Performance Assessment of Multi-source Remote Sensing Precipitation Products for Meteorological Drought in the Arid Region of Northwest China: Postprint

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Abstract

Multi-source remote sensing precipitation products play a crucial role in drought monitoring in regions with sparse or unevenly distributed meteorological stations, such as the arid areas of northwestern China. This study selected five typical remote sensing precipitation products (PERSIANN, CHIRPS, CMORPH, TMPA, and MSWEP) and evaluated their performance in meteorological drought across three temporal scales based on the Standardized Precipitation Evapotranspiration Index (SPEI). Drought events were identified using run theory to assess the capability of remote sensing precipitation products in capturing drought events. The results demonstrate that: (1) In the arid regions of northwestern China, all five remote sensing precipitation products can adequately capture the spatial distribution patterns of multi-year average precipitation, yet they struggle to accurately capture precipitation variation trends. (2) Regarding SPEI capture performance, MSWEP performs optimally, followed by TMPA, PERSIANN, and CHIRPS, while CMORPH exhibits the poorest performance. The 1-month scale (SPEI1) represents the optimal temporal scale for remote sensing precipitation products to identify meteorological drought. (3) In characterizing drought event properties, CHIRPS shows the best capability in identifying the number of drought events, whereas PERSIANN performs the worst; MSWEP and TMPA best characterize drought severity, with CHIRPS performing relatively poorly; except for CMORPH, the remaining four products can adequately capture the intensity and extremes of drought events. In summary, although the five remote sensing precipitation products can generally capture drought characteristics in the arid regions of northwestern China, it is challenging to identify a single precipitation product that performs optimally across all aspects of drought characteristic capture due to influences from precipitation product retrieval algorithms, terrain complexity, and the density of ground validation stations. The research findings can provide references for selecting optimal precipitation products for regional meteorological drought monitoring and for improving retrieval algorithms for remote sensing precipitation products in extreme arid environments.

Full Text

Evaluation of Meteorological Drought Performance of Multisource Remote-Sensing Precipitation Products in Arid Northwest China

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Abstract

Multisource remote-sensing precipitation products play a crucial role in drought monitoring in regions with sparse or unevenly distributed meteorological stations, such as the arid areas of northwest China. This study selected five typical remote-sensing precipitation products (PERSIANN, CHIRPS, CMORPH, MSWEP, and TMPA) and evaluated their meteorological drought performance at three timescales based on the Standardized Precipitation Evapotranspiration Index (SPEI). Drought events were identified using run theory to assess the capability of remote-sensing precipitation products to capture drought characteristics. The results indicate that: (1) All five remote-sensing precipitation products could reasonably capture the spatial distribution pattern of multi-year average precipitation in arid northwest China, but they struggled to accurately reproduce precipitation trends. (2) MSWEP demonstrated the best performance in capturing SPEI, followed by TMPA, PERSIANN, and CHIRPS, while CMORPH performed the worst. SPEI1 (1-month timescale) was identified as the optimal timescale for remote-sensing precipitation products to identify meteorological drought. (3) CHIRPS showed the best capability for identifying the number of drought events, whereas PERSIANN performed the worst. MSWEP and TMPA were the best indicators of drought severity, while CHIRPS was the worst. Except for CMORPH, the other four products could effectively capture the intensity and extreme values of drought events. In summary, although the five remote-sensing precipitation products could generally capture drought characteristics in northwest China's arid region, no single product exhibited optimal performance across all aspects due to influences from retrieval algorithms, terrain complexity, and the density of ground validation stations. These findings provide valuable references for selecting optimal precipitation products for regional meteorological drought monitoring and for improving remote-sensing precipitation retrieval algorithms in extreme drought environments.

Keywords: remote-sensing precipitation; SPEI; drought characteristics; run theory; arid northwest China

1 Introduction

Drought is a climate phenomenon triggered by persistent precipitation deficits. Compared with other extreme meteorological disasters such as floods and typhoons, drought develops more slowly, often over several months, making it easily overlooked. Once drought becomes established, it persists for extended periods and affects vast areas, causing significant damage to natural ecosystems and human socioeconomic systems, particularly in ecologically fragile arid and semi-arid regions. Therefore, monitoring drought evolution and quantifying its characteristics are essential for drought early warning, water resource management, and sustainable socioeconomic development.

Numerous drought analysis and monitoring techniques have been developed, with the most common approach being the design of applicable drought indices. For meteorological drought assessment, commonly used indices include the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI). PDSI is based on water supply and demand balance theory, considering factors such as precipitation, soil moisture, and temperature, and can characterize long-term drought processes. However, PDSI has limitations, including high sensitivity to soil information and a fixed timescale. SPI is relatively simple to calculate, offers flexible timescales, and requires only precipitation as input, overcoming some of PDSI's shortcomings. Nevertheless, SPI is based on two key assumptions: first, that precipitation variability is much higher than other variables such as temperature and potential evapotranspiration (PET); and second, that temporal trends in other variables are negligible. Under climate change conditions, with increasing temperatures and evaporation, SPI's applicability becomes questionable.

In contrast, the Standardized Precipitation Evapotranspiration Index (SPEI) is based on the climatic water balance concept. SPEI not only considers the sensitivity of evapotranspiration to drought but also retains SPI's advantages, making it better suited for capturing drought dynamics in regions with increasing temperature and evapotranspiration. Consequently, SPEI has been widely applied for drought monitoring and early warning at various timescales.

When using SPEI for drought monitoring, the accuracy of precipitation data is critical. Although ground-based station observations can provide approximate true precipitation values, sparse and unevenly distributed meteorological stations due to complex terrain and underdeveloped economies make it difficult to obtain precise spatial precipitation patterns. Remote-sensing precipitation products, characterized by consistent and homogeneous data, quasi-global coverage, near-real-time estimation, and high spatiotemporal resolution, offer a viable alternative for acquiring large-scale precipitation distributions. With advances in satellite remote-sensing technology, numerous global precipitation products have emerged, such as PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks), CHIRPS (Climate Hazards Group InfraRed Precipitation with Stations), CMORPH (CPC MORPHing technique), MSWEP (Multi-Source Weighted-Ensemble Precipitation), and TMPA (TRMM Multi-satellite Precipitation Analysis). These products provide high-precision, high-resolution precipitation estimates.

To clarify the drought monitoring performance of different remote-sensing precipitation products, numerous evaluation studies have been conducted worldwide. For example, research in the lower Mekong Basin found that CHIRPS could effectively capture drought characteristics at various timescales, with the 3-month timescale performing best. Studies in Pakistan demonstrated that MSWEP consistently showed good performance, though with some regional variability. In the Tibetan Plateau, MSWEP exhibited higher accuracy than CHIRPS despite CHIRPS's higher spatial resolution, making it more suitable for small-scale regional studies. However, comprehensive research on the capability of remote-sensing precipitation products to capture drought characteristics in northwest China's arid region remains relatively limited.

Northwest China's arid region, located in central Eurasia, is characterized by low and unevenly distributed rainfall, high temperatures, and intense evaporation, making it a typical semi-arid to arid climate zone. The region's complex terrain includes the high-altitude Kunlun Mountains and low-elevation inland basins. Despite its extreme aridity, variable precipitation still triggers numerous drought events that threaten local agricultural production and ecosystems. This study selected northwest China's arid region as the study area and used ground-based precipitation data and run theory to evaluate the meteorological drought monitoring performance of five remote-sensing precipitation products (PERSIANN, CHIRPS, CMORPH, MSWEP, and TMPA). The findings will provide scientific references for selecting optimal data sources and improving remote-sensing precipitation retrieval algorithms in arid environments.

1.1 Study Area

The study area is located in arid northwest China, between 69°–108°E and 33°–46°N, situated in central Eurasia. Due to scarce and unevenly distributed rainfall, high temperatures, and strong evaporation, the region exhibits a typical semi-arid to arid climate. The multi-year average precipitation is approximately 122 mm, with a mean annual temperature of 6–9°C. The terrain is complex, featuring the Kunlun Mountains with elevations up to 7,900 m and inland basins as low as -190 m. Despite the extreme aridity, unstable precipitation patterns have triggered numerous drought events that pose significant threats to local agricultural production and ecosystems.

1.2 Data Sources

Meteorological data were obtained from the China Meteorological Administration (CMA) data service platform (http://data.cma.cn/), comprising 756 national stations with daily observations of precipitation, temperature, wind speed, relative humidity, and sunshine duration. The study area includes 89 meteorological stations, with data covering 1998–2019. To generate gridded datasets, daily precipitation data were interpolated to a 0.05°$×$0.05° grid using Anusplin software. Anusplin employs thin-plate spline theory with multiple covariates (latitude, longitude, elevation) and has been shown to produce higher accuracy compared with inverse distance weighting and ordinary kriging methods.

Five remote-sensing precipitation products were evaluated: PERSIANN, CHIRPS, CMORPH, MSWEP, and TMPA. PERSIANN uses satellite GridSat data and artificial neural networks to generate a consistent, long-term global precipitation dataset. CHIRPS combines high-resolution satellite imagery with station data, providing low-latency, high-resolution precipitation estimates suitable for climate trend analysis and drought monitoring. CMORPH, developed by the U.S. Climate Prediction Center, integrates multiple microwave and infrared precipitation datasets to produce global high spatiotemporal resolution precipitation data applicable for mesoscale to interannual studies. MSWEP leverages the complementary strengths of gauge, satellite, and reanalysis data to provide reliable global precipitation estimates. TMPA is a widely used, high-performance multisatellite precipitation analysis product. For consistency, all datasets were resampled to 0.05° spatial resolution, covering the period 1998–2019.

1.3 Methods

1.3.1 Standardized Precipitation Evapotranspiration Index (SPEI) SPEI is a widely used meteorological drought index calculated by standardizing the difference between precipitation and potential evapotranspiration. It has clear physical meaning and multi-timescale advantages, enabling better capture of drought dynamics. This study selected three typical timescales—SPEI1, SPEI3, and SPEI6—to evaluate the drought monitoring performance of remote-sensing products. Potential evapotranspiration was calculated using the Penman-Monteith equation recommended by the Food and Agriculture Organization (FAO-56):

$$PET = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2 VPD}{\Delta + \gamma(1 + 0.34u_2)}$$

where PET is daily potential evapotranspiration (mm), R_n is net radiation at the surface ($MJ \cdot m^{-2} \cdot d^{-1}$), G is soil heat flux density ($MJ \cdot m^{-2} \cdot d^{-1}$), T is mean daily air temperature at 2 m height (°C), u_2 is wind speed at 2 m height ($m \cdot s^{-1}$), VPD is vapor pressure deficit (kPa), Δ is the slope of the vapor pressure curve ($kPa \cdot °C^{-1}$), and γ is the psychrometric constant ($kPa \cdot °C^{-1}$). Drought severity was classified according to SPEI values, ranging from mild to extreme drought .

1.3.2 Statistical Evaluation Metrics To quantitatively assess the meteorological drought performance of remote-sensing precipitation products in northwest China's arid region, this study selected three statistical metrics: the Kling-Gupta Efficiency (KGE), correlation coefficient (CC), and relative bias (BIAS). The formulas are as follows:

$$KGE = 1 - \sqrt{(1-CC)^2 + (1-\alpha)^2 + (1-\beta)^2}$$

$$CC = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2 \sum_{i=1}^{n}(S_i - \bar{S})^2}}$$

$$BIAS = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n} G_i} \times 100\%$$

where n is the sample size; G_i and $\bar{G}$ are observed precipitation values and their mean; S_i and $\bar{S}$ are remote-sensing estimated precipitation values and their mean; α is the ratio of observed to remote-sensing mean precipitation; and β is the ratio of observed to remote-sensing standard deviation.

1.3.3 Run Theory and Drought Event Characteristics Run theory was employed to identify drought events, defined as periods when SPEI falls below -0.5 for one month or longer. Four metrics were used to characterize drought events: number of events (N), drought severity (DS), mean drought intensity (DI), and mean drought peak (DP). The calculations are:

$$DS = \sum_{j=1}^{D} |SPEI_j|$$

$$DI = \frac{DS}{D}$$

$$DP = \max(|SPEI_j|)$$

where DS, DI, and DP represent drought severity, intensity, and peak for a single event; D is drought duration; $SPEI_j$ is the SPEI value for month j; i indexes drought events; and N is the total number of drought events.

2 Results

2.1 Spatial Patterns of Precipitation from Remote-Sensing Products

presents the multi-year average precipitation and trend spatial distributions for the five remote-sensing products. All products generally captured the spatial pattern of mean annual precipitation but underestimated precipitation amounts. PERSIANN and MSWEP showed multi-year averages closer to observations (150 mm and 180 mm, respectively) but exhibited regional differences. PERSIANN displayed smoother spatial patterns but failed to capture local orographic precipitation, notably underestimating high precipitation in the Tianshan Mountains. CHIRPS showed significant underestimation across large areas in the southwestern region. CMORPH's spatial distribution was similar to MSWEP and performed better than other products, though differences remained in high mountain terrain. These discrepancies likely stem from complex terrain and sparse ground station distribution.

In terms of annual precipitation trends, 79.7% of the study area showed increasing trends, with 21.1% reaching statistical significance ($P < 0.05$), primarily concentrated in the Tarim Basin and northern Qilian Mountains. However, the remote-sensing products struggled to accurately capture these trends. Compared with the observed trend mean ($-1.1\ \mathrm{mm \cdot a^{-1}}$), PERSIANN overestimated trends in the Junggar Basin, Turpan Basin, and northern Altun Mountains, resulting in a 72.7% overestimation across the entire region. CMORPH overestimated trends by 36.4%, while CHIRPS underestimated trends by 27.3% in the central basin area. MSWEP showed the best consistency with observations, underestimating by only 4.69%, whereas CHIRPS performed poorly with a KGE of -1.32.

2.2 Capture of SPEI at Different Timescales

The spatial distribution of KGE values for different timescales revealed that remote-sensing products showed timescale-dependent performance in northwest China. Overall, KGE values indicated that MSWEP performed best, followed by TMPA, PERSIANN, and CHIRPS, while CMORPH performed worst. SPEI1 showed the best consistency, followed by SPEI3, with SPEI6 performing poorest. Therefore, SPEI1 is identified as the optimal timescale for remote-sensing precipitation products to identify meteorological drought in this region.

2.3 Analysis of Meteorological Drought Event Characteristics

Based on the above conclusion that SPEI1 is the optimal timescale, drought events were identified using SPEI1, and four metrics (N, DS, DI, DP) were used to characterize drought events and comprehensively evaluate monitoring performance.

In northwest China's arid region, the number of drought events ranged from 15 to 25. Areas with fewer events were located west of the Qilian Mountains, north of the Altun Mountains, the Tianshan region, and the northern Altai Mountains, while more events occurred in the Tarim Basin and most of the Hexi Corridor. Remote-sensing products generally overestimated drought event numbers, with PERSIANN overestimating by 2.95% and CHIRPS by 0.42%—the closest to observations.

For drought severity, CHIRPS overestimated by 7.19%, while PERSIANN overestimated by 4.69%. The spatial patterns and biases of the five products were relatively similar, though CMORPH significantly underestimated severity in the northern Tarim Basin. For mean drought intensity, the five products showed consistent spatial patterns and statistical results, with biases fluctuating around 1.81% compared with observations. Regarding mean drought peaks, CMORPH overestimated extreme values in most areas by 2.25%, while other products showed similar spatial patterns and smaller biases.

In summary, for the four drought characteristics based on SPEI1, CHIRPS showed the best capability for identifying event numbers, while PERSIANN performed worst. MSWEP and TMPA best characterized drought severity, while CHIRPS performed worst. All products except CMORPH effectively captured drought intensity and extremes.

3 Discussion

This study found that the five remote-sensing precipitation products could capture the spatial distribution of multi-year average precipitation in northwest China's arid region but struggled to accurately reproduce precipitation trends. This aligns with previous findings that remote-sensing products perform poorly in capturing precipitation trends in arid regions. In evaluating SPEI performance, MSWEP significantly outperformed other products, consistent with conclusions from other studies. For drought event characteristics, CHIRPS generally overestimated event numbers while CMORPH underestimated them, differing from some previous studies possibly due to different drought indices used (SPEI in this study versus others) or different timescales analyzed.

Although strict quality control was applied to data sources and methods, several uncertainties remain. First, due to complex terrain and sparse ground validation stations in northwest China, using interpolated precipitation datasets to evaluate product performance may introduce uncertainty. Future studies should consider using more stations for comparative analysis. However, the Anusplin interpolation method used in this study adequately accounted for terrain effects, and since the focus was on large-scale drought patterns, this limitation has minimal impact on the conclusions. Second, only three timescales (SPEI1, SPEI3, SPEI6) were analyzed; whether conclusions hold for other timescales requires further investigation. Nevertheless, numerous studies have identified SPEI1 as the optimal timescale for meteorological drought, consistent with our findings. Additionally, this study only evaluated meteorological drought characteristics, while hydrological and agricultural drought are also crucial for human society. Whether these products can accurately capture hydrological and agricultural drought characteristics will be explored in future research to further improve the assessment of remote-sensing precipitation performance in arid regions.

4 Conclusions

This study evaluated five typical remote-sensing precipitation products (PERSIANN, CHIRPS, CMORPH, MSWEP, and TMPA) for their meteorological drought monitoring performance in northwest China's arid region using SPEI at three timescales and run theory. The main conclusions are:

1) In northwest China's arid region, all five remote-sensing precipitation products could capture the spatial distribution pattern of multi-year average precipitation. PERSIANN and MSWEP showed multi-year averages closest to observations (150 mm and 180 mm, respectively) but with regional differences. CHIRPS exhibited significant underestimation across large areas in the southwestern region. CMORPH's spatial distribution was similar to MSWEP and performed better than other products, though differences remained in high mountain terrain. Regarding annual precipitation trends, 79.7% of the region showed increasing trends, with 21.1% reaching significance ($P < 0.05$). However, remote-sensing products struggled to accurately capture these spatial trends.

2) For SPEI performance, MSWEP performed best, followed by TMPA, PERSIANN, and CHIRPS, while CMORPH performed worst. SPEI1 was the optimal timescale for remote-sensing products to identify meteorological drought. As timescale increased, SPEI trends became more pronounced. All products could capture spatial patterns of SPEI at different scales, though with varying performance.

3) For drought event characteristics in northwest China, the number of drought events ranged from 15 to 25. Remote-sensing products generally overestimated event numbers, with CHIRPS showing the closest agreement (overestimating by only 0.42%). CHIRPS overestimated drought severity by 7.19%, while PERSIANN overestimated by 4.69%. For mean drought intensity, all products showed consistent spatial patterns with small biases (around 1.81%). For mean drought peaks, CMORPH overestimated extremes by 2.25%, while other products showed similar patterns and smaller biases.

In conclusion, the five remote-sensing precipitation products can effectively capture drought spatial distribution characteristics in northwest China's arid region. However, due to influences from retrieval algorithms, terrain complexity, and ground station density, no single product performs optimally in all aspects.

These results provide valuable references for selecting appropriate precipitation products for regional drought monitoring and for improving remote-sensing precipitation algorithms.

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