Postprint: Applicability Evaluation of MSWEP Precipitation Products for Meteorological Drought Monitoring in the Yellow River Basin

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Abstract

The accuracy of the MSWEP (Multi-source weighted-ensemble precipitation) precipitation product in drought monitoring over the Yellow River Basin from 1981 to 2020 was evaluated using multiple statistical indicators and the Standardized Precipitation Index (SPI) at multiple time scales, and drought events were identified using run theory to quantitatively analyze their spatiotemporal characteristics. The results indicate that: (1) The monthly precipitation from the MSWEP precipitation product shows high correlation with ground-based observed precipitation represented by the Chinese Precipitation Analysis Product (CPAP), with a coefficient of determination reaching 0.9347. (2) The MSWEP precipitation product can effectively capture the spatial patterns and temporal evolution of multi-year precipitation. (3) The SPI calculated based on the MSWEP precipitation product can generally reproduce the patterns of SPI calculated from CPAP, but the correlation varies by region. In terms of capturing wet and dry conditions, the MSWEP precipitation product performs well in the middle and lower reaches of the Yellow River Basin, but poorly in the source region of the Yellow River, with correlation coefficients below 0.5. Notably, the ability of the MSWEP precipitation product to capture wet-dry variations decreases with increasing SPI time scales. (4) The performance of the MSWEP precipitation product in the middle and lower reaches of the Yellow River Basin is significantly better than that in the upper reaches. (5) The MSWEP precipitation product can effectively capture drought event characteristics such as duration, intensity, and severity. Overall, the MSWEP precipitation product is suitable for drought monitoring in the middle and lower reaches of the Yellow River Basin, but its application for drought monitoring in the topographically complex source region of the Yellow River requires further correction of its precipitation overestimation errors.

Full Text

Applicability Evaluation of MSWEP Precipitation Product for Meteorological Drought Monitoring in the Yellow River Basin

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Abstract

This study evaluates the accuracy of the Multi-Source Weighted-Ensemble Precipitation (MSWEP) product for drought monitoring in the Yellow River Basin using multiple statistical indicators and the Standardized Precipitation Index (SPI) at multiple time scales. The run theory is applied to identify drought events and quantitatively analyze their spatiotemporal characteristics. The results indicate: (1) The monthly precipitation from MSWEP shows strong correlation with ground observation data represented by the Chinese Precipitation Analysis Product (CPAP), with a determination coefficient reaching 0.9347. (2) The MSWEP product successfully captures the spatial pattern and temporal evolution of multi-year precipitation. (3) The SPI calculated from MSWEP can generally reproduce the SPI pattern derived from CPAP, though correlations vary regionally. The MSWEP product performs well in capturing wetness/dryness conditions in the middle and lower reaches of the Yellow River Basin, but poorly in the source region, with correlation coefficients below 0.5. Notably, its capability to capture wetness/dryness changes decreases with increasing time scales. (4) The MSWEP product's performance in the middle and lower reaches is significantly superior to that in the upper reaches. (5) The MSWEP product effectively captures drought event characteristics including duration, intensity, and severity. Overall, the MSWEP product is suitable for drought monitoring in the middle and lower reaches of the Yellow River Basin, but requires further correction of precipitation overestimation errors when applied to drought monitoring in the complex terrain of the source region.

Keywords: drought monitoring; MSWEP precipitation product; standardized precipitation index; applicability evaluation; Yellow River Basin

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1 Introduction

Drought is a complex extreme climate phenomenon. Compared with other natural disasters, drought develops slowly, lasts long, and affects extensive areas, impacting agriculture, ecology, and social development. While drought lacks a unified definition, it can be categorized into meteorological, agricultural, hydrological, and socio-economic drought based on its characteristics and impacts. Effective drought monitoring requires establishing or selecting appropriate drought indices for the study area. Drought indices comprehensively represent the wetness/dryness conditions of the atmosphere or underlying surface. Currently, several drought monitoring indices are widely applied, including the Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), Precipitation Evapotranspiration Index, and Standardized Precipitation Index (SPI). Among these, PDSI is a physically-based meteorological drought index that incorporates precipitation, evapotranspiration, and soil moisture conditions, clearly characterizing drought causes, severity, and duration. However, PDSI has high data requirements, complex calculations, and difficulty reflecting short-term drought characteristics. In contrast, SPI is a dimensionless index representing precipitation deficit over a period, offering advantages of low data requirements, simple calculation, and strong capability to reflect drought intensity and duration. SPI can represent drought conditions across different time scales and regions, and has been adopted as an operational drought monitoring indicator by the World Meteorological Organization, China Meteorological Administration, and numerous researchers.

Drought monitoring comprises conventional station-based and remote sensing approaches. Station observation data feature long records and high accuracy, making station-based drought monitoring a standard for other data sources. However, station observations are influenced by underlying surface properties, with sparse, unevenly distributed stations in some regions and limited spatial representativeness, making it difficult to obtain long-term precipitation data covering the entire area. With advances in remote sensing precipitation retrieval technology, the accuracy of remote sensing precipitation products has continuously improved. These products offer broad coverage, high spatiotemporal resolution, and easy accessibility, becoming important data sources for precipitation monitoring. Currently, numerous precipitation observation missions have been conducted globally, producing various satellite precipitation products. Representative examples include the Tropical Rainfall Measuring Mission (TRMM) and its derived multi-satellite precipitation analysis, the Global Precipitation Measurement (GPM) mission and its Integrated Multi-satellite Retrievals for GPM (IMERG) products, the Global Satellite Mapping of Precipitation (GSMaP) series, and the CPC MORPHing technique (CMORPH). With numerous precipitation products available and precipitation distribution affected by factors such as topography and climate, error evaluation is necessary to select products with higher accuracy and stronger applicability.

The Yellow River Basin spans China's eastern, central, and western regions, forming an important economic zone and ecological barrier. Due to its vast area, complex surface morphology, and uneven spatiotemporal precipitation distribution, drought disasters occur frequently, severely affecting people's livelihoods and regional economic development. Against the strategic background of ecological protection and high-quality development in the Yellow River Basin, drought monitoring in this region is essential. This study uses the station-interpolated grid precipitation product—China Daily Precipitation Analysis

Product (CPAP)—as standard data to evaluate the accuracy of MSWEP precipitation data in the Yellow River Basin from 1981 to 2020 using conventional correlation statistics and other indicators. Combined with the SPI drought index and run theory, drought events are identified and their characteristics quantitatively described to provide scientific reference for drought monitoring research and decision-making support for drought disaster prevention and mitigation in the Yellow River Basin.

2 Data and Methods

2.1 Study Data

The MSWEP V2.8 precipitation product is a global multi-source integrated precipitation dataset with long time series (1979–present), short time latency, and high spatial resolution (3-hourly/0.1°). This study uses CPAP data (0.5°$×$0.5°) from the National Meteorological Information Center and China Meteorological Administration as ground reference data, obtained from the National Meteorological Science Data Sharing Service Platform (http://data.cma.cn). Due to different spatiotemporal resolutions between MSWEP and CPAP, the MSWEP data were aggregated to monthly scale and resampled to 0.5° spatial resolution for direct comparison.

2.2 Methods

2.2.1 Standardized Precipitation Index (SPI) Proposed by McKee et al., SPI is calculated by dividing the difference between precipitation for a specific period and its mean by the standard deviation. Negative values indicate precipitation below the regional climatic average (drought conditions), while positive values indicate above-average precipitation (wet conditions). Since precipitation generally does not follow a normal distribution, SPI uses the gamma distribution to fit precipitation data before standardizing to a normal distribution. The specific calculation method is as follows:

For a given precipitation value x_0 in a year, the probability that precipitation sample x is less than x_0 is calculated as:

$$F = \int_0^{x_0} f(x)dx$$

where $f(x)$ is the probability density function of the gamma distribution:

$$f(x) = \frac{1}{\beta^\gamma \Gamma(\gamma)} x^{\gamma-1} e^{-x/\beta}, \quad x > 0$$

The parameters β (>0) and γ (>0) are scale and shape parameters, respectively, estimated using the maximum likelihood method:

$$\hat{\gamma} = \frac{1 + \sqrt{1 + 4A/3}}{4A}, \quad \hat{\beta} = \frac{\bar{x}}{\hat{\gamma}}$$

where $\bar{x}$ is the mean of the precipitation sample series, n is the total sample size, and $A = \ln(\bar{x}) - \frac{1}{n}\sum_{i=1}^{n}\ln(x_i)$.

When precipitation is not zero, the SPI value is calculated as:

$$SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right)$$

where $t = \sqrt{\ln\left(\frac{1}{F^2}\right)}$, $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

Drought classification based on SPI values is shown in .

2.2.2 Evaluation Metrics This study employs traditional error metrics including relative bias (RB), root mean square error (RMSE), and Pearson correlation coefficient (R) to evaluate errors in MSWEP precipitation estimates and wetness/dryness variations, thereby assessing its applicability for drought monitoring.

Relative bias represents the deviation between estimated and reference values, with values closer to 0 indicating higher accuracy. RMSE represents data precision, with smaller values indicating higher accuracy. The correlation coefficient quantifies linear correlation between estimated and reference values, with absolute values closer to 1 indicating stronger correlation.

2.2.3 Run Theory Run theory is a time series analysis method for identifying drought events. Based on SPI time series, this study identifies drought events pixel by pixel and quantitatively describes drought characteristics. Given that short-duration drought events generally have limited impact, this study uses the 12-month SPI (SPI12) to define drought events, considering SPI12 $\leq$ -1.0 as a drought event (see [Figure 2: see original paper] for schematic diagram). For each drought event, characteristics including drought duration, severity, intensity, and peak are calculated. Drought duration is the time difference between drought end and start; drought severity is the absolute value of accumulated SPI during the event; drought intensity is the ratio of severity to duration, describing event strength; and drought peak is the absolute value of the minimum SPI during the event. For spatial comparison, mean drought duration (MDD), mean drought severity (MDS), mean drought intensity (MDI), and mean drought peak (MDP) are calculated for each pixel.

3 Results

3.1 Accuracy Evaluation of MSWEP Precipitation Product

3.1.1 Spatiotemporal Distribution of MSWEP Precipitation Product To visually compare numerical differences between MSWEP and CPAP across different sub-regions of the Yellow River Basin, monthly mean precipitation time series were plotted for the entire basin and its upper, middle, and lower reaches (see [Figure 3: see original paper]). Overall, MSWEP precipitation data show no significant deviation from CPAP data, successfully capturing periodic variations in monthly precipitation with similar fluctuation patterns across different regions. However, its capability to capture temporal precipitation variations differs across periods and regions. For instance, MSWEP successfully captures precipitation variation trends and extreme points but tends to overestimate precipitation peaks.

Further analysis of intra-annual variation in monthly precipitation (see [Figure 4: see original paper]) reveals that MSWEP performs well in capturing intra-annual precipitation cycles. Specifically, MSWEP generally overestimates precipitation, though the degree varies by season, with underestimation occurring during high-precipitation months (July–September). This may be attributed to numerous climate zones within the basin and large spatiotemporal precipitation differences.

Spatial accuracy analysis based on 40-year mean monthly precipitation shows that MSWEP accurately captures the spatial pattern of decreasing precipitation from southeast to northwest, with clear boundaries near the 400 mm isohyet. However, overestimation occurs in high-precipitation areas in the southern upper-middle reaches and in the lower reaches (see [Figure 5: see original paper]).

3.1.2 Accuracy Assessment of MSWEP Precipitation Product Scatter plots of monthly precipitation values between MSWEP and CPAP for the entire Yellow River Basin and its sub-regions show good consistency, with determination coefficient (R^2) of 0.9347 and regression line slope of 0.95, though some outliers exist (see [Figure 6: see original paper]).

Spatial distribution of statistical indices reveals that areas with $R^2 > 0.8$ cover 85.3% of the basin, indicating good MSWEP performance in most regions (see [Figure 7: see original paper]). However, deviations mainly occur in the Yellow River source region, where RMSE exceeds 80 $\mathrm{mm \cdot month^{-1}}$. This may result from sparse station coverage and complex terrain affecting MSWEP's ability to accurately retrieve precipitation. Notably, alternating overestimation and underestimation in the source region may offset each other, resulting in relatively low RB but high RMSE (up to 216.7 $\mathrm{mm \cdot month^{-1}}$). Other sub-regions also show high R^2 and RMSE values, with the lower reaches showing R^2 of 0.95 and RMSE of 347.4 $\mathrm{mm \cdot month^{-1}}$.

3.1.3 SPI Accuracy Validation Based on MSWEP Precipitation Product Spatial patterns of SPI accuracy at different time scales show that SPI calculated from MSWEP generally reproduces the spatial pattern derived from CPAP across most of the basin (see [Figure 8: see original paper]). As time scale increases, R^2 gradually decreases while RMSE increases. Overall, MSWEP-based SPI shows good consistency with CPAP-based SPI in the middle and lower reaches, indicating that precipitation estimation errors directly affect SPI accuracy. Poor correlations persist in the upper reaches, particularly in the Datong River and Huangshui River basins, likely due to complex terrain and sparse stations.

Time series analysis of SPI at different time scales reveals similar fluctuation patterns between MSWEP and CPAP (see [Figure 9: see original paper]). MSWEP captures drought trends and characteristics well but shows increasing errors in capturing wetness/dryness intensity as time scales increase, due to cumulative errors in precipitation estimates over longer periods.

3.2 Drought Monitoring Based on MSWEP Precipitation Product

3.2.1 Spatial Distribution of Drought Characteristics Using 12-month SPI and run theory, drought events during 1981–2020 were identified and their duration, intensity, severity, and peak calculated. To analyze spatial patterns, mean values of drought characteristics were computed and mapped (see [Figure 10: see original paper]).

Mean drought duration analysis shows that MSWEP tends to underestimate drought duration, particularly in central Shaanxi Province at the upper-middle reach boundary, with differences up to 2 months. Similarly, MSWEP underestimates drought severity overall, primarily due to underestimated duration. However, overestimation occurs in central and southern parts of the middle reaches, consistent with overestimated intensity. Mean drought peak analysis reveals significant underestimation in the Yellow River source region (differences up to 0.5), aligning with MSWEP's underestimation of wetness/dryness magnitude there.

3.2.2 Typical Drought Event Analysis Three typical drought events with different characteristics were selected for detailed analysis (see and [Figure 11: see original paper]):

Event 1 (June 1997–August 1997): Short-duration (3 months) but high-intensity drought with intensity of 1.47. MSWEP accurately captured timing but overestimated intensity, severity, and peak by 11.6%, 11.6%, and 8.1%, respectively.

Event 2 (September 1999–August 2002): Long-duration (36 months) drought with relatively low intensity (0.58) but high severity (20.9). MSWEP performed best in this event, accurately capturing timing with only 1.7% overestimation in intensity, severity, and peak.

Event 3 (September 2014–August 2016): The most severe drought during the study period (22 months duration, severity of 23.7, intensity of 1.08, peak of 2.1). MSWEP accurately captured timing but underestimated intensity by 7.4% while overestimating peak by 4.8%.

Spatial pattern analysis shows that MSWEP captures overall drought patterns but has room for improvement in depicting the spatial distribution of different drought severity levels. For severe droughts, MSWEP overestimates drought area in the northern basin and source region.

4 Discussion

The MSWEP precipitation product demonstrates good application potential for drought monitoring in the Yellow River Basin, particularly in the middle and lower reaches, but shows unsatisfactory performance in the source region, requiring further improvement in precipitation and wetness/dryness feedback accuracy. This may result from comprehensive factors: the middle and lower reaches have flat terrain, while the upper reaches lie on the Qinghai-Tibet Plateau with complex surface morphology. Additionally, sparse meteorological stations in the plateau region lead to large CPAP errors that cannot effectively reflect true precipitation distribution, consistent with MSWEP's performance across China. However, different standard datasets lead to varying performance assessments. Compared with studies using meteorological station data as reference, using station-interpolated precipitation products as standard data covers the entire study area rather than specific stations, making regional differences more significant and enabling comprehensive evaluation of remote sensing precipitation products. However, interpolated products themselves contain errors from station data and interpolation methods. With continuous updates and development of interpolation techniques, more accurate precipitation products can be obtained.

5 Conclusions

This study evaluates the applicability of the multi-source integrated MSWEP precipitation product for drought monitoring in the Yellow River Basin, using the station-interpolated CPAP as standard data. Multiple accuracy evaluation metrics were applied to assess MSWEP precipitation data from 1981–2020, and its capability to capture wetness/dryness changes and drought characteristics was analyzed using SPI and run theory. The main conclusions are:

1. The MSWEP precipitation product generally performs well, effectively reflecting basic temporal variations and spatial distribution patterns of monthly precipitation. It successfully captures temporal characteristics of SPI at different time scales, basically meeting drought monitoring requirements in the Yellow River Basin.

2. The MSWEP product shows obvious overestimation errors in certain

periods (e.g., 1985–1986, 1990–1992) and some underestimation (e.g., 2018–2020). For wetness/dryness conditions, MSWEP-based SPI performs well overall, accurately identifying drought onset and termination times and reasonably reflecting drought spatiotemporal characteristics. Spatially, MSWEP shows lower accuracy in the upper reaches but excellent performance in the middle and lower reaches. For typical drought events, MSWEP accurately captures drought timing but shows varying degrees of overestimation or underestimation in drought intensity. Spatially, MSWEP captures overall drought patterns but requires improvement in depicting the spatial distribution of different drought severity levels.

3. MSWEP precipitation monitoring errors show significant spatial differences, with high accuracy in the middle and lower reaches but unsatisfactory performance in the complex terrain of the upper reaches. Temporal evaluation shows that MSWEP's capability to capture wetness/dryness changes decreases with increasing time scales.

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