Simulation Performance Analysis of Remote Sensing Precipitation Products for Hydrological Drought Characteristics in the Yellow River Source Region (Postprint)

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Abstract

Remote sensing precipitation products provide crucial data for research on hydro-meteorological disaster mechanisms and early warning in data-scarce regions; however, the performance of different remote sensing precipitation products exhibits substantial regional heterogeneity. Prior to conducting hydro-meteorological research and applications utilizing remote sensing precipitation products, a comprehensive evaluation of their performance is necessary. Accordingly, taking the data-scarce Yellow River source region as the study area, observed precipitation data (CMA) from 1983–2018 were used to drive and calibrate the ABCD hydrological model, and the Standardized Runoff Index (SRI) was employed to evaluate the hydrological drought simulation performance of three typical remote sensing precipitation products (PERSIANN-CDR, CHIRPS v2.0, MSWEP v2.0). Run theory was utilized to identify hydrological drought events and elucidate the capability of remote sensing precipitation to capture hydrological drought characteristics. The results indicate that: (1) All three remote sensing precipitation products can effectively capture the spatiotemporal distribution patterns of the multi-year mean of CMA. The hydrological simulation performance of the CHIRPS product (Nash-Sutcliffe efficiency coefficient NSE=0.72) surpasses that of the other two products. (2) The SRI at four temporal scales (SRI1, SRI3, SRI6, and SRI12) simulated by both CMA and precipitation products demonstrates a significant increasing trend ($P<0.01$), indicating that river runoff in the source region has increased and hydrological drought has been alleviated over the past 36 years; however, the precipitation products consistently overestimated SRI, suggesting that bias correction of precipitation products for the Yellow River source region is warranted. In terms of basic statistical metrics, the SRI calculated from the MSWEP product is most consistent with that from CMA, exhibiting the best performance, yet at the annual scale (SRI12), PERSIANN demonstrates optimal performance. (3) All three products overestimated the drought duration and severity of SRI1 and SRI3; the MSWEP product shows optimal simulation performance for SRI6, while PERSIANN shows optimal simulation performance for SRI12. The research findings can provide scientific decision-making support for the selection of precipitation product data in hydrological drought studies within the Yellow River source region.

Full Text

Simulation Performance of Remote Sensing Precipitation Products on Hydrological Drought Characteristics in the Source Region of the Yellow River

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Abstract: Remote sensing precipitation products provide crucial data for hydrometeorological disaster mechanism and early warning research in data-scarce regions, yet their performance exhibits substantial regional heterogeneity. Comprehensive evaluation is essential before applying these products to hydrometeorological studies. This study examines the data-scarce source region of the Yellow River, using observed precipitation data (CMA) from 1983 to 2018 to drive and calibrate the ABCD hydrological model. The standardized runoff index (SRI) was employed to evaluate the simulation performance of three typical remote sensing precipitation products (PERSIANN-CDR, CHIRPS v2.0, MSWEP v2.0) for hydrological drought. Run theory was applied to identify hydrological drought events and clarify the capability of remote sensing precipitation to capture drought characteristics. Results show that: (1) All three products effectively captured the spatiotemporal distribution pattern of multi-year mean precipitation, with CHIRPS v2.0 demonstrating optimal hydrological simulation performance (Nash-Sutcliffe efficiency coefficient NSE = 0.72). (2) SRI values at four time scales (SRI1, SRI3, SRI6, SRI12) calculated from both observed and remote sensing precipitation products showed significant increasing trends ($P < 0.01$), indicating increased river runoff and alleviated hydrological drought in the source region over the past 36 years. However, all three remote sensing products overestimated SRI values, suggesting the need for bias correction. In terms of basic statistical indicators, MSWEP performed best, showing the highest consistency with observations. (3) All three products overestimated drought duration and intensity at short time scales (SRI1 and SRI3). MSWEP performed optimally at the 6-month scale (SRI6), while PERSIANN showed the best performance at the annual scale (SRI12). These findings provide scientific support for selecting appropriate precipitation products for hydrological drought research in the Yellow River source region.

Keywords: remote sensing precipitation; hydrological drought; ABCD hydrological model; standardized runoff index (SRI); Yellow River source region

1 Introduction

Under the combined influence of climate change and human activities, regional and global mean and extreme temperatures have increased significantly. Rising temperatures accelerate the hydrological cycle, leading to more frequent, prolonged, and intense drought events that threaten ecological civilization and high-quality economic development. Hydrological drought, as a typical drought type, represents a critical process in the propagation from meteorological to agricultural and socioeconomic drought. Studying its evolution and propagation mechanisms is essential for drought early warning and monitoring.

To quantify hydrological drought severity, constructing hydrological drought indices is commonly employed. Among various drought indicators, Ding et al. [1] used negative run-length indices to quantitatively analyze hydrological drought characteristics at major Chinese river stations. Kang et al. [2] proposed an S-index based on temperature and precipitation to evaluate hydrological drought in the middle Yellow River, though determining weight coefficients proved challenging. The standardized runoff index (SRI) [3] has become widely applied in hydrological drought research due to its requirement of only runoff data, computational simplicity, and flexible temporal scales.

Precipitation is the core input for hydrological models, and its accuracy significantly affects drought event identification. Current precipitation data acquisition methods include ground observations, radar monitoring, and remote sensing satellite retrieval [4]. Ground observations provide near-true values but suffer from uneven rain gauge distribution, particularly in economically underdeveloped areas and complex terrain where sparse gauge networks fail to capture precipitation spatiotemporal patterns [5]. Radar offers accurate precipitation over large areas but is costly and vulnerable to multiple error sources, performing poorly in complex terrain [6]. Remote sensing precipitation products provide relatively accurate, temporally continuous data and have been widely applied in hydrometeorological research [7].

Numerous global remote sensing precipitation products exist, including CHIRPS v2.0, MSWEP v2.0, CMORPH, TRMM 3B42V7, and PERSIANN-CDR [8]. Previous performance evaluations include: Liu et al. [9] assessed four products in the Tarim River Basin, finding CMORPH most suitable for runoff simulation; Li et al. [10] evaluated TRMM 3B42V7 and MSWEP V2.0 in the Wei River Basin, concluding MSWEP V2.0 showed superior hydrological performance; Wang et al. [11] analyzed TRMM data for August drought in the Three-River Headwaters region; Zhang et al. [12] found PERSIANN significantly overestimated precipitation in the Yellow River source region.

However, most studies focus on precipitation spatiotemporal patterns and meteorological drought capture, with limited research on hydrological drought simulation performance. Additionally, significant regional differences exist among remote sensing products. Therefore, evaluating their performance in capturing hydrological drought characteristics in specific regions can expand their application in hydrological drought research. This study selects three typical remote sensing precipitation products (PERSIANN-CDR, CHIRPS v2.0, MSWEP v2.0) to investigate their hydrological drought monitoring performance in the Yellow River source region using the ABCD hydrological model and SRI.

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2 Study Area and Methods

2.1 Study Area Overview

The Yellow River source region (32°06 –36°12 N, 95°48 –103°24 E) is located in the northeastern Tibetan Plateau with terrain sloping from west to east. The basin area is approximately 12×10^4 km^2, accounting for about 15% of the entire Yellow River basin. The region contributes approximately 35% of the Yellow River's total runoff and is known as the "Water Tower of the Yellow River" [13]. The ecosystem is fragile with weak disaster prevention capacity, and the region is sensitive to climate change and human activities [14]. The climate is characterized as plateau sub-frigid semi-humid with a multi-year average precipitation of approximately 508 mm and average temperature of -4.9°C [15]. The average elevation exceeds 4000 m, with alpine meadow as the dominant vegetation type and extensive seasonal and permafrost areas [16].

2.2 Data Sources

Accurate precipitation data form the foundation of hydrometeorological research. Daily meteorological data from 12 national meteorological stations were obtained from the China Meteorological Administration (http://data.cma.cn/en). The Anusplin software was used for spatial interpolation, considering elevation and terrain factors to generate precipitation data at 0.05° × 0.05° resolution from 1983 to 2018. Monthly runoff data from 1983 to 2018 were obtained from hydrological yearbooks compiled by the Ministry of Water Resources.

Three typical remote sensing precipitation products were selected:

1. **PERSIANN-CDR**: A retrospective precipitation product using GridSat-B1 infrared radiation data as input, calibrated with GPCP monthly data.

Spatial coverage: 60°S–60°N. No bias correction applied.

2. **CHIRPS v2.0**: Developed by the US Geological Survey and University of California Climate Hazards Group, integrating ground station, satellite, and climatology data. Spatial coverage: 50°S–50°N.
3. **MSWEP v2.0**: A global precipitation dataset uniquely merging gauge measurements, satellite data, and reanalysis. Demonstrated superior performance compared to 22 other global products [17] and shows great potential in poorly gauged or ungauged regions [18].

For consistency, all products were resampled to 0.25° × 0.25° resolution for the study period 1983–2018. Basic information is summarized in Table 1.

2.3 Standardized Runoff Index (SRI)

The standardized precipitation index (SPI) is a common meteorological drought indicator [19], calculated using precipitation series data fitted to a Gamma distribution to transform skewed distributions to normal. SRI is the hydrological analog of SPI, using runoff series instead of precipitation. Shi et al. [20] demonstrated that the generalized extreme value (GEV) distribution is most suitable for flow data in the Yellow River source region.

SRI can quantify drought events at flexible temporal scales. This study examined four typical time scales: 1-month (SRI1), 3-month (SRI3), 6-month (SRI6), and 12-month (SRI12). Drought classification criteria follow McKee et al. [21] (Table 2).

2.4 ABCD Hydrological Model

Among numerous hydrological models, the ABCD model [22] is selected for its minimal parameters, high simulation accuracy, and strong adaptability. Model inputs include precipitation (P) and potential evapotranspiration (PET), while outputs include runoff depth (R), soil moisture (S), and groundwater storage (G). PET is calculated using the FAO Penman-Monteith formula:

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

where R_n is net radiation ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$), G is soil heat flux ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$), T is mean daily temperature (°C), u_2 is wind speed at 2 m height ($\mathrm{m \cdot s^{-1}}$), e_s is saturation vapor pressure (kPa), e_a is actual vapor pressure (kPa), Δ is the slope of the vapor pressure curve ($\mathrm{kPa \cdot °C^{-1}}$), and γ is the psychrometric constant ($\mathrm{kPa \cdot °C^{-1}}$).

The ABCD model state variables are defined as: - $Y = S + G$ (total water storage) - $R = R_s + R_g$ (total runoff = direct runoff + groundwater runoff) -

$R_s = (1-a) \cdot \max(P - PET, 0)$ - $R_g = d \cdot G$ - $S_{t+1} = S_t + a \cdot \max(P - PET, 0) - R_s$ - $G_{t+1} = G_t + c \cdot \min(P, PET) - R_g$

where a is the probability of runoff generation before soil saturation (0,1], b is the upper limit of unsaturated aquifer storage (0,1000], c is the proportion of soil moisture recharging groundwater (0,1], and d is the groundwater outflow rate (0,1].

2.5 Statistical Evaluation Metrics

To quantitatively assess the hydrological drought performance of three remote sensing products, correlation coefficient (CC), root mean square error (RMSE), Nash-Sutcliffe efficiency coefficient (NSE), and Kling-Gupta efficiency coefficient (KGE) were selected:

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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(G_i - S_i)^2}$$

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

$$KGE = 1 - \sqrt{(CC-1)^2 + \left(\frac{\mu_s}{\mu_G} - 1\right)^2 + \left(\frac{\sigma_s}{\sigma_G} - 1\right)^2}$$

where G_i and $\bar{G}$ are observed and mean precipitation, S_i and $\bar{S}$ are remote sensing estimated and mean precipitation, μ_G and μ_s are means, σ_G and σ_s are standard deviations, and n is sample size.

2.6 Run Theory

Drought events are identified using run theory [23]. Following McKee et al. [21], when SRI is negative with magnitude less than -1.0 and duration exceeds one month, a drought event is recorded. Drought characteristics include: - **Drought duration (DD)**: Months between event start and end - **Drought severity (DS)**: Absolute sum of SRI values during the event - **Mean drought duration (MDD)**: $\frac{1}{N}\sum_{i=1}^{N} DD_i$ - **Mean drought severity (MDS)**: $\frac{1}{N}\sum_{j=1}^{N} DS_j$

where N is the number of drought events.

3 Results and Analysis

3.1 Spatiotemporal Distribution of Remote Sensing Precipitation Products

Figure 2 shows monthly average precipitation spatial distributions and scatter plots for observed data (CMA) and three remote sensing products. All three products captured the southeast-to-northwest decreasing precipitation gradient. However, they underestimated northwestern precipitation while overestimating southeastern precipitation. Scatter plots (Figure 3) reveal CHIRPS performed best (CC > 0.95, KGE = 0.95), followed by MSWEP (KGE = 0.94) and PERSIANN (KGE = 0.95). RMSE values were 8.9 mm, 9.8 mm, and 14.1 mm for CHIRPS, MSWEP, and PERSIANN, respectively.

3.2 ABCD Hydrological Model Performance

Using calibrated model parameters, the three remote sensing products were input into the ABCD model. Performance metrics (Figure 4) show CHIRPS achieved the best runoff simulation (NSE = 0.72), followed by MSWEP (NSE = 0.67) and PERSIANN (NSE = 0.57). Both calibration (1983–2005) and validation (2006–2018) periods demonstrated good model fit, confirming the ABCD model's strong applicability in the Yellow River source region.

3.3 Hydrological Drought Index Evaluation

Trend Analysis: Table 3 presents SRI trends from observed and remote sensing precipitation. All SRI time scales showed significant increasing trends ($P < 0.01$), indicating increased runoff and alleviated hydrological drought over the past 36 years. However, remote sensing products showed stronger increasing trends than observations because their original precipitation data had greater upward trends.

Correlation: Correlation coefficients between remote sensing and observed SRI were generally high across all time scales, with MSWEP showing the highest values. No clear trend emerged with increasing time scale.

RMSE: MSWEP exhibited the smallest RMSE across all time scales, indicating minimal bias relative to observations, followed by CHIRPS. PERSIANN performed worst.

KGE: Kling-Gupta efficiency coefficients revealed MSWEP's optimal performance at short time scales (SRI1, SRI3). At longer scales (SRI6, SRI12), all three products performed similarly.

3.4 Drought Characteristics from Run Theory

Figure 5 shows drought characteristics captured by remote sensing products. At short time scales (SRI1, SRI3), all three products significantly overestimated drought duration and severity. At longer scales: - **SRI6**: MSWEP showed the closest match to observations for mean drought duration and severity - **SRI12**: PERSIANN most closely matched observed mean drought duration, while MSWEP best captured drought severity

All products underestimated drought event numbers while overestimating duration and intensity, particularly at short time scales. MSWEP demonstrated relatively better performance compared to the other two products.

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4 Discussion

Although strict quality control was applied, uncertainties remain. First, while the Anusplin interpolation method considered elevation and terrain effects, interpolation errors persist [24]. Second, using a single hydrological model and drought index may introduce uncertainty; future studies should incorporate multiple models and indices for more comprehensive evaluation. Third, this study focused on objective performance assessment without quantitative bias correction. Remote sensing products generally overestimated precipitation in the Yellow River source region, with PERSIANN overestimating by approximately 2×, which introduces substantial uncertainty for drought analysis. Complex terrain and sparse stations constrain product accuracy [25]. Future work will employ Bayesian convolutional neural networks [26] and machine learning algorithms for quantitative product correction.

Previous studies in the Yellow River source region reported warming-drying trends and decreasing runoff [27]. However, this study found significant increasing trends in SRI across all time scales from 1983–2018, indicating increased runoff and alleviated hydrological drought, consistent with Liang et al. [28]. Zhang et al. [12] found PERSIANN significantly overestimated precipitation in this region, supporting our findings. Xu et al. [29] reported MSWEP's superior performance in the Yellow River Basin, aligning with our results.

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5 Conclusions

This study evaluated three remote sensing precipitation products for hydrological drought simulation in the Yellow River source region. Key conclusions are:

1. All three products effectively captured the spatiotemporal distribution of observed precipitation, with CHIRPS showing optimal hydrological simulation performance (NSE = 0.72).

2. SRI values at all time scales from both observed and remote sensing data showed significant increasing trends ($P < 0.01$), indicating increased runoff and alleviated hydrological drought from 1983–2018. However, remote sensing products overestimated SRI values, necessitating bias correction.

MSWEP demonstrated the best statistical performance with high correlation and low RMSE, while PERSIANN performed best at the annual scale (SRI12).

3. All products overestimated drought duration and intensity at short time scales. MSWEP performed optimally at the 6-month scale, while PERSIANN excelled at the annual scale. The results provide scientific support for selecting appropriate precipitation products for hydrological drought research in the Yellow River source region.

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Table 1 Basic information of remote sensing precipitation products

Product	Spatial Coverage	Data Source
PERSIANN-CDR	60°S–60°N	http://chrsdata.eng.uci.edu/
CHIRPS v2.0	50°S–50°N	ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS
MSWEP v2.0	Global	http://gloh2o.org/

Table 2 Classification criteria of standardized runoff index (SRI)

SRI Value	Drought Category
-0.5 < SRI	Normal
-1.0 < SRI ≤ -0.5	Mild drought
-1.5 < SRI ≤ -1.0	Moderate drought
-2.0 < SRI ≤ -1.5	Severe drought
SRI ≤ -2.0	Extreme drought

Table 3 SRI trends of observation data and remote sensing precipitation products

Data Source	SRI1	SRI3	SRI6	SRI12
CMA	0.03***	0.03***	0.03***	0.03***
PERSIANN	0.04***	0.04***	0.04***	0.04***
MSWEP	0.04***	0.04***	0.04***	0.04***
CHIRPS	0.04***	0.04***	0.04***	0.04***

Note: *** indicates significance at 99% confidence level. SRI1, SRI3, SRI6, and SRI12 represent 1-, 3-, 6-, and 12-month time scales, respectively.

Figure 1 [Figure 1: see original paper] Schematic diagram of the source region of the Yellow River

Figure 2 [Figure 2: see original paper] Spatial distributions of monthly average precipitation of CMA and three remote sensing precipitation products at the source of the Yellow River

Figure 3 [Figure 3: see original paper] Precipitation scatter maps of CMA and three remote sensing precipitation products

Figure 4 [Figure 4: see original paper] Simulation performance of ABCD hydrological model and different remote sensing precipitation products

Figure 5 [Figure 5: see original paper] Hydrological drought characteristics captured by remote sensing precipitation products

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

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