Postprint: Analysis of Drought and Its Influencing Factors in Turpan City Based on TVDI Over the Past 20 Years

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Date: 2025-02-27T00:00:00+00:00

Abstract

Against the backdrop of intensifying global greenhouse effect, drought monitoring holds important guiding significance for safeguarding regional ecological security, economic development, and agricultural production. In recent years, due to its geographical location, climate change, and water resource shortages, Turpan City has experienced increasingly prominent drought issues, hindering the long-term, stable development of its own and surrounding regions' socioeconomies. Based on MODIS Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) data from 2001–2022, a Temperature Vegetation Dryness Index (TVDI) model was established. Using methods such as trend analysis, Mann-Kendall trend test (M-K trend test), and Geographical Detector, this study reveals the spatiotemporal variation and characteristics of drought, drought evolution patterns in Turpan City over the past 20 years, and explores the influence of different factors (temperature, rainfall, potential evapotranspiration, land cover type, population density, elevation, slope) on TVDI. The results indicate: (1) The spatial distribution of TVDI in drought-affected areas of Turpan City exhibits distinct regional characteristics, showing a gradually increasing trend from north to south. Turpan City overall demonstrates intensifying aridification, with 89.6% of areas showing significant increases in TVDI and only 3.5% of areas experiencing no intensification of drought severity. (2) Interannual variation in TVDI indicates that drought severity in Turpan City has shown an increasing trend over the past 20 years. Monthly variation in TVDI exhibits obvious seasonal differences, generally following the pattern of spring > autumn > summer. (3) Single-factor monitoring results indicate that the factors with the greatest influence on drought change trends in Turpan City are potential evapotranspiration, temperature, and elevation, respectively. Under multi-factor interactions, the interaction among potential evapotranspiration, elevation, temperature, precipitation, and land cover factors jointly drives the occurrence of aridification, providing a theoretical basis for formulating drought

prevention and control measures and improving the capacity to address ecological risks and geopolitical risks in the region.

Full Text

Abstract

In the context of intensifying global greenhouse effects, drought monitoring serves as a critical guide for ensuring regional ecological security, economic development, and agricultural production. In recent years, Turpan City has experienced increasingly severe drought problems due to its geographic location, climate change, and water resource scarcity, which have hindered long-term, stable socio-economic development in the region and its surroundings. This study establishes a Temperature-Vegetation Drought Index (TVDI) model based on MODIS Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) data. Using trend analysis, Mann-Kendall trend tests, and Geodetector methods, we reveal the spatio-temporal variations, characteristics, and evolution patterns of drought in Turpan City over the past 20 years, and explore the influence of different factors (temperature, rainfall, potential evapotranspiration, land cover type, population density, elevation, and slope) on TVDI. The results indicate that: (1) The spatial distribution of TVDI in Turpan City exhibits distinct regional characteristics, showing a gradual increasing trend from north to south. Overall, Turpan City demonstrates intensifying aridification, with 89.6% of the area showing a significant increase in TVDI, 6.9% showing a non-significant increase, and only 3.5% showing no increase in drought severity. (2) Interannual variations indicate a slight intensification of drought in Turpan City over the past 20 years, peaking in 2022. Monthly variations show clear seasonal differences, generally following the pattern of spring > autumn > summer. (3) Single-factor monitoring results reveal that potential evapotranspiration, temperature, and elevation are the most influential factors affecting drought change trends in Turpan City. Under multi-factor interactions, the combined effects of potential evapotranspiration with elevation, temperature, precipitation, and land cover factors collectively drive aridification. These findings provide a theoretical basis for formulating drought prevention measures and improving capabilities to address ecological hazards and geopolitical risks in the region.

Keywords: drought; Temperature-Vegetation Drought Index (TVDI); trend analysis; Geodetector; Turpan City

Introduction

Drought is a meteorological phenomenon caused by a lack of continuous rainfall. Compared with other extreme meteorological disasters such as floods and hurricanes, drought is characterized by long duration and wide impact range, posing serious threats to agricultural development, ecological environmental systems, and human habitats, particularly in arid and semi-arid regions with simple ecological structures and weak restoration capabilities. Therefore, monitoring drought conditions and studying their spatial distribution patterns are crucial for understanding drought trend changes, rationally allocating water resources, and promoting sustainable socio-economic growth.

In recent years, scholars have made significant progress in drought monitoring. Commonly used drought monitoring indices include the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), and Standardized Precipitation Evapotranspiration Index (SPEI). Additionally, remote sensing-based indices such as the Normalized Difference Vegetation Index (NDVI) and Temperature-Vegetation Drought Index (TVDI) have been widely applied. TVDI, proposed by Sandholt et al., is a simplified trapezoidal feature space model based on the relationship between surface temperature and vegetation index, which has proven effective for drought monitoring in arid and semi-arid regions.

While previous studies have used TVDI to investigate drought changes in arid regions, most have relied on short time-series remote sensing data, with relatively insufficient research on long-term dynamic monitoring. Moreover, studies on Turpan City have focused primarily on meteorological factors while often neglecting topographic factors such as elevation. Building on existing research and considering local drought conditions, this study analyzes drought during both the full year and vegetation growing season (April-October) in Turpan City from 2001 to 2022 using MOD13A2 NDVI and MOD11A2 LST data. We employ Sen' s slope estimator, Mann-Kendall significance testing, and Geodetector techniques to analyze spatio-temporal drought trends and predict future changes, providing a theoretical basis for drought prevention and ecological risk management.

1.1 Study Area Overview

Turpan City is located in the eastern part of the Xinjiang Uygur Autonomous Region in northwestern China, within the intermountain basin of the eastern Tianshan Mountains (87°16 -91°55 E, 41°12 -43°40 N). The study area covers 70,049.03 km^2, accounting for a significant portion of Xinjiang' s total land area. It is the region with the lowest elevation and highest summer temperatures in China, with most areas below 500 m in elevation. The terrain is characterized by low-lying central areas surrounded by higher elevations, with northern regions reaching up to 4,000 m. The region experiences strong solar radiation and minimal precipitation, dominated by a continental desert climate. Due to its basin topography surrounded by high mountains, atmospheric circulation with the ocean is blocked, resulting in precipitation that decreases from north to south, with annual precipitation below 31.5 mm.

1.2 Data Sources

The primary data sources for this study include: - MODIS NDVI data (MOD13A2) and Land Surface Temperature data (MOD11A2) from NASA' s Terra satellite, with temporal resolutions of 16 days and 8 days, respectively, and spatial resolution of 1 km - Digital Elevation Model (DEM) data from the CGIAR-CSI SRTM dataset with 90 m spatial resolution - Population density data from the LandScan dataset - Monthly climate data (temperature, precipitation, and potential evapotranspiration) from the National Tibetan Plateau Data Center - Land cover data from annual high-resolution land cover products processed through visual interpretation, random forest classification, and spatiotemporal filtering

1.3 Methods

1.3.1 Data Preprocessing

Using the Google Earth Engine Python environment, we filtered the study period and region, applied cloud removal functions to eliminate anomalous values, and processed the data using time-series linear interpolation and Savitzky-Golay filtering to remove low-quality values and fill gaps. NDVI data were processed using the Maximum Value Composite (MVC) method, while LST data were averaged to generate monthly and annual datasets at 1 km resolution.

1.3.2 Ts-NDVI Model

NDVI is calculated as the ratio of the difference between near-infrared and red bands to their sum, with values ranging from -1 to 1. Higher values indicate greater vegetation abundance. Sandholt et al. constructed a surface temperature-vegetation index feature space and proposed the Temperature-Vegetation Drought Index (TVDI), defined as:

$$TVDI = \frac{T_s - T_{smin}}{T_{smax} - T_{smin}}$$

where the dry edge equation is $T_{smax} = a_1 \times NDVI + b_1$ and the wet edge equation is $T_{smin} = a_2 \times NDVI + b_2$. Here, a_1, b_1, a_2, and b_2 are the intercepts and slopes of the dry and wet edge equations, respectively; T_s is the land surface temperature; T_{smax} and T_{smin} represent the maximum and minimum land surface temperatures under a given NDVI. TVDI values range from 0 to 1, with higher values indicating drier conditions.

1.3.3 Trend Analysis

We applied trend analysis to annual TVDI data from 2001 to 2022 using a linear regression model:

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

where $Slope$ represents the trend slope and $TVDI_i$ is the drought index for year i. A positive slope indicates intensifying drought, while a negative slope indicates alleviating drought. The Mann-Kendall test was used to assess significance, with trends classified into five categories: significant decrease, non-significant decrease, no significant change, non-significant increase, and significant increase.

1.3.4 Geodetector Model

Geodetector is a statistical method that detects spatial heterogeneity and identifies driving factors behind spatial patterns. It includes factor detection and interaction detection:

Factor Detector: This quantifies the spatial stratified heterogeneity of the dependent variable and measures the influence of independent variables using the q-statistic:

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

where h is the stratum of influencing factors, N_h is the number of units in stratum h, N is the total number of units, σ_h^2 is the variance within stratum h, and σ^2 is the total variance. The q-value ranges from 0 to 1, with higher values indicating stronger influence.

Interaction Detector: This examines whether two factors X_1 and X_2 have interactive effects on Y by comparing $q(X_1)$, $q(X_2)$, and $q(X_1 \cap X_2)$. The interaction can be classified as non-linear weakening, single-factor non-linear weakening, independent, dual-factor enhancement, or non-linear enhancement.

1.3.5 Mapping Method

Based on the TVDI data, we used ENVI 4.8 and ArcGIS 10.8 software to reclassify the TVDI values according to drought severity levels, generating annual and monthly drought distribution maps. Trend analysis results were processed in ArcGIS to produce drought change trend distribution maps. All charts were created using Origin 2019 and Excel 2018.

2.1 Ts-NDVI Feature Space and Dry-Wet Edge Fitting Equations

We constructed annual Ts-NDVI feature spaces for each year from 2001 to 2022 by identifying the maximum and minimum land surface temperatures within each NDVI interval . The dry and wet edges were fitted using linear regression equations. The results show that the temperature difference between the dry and wet edges decreases with increasing NDVI, exhibiting an approximately linear relationship. Both dry and wet edge slopes are negative, with dry edge slopes less than zero and wet edge slopes greater than zero, indicating that larger temperature differences correspond to drier conditions.

2.2 Spatial Distribution Characteristics and Change Trends of Drought

The spatial distribution of annual mean TVDI from 2001 to 2022 shows significant regional differentiation [Figure 2: see original paper]. Northern and western Turpan are relatively humid, while aridity extends continuously from the central to southeastern regions. The overall area is characterized by severe drought, with more humid conditions distributed in the northern Bogda Mountain foothills and western Toksun County near the Alashan Pass. The central Gaochang District and eastern Shanshan County experience more severe drought.

Trend analysis using linear regression and Mann-Kendall significance testing reveals that Toksun County, Gaochang District, and Shanshan County all show increasing TVDI trends, though with regional variations. Since 2001, 89.6% of Turpan City has experienced significant increases in TVDI, primarily in the central region, while 6.9% shows non-significant increases. Only 3.5% of the area shows no increase in drought severity, mainly in urban areas and nature reserves where agricultural structure adjustments and land use changes have converted some cropland to forest and grassland.

2.3 Interannual Variation Trends of TVDI (2001-2022)

Following the classification standards of Qi et al., we categorized TVDI values into different drought severity levels. The interannual variation curve shows a progressive increase in drought severity over the past 20 years, rising at a rate of $0.0047 \cdot \mathrm{a}^{-1}$ [Figure 4: see original paper]. The proportion of severely drought-affected areas is largest, followed by moderately drought-affected areas. Between 2001 and 2010, Turpan City was dominated by severe and moderate drought areas. After 2015, the area of moderate drought decreased significantly, while severe drought areas became absolutely dominant. The interannual TVDI variation is primarily influenced by changes in the proportion of moderate drought areas, showing a negative correlation where TVDI increases are accompanied by decreases in moderate drought area proportion.

2.4 Monthly Variation Analysis of TVDI (2001-2022)

Monthly mean TVDI values during the vegetation growing season (April-October) show non-regular fluctuations [Figure 5: see original paper]. May represents the most severe drought month, with approximately 96.5% of days being precipitation-free. As temperatures rise and snow melts, vegetation grows rapidly, causing NDVI to exceed 0.1 and TVDI to decrease, which corresponds to the rising proportion of moderate drought areas. TVDI reaches its minimum in August-September when autumn temperatures begin to drop, surface evaporation decreases, and plant growth slows. At high elevations, snowmelt increases soil moisture content, further reducing TVDI values.

2.5 Analysis of Influencing Factors

To comprehensively evaluate the impacts of meteorological, topographic, and anthropogenic factors, we selected seven variables: potential evapotranspiration, mean annual temperature, annual rainfall, elevation, slope, population density, and land cover type. Using ArcGIS 10.8, we extracted grid sampling points for Geodetector analysis.

Single-factor detection results show that all factors pass significance tests ($P < 0.05$). Potential evapotranspiration, temperature, and elevation are the most influential factors, with q-values of 0.914, 0.887, and 0.853, respectively . Rainfall shows relatively lower influence ($q = 0.514$), likely due to Turpan' s minimal precipitation and reliance on river and groundwater sources. Land cover type also has relatively small impact because the dominant land cover (unused land) has stable water demand.

Interaction detection reveals that all factor pairs show enhanced effects compared to single factors. The interaction between potential evapotranspiration and rainfall has the strongest influence ($q = 0.914$), while the interaction between slope and population density has the weakest ($q = 0.514$). The combinations of potential evapotranspiration with elevation, temperature, precipitation, and land cover are particularly important driving factors of drought change in Turpan City.

Discussion

Our analysis of meteorological factors shows that mean annual temperature in Turpan City is 10.40°C, with a slight increasing trend of $0.0086°C \cdot a^{-1}$. Annual rainfall averages 9.53 mm, with a small decreasing trend of $-0.032\ mm \cdot a^{-1}$. Potential evapotranspiration averages 96.99 mm, showing a slight increasing trend of $0.8132\ mm \cdot a^{-1}$ [Figure 6: see original paper]. The intensification of potential evapotranspiration is the primary cause of TVDI increase, with decreasing rainfall and rising temperatures collectively aggravating drought conditions.

Previous studies indicate that the relative humidity index in Turpan has decreased due to warming trends and reduced rainfall, which aligns with our TVDI-based conclusions. The seasonal pattern of TVDI (spring > autumn > summer) reflects local climate characteristics where snowmelt in spring alleviates drought temporarily, but subsequent temperature increases intensify aridity. The dominant role of potential evapotranspiration and temperature differs from studies in other regions where rainfall is typically the primary factor, likely due to Turpan' s extreme aridity and minimal precipitation.

While the TVDI model demonstrates good applicability for monitoring drought in Turpan City, future research could develop a comprehensive drought index combining multiple indicators. Comparison with other vegetation drought indices such as the improved Temperature-Vegetation Dryness Index (iTVDI) and Drought Severity Index (DSI) would provide further validation. Additionally, integrating more drought influence factors could enhance research precision and provide stronger support for local drought prevention strategies.

Conclusion

This study analyzes drought spatio-temporal variations in Turpan City, Xinjiang, using MODIS data from 2001 to 2022, revealing the following key findings:

1. **Spatial Distribution:** TVDI shows distinct regional characteristics with increasing aridity from north to south. Overall, Turpan City exhibits intensifying drought, with 89.6% of the area showing significant TVDI increases, 6.9% showing non-significant increases, and only 3.5% showing no drought intensification.
2. **Temporal Trends:** Over the past 20 years, drought severity has increased slightly, peaking in 2022. Monthly variations show significant seasonal differences, following the pattern spring > autumn > summer, with May being the most severe drought month.
3. **Driving Factors:** Single-factor analysis identifies potential evapotranspiration, temperature, and elevation as the dominant factors influencing drought formation and intensification. Multi-factor interaction analysis reveals that the combined effects of potential evapotranspiration with elevation, temperature, precipitation, and land cover are key drivers of aridification.

These findings further reveal the spatio-temporal evolution characteristics of dry-wet changes in Turpan City during the full year and vegetation growing season, providing a theoretical basis for formulating drought prevention measures and improving capabilities to address ecological hazards and geopolitical risks.

References

[1] Huang M J, Li Y Z, Wang Y G, et al. Evaluation of meteorological drought performance of multi-source remote sensing precipitation products in arid northwest China[J]. Arid Land Geography, 2024, 47(4): 549-560.

[2] Xu X T, Zhu L, Lü X Y, et al. Applicability evaluation of MSWEP product for meteorological drought monitoring in the Yellow River Basin[J]. Arid Land Geography, 2023, 46(3): 371-384.

[3] Rouse J W, Haas R H, Schell J A, et al. Monitoring vegetation systems in the Great Plains with ERTS[J]. Proceedings of the Third ERTS Symposium, 1973, 3(8): 309-317.

[4] Sandholt I, Rasmussen K, Andersen J. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status[J]. Remote Sensing of Environment, 2002, 79(2): 213-224.

[5] Chen S D, Zhang L P, Tang R X, et al. Analysis on temporal and spatial variation of drought in Henan Province based on SPEI and TVDI[J]. Transactions of the Chinese Society of Agricultural Engineering, 2017, 33(24): 126-132.

[6] Wang F J, Feng W L, Zhaxi Y Z, et al. The comparison of FY-3A/VIRR and TERRA/MODIS data for drought monitoring[J]. Journal of Natural Resources, 2017, 32(7): 1229-1239.

[7] Yang Y K, Sheng Q, Shao P K, et al. Reconstruction of PDSI sequence in central part of Yellow River based on tree rings density data[J]. Water Resources and Power, 2022, 40(8): 1-4, 31.

[8] Wang H, Zhang Y, Shao X. A tree-based drought reconstruction from 1466 to 2013 CE for the Aksu area, western China[J]. Climatic Change, 2021, 165(1-2): 39.

[9] Li Y Z, Zhuang J C, Bai P, et al. Evaluation of three long-term remotely sensed precipitation estimates for meteorological drought monitoring over China[J]. Remote Sensing, 2022, 15(1): 86-86.

[10] Wang J F, Liu Z Y, Yuan Z Y, et al. Impacts of reservoir operations on multi-scale correlations between hydrological drought and meteorological drought[J]. Journal of Hydrology, 2018, 563: 726-736.

[11] Liu Y. Spatio-temporal dynamics and driving forces of vegetation restoration in western China in recent 20 years[D]. Xianyang: Northwest A & F University, 2023.

[12] Chen S L, Li X, Qian Z H, et al. Drought trend and its impact on ecosystem carbon sequestration in Lancang-Mekong River Basin[J]. Acta Geographic Sinica, 2024, 79(3): 747-764.

[13] Li L X, Shen R P, Li X H, et al. Comparison of forest disturbance indices based on MODIS time series data[J]. Remote Sensing Technology and Application, 2016, 31(6): 1083-1090.

[14] Wu B. Study on inversion of soil moisture in arid area based on VIIRS TVDI[D]. Tai' an: Shandong Agricultural University, 2024.

[15] Xia Z H. The studies on dynamic of vegetation based on NDVI time series[D]. Beijing: Beijing Forestry University, 2007.

[16] Yu W, Ke F Y, Cao Y C. Spatial-temporal analysis of drought characteristics of Yunnan Province based on MODIS TVDI/GNSS PWV data[J]. Remote

Sensing for Natural Resources, 2021, 33(3): 202-210.

[17] Yang X, Wu J J, Yan F, et al. Assessment of regional soil moisture status based on characteristics of surface temperature/vegetation index space[J]. Acta Ecologica Sinica, 2009, 29(3): 1205-1216.

[18] Yu H Z, Li L J, Li J Y. Establishment of comprehensive drought monitoring model based on downscaling TRMM and MODIS data[J]. Journal of Natural Resources, 2020, 35(10): 2553-2568.

[19] Cheng X Q, Zhou Z Y, Li W P, et al. Monitoring drought situation and analyzing influencing factors in Central Asia using MODIS data[J]. Transactions of the Chinese Society of Agricultural Engineering, 2022, 38(10): 128-137.

[20] Liu Q, Zhang S, Zhang H R, et al. Monitoring drought using composite drought indices based on remote sensing[J]. Science of the Total Environment, 2020, 711: 134585.

[21] Zhang Z, Xu W, Shi Z, et al. Establishment of a comprehensive drought monitoring index based on multisource remote sensing data and agricultural drought monitoring[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021, 14: 2113-2126.

[22] Keranmu A, Abudouzhalake N. Analysis of temperature and rainfall changes in recent 52 years in Turpan City, Xinjiang[J]. Journal of Arid Land Resources and Environment, 2014, 28(12): 45-50.

[23] Gou A P, Zhang Z, Wang J B. Evolution characteristics and driving factors of Shanghai urban functional area based on POI perspective[J]. Resource Development & Market, 2022, 38(9): 1052-1062.

[24] Zhang X Y, Wei W, Zhou L, et al. Analysis on spatio-temporal evolution of ecological vulnerability in arid areas of northwest China[J]. Acta Ecologica Sinica, 2021, 41(12): 4707-4719.

[25] Kuang Z M. Sugarcane drought monitoring models and its application with remotely sensed data from EOS/MODIS[D]. Nanjing: Nanjing University of Information Science & Technology, 2007.

[26] Xu N, Ding J L, Liu H X. Extraction of vegetation information in arid area based on NDVI and LSMM: A case study of Turpan[J]. Geomatics & Spatial Information Technology, 2012, 35(7): 52-57.

[27] Ye J M, Xie S Q. Cross-sensitivity analysis of land use transformation and ecosystem service functions in Turpan City, China[J]. Pratacultural Science, 2024, 41(9): 2164-2180.

[28] Qi S H, Wang C Y, Niu Z. Evaluating soil moisture status in China using the temperature vegetation dryness index (TVDI)[J]. Journal of Remote Sensing, 2003, 7(5): 420-427.

[29] Zhang X Q. Topography and weather in Turpan Basin[J]. Xinjiang Meteorology, 1998(6): 11-13.

[30] Wu Y. The evapotranspiration estimation and evolution characteristics of vegetation in Turpan Basin[D]. Beijing: China University of Geosciences Beijing, 2013.

[31] Cao X, Wan Y, Hu S Q, et al. Variation of relative moisture index in Turpan Basin under arid condition[J]. Desert and Oasis Meteorology, 2013, 7(6): 42-49.

[32] Wang F, Ma H, Xiong Y, et al. Arid climate characteristics and artificial precipitation work in Turpan City[J]. Farm Staff, 2019(19): 141.

[33] Deng X Y, Liu Y L. Temporal-spatial dynamic change characteristics of evapotranspiration in arid region of northwest China[J]. Acta Ecologica Sinica, 2017, 37(9): 2994-3008.

[34] Guo J H, Huang F J, Liu B, et al. Spatiotemporal analysis of smart growth of artificial oasis in Turpan Basin in recent 47 years[J]. Acta Agriculturae Jiangxi, 2024, 36(1): 76-86.

[35] Qin G Q. Research on evolution law and trend of groundwater in the Turpan-Hami Basin[D]. Urumqi: Xinjiang Agricultural University, 2023.

[36] Yang R, Wang H, Hu J, et al. An improved temperature vegetation dryness index (iTVDI) and its applicability to drought monitoring[J]. Journal of Mountain Science, 2017, 14(11): 2284-2294.

[37] Ali S, Tong D, Xu Z, et al. Characterization of drought monitoring events through MODIS and TRMM based DSI and TVDI over South Asia during 2001–2017[J]. Environmental Science and Pollution Research, 2019, 26: 33568-33581.

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