Agricultural Drought Research in Gansu Province Based on Multi-Source Remote Sensing Data (Postprint)

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Abstract

Drought is a major environmental stress factor for crop growth and development, and also a key natural element constraining agricultural productivity and harvest. Agricultural drought monitoring is typically based on observational data from meteorological stations, which to some extent cannot reflect regional-scale agricultural drought conditions. Taking Gansu Province as the study area, based on remote sensing data products such as MODIS, TRMM, and ESA CCI as well as meteorological station data, a random forest regression model was used to construct a Comprehensive Meteorological Drought Index (CMDI), and the spatiotemporal patterns and variation trends of drought conditions during the crop growing season (April–September) in Gansu Province from 2011 to 2019 were analyzed. The results show that: (1) The coefficient of determination (R^2) between CMDI and observed values was higher than 0.634 in each month, and it had a certain spatial correlation with the Standardized Precipitation Evapotranspiration Index (SPEI), indicating that this index can reflect the occurrence and development process of agricultural drought. (2) Agricultural drought in Gansu Province shows obvious regional differentiation patterns, with drought severity gradually increasing from southeast to northwest, where the Hexi region is mostly extreme and severe drought areas, the Longzhong region is severe (moderate) drought areas, and Longnan, Longdong, and Gannan regions are fluctuating zones between drought and no drought. (3) From 2011–2019, agricultural drought in Gansu Province showed large fluctuation trends at both annual and monthly scales, with the lightest drought severity in 2012 and the most severe in 2017; agricultural drought conditions were alleviated in most areas of Gansu Province in April and June, in Longdong and Longnan regions in May and September respectively, and in Gannan region from April to September, while drought conditions in other areas during the crop growing season showed a trend of aggravation.

Full Text

Agricultural Drought Research Based on Multi-Source Remote Sensing Data in Gansu Province

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Abstract

Drought is the primary environmental stressor affecting crop growth and development and represents a critical natural constraint to agricultural productivity and harvest stability. Agricultural drought monitoring has traditionally relied on meteorological station observations, which are limited in their ability to capture regional-scale agricultural drought conditions. This study focuses on Gansu Province as the research area, constructing a composite meteorological drought index (CMDI) using a random forest regression model based on MODIS, TRMM, ESA CCI, and other remote sensing data products alongside meteorological station data. The spatiotemporal patterns and variation trends of agricultural drought during the crop-growing season (April–September) from 2011 to 2019 were analyzed. The results demonstrate: (1) The coefficient of determination (R^2) between CMDI and measured values exceeded 0.634 for all months, and CMDI exhibited spatial correlation with the Standardized Precipitation Evapotranspiration Index (SPEI), indicating that CMDI can effectively reflect the occurrence and development processes of agricultural drought. (2) Agricultural drought in Gansu Province displays pronounced regional differentiation, with drought severity gradually intensifying from southeast to northwest. The Hexi region predominantly experienced exceptional and severe drought, the Longzhong region suffered severe (moderate) drought, while Longdong, Longnan, and Gannan regions exhibited fluctuating drought conditions. (3) From 2011 to 2019, agricultural drought in Gansu Province showed substantial fluctuation trends at both annual and monthly scales, with the mildest drought occurring in 2012 and the most severe in 2017. Drought conditions alleviated in the Gannan region during April–September, in most areas during April and June, in the Longdong region during May, and in the Longnan region during September. However, all other regions experienced intensifying drought trends during the crop-growing season.

Keywords: drought; agricultural; remote sensing; random forest; Gansu Province

1 Introduction

Under global climate warming, extreme weather events have become increasingly frequent, with drought attracting particular attention due to its prolonged duration and extensive impact range. Agricultural drought refers to water deficiency during crop growth that restricts normal water requirements, leading to substantial yield reduction. Drought not only directly impairs crop productivity but also indirectly affects human livelihoods and income, making it a persistent global environmental concern. Mature monitoring indices for agricultural drought include the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Palmer Drought Index (PDSI), Soil Moisture Deficit Index (SMDI), Normalized Difference Vegetation Index (NDVI), Vegetation Health Index (VHI), Vegetation Drought Response Index (VegDRI), Potential Evapotranspiration (PET), and Microwave Integrated Drought Index (MIDI). Scholars have integrated these indices to characterize agricultural drought states. For instance, Hu et al. analyzed agricultural drought variation characteristics and frequency on the Loess Plateau using MODIS data, demonstrating that the TVDI index effectively monitors drought conditions during the crop-growing season. Wen et al. constructed a comprehensive remote sensing drought monitoring model (CMDI) and applied it to analyze spatiotemporal characteristics of agricultural drought in the Huai River Basin. Liu et al. developed a decision tree model integrating atmospheric anomalies, vegetation status, and soil moisture, which improved monitoring accuracy compared to single indicators and effectively indicated agricultural drought events in Henan Province. Brown proposed the VegDRI index, which incorporates anomalies in vegetation growth, precipitation, topography, land cover types, and other information. Wu established the Integrated Surface Drought Index (ISDI) based on the VegDRI framework. These models and indices provide valuable references for agricultural drought monitoring and assessment across different regions.

Random Forest (RF) is an ensemble model based on classification and regression trees that offers advantages in handling high-dimensional data, rapid training speed, strong anti-interference capability, and balanced error reduction compared to other algorithms. In recent years, scholars have applied random forest models to drought prediction research. Shen et al. constructed a drought monitoring model using random forest concepts, while Dong et al. developed a multifactor integrated drought condition index (IRSDI) based on multi-source remote sensing data, demonstrating strong applicability for large-area drought monitoring. Gansu Province, located primarily in arid and semi-arid regions with fragile ecological environments, represents a high-frequency zone for agricultural drought. Previous studies on agricultural drought in Gansu have mostly relied on meteorological station data or single-factor remote sensing indices, leaving significant gaps in regional agricultural drought monitoring and assessment. This study integrates multi-source remote sensing data products (MODIS, TRMM, ESA CCI) with meteorological, hydrological (soil moisture), vegetation (vegetation status), and topographic (elevation, slope, aspect) factors to construct a random forest model for agricultural drought monitoring in Gansu Province. The model analyzes spatiotemporal patterns and variation trends of agricultural drought from 2011 to 2019, providing methodological support and scientific basis for understanding agricultural drought occurrence and development patterns and for agricultural drought prediction in northwestern arid regions.

2 Study Area and Methods

2.1 Study Area Overview

Gansu Province is situated in northwestern inland China at the intersection of the Qinghai-Tibet Plateau, Loess Plateau, and Inner Mongolia Plateau (92°13 – 108°46 E, 32°31 –42°57 N). The terrain is narrow and elongated, extending approximately 1600 km from east to west and 500 km from north to south, with elevation gradually sloping from southwest to northeast and an average altitude of 1500 m. The province is divided into exorheic and endorheic regions by the Wushaoling Mountains. Climate types are diverse, ranging from north subtropical humid zones, warm temperate humid zones, alpine cold zones, cold temperate semi-humid zones, to cold temperate semi-arid zones from south to north. Based on natural geographical conditions, Gansu is typically divided into five regions: Hexi, Longzhong, Longdong, Longnan, and Gannan. Most agricultural areas in Gansu belong to the northern arid and semi-arid region, with a small portion in the Qinghai-Tibet Plateau region and Loess Plateau region. According to Gansu' s third national land survey data, the province' s cultivated land area in 2019 was approximately 0.52×10^{4} km^2, primarily located in the Longzhong and Longdong regions, as well as in the piedmont oases of the Hexi region and river valleys of the Longnan region.

2.2 Data Sources

Meteorological data comprised monthly precipitation and average temperature from 20 meteorological stations, obtained from the China Meteorological Data Network (http://data.cma.cn/). MODIS data included: 16-day, 1 km resolution NDVI products (MOD13A2) from 2011–2019; 8-day, 1 km resolution land surface temperature products (MOD11A2); and 500 m resolution land cover type products (MCD12Q1). All MODIS data were obtained from NASA' s LAADS website (https://ladsweb.modaps.eosdis.nasa.gov/), covering tiles h25v04, h25v05, and h26v05. Precipitation data used the TRMM 3B43 monthly product at 0.25°×0.25° resolution from NASA (https://disc.sci.gsfc.nasa.gov/). Soil moisture data employed the ESA CCI global soil moisture combined active–passive microwave dataset at 0.25°×0.25° resolution and monthly temporal resolution, obtained from the European Space Agency (https://www.soilmoisture cci.org/). Topographic data used SRTM DEM data at 90 m resolution from the Geospatial Data Cloud (http://www.gscloud.cn/).

2.3 TRMM and ESA CCI Data Downscaling

Given that the study period focused on the crop-growing season (April-September) and considering the substantial spatial resolution differences among datasets, all data were first synthesized to monthly temporal resolution using averaging methods. The TRMM 3B43 and ESA CCI data at 0.25° resolution were downscaled to 1 km×1 km using bilinear interpolation. The downscaling process for precipitation data followed the method of Li et al., using longitude, latitude, elevation, and NDVI as independent variables in a linear regression model due to their strong correlation with precipitation. For soil moisture downscaling, the method of Yu and Di was adopted, utilizing high-resolution DEM data to decompose low-resolution soil moisture data. The specific process for precipitation downscaling is as follows:

Let P represent the downscaled precipitation value (mm), Lon and Lat represent longitude and latitude, DEM represent elevation, and NDVI represent the normalized difference vegetation index from MOD13A2 products. The multivariate linear regression equation is:

$$P = a_0 + a_1\text{Lon} + a_2\text{Lat} + a_3\text{DEM} + a_4\text{NDVI} + \epsilon$$

where a_0 is the constant term, a_1-a_4 are linear regression coefficients, and ϵ is the residual. First, high-resolution DEM and NDVI data were resampled to low resolution (0.25°) and regressed with TRMM 3B43 precipitation data to obtain fitted coefficients. Precipitation residuals (ΔP) were calculated as the difference between TRMM 3B43 data (P_{TRMM}) and estimated precipitation (P_{est}):

$$\Delta P = P_{\text{TRMM}} - P_{\text{est}}$$

The fitted coefficients were then applied to high-resolution (1 km$×1km)datatoobtainhigh−resolutionpredictedprecipitation(P_{pre}).Residualswereinterpolatedto1km×$1 km resolution and added to P_{pre} to produce final downscaled precipitation data:

$$P_{\text{final}} = P_{\text{pre}} + \Delta P$$

2.4 Calculation of Different Drought Indices

Agricultural drought involves not only soil moisture, precipitation, crop growth status, and canopy temperature, but also landform and land cover types. The Vegetation Condition Index (VCI) characterizes crop growth status and effectively monitors historical droughts in most of northwestern China, showing significant spatial evolution characteristics. The Temperature Condition Index (TCI) characterizes crop canopy temperature; under drought conditions, canopy temperature rises and reduced water availability affects normal crop growth, causing drought stress. The Precipitation Condition Index (PCI), derived from normalized TRMM precipitation data, monitors precipitation deficits and characterizes continuous precipitation anomalies. Soil moisture determines water supply for crops, and soil drought directly results from low soil moisture. Microwave remote sensing offers unique advantages, so the Soil Moisture Condition Index (SMCI) was derived from normalized monthly soil moisture data to characterize soil moisture anomalies. Integrating multiple remote sensing drought indices provides greater advantages than single remote sensing factors.

The Temperature Vegetation Drought Index (TVDI), constructed from the LST-NDVI feature space, shows strong correlation with soil moisture and overcomes resolution limitations to effectively reflect soil moisture information. The Microwave Integrated Drought Index (MIDI) considers precipitation, temperature, and soil moisture simultaneously, representing key drought factors. Elevation (DEM) and slope also significantly influence regional drought. Following Zhang et al.' s weight determination for northwestern arid regions, DEM and slope weights were set to 0.2 and 0.1, respectively. The Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) were used as model output variables, with SPEI serving as an ideal indicator for drought trend analysis as it characterizes deviations from normal wet/dry conditions. To avoid impacts from extreme weather events, monthly precipitation and temperature data were used to calculate SPEI values within normal ranges. Drought severity was classified into five levels based on CMDI and SPEI values according to national standards .

2.5 Random Forest Model Construction

Random forest models achieve better fitting results with reduced root mean square error for nonlinear data. In this study, multi-source remote sensing data were used to extract drought characterization factors (VCI, TCI, PCI, SMCI, TVDI, MIDI, DEM, SLOPE, ASPECT) as input variables, with SPEI as the model output variable. Data from meteorological stations from April-September 2011-2018 served as the training set, while Gansu' s farmland area in 2019 was used as the test dataset. Model performance was evaluated using R^2, RMSE, and MAE, and spatial reliability was verified through correlation analysis between predicted values and SPEI. The model construction process is illustrated in [Figure 2: see original paper].

3 Results

3.1 Model Performance Evaluation

Due to random sampling, the trained model exhibited low variance, indicating good generalization capability without overfitting. To verify spatial reliability, predicted values were correlated with SPEI [Figure 4: see original paper]. The results showed good correlation, with the highest correlation in September ($R > 0.6$). Most regions showed correlations above 0.3 in other months, with the Gannan region maintaining correlations above 0.5 monthly. Some areas in central and southern Hexi, southern Longzhong, and parts of Longdong showed correlations above 0.4. Negative correlations occurred in some areas, primarily in mid-western Hexi (sparse vegetation causing uncertainty), southeastern Longzhong (hail damage in May), and southeastern Longnan (intense human activity). Overall, the model demonstrates reliable agricultural drought monitoring capability for Gansu' s farmland regions.

3.2 Spatiotemporal Patterns of Agricultural Drought

3.2.1 Spatial Distribution and Trends The spatial distribution of drought during the crop-growing season across different years revealed substantial regional variation in drought severity [Figure 5: see original paper]. Generally, drought-prone areas concentrated in the Hexi and Longzhong regions, while Gannan, Longnan, and Longdong experienced milder conditions. The most severe drought year was 2017, while 2012 was the mildest. Agricultural drought showed large fluctuations and complex interannual variation but clear regional differentiation, intensifying from southeast to northwest, consistent with previous research. In 2011, the most severely affected areas were eastern and central Hexi, with moderate drought in Longzhong and Longdong and light drought in Longnan. In 2012, drought was minimal across the province except for moderate conditions in Hexi. In 2013, drought severity persisted in Hexi while easing in Longzhong and Longnan. In 2014, drought intensified in eastern Hexi but decreased elsewhere. In 2015, drought increased in Longnan but decreased in other regions. In 2016, drought was most severe in eastern Hexi. In 2017, exceptional and severe drought dominated Hexi, with moderate drought in Longnan and Longdong. In 2018, drought decreased in most areas except parts of Hexi and Longnan. In 2019, drought severity increased in most regions, particularly in Longnan.

Monthly trends from 2011–2019 showed significant spatial heterogeneity [Figure 6: see original paper]. Negative linear tendency rates indicate intensifying drought, while positive values suggest alleviation. In April, most regions showed decreasing drought trends, particularly in Longnan. In May, drought intensified across most of Hexi, Longzhong, and Longnan, except for western Hexi. In June, drought decreased significantly in Longdong and Longnan but increased in Longzhong. In July, Longnan showed the most severe intensification, while Hexi experienced relief. In August, most regions except Longnan and parts of Longzhong showed increasing drought. In September, drought decreased in Longnan and central Longzhong but increased elsewhere. Notably, the Gannan region showed decreasing drought trends throughout the growing season.

3.2.2 Temporal Variation Patterns Monthly average CMDI values varied substantially [Figure 7: see original paper]. According to the classification system, values greater than -0.6 indicate no drought, while values below -2.4 indicate exceptional drought. The study period average ranged from -1.25 to 0.33 (light drought). April values ranged from -1.82 to -0.06, with 2017 showing moderate drought and other years light drought. May values ranged from -2.54 to 1.01, with 2017 showing exceptional drought, 2015 moderate drought, and 2012 no drought. June values ranged from -1.98 to 1.10, with 2017 showing severe drought and 2012 no drought. July values ranged from -1.22 to 1.05, with 2017 showing moderate drought and other years light or no drought. August values ranged from -1.32 to 1.03, with 2017 showing light drought and other years no drought. September values ranged from -1.32 to 1.03, with 2017 showing moderate drought and other years no drought. Overall, 2017 was the most severe drought year, with drought occurring in all months of the growing season.

4 Discussion

Compared with previous studies that used meteorological station data to construct agricultural drought disaster risk indices, this study’ s CMDI model compensates for the discontinuity of station-based monitoring. Lai et al. used SPEI to characterize meteorological and agricultural drought, finding that agricultural drought responds most sensitively to 3-month SPEI. This study integrated multiple factors including precipitation, temperature, soil moisture, and topography, providing more accurate representation of meteorological drought as the external driving force of agricultural drought. The correlation analysis between SPEI and model results used 1-month SPEI; employing multiple SPEI timescales could identify the most sensitive temporal scale. Additionally, input parameters were selected based on previous research without optimization; future work should focus on screening and validating multiple factors and incorporating more mature remote sensing drought indices into random forest models.

Comparison with Pang et al.’ s research reveals consistent findings: agricultural drought occurs annually in Gansu, with severe conditions in Hexi and mild conditions in Gannan, showing clear regional differentiation (“dry northwest, moist southeast”). This study focused on farmland areas using multi-factor integration, while Pang et al. analyzed the relationship between sea surface temperature and TVDI. The Hexi region, as a special drought zone, suffers from desertification, salinization, and severe soil erosion. Implementing ecological protection policies, limiting oasis overdevelopment, and promoting water-saving measures such as Gobi agriculture and facility agriculture could alleviate agricultural drought. Long-term strategies include increasing drought-resistant crop cultivation and implementing inter-basin water transfer projects. The Longzhong region (including Qingyang, Pingliang, and Dingxi) is a severe drought area with limited rainfall, scarce groundwater, and no major external water sources. Efficient utilization of upper Yellow River water, enhanced watershed ecological protection, full reservoir regulation functions, and widespread development of greenhouse and water-saving irrigation agriculture could effectively mitigate drought.

5 Conclusions

This study extracted agricultural drought-inducing factors from multi-source remote sensing data, constructed CMDI using a random forest model, evaluated results against measured SPEI data, and analyzed spatial differentiation and variation patterns of agricultural drought in Gansu Province. The main conclusions are:

1) Model results correlated well with measured SPEI data (R^2 up to 0.78), demonstrating high accuracy and strong spatial reliability (correlation mostly above 0.3). This indicates that integrating multiple factors through

random forest models effectively monitors agricultural drought and reflects its occurrence and development.

2) From 2011–2019, agricultural drought severity was highest in 2017 and lowest in 2012. Agricultural drought exhibited large fluctuations and complex interannual variation but clear regional differentiation, intensifying from southeast to northwest. The Hexi region was primarily an exceptional and severe drought zone, Longzhong was a severe (moderate) drought zone, and Longdong, Longnan, and Gannan were fluctuating drought/no-drought zones.
3) During the crop-growing season, the Gannan region showed consistent drought alleviation trends. Except for most areas in April and June, Longdong in May, and Longnan in September, which showed decreasing drought trends, other regions experienced increasing drought trends during the growing season.

Future research should optimize input parameter selection and validation to improve model performance.

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