water capacity, and organic carbon content. Population density data (2020) were obtained from the Global Population Distribution Dataset (https://landscan.ornl.gov/) at annual scale. Nighttime light index data (2020) were sourced from the National Earth System Science Data Center (https://www.geodata.cn/) at 500 m spatial resolution and annual temporal scale.

Due to varying spatial resolutions, all raster data were preprocessed through clipping and resampling to a unified 500 m resolution.

1.3 Methods

1.3.1 Standardized Precipitation Evapotranspiration Index (SPEI)

The SPEI quantifies drought severity by measuring the deviation of monthly precipitation minus potential evapotranspiration from its long-term mean. Calculation procedures follow Vicente-Serrano et al. (2010):

1) Compute monthly precipitation (P_i) and potential evapotranspiration (PET_i) differences:

$$D_i = P_i - PET_i$$

where D_i is the difference between precipitation and evapotranspiration for month i (mm · month^{-1}), P_i is monthly precipitation (mm · month^{-1}), and PET_i is monthly potential evapotranspiration (mm · month^{-1}).

2) Normalize D_i using a three-parameter log-logistic probability distribution:

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

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

3) Standardize the cumulative probability density to obtain SPEI:

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

where $\omega = \sqrt{-2\ln(P)}$ for $P \le 0.5$, and $\omega = \sqrt{-2\ln(1-P)}$ for $P > 0.5$; $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

Validation against meteorological station data showed mean correlation coefficients of 0.85, with significance at $P < 0.01$, confirming the reliability of remote sensing-based SPEI for drought analysis in the Loess Plateau.

1.3.2 Vegetation Drought Resistance The maximum correlation coefficient method was employed to investigate vegetation-drought response mechanisms, accounting for lag effects. Three key indicators were defined:

- **Maximum correlation coefficient (Y_1)**: Quantifies drought impact magnitude (higher values indicate greater impact)
- **Lag time (Y_2)**: Reflects vegetation sensitivity to drought (shorter lags indicate higher sensitivity)
- **Vegetation resilience (Y_3)**: Measures recovery capacity after drought disturbance (higher resilience indicates lower drought resistance)

Given the Loess Plateau' s inland location, maximum lag time was set to 12 months based on literature findings:

$$R_{i,j} = \text{corr}(NDVI_i, SPEI_{i-j}) \quad \text{for} \quad 0 \le j \le 12$$

where $R_{i,j}$ represents the correlation between month i NDVI and SPEI from j months prior. When $i \le j$, $SPEI_{i-j}$ refers to the previous year.

Vegetation resilience was calculated using GPP data:

$$Y_3 = \frac{\mathrm{GPP}_{\mathrm{mean}} - \mathrm{GPP}_z}{\mathrm{GPP}_{\mathrm{mean}}}$$

where $\mathrm{GPP}_{\mathrm{mean}}$ is multi-year average GPP and GPP_z is annual GPP.

A comprehensive drought resistance index was constructed using entropy weighting:

$$Y = aY_1 + bY_2 + cY_3$$

where a, b, and c represent weights for impact degree, lag time, and resilience, respectively.

1.3.3 Optimal Parameter Geographic Detector Geographic detector analyzes spatial heterogeneity by identifying driving factors. This study applied the optimal parameter geographic detector (OPGD) to examine 11 factors: LST, rainfall, PET, pH, population density, nighttime light index, organic carbon content, soil type, effective water capacity, slope, and aspect. OPGD automatically determines optimal discretization methods and classification levels to maximize q values:

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

where SSW is within-stratum variance sum, SST is total variance, and q measures explanatory power of individual factors on vegetation drought resistance ($0 \leq q \leq 1$).

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2. Results and Analysis

2.1 Drought Impact on Loess Plateau Vegetation

Analysis of maximum correlation coefficients across different lag times revealed that at 1-month lag [Figure 3: see original paper], correlation coefficients exceeded 0.4 across most of the Loess Plateau, with statistically significant relationships. As lag time increased, maximum correlation coefficients gradually decreased in northern regions while remaining stable in southern areas. At 3-month lag, northern region coefficients dropped to 0.0–0.3, whereas southern temperate zone values remained above 0.4. At 6-month lag, regional coefficients fell below 0.2, with significant correlations disappearing. These patterns demonstrate that correlation coefficients decrease from south to north as lag time increases.

2.2 Vegetation Drought Resistance on the Loess Plateau

Drought impact magnitude, reflected by maximum correlation coefficients across different lag times [Figure 4: see original paper], was concentrated at the boundary between southern and mid-temperate zones, northeastern mid-temperate zone, and southern temperate zone. Impact was less pronounced in northern and central mid-temperate zones and eastern southern temperate zones. Desert and bare land areas in the mid-temperate zone showed minimal vegetation impact variation. After excluding these non-vegetated areas, drought impact exhibited higher magnitude in western versus eastern regions, and northern versus southern regions.

Sensitivity analysis [Figure 4: see original paper] indicated that most vegetation responded within 1-month lag, particularly in grassland-dominated areas with shallow root systems unable to access deep soil moisture. Southern temperate zone vegetation showed 3-month lag responses, dominated by forest and farmland with deeper root systems accessing groundwater, plus human management practices in farmland enhancing drought resistance. Few 6-month lag sensitivity areas existed, primarily resulting from combined human activity and natural environmental factors.

Vegetation resilience, assessed through normalized GPP data, was lower in southern temperate and plateau climate zones compared to mid-temperate zones [Figure 5: see original paper]. This reflects longer recovery times for extensive farmland and forest distributions in southern temperate zones, and environmental constraints in plateau zones. Mid-temperate zones, dominated by grassland with lower biomass and transpiration rates, exhibited higher resilience.

The comprehensive drought resistance assessment, using entropy weighting with impact degree and resilience as negative indicators and sensitivity as positive indicator (weights: 0.35, 0.45, 0.20), revealed spatial patterns [Figure 5: see original paper]. Drought resistance ranged 0.0–0.2 in southern temperate and plateau climate zones, 0.2–0.4 in mid-temperate zones, with higher values indicating lower resistance. Across vegetation types , grassland and farmland showed lower resistance than forest and shrubland. In plateau climate zones, grassland resistance was 0.12–0.14, higher than in mid-temperate and southern temperate zones due to enhanced cold tolerance improving drought adaptation. Overall, drought resistance followed the pattern: shrubs > forest > farmland > grassland.

2.3 Influencing Factors of Vegetation Drought Resistance

2.3.1 Linear Regression Analysis Vegetation drought resistance is influenced by terrain, climate, human activity, and soil conditions. Ten continuous variables were selected for linear regression analysis across climate zones: LST, rainfall, PET, pH, population density, nighttime light index, organic carbon content, soil type, effective water capacity, slope, and aspect.

Results showed LST correlated most strongly with drought resistance ($r = -0.68$, $P < 0.01$), followed by rainfall ($r = 0.65$) and pH ($r = -0.61$) [Figure 6: see original paper]. LST showed negative correlation, indicating higher temperatures reduce resistance through increased transpiration. Rainfall exhibited positive correlation, enhancing resistance. pH also showed negative correlation, with higher pH values in southern regions. Population density and nighttime light index negatively correlated with resistance ($r = -0.45$ and -0.38, respectively), with grassland most affected. Organic carbon content positively correlated ($r = 0.42$), benefiting forest and shrubland most due to higher carbon stocks. DEM showed strong negative correlation ($r = -0.71$), as higher elevations enhance cold tolerance, indirectly improving drought resistance.

2.3.2 Optimal Parameter Geographic Detector Analysis Single-factor detection [Figure 7: see original paper] identified dominant factors across climate zones: LST and pH in southern temperate zone ($q = 0.42$ and 0.38); pH and soil type in mid-temperate zone ($q = 0.35$ and 0.31); and LST and pH in plateau climate zone ($q = 0.45$ and 0.41). Overall, LST and pH were primary factors controlling vegetation drought resistance.

Two-factor interaction detection revealed synergistic effects exceeding individual factor contributions. In southern temperate zone, LST pH interaction showed highest q value (0.51). Mid-temperate zone exhibited strongest interactions between pH soil type and rainfall pH ($q = 0.48$). Plateau climate zone showed dominant LST aspect interaction ($q = 0.53$). These results indicate soil environmental factors consistently play crucial roles, with climate factors creating multidimensional impacts on vegetation drought resistance.

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3. Discussion

Recent frequent drought events have severely damaged Loess Plateau vegetation, profoundly impacting human society and ecological systems. Drought imposes dual stresses: water deficit limiting vegetation growth, and elevated temperatures triggering stomatal closure to reduce transpiration while simultaneously decreasing photosynthesis, causing wilting. Meteorological drought serves as a precursor to agricultural drought, often forecasting large-scale vegetation mortality.

This study employed remote sensing-derived SPEI to overcome limitations of meteorological station data (sparse distribution, uneven spatial coverage) and better capture spatial heterogeneity. The 1-month lag response aligns with grassland physiology—shallow root systems cannot access deep soil moisture, making it most sensitive. Farmland resistance benefits from irrigation and mulching practices, while forest deep root systems access groundwater. Our finding that grassland resistance is lower than farmland and forest is consistent with previous research.

Plateau climate zone vegetation showed higher drought resistance than mid-temperate and southern temperate zones, attributable to altitude-climate interactions. Grassland and farmland exhibited lower resistance than forest and shrubland due to shallow roots. The pattern shrubs > forest > farmland > grassland matches established ecological understanding.

However, NDVI limitations include saturation in dense vegetation areas. Future research should incorporate alternative indices like kernel NDVI (kNDVI) to improve accuracy, and consider CO_2 concentration effects on vegetation water use efficiency. Integrating multiple vegetation indices and environmental variables will provide deeper insights into ecosystem responses to climate change.

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4. Conclusions

1) At 1-month lag, vegetation on the Loess Plateau showed most significant drought responses, with maximum correlation coefficients exceeding 0.4 across 73% of the region. As lag time increased, coefficients decreased from north to south while remaining stable in southern humid zones, indicating lower drought sensitivity in southern temperate regions.

2) Vegetation drought resistance varied by climate zone (0.0–0.2 in southern temperate and plateau zones; 0.2–0.4 in mid-temperate zone) and vegetation type (shrubs > forest > farmland > grassland). Plateau climate zones exhibited higher overall resistance.

3) Linear regression and OPGD analyses consistently identified LST, rainfall, and pH as primary factors influencing vegetation drought resistance. Two-factor interactions, particularly LST pH and pH soil type, demonstrated synergistic effects exceeding individual factor contributions.

These findings enhance understanding of vegetation drought resistance mechanisms and provide theoretical support for ecological restoration, soil erosion control, and dynamic vegetation protection on the Loess Plateau.

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