Postprint: Geodetector-Based Analysis of Driving Factors for Spatiotemporal Drought Variation in Ordos

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Abstract

Drought is one of the most severe natural disasters in Ordos City, with frequent droughts accelerating land desertification processes and causing grassland vegetation degradation. Therefore, studying drought in this region is of great significance for scientific drought prevention and resistance, desertification control, and ecological construction. Based on the Drought Severity Index (DSI), this study explores the spatiotemporal dynamics and variation trends of drought and utilizes the Geographical Detector Model to analyze the driving factors of DSI spatial differentiation. The results show that: (1) Evapotranspiration (ET) and Normalized Difference Vegetation Index (NDVI) in Ordos both exhibit significant increasing trends ($P<0.05$), with increasing rates of 4.291 $\mathrm{mm \cdot a^{-1}}$ and 0.004 $\mathrm{a^{-1}}$, respectively. (2) The interannual variation of DSI also shows a significant overall increasing trend, with a trend rate of 0.089. ET and NDVI exhibit a spatial pattern of low values in the southwest and high values in the northeast, PotentialEvapotranspiration (PET) shows a spatial pattern of high values in the southwest and low values in the northeast, while DSI demonstrates a distribution characteristic of drought in the west and humidity in the east. (3) The spatial differentiation of DSI is mainly influenced by five factors: temperature, precipitation, land use type, soil type, and elevation (Digital Elevation Model, DEM), which are the main driving factors of drought in Ordos; under multi-factor interactions, temperature and DEM, precipitation and DEM, sunshine duration and DEM, and relative humidity and DEM jointly drive drought, among which precipitation (0.156) DEM (0.248) has the strongest influence on drought occurrence, with q reaching 0.389. These research results can provide a scientific basis for ecological environmental protection and drought management measure formulation in Ordos.

Full Text

Abstract

Drought is one of the most severe natural disasters in Ordos City, intensifying land desertification and causing grassland vegetation degradation. Therefore, investigating drought in this region is of great significance for scientific drought prevention and resistance, desertification control, and ecological construction. Based on the Drought Severity Index (DSI), this study explores the spatiotemporal dynamics and trends of drought and employs a geographic detector model to analyze the driving factors behind the spatial differentiation of DSI. The results indicate that evapotranspiration (ET) and the Normalized Difference Vegetation Index (NDVI) in Ordos show significant increasing trends ($P < 0.05$), with rates of 4.291 $mm \cdot a^{-1}$ and 0.004 a^{-1}, respectively. Additionally, the interannual variation of DSI exhibits a significant upward trend with a change rate of 0.089. Spatially, ET and NDVI display a pattern of low values in the southwest and high values in the northeast, while Potential Evapotranspiration (PET) shows the opposite pattern. DSI demonstrates a distribution characteristic of dry conditions in the west and wet conditions in the east. The spatial differentiation of DSI is primarily influenced by five factors: air temperature, precipitation, land use type, soil type, and Digital Elevation Model (DEM), with q values exceeding 0.15, indicating these are the main driving factors of drought in Ordos. Under multi-factor interactions, four key factor combinations —temperature and DEM, precipitation and DEM, sunshine duration and DEM, and relative humidity and DEM—jointly drive drought. Among these, the combination of precipitation and DEM exerts the strongest influence on drought occurrence, with a q value reaching 0.389. These findings can provide a scientific basis for ecological environmental protection and drought management strategy formulation in Ordos.

Keywords: Ordos; DSI drought index; geographical detector; spatiotemporal change; driving factor

Introduction

Drought is one of the most severe natural disasters worldwide, primarily exerting adverse effects on agriculture and human health through precipitation reduction and temperature rise. Additionally, drought can inhibit vegetation growth, trigger forest fires, and reduce crop yields. Therefore, timely and accurate acquisition of drought conditions in a study area can provide effective technical support for agricultural production and drought mitigation.

Traditional drought monitoring methods rely on meteorological station data and manually measured soil moisture parameters. Although these methods offer high temporal resolution, their spatial resolution is limited by station density. Moreover, manual drought monitoring consumes substantial manpower and resources, making it difficult to achieve continuous spatial monitoring of drought dynamics. In contrast, satellite remote sensing data offer broad spatial coverage and temporal continuity, enabling continuous drought monitoring across space.

Compared with conventional satellite remote sensing drought monitoring indices, the Drought Severity Index (DSI) demonstrates significant advantages in comprehensiveness, applicability, and accuracy. First, DSI integrates the Normalized Difference Vegetation Index (NDVI), which reflects vegetation growth conditions, and the evapotranspiration ratio (ET/PET), enabling multi-dimensional comprehensive assessment of drought conditions. This approach provides stronger explanatory power compared to indices that rely solely on single meteorological or vegetation indicators, such as the Vegetation Condition Index (VCI), Vegetation Supply Water Index (VSWI), Crop Water Stress Index (CWSI), Temperature Vegetation Drought Index (TVDI), Vertical Drought Index (VDI), and Modified Perpendicular Drought Index (MPDI). Second, DSI exhibits good adaptability at multiple spatial scales, making it suitable for regional to global drought monitoring and capable of capturing dynamic drought changes, particularly in response to long-term drought and short-term extreme drought events triggered by climate change. In contrast, indices like VDI and MPDI have relatively limited applicability in describing vegetation water stress. Finally, DSI performs excellently not only in agricultural drought monitoring but also in ecological and meteorological drought monitoring, providing more accurate descriptions of spatiotemporal drought variation characteristics and demonstrating broad application prospects across various climate conditions.

Numerous studies have evaluated drought conditions using DSI. For instance, research on global grassland ecosystems from 2000 to 2011 found that most grassland ecosystems were in a near-normal state. Other studies using DSI have revealed that drought occurs repeatedly worldwide, with some regions experiencing more extreme dry seasons than others. The relationship between DSI and soil moisture is primarily controlled by the relationship between evapotranspiration and soil moisture, enabling accurate capture of typical drought processes in Inner Mongolia. An analysis of drought characteristics in Shanxi Province using a modified DSI showed high correlation between the modified DSI monitoring levels and actual drought-affected areas. However, current remote sensing drought research on Ordos remains insufficiently comprehensive and in-depth. Additionally, uneven station distribution can compromise the accuracy of meteorological drought monitoring, a limitation that remote sensing drought indices can compensate for.

Traditional correlation analysis methods cannot accurately describe the complex response of drought to driving factors. Geographic detectors can detect spatial differentiation and reveal underlying driving mechanisms without time lag limitations, while simultaneously coupling natural and other influencing factors for joint analysis.

Ordos is located in the transition zone between temperate grassland and desert, with sparse vegetation and fragile ecological conditions, representing a typical agriculture-pasture region in China. Drought is the primary meteorological disaster in Ordos, causing prominent ecological drought losses, including crop yield reduction and forage shortages for livestock. Given this context, this study aims to: (1) quantitatively evaluate the spatiotemporal evolution of drought in Ordos based on DSI, revealing changes in wet, normal, and dry conditions; (2) analyze the impact of 11 factors including meteorological factors (temperature, precipitation), land use type, and soil type on DSI and the interactions between factors. The research results aim to clarify the driving mechanisms of drought variation in Ordos, providing scientific references for regional disaster prevention and mitigation.

1. Materials and Methods

1.1 Study Area

Ordos City (106°42 40 ~111°27 20 E, 37°35 24 ~40°51 40 N) is characterized by a typical temperate arid and semi-arid continental climate, with an average annual temperature of 6.2°C and average annual precipitation of 348.3 mm, with most precipitation concentrated in June-September. The terrain slopes from high in the southwest to low in the northeast, with complex landforms and diverse soil types exhibiting significant differences in water retention capacity, further intensifying the spatial heterogeneity of drought. The main land use types are grassland and sandy land, with grassland widely distributed in the eastern areas and along the Yellow River, while the western sandy land faces desertification threats due to long-term drought.

1.2 Data Sources

MODIS data products were obtained from NASA' s Land Processes Distributed Active Archive Center (LP DAAC). The MOD16A2 product provides 8-day composite actual evapotranspiration (ET) and potential evapotranspiration (PET) at 0.5 km resolution, suitable for climate change and ecohydrological research. The MOD13A3 product provides monthly composite NDVI at 1 km resolution for continuous monitoring of vegetation coverage and growth conditions. ET, PET, and NDVI data from 2001-2020 were processed to calculate annual averages.

Monthly mean temperature, total precipitation, wind speed, and sunshine hours data from 2001-2020 were obtained from the Loess Plateau Sub-center of the National Earth System Science Data Center. High-resolution climate data from the WorldClim dataset were downscaled using the Delta method to generate climate data with a spatial resolution of 0.0083333° for the study area.

Elevation data were derived from the Geospatial Data Cloud platform (GDEMV3 digital elevation data) at 30 m resolution, from which slope information was extracted. Land use type data, soil type distribution data, and surface roughness data were obtained from the Resource and Environmental

Science Data Center of the Chinese Academy of Sciences. The land use data (1 km resolution) provide nationwide land use information including cropland, forest, grassland, and built-up areas, which are crucial for assessing human activity impacts on ecosystems and water balance. Soil type distribution data (1:1,000,000 scale) describe soil texture, permeability, and water retention capacity across different regions. To ensure consistency and comparability, all data were resampled to a uniform resolution of 0.0083333°.

1.3 Research Methods

1.3.1 Drought Severity Index Calculation The Drought Severity Index (DSI) simultaneously indicates vegetation growth conditions using NDVI and reflects vegetation water stress using the ET/PET ratio, enabling comprehensive monitoring of both meteorological and agricultural drought. Higher DSI values indicate wetter conditions. The calculation formula is as follows:

$$\mathrm{DSI}_i = \frac{\mathrm{NDVI}_i - \overline{\mathrm{NDVI}}}{\sigma_{\mathrm{NDVI}}} + \frac{(\mathrm{ET/PET})_i - \overline{\mathrm{ET/PET}}}{\sigma_{\mathrm{ET/PET}}}$$

where NDVI_i and (ET/PET)_i represent the values for year i; $\overline{\mathrm{NDVI}}$ and $\overline{\mathrm{ET/PET}}$ are the multi-year averages; and σ_{NDVI} and $\sigma_{\mathrm{ET/PET}}$ are the standard deviations.

1.3.2 Linear Trend Analysis The Theil-Sen trend analysis method was used to simulate change trends for each pixel over the study period. Annual average ET, PET, NDVI, and DSI values were calculated for each pixel from 2001-2020. The trend slope was computed as:

$$\theta_{\mathrm{Slope}} = \frac{\sum_{i=1}^{n}(i-\bar{i}) \times A_i}{\sum_{i=1}^{n}(i-\bar{i})^2}$$

where A_i is the annual average value for year i, and n is the study period length (20 years).

1.3.3 Geographic Detector Geographic detector is a statistical tool based on spatial heterogeneity analysis designed to reveal spatial distribution patterns and mechanisms behind driving factors. This study employed the factor detection and interaction detection modules to quantitatively analyze the influence intensity (q value) of each driving factor on DSI and explore interactive effects between different factors.

The factor detection module calculates the q value as:

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

where $h = 1, \ldots, L$ represents strata of variable Y or factor X; N and N_h are the number of units in the entire region and stratum h, respectively; σ^2 and σ_h^2 are the variances of Y in the entire region and stratum h, respectively; and SSW and SST are the within-sum-of-squares and total sum of squares, respectively.

The interaction detection module examines interactive effects between different factors on DSI, with interaction types classified as shown in .

1.3.4 Selection of Driving Factors This study selected 11 driving factors encompassing natural environment and human activities: air temperature, precipitation, wind speed, sunshine hours, relative humidity, land use type, soil type, elevation, slope, and aspect. Temperature and precipitation are core climatic factors directly affecting drought occurrence and evolution. Temperature regulates evaporation and surface water budgets, while precipitation is the primary source of surface water replenishment. Relative humidity reflects atmospheric moisture content and is closely related to drought occurrence and surface hydrological processes. Elevation significantly affects temperature and precipitation distribution, with higher altitudes typically having lower temperatures and more precipitation. Slope and aspect are topographic factors critical for water distribution—steep slopes experience greater water loss and soil erosion, while aspect determines solar radiation intensity and duration. Soil type significantly influences drought processes; for example, sandy soils have strong permeability and lose water easily, whereas clay soils have better water retention. Land use type reveals human activity impacts on regional hydrological processes, with different land uses (cropland, grassland, forest, urban land) affecting soil moisture, surface hydrology, and evapotranspiration differently.

2. Results

2.1 Spatiotemporal Variation Characteristics of Drought

During 2001-2020, ET, PET, and NDVI in Ordos showed significant increasing trends ($P < 0.05$), with rates of 4.291 $\mathrm{mm \cdot a^{-1}}$, 0.299 $\mathrm{mm \cdot a^{-1}}$, and 0.004 $\mathrm{a^{-1}}$, respectively. The interannual variation of DSI also showed a significant upward trend with a change rate of 0.089. The spatial distribution of multi-year average ET, PET, NDVI, and DSI exhibited obvious heterogeneity. ET and NDVI showed a southwest-low, northeast-high pattern, while PET showed the opposite pattern. DSI demonstrated a distribution characteristic of dry conditions in the west and wet conditions in the east. The multi-year average ET ranged from 26.515-445.730 mm, PET ranged from 430.650-1690.810 mm, NDVI ranged from 0.028-0.816, and DSI ranged from -0.230-0.209. Specifically, low DSI values were mainly located in central Ordos, while high vegetation coverage areas were primarily distributed along the Yellow River belt and in eastern Ordos.

The study area experienced varying degrees of drought during 2001-2020, with drought area showing a decreasing trend. Before 2010, Ordos was mainly drought-prone, but after 2010, wet conditions dominated. The maximum drought area occurred in 2001, accounting for 93.23% of the region. Normal conditions also showed a decreasing trend, peaking in 2001 at 34.95% coverage. Wet conditions showed an increasing trend, reaching maximum coverage of 85.57% in 2020.

Spatial change rates of ET ranged from -7.194 to 18.515 $mm \cdot a^{-1}$, with 72.35% of the study area showing increasing trends, though only 27.65% passed significance testing ($P < 0.05$). Decreasing trends were mainly distributed near the Kubuqi Desert. PET change rates ranged from -48.358 to 28.323 $mm \cdot a^{-1}$, with 64.36% of the area showing increasing trends and 19.34% passing significance testing. Decreasing trends were mainly located in the southwestern Mu Us Sandy Land. NDVI change rates ranged from -0.037 to 0.038 $mm \cdot a^{-1}$, with 28.94% of the area showing increases, primarily in eastern Ordos, while decreases occurred mainly in central and western regions. DSI change rates ranged from -0.151 to 0.171, with 86.98% of the area showing increasing trends, 74.65% of which passed significance testing. Decreasing DSI trends were mainly distributed in central Ordos.

2.2 Analysis of Driving Factors

2.2.1 Single Factor Influence Climate factors showed significant influence on DSI, with q values for temperature and precipitation reaching 0.156 and 0.248, respectively, both above 0.15. Sunshine hours and relative humidity had lower explanatory power at 0.089 and 0.067, respectively. Among underlying surface factors, land use type and soil type showed strong influence with q values of 0.152 and 0.168, respectively. Elevation also demonstrated significant impact with a q value of 0.151. Temperature, precipitation, soil type, and DEM emerged as the dominant factors driving DSI variation.

2.2.2 Factor Interaction Analysis While temperature alone explained 14.1% of DSI variation, its interaction with other factors showed significant non-linear enhancement effects. The interaction between temperature and DEM, precipitation and DEM, sunshine hours and DEM, and relative humidity and DEM all demonstrated non-linear enhancement, with precipitation and DEM showing the strongest combined effect ($q = 0.389$). The interaction between precipitation and soil type also exceeded 0.35, indicating that these factor combinations substantially improve explanatory power. In water-deficient areas, temperature increases do not promote effective evaporation; instead, water shortage causes PET to increase while ET cannot correspondingly rise, widening the gap between PET and ET and intensifying drought. This reflects the negative impact of temperature rise on regional drought under water-scarce conditions. Therefore, the effects of various factors on DSI are not independent but interact synergistically.

2.2.3 Correlation Between Climate Factors and DSI Spatial correlation analysis revealed that DSI was negatively correlated with temperature across 69.64% of the area, with 43.58% passing significance testing. Positive correlation areas accounted for 72.25% of the total area, while negative correlation areas accounted for 27.75%. However, only 27.75% of the area passed significance testing. Negative correlations were particularly significant in central Ordos.

3. Conclusions and Discussion

Using MODIS data products, this study calculated the DSI index to analyze spatiotemporal variation characteristics of drought in Ordos from 2001-2020, and employed geographic detector single-factor and interaction detection to analyze influencing mechanisms of 11 factors. The main conclusions are:

1) Multi-year average ET, PET, NDVI, and DSI in Ordos showed obvious spatial heterogeneity, with ET and NDVI displaying a southwest-low, northeast-high pattern, PET showing the opposite pattern, and DSI demonstrating a west-dry, east-wet distribution.
2) During 2001-2020, Ordos experienced varying drought degrees, with drought area showing a decreasing trend that peaked in 2001 at 93.23% coverage. Normal conditions also decreased, peaking in 2001 at 34.95% coverage, while wet conditions increased, reaching maximum coverage of 85.57% in 2020.
3) Single-factor detection revealed that air temperature, precipitation, land use type, soil type, and DEM are the main factors driving drought formation in the study area, with q values exceeding 0.15. Multi-factor interactions showed that temperature and DEM, precipitation and DEM, sunshine hours and DEM, and relative humidity and DEM jointly drive drought formation, with precipitation and DEM exerting the strongest influence ($q = 0.389$).

These findings align with studies in the Loess Plateau region and North China Plain regarding dominant drought factors. However, some studies in Inner Mongolia emphasize precipitation and temperature, while others in China highlight temperature, rainfall, and land cover. Beyond climate change and underlying surface conditions, human activities also significantly influence drought dynamics. Future research should explore the impact mechanisms of human activities on drought evolution to more comprehensively understand regional drought formation and development.

Although remote sensing technology offers advantages in improving spatial precision of meteorological drought monitoring, remote sensing products contain retrieval errors, and the complex topography of Ordos poses higher demands and challenges for retrieval accuracy. This study analyzed natural and land surface factors affecting drought, concluding that DSI spatial differentiation in Ordos is primarily influenced by five factors: temperature, precipitation, land use type, soil type, and DEM. These represent the main driving factors of drought in Ordos and provide a scientific basis for regional disaster prevention and mitigation.

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