

Evaluation of CHIRPS and its application for drought monitoring over the Haihe River Basin, China

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Abstract Climate Hazards Group Infrared Precipitation with Stations data (CHIRPS) rainfall dataset was early evaluated and compared with 29 meteorological stations over the Haihe River basin in China, for the period 1981–2015. Seven statistical and categorical metrics were applied to evaluate the performance of CHIRPS with gauge measurements at multi-time scales (monthly, seasonally and annually). Using the Standardized Precipitation Index (SPI) as the drought indicator, the applicability of this new long-term satellite precipitation product for drought monitoring was investigated in this study. Results indicate that the good performances were performed at multiple temporal scales (monthly, seasonally and annually). Although it tends to overestimate the higher precipitation in this region, CHIRPS demonstrated good agreement ($R^2 > 0.70$) with gauge observations at monthly scale and greater agreements ($R^2 > 0.78$) at seasonal and annual scales. Meanwhile, CHIRPS performed a good score of BIAS and lower error in a majority of months at multi-time scales. Because of its good performance at multi-time scales and the advantages of high spatial resolution and long-time record, CHIRPS was applied to derive the SPI over the Haihe River basin. It is evaluated and compared with stations observations to derive SPI at time scale of 1, 3 and 6 months. The results indicate that it performed good ability to monitor drought ($R^2 > 0.70$) and successfully captured the historical drought years (1981, 1999, 2001 and 2012). Overall, this study concludes that CHIRPS can be a valuable

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complement to gauge precipitation data for estimating precipitation and drought monitoring in this region.

Keywords CHIRPS · Precipitation · Drought monitoring · Standardized Precipitation Index (SPI)

1 Introduction

Precipitation is an essential component of global water and energy cycles and has been widely used for various applications in hydrology and meteorology (Behrangi et al. 2012; Loucks and Jia 2012; Vergara et al. 2014). Accurate precipitation data are essential for drought monitoring and prediction (Sahoo et al. 2015; Toté et al. 2015; Zheng and Bastiaanssen 2013). With the decreasing trends of annual precipitation and potential evapotranspiration, in the past decades, drought became more frequent and serious in the Haihe River basin (He et al. 2015; Qin et al. 2015). Due to the gathered population and cities, the accurate precipitation is vital to the water resource management and the drought monitoring in this region.

Traditionally, rain gauges provided the direct and accurate rainfall around the gauge locations. However, rain gauges had bad performance in detecting spatial precipitation distribution and were often relatively sparse in some regions of the world (Tang et al. 2016). Rain gauges had the obvious queries such as the density of site networks, the continuous time series and the financial limitation. Notably, it should be pointed out that satellite precipitation products provide a practical and alternative way to obtain accurate rainfall data with high spatial and temporal resolutions (Li et al. 2013; Xie and Xiong 2011; Zhang and Jia 2013; Zhang et al. 2016). Over the past decades, a great number of quasi-global satellite precipitation products have been produced and used worldwide for hydrometeorological applications (Pan et al. 2010; Sahoo et al. 2015; Vergara et al. 2014; Yong et al. 2015), such as the TRMM Multi-satellite Precipitation Analysis (TMPA), the Climate Prediction Center morphing technique (CMOPRH) satellite-based rainfall product and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN). Those precipitation products can provide accurate estimation of precipitation with high spatiotemporal resolution and show good performance in drought and other natural hazards (Bayissa et al. 2017).

Although satellite-based products could be valuable options for precipitation information, it subjects to a variety of errors and uncertainties (Tong et al. 2014). Evaluation of satellite precipitation products with ground rainfall measurements is significant for specific applications in study area. The performance of satellite precipitation products also varies from region to region. In previous studies, a large number of studies have been done to evaluate the accuracy of satellite rainfall products regionally and globally (Aghakouchak et al. 2011; Long et al. 2015; Yong et al. 2015). In summary, great efforts were devoted to validate and evaluate the accuracy of satellite precipitations products. Unfortunately, most of previous satellite precipitation products had short historical record (less than 30 year) and lower spatial resolution (0.25° or 0.1°). Under the climate change, accurate long-record (at least 30 years) precipitation data are helpful to deal with natural studies like droughts and flooding. The Standard Precipitation Index (SPI) was a usefully meteorological drought index and widely applied in drought monitoring and forecasting (Hao and Aghakouchak 2013; Zhang et al. 2012, 2017). SPI was proposed by (Mckee et al. 1993, 1995)

and computed by continuous time series of monthly precipitation data for at least 30 years (Zhang et al. 2015b). Fortunately, CHIRPS offers a viable option for estimating precipitation and drought monitoring. It was an useful rainfall dataset for trend analysis and seasonal drought monitoring (Chris et al. 2015) and had long time-series records (more than 30 years) and high spatial resolution (0.05°). Compared to PERSIANN-CDR and TRMM 3B43 monthly satellite precipitation products, the CHIRPS 2.0 showed the highest agreement with gauges observations (Zambrano et al. 2017). It has been shown to be a useful substitute for gauge data in Northeast Brazil and the Upper Blue Nile Basin, Ethiopia (Bayissa et al. 2017; Paredes-Trejo et al. 2017). To date, there is little evaluation focusing on the accuracy and application over the Haihe River basin of this newly satellite precipitation dataset. Accurate precipitation data would be valuable for this region to deal with drought and water resource crisis. Thus, it is urgent and significant to evaluate the performance of this newly satellite rainfall dataset and its applicability for drought monitoring in the Haihe River basin.

The objectives of this study were to (1) evaluate the performance of CHIRPS at multiple time scales over the Haihe River basin with the seven statistic and categorical metrics; (2) explore the applicability of this dataset for drought monitoring over the Haihe River basin. This study proceeds as follows. Section 2 introduces the study area and data. Section 3 introduces the methodology and SPI. The evaluations and comparisons of the CHIRPS with gauge observations at multiple temporal scales (monthly, seasonally and annually) are provided in Sect. 4, followed by the evaluation of the CHIRPS for drought monitoring. The conclusions are provided in Sect. 5.

2 Study area and data

2.1 Study area

The study area is the Haihe River basin, with an area of 0.32 million square kilometers, located between 35° – 43° N and 112° – 120° E in the east of China. The study area belongs to the East Asian monsoon climate with the average annual temperature of 10.4°C , average annual precipitation and evaporation of approximately 541.6 and 470 mm, respectively (Jia et al. 2012). The main character of this climate is hot and wet in summer. However, it is cold and dry in winter (Yang et al. 2016). The distribution of rainfall is characterized by strong spatial and temporal variability with precipitation decreasing from west and north-east low hills to southeast plain. The rain season spans from July through August, with about 60% of the annual rainfall. The main evapotranspiration season spans from March through June, with about 55% of the annual evapotranspiration. Drought often occurs in spring (Cai et al. 2015b), but sometimes may be delayed to summer.

The combination of the uncertain monsoon climate and the huge demands of the dense people caused water shortage and drought disaster (Xia et al. 2007). Inaccurate precipitation information across the Haihe River basin may be led to tremendous economic and societal losses, causing it vital and urgent to obtain accurate rainfall data in this region. Therefore, it is meaningful to quantitatively evaluate this new rainfall dataset and its application in this area.

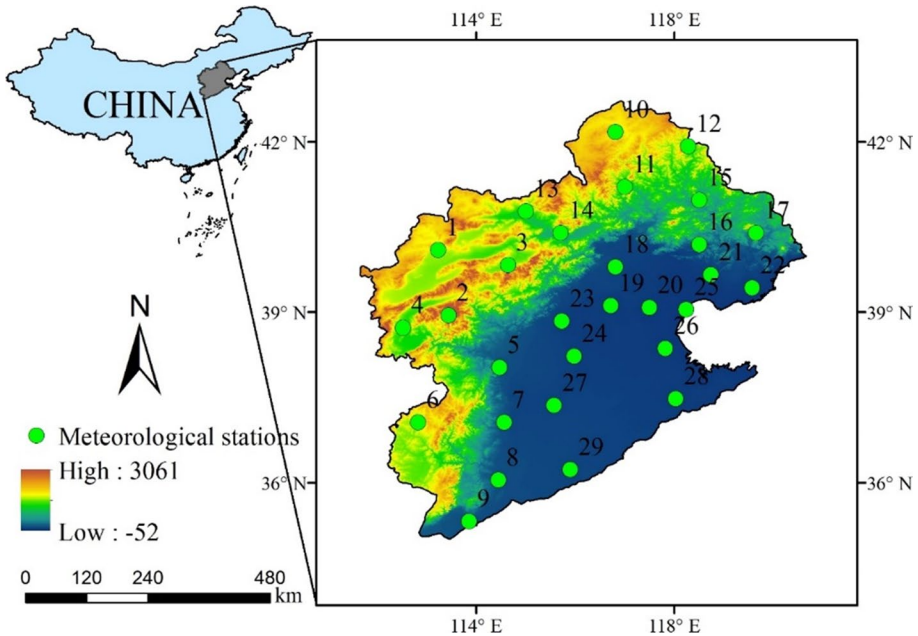


Fig. 1 The distribution of meteorological stations and the elevation of this region

2.2 Meteorological stations data

A total of 29 monthly precipitation meteorological stations data from 1981 to 2015 were used (Fig. 1), which could be downloaded for free on the official Web site of China Meteorological Data Network (<http://data.cma.cn>). The brief description of 29 meteorological stations, including geographical characteristics (latitude, longitude and elevation) and annual average precipitation, is illustrated in Table 1. The names of 29 meteorological stations were expressed by the number from 1 to 29. If the meteorological stations data are missing, the average value from the near station was used to calculate.

2.3 CHIRPS

At present, there is an obvious query existed in current precipitation products. There are some precipitation datasets based on the stations measurements with the long-time record, but most of them were uneven distribution or sparse in the world. Satellite precipitation products offer an ideal way to capture the accurate precipitation on a quasi-global scale with high spatial and temporal resolution, such as: TRMM 3B43, CMORPH, PERSIANN and the like. Unfortunately, most of satellite precipitation products fall short of the time series for a historical record. Thus, it is challenging for scientists and analysts to research the spatial and temporal variations for precipitation patterns and better monitoring and predicting the future trend of climate change in a region even to the world.

Nowadays, CHIRPS is an IR-based quasi-global satellite precipitation dataset and will be the useful and ideal precipitation dataset for drought monitoring and warning (Chris et al. 2015). CHIRPS which has a relatively long-term records (> 30 years) than other satellite precipitation products is developed to support the United States Agency

Table 1 The detail information of 29 meteorological stations

No	Site name	Latitude	Longitude	Elevation (m)	Mean (mm)
1	Datong	40.10	113.33	1067.20	376.44
2	Wutaishan	38.95	113.52	2208.30	675.53
3	Weixian	39.83	114.57	909.50	403.21
4	Yuanping	38.73	112.72	828.20	412.25
5	Shijiazhuang	38.03	114.42	81.00	518.51
6	Yushe	37.07	112.98	1041.40	519.72
7	Xingtai	37.07	114.50	77.30	497.31
8	Anyang	36.05	114.40	62.90	451.39
9	Xinxiang	35.32	113.88	73.20	547.10
10	Duolun	42.18	116.47	1245.40	377.08
11	Fengning	41.22	116.63	661.20	447.18
12	Weichang	41.93	117.75	842.80	439.82
13	Zhangjiakou	40.78	114.88	724.20	391.62
14	Huailai	40.40	115.50	536.80	372.65
15	Chengde	40.98	117.95	385.90	505.72
16	Zunhua	40.20	117.95	54.90	668.54
17	Qinglong	40.40	118.95	227.50	656.87
18	Beijing	39.80	116.47	31.30	538.10
19	Bazhou	39.12	116.38	9.00	484.33
20	Tianjin	39.08	117.07	2.50	514.63
21	Tangshan	39.67	118.15	27.80	593.65
22	Laoting	39.43	118.88	10.50	578.36
23	Baoding	38.85	115.52	17.20	499.07
24	Raoyang	38.23	115.73	19.00	500.25
25	Tianjintanggu	39.05	117.72	4.80	548.65
26	Huanghua	38.37	117.35	6.60	545.14
27	Nangong	37.37	115.38	27.40	464.42
28	Huimin	37.48	117.53	11.70	557.95
29	Xinxian	36.23	115.67	37.80	502.87

for International Development Famine Early Warning System Network (FEWS NET) and combined through the ‘smart’ interpolation techniques with high spatial resolution ($0.05^\circ \times 0.05^\circ$). It is a blended product which combined the precipitation climatology, quasi-global satellite estimates and in situ measurements. The latest version of CHIRPS (CHIRPS v2.0) is available from 1981 to near present at different temporal resolution (daily, monthly and annually) from the Web site (<http://chg.geog.ucsb.edu/data/chirps/>).

3 Method

3.1 Evaluation method

This study is a typical evaluation between satellite precipitation product and ground observation. In order to evaluate the performance of satellite precipitation products, 29 gauges

rainfall data were used in this study (in Fig. 1). The gauge monthly rainfall data were accumulated by daily rainfall data. The satellite rainfall data were extracted by the point-based station locations instead of interpolating the gauge data into the gridded product to reduce the systematic error. Corresponding to the 29 stations locations, monthly satellite rainfall data were extracted from the grid cell locations. In order to comprehensively evaluate the performance of CHIRPS monthly rainfall data, this study was divided into two parts. The first part was to evaluate the performance of CHIRPS at multi-time scales with seven statistical and categorical metrics. Meanwhile, the IDW method was used to compare the spatial distribution of precipitation. IDW method was relatively easy to implement and widely applied in former studies (Duan et al. 2016). In order to better compare the spatial distribution of precipitation, the inverse distance weighting (IDW) method was used to interpolate the rainfall data into the gridded datasets to reflect the spatial distribution characteristics. Using SPI as the drought indicator, the second part was to detect the applicability of CHIRPS for drought monitoring.

To further evaluate and compare the long precipitation product, a set of widely used statistic metrics were used in this study to comprehensively evaluate the performance of the satellite precipitation product (Table 2). The first statistic metric is the correlation coefficient (CC), which was used to assess the agreement between satellite estimate and ground observations. In addition, three representative metrics were used to describe the error and bias of satellite estimates compared with ground observations, including the root mean square error (RMSE), the relative bias (BIAS) and the mean error (ME). Additionally, three categorical statistics, including probability of detection (POD), false alarm ration (FAR) and the critical success index (CSI), were used to describe the contingency of satellite precipitation estimates.

Table 2 List of the metrics used in this study

Statistic metrics	Formula	Values range	Optimal value
CC	$CC = \frac{\frac{1}{N} \sum_{i=1}^N (C_i - \bar{C})(G_i - \bar{G})}{\sigma_C \sigma_G}$	- 1 to 1	1
RMSE	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (C_i - G_i)^2}$	0 to ∞	0
BIAS	$BIAS = \frac{\sum_{i=1}^N (C_i - G_i)}{\sum_{i=1}^N G_i} \times 100\%$	0 to ∞	0
ME	$ME = \frac{1}{N} \sum_{i=1}^N (C_i - G_i)$	- ∞ to ∞	0
POD	$POD = \frac{A}{A+B}$	0–1	1
FAR	$FAR = \frac{C}{A+C}$	0–1	0
CSI	$CSI = \frac{A}{A+B+C}$	0–1	1

G_i means observed gauge precipitation; C_i means the precipitation estimates from CHIRPS; n refers to the number of samples; A means the number of precipitation observed by the gauge and CHIRPS; B represents the number of precipitation observed by the gauge but not detected by CHIRPS; C means the number of precipitation detected by CHIRPS not observed by the gauge

3.2 The Standardized Precipitation Index

The Standardized Precipitation Index (SPI) is recommended by the World Meteorological Organization (WMO) as index to characterize droughts (Hayes et al. 2011). It is based on precipitation data alone and can be calculated to describe drought on multiple time scale (Cai et al. 2015a; Hao and Singh 2015; Liu et al. 2011; Zhang et al. 2015a). Diverse time scales reflect the soil moisture conditions (small time scale) or the underground water, river flows and lake water levels (large time scales) (Livada and Assimakopoulos 2007). SPI can be used to distinguish the drought beginning and ending times by setting application-specific thresholds (Belayneh et al. 2014). In this study, it was calculated on 1-, 3- and 6-month time scales to reflect the drought condition. While the former studies indicate that precipitation is subject to the law of gamma distribution (Edwards 1997). SPI values can be categorized according to classes as followed in Table 3. The parameters of scaling and the forms of precipitation probability density function:

$$g(x) = \frac{1}{\beta^\alpha \cdot \Gamma(\alpha)} x^{\alpha-1} \cdot e^{-\frac{x}{\beta}}, \quad x > 0 \tag{1}$$

where α, β are the form parameter and the scale parameter; x is the quality of precipitation; and the expression form of $\Gamma(\alpha)$ is:

$$\Gamma(\alpha) = \int_0^{+\infty} x^{\alpha-1} e^{-x} dx \tag{2}$$

According to the method of maximum probability for a multiyear data sequence, the α and β are:

$$\hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \tag{3}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{4}$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \tag{5}$$

Table 3 Classification of SPI values

SPI Classification	SPI values
Extremely dry	$SPI \leq -2$
Severely dry	$-2.0 < SPI \leq -1.5$
Moderately dry	$-1.5 < SPI \leq -1.0$
Near normal	$-1 < SPI < 1$
Moderately wet	$1 < SPI \leq 1.5$
Very wet	$1.5 < SPI \leq 2$
Extreme wet	$SPI > 2$

where \bar{x} is the average value of precipitation quantity; n is number of the precipitation measurements; after $g(x)$ is integrated with respect to x , we can obtain the expression for cumulative probability $G(x)$:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}} \Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-\frac{x}{\hat{\beta}}} dx \tag{6}$$

The cumulative probability becomes:

$$H(x) = q + (1 - q)G(x) \tag{7}$$

where q is the probability of no precipitation, which is calculated using the following equation:

$$q = m/n \tag{8}$$

where m represented the amount of how many times the precipitation was zero in a temporal sequence of data; n is the precipitation observation number in a sequence of data. The calculation of the SPI bases on following equation (Lloyd-Hughes and Saunders 2002):

$$SPI = \begin{cases} -\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right), & 0 < H(x) \leq 0.5 \\ +\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right), & 0.5 < H(x) \leq 1.0 \end{cases} \tag{9}$$

and the expression form of t is

$$t = \begin{cases} \sqrt{\ln \frac{1}{(H(x))^2}}, & 0 < H(x) \leq 0.5 \\ \sqrt{\ln \frac{1}{(1-H(x))^2}}, & 0.5 < H(x) \leq 1.0 \end{cases} \tag{10}$$

The values of c_0, c_1, c_2, d_1, d_2 and d_3 were followed: $d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308; c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328$.

4 Results and discussion

4.1 Evaluation of the performance of CHIRPS at multi-time scales

4.1.1 Evaluation at monthly scale

A comparison of the average monthly rainfall data between in situ measurements and CHIRPS is presented in Table 4 for the 1981–2015 period. The gauges monthly rainfall were accumulated by the daily rainfall data. The number of comparison pairs was 12,180 for point-based evaluation during the 35-year period, based on the average monthly precipitation from gauge measurements and CHIRPS. Table 4 shows the R^2 , ME, BIAS and RMSE between the ground-measured and the satellite-estimated. Strong correlation coefficients were observed for CHIRPS in majority of months (R^2 mainly over 0.70, $p < 0.01$). It reflected the good agreement between in situ measurements and CHIRPS. Meanwhile, the ME varies from 0.19 to 15.40 mm/month. Similarly, the RMSE varies from 1.23 to 23.91 mm/month and the BIAS varies from -0.20 to 1.11%. Both of the ME and RMSE

Table 4 Summary of statistical metrics at monthly scale

Month	R^2	ME (mm/month)	RMSE (mm/month)	BIAS (%)
January	0.64	0.87	1.47	1.11
February	0.81	0.19	1.23	0.13
March	0.78	0.75	3.07	0.26
April	0.34	- 0.80	5.02	- 0.13
May	0.84	0.72	3.61	0.06
June	0.83	1.02	7.05	0.05
July	0.72	15.40	23.91	0.38
August	0.77	8.95	16.41	0.27
September	0.73	0.82	5.97	0.05
October	0.65	1.60	3.94	0.23
November	0.85	- 0.74	2.48	- 0.20
December	0.71	0.82	1.59	0.87

were obviously observed that the higher error was concentrated on the months of July and August. As is shown in Table 4, the ME in July and August were 15.40 and 8.95 mm which is obviously higher than other months (mainly lower than 2.00 mm). Similarly, the RMSE in July and August was 23.91 and 16.41 mm which is obviously higher than other months (mainly lower than 8.00 mm).

To fairly explain the reason of this result, the average month precipitation in July and August is compared in Fig. 2. Compared with other stations, it is interesting to note that the Wutaishan station was obviously showed the higher error in July and August. It may be the reason of elevation (in Table 1), which was consistent with the former study that satellite is accurately to detect rainfall data in mountains (Yong et al. 2015). CHIRPS should be adjusted to improve the performance when estimated the precipitation in mountain regions (such as Wutaishan station). This result illustrates that the elevation is one reason that affected the performance of CHIRPS. Meanwhile, Xinxiang, Anyang and Qinglong stations also were found some random errors in specific time. In addition, some errors of overestimation were found in July and August when precipitation over 100 mm. Another interesting finding was that the agreement in April is obviously lower than other months. April was the month of monsoon alternation and the unstable strength of the monsoon caused this error. The better fits are found during the period from October to May in Table 4. CHIRPS overestimated the precipitation with BIAS ranging from 0.05 to 1.11% in most months. This error may be the reason of the satellite precipitation algorithms and the unstable monsoon climate (Shen et al. 2010). The CHIRPS shows high POD (near 0.90) and CSI (more than 0.73), and low FAR (lower than 0.28). These results can well illustrate that CHIRPS can capture the most precipitation events over Haihe River basin. CHIRPS overestimated monthly average precipitation slightly with small BIAS over Haihe River basin. The performance of CHIRPS was satisfactory in terms of the mosy metrics except in some particular months. Overall, CHIRPS has a good performance over Haihe River basin at monthly scale and can be a valuable precipitation product in this region.

4.1.2 Evaluation at seasonal scale

For this section, the comparisons between in situ measurements and satellite estimates in each season are presented in Fig. 3. The seasonal rainfall data were accumulated by the monthly rainfall data from gauge data and CHIRPS. It can be divided by four seasons, including spring (March to May), summer (June to August), autumn (September to November) and winter (December to February). The number of comparison pairs was 4060 for point-based evaluation during the 35-year period. Strong correlations were denoted for CHIRPS in each season ($R^2 > 0.78$, $p < 0.01$, in Fig. 4). But CHIRPS overestimated the rainfall values in each season with the small positive BIAS (in Table 5). This overestimation can be the result of the sensor's inability as their spatial resolution is much larger than the point locations of rain gauges (Thiemig et al. 2011). The unstable monsoon climate may cause the high values of ME and RMSE in summer which were obviously higher than other seasons. As shown in Fig. 5, the similar spatial patterns were observed between the in situ measurements and the satellite estimates across the four seasons. It obviously showed that the precipitation center of Wutaishan station in all seasons, which may be the reason of high elevation (more than 2000 m). caused the orographic precipitation. Consistent with

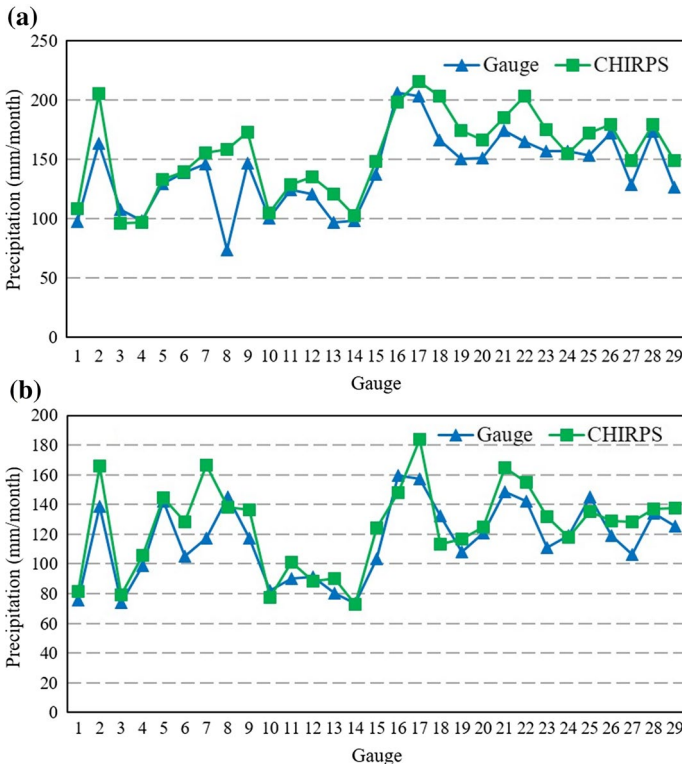


Fig. 2 Comparisons of average month precipitation from gauge measurements and CHIRPS in July (a) and August (b)

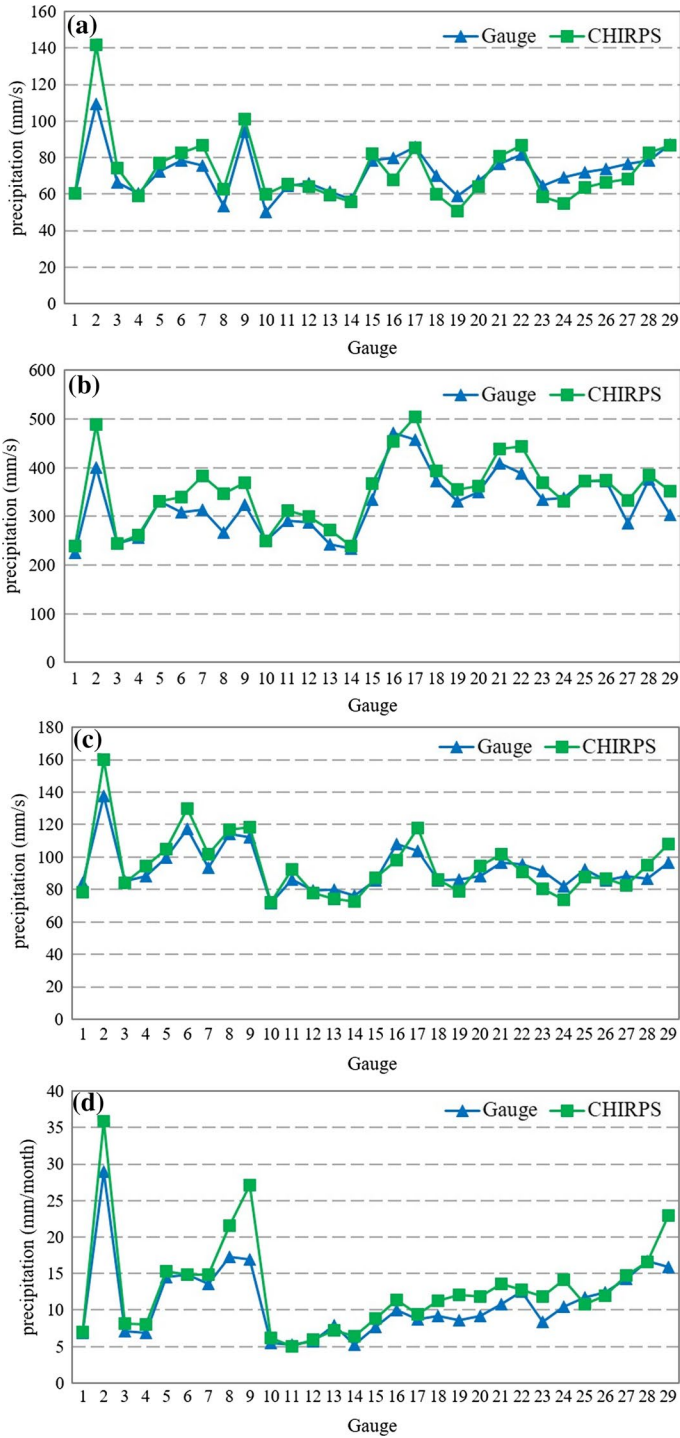


Fig. 3 Line charts of average seasonal rainfall from gauge measurements and CHIRPS at seasonal scale in spring (a), summer (b), autumn (c) and winter (d)

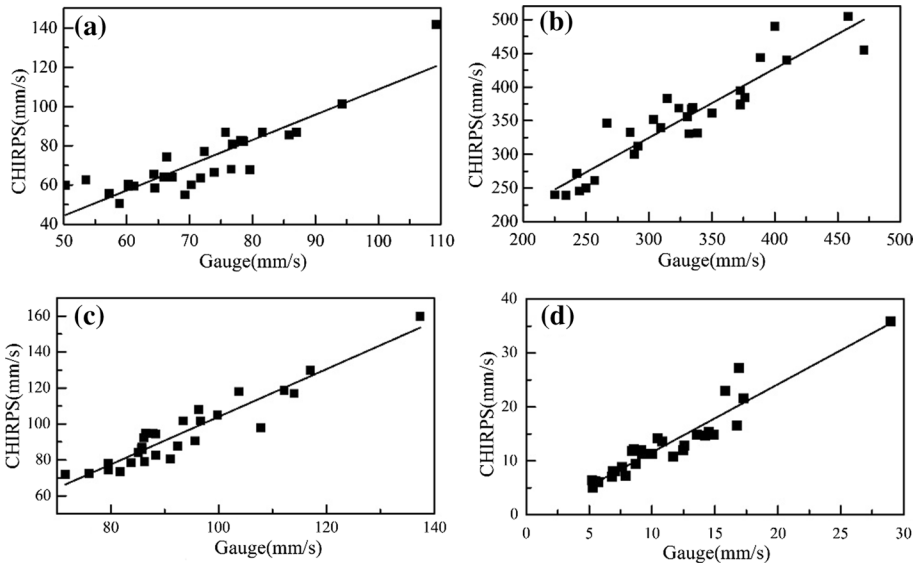


Fig. 4 Scatter plots of average seasonal rainfall from gauge measurements and CHIRPS at seasonal scale from spring (a), summer (b), autumn (c) to winter (d)

Table 5 The list of statistical metrics in each season

Season	R^2	ME	RMSE	BIAS (%)
Spring	0.79	0.67	9.03	0.03
Summer	0.86	25.38	36.25	0.27
Autumn	0.89	1.69	7.98	0.06
Winter	0.89	1.88	3.16	0.58

the result in month scale, CHIRPS overestimated the precipitation in Wutaishan station. It was obviously founded a precipitation center in summer, including the Zunhua, Qinglong, Tangshan and Laoting stations in Fig. 5. This precipitation center may be the reason that these rain gauges located in the windward slope of mountains.

4.1.3 Evaluation at annual scale

For the third part, the statistics used to compare the different average annual precipitation datasets (1981–2015) were calculated between meteorological station rainfall data and satellite precipitation estimate. The number of comparison pairs was 1015 for point-based evaluation during the 35-year period, based on the average annual precipitation from CHIRPS estimate and gauge measurement. Figure 6 illustrates scatter plots of a comparison between average annual-estimated and ground-measured precipitation. Strong correlation was denoted for CHIRPS ($R^2 = 0.8663$, $p < 0.01$). The ME is 29.61 mm/year, the RMSE is 48.41 mm/year, and the BIAS is 0.2%. We notice that the CHIRPS exhibited an overestimation of the high values, when the precipitation was more than 350 mm. The satellite product was compared with station rainfall data to compare the spatial distribution

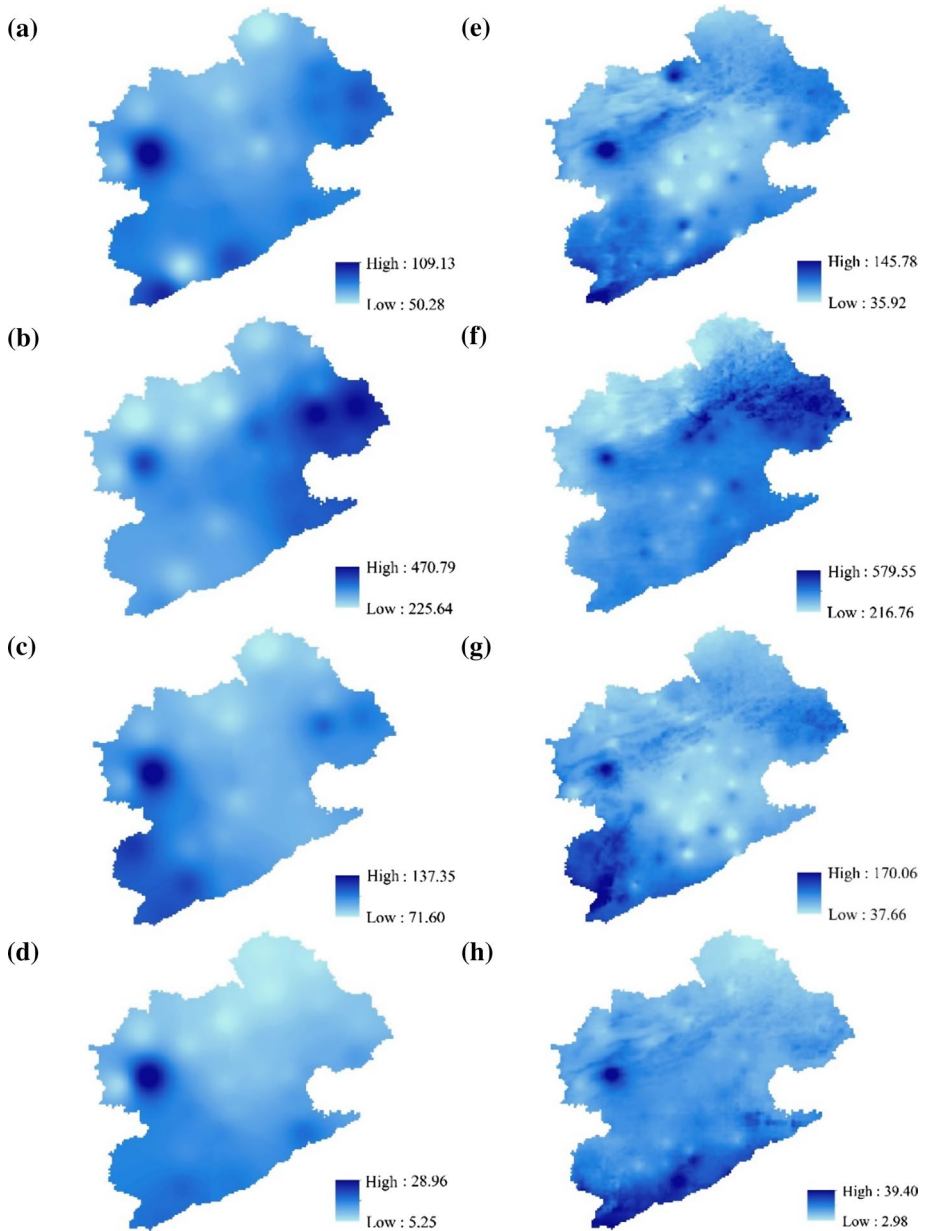


Fig. 5 Spatial comparisons of average seasonal precipitation for gauge measurements and CHIRPS in each season. **a** Gauge-spring, **b** gauge-summer, **c** gauge-autumn, **d** gauge-winter, **e** CHIRPS-spring, **f** CHIRPS-summer, **g** CHIRPS-autumn and **h** CHIRPS-winter

of precipitation in Fig. 7. As would be expected, CHIRPS captured good agreement in precipitation spatial pattern with stations data. The extreme precipitation mainly resided in Wutaishan, Zunhua and Qinglong stations (Fig. 8), which form the west and northeast

Fig. 6 The scatter plot of average annual rainfall from meteorological stations and CHIRPS

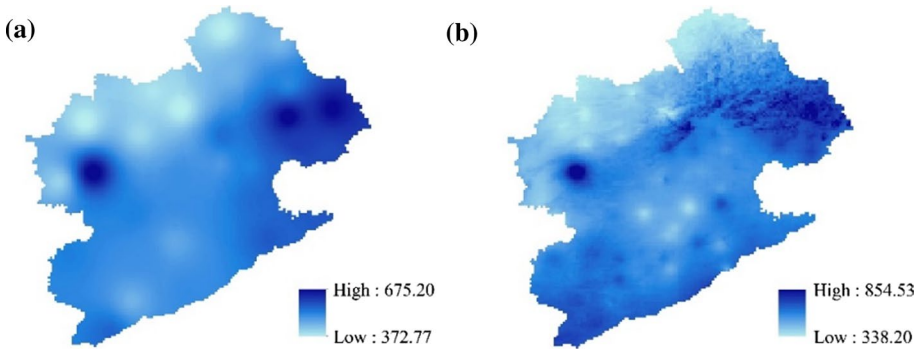
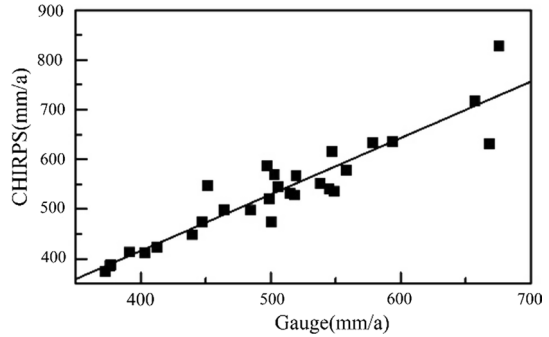


Fig. 7 Spatial comparison of average annual precipitation for gauge measurements and CHIRPS at annual scale. **a** Gauge, **b** CHIRPS

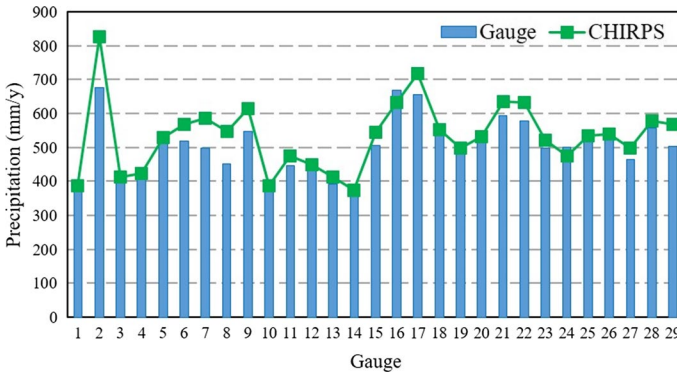


Fig. 8 Comparison between rain gauge measurements and CHIRPS of average annual rainfall at annual scale

precipitation center. Precipitation is relatively less in northern area, which including the Datong, Weixian, Huailai, Zhangjiakou, Duolun and Fengning stations. The spatial distribution of precipitation was consistent with the analysis in seasonal scale. In general, these results indicate that CHIRPS has a good performance at multi-time scale over Haihe River

basin. Overall, these three parts indicate that CHIRPS is good at reflecting the precipitation patterns and will be a very useful precipitation dataset for drought monitoring.

4.2 Drought monitoring with CHIRPS

CHIRPS was selected here because it has a higher spatial resolution and relatively satisfactory performance in the precipitation estimates with in situ observations over Haihe River basin at the multi-time scales (in Sect. 4.1). For these reasons, we attempt to assess the applicability of CHIRPS for drought monitoring in this section. The number of comparison pairs was 12,873 for point-based evaluation during the 35-year period. The SPI was computed by gauge precipitation and CHIRPS separately at 1-, 3- and 6-month scales. In order to better assess the applicability of CHIRPS, R^2 between station SPI and CHIRPS SPI was computed at times scales of one, three and six months. The results indicate that the good agreement (R^2 mainly over 0.70, $p < 0.01$) of SPI between in gauge measurements and CHIRPS at multi-time scales. The good agreements indicated that CHIRPS was a good dataset for drought monitoring in this region.

Another founding is that the R^2 of SPI-3 was higher than SPI-1 and SPI-6. To further assess how well the CHIRPS for drought monitoring, we have compared the average SPI between in situ measurements and satellite measurements in the long time-series comparison in Fig. 9. From the results in former studies, SPI-3 had the best correlation over cropland areas and applied for agricultural drought monitoring. The historical drought events can be reflected with the values of SPI, including 1981, 1986, 1989, 1999, 2001, 2002 and 2012. These years were consistent with the former studies (Qin et al. 2015). Although CHIRPS shows good performance in most stations, it also has some slightly errors. Figure 9 demonstrates that CHIRPS often overestimated the degree of drought in some specific time (such as in 1996, 2006 and 2012 years) over the Haihe River basin.

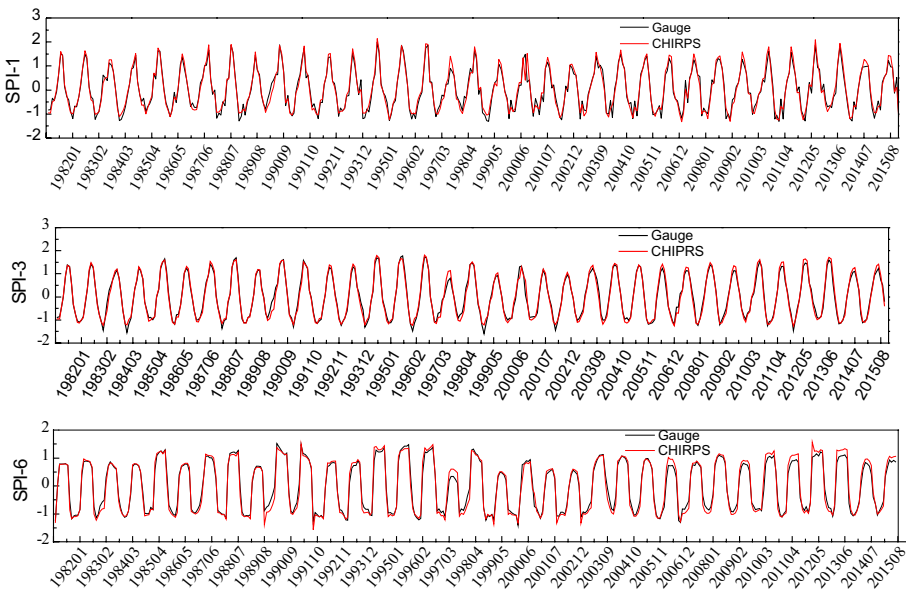


Fig. 9 Long time-series comparisons of SPI-1, SPI-3 and SPI-6 time scales for gauge measurements and CHIRPS

The mismatch in spatial scale can be used to express the reason for this error. In addition, it is need to improve the algorithm combined with the local characteristics. Overall, good agreements of SPI between CHIRPS and gauge rainfall data at multi-time scales responded that CHIRPS has good applicability for drought monitoring.

5 Conclusions

In this study, CHIRPS was comprehensively evaluated by the gauge observations from 29 stations during 1981–2015. Seven statistical and categorical metrics were used to evaluate and compare CHIRPS with gauge measurements over Haihe River basin, China. CHIRPS was in excellent to good agreement with gauge rainfall data at multi-time scales, with the higher R^2 (mainly over 0.70), lower BIAS (mainly under 0.01), ME and RMSE. The good agreement of CHIRPS was increased from monthly scale to annual scale. Based on the IDW methods, the analysis revealed that CHIRPS which has the highly spatial resolution attributes well the spatial distribution over Haihe River basin at multi-time scale. Based on the high values of R^2 at multi-time scale of SPI, CHIRPS shows better applicability for drought monitoring. But it generally shows overestimation of the values of precipitation in Wutaishan station, especially in the region which closed to the mountains. Similarly, CHIRPS overestimated the drought condition. These errors may due to the mismatch in spatial scale. Overall, the good performance of CHIRPS demonstrated that it is a valuable dataset for drought monitoring in this monsoon climate region and also could be worth of the spatial and temporal variability in this region for historical records.

However, some errors still existed which may be caused by the complex terrain and the sparse data observations at mountainous regions. The effects of different terrains were ignored in this study, which may cause additional uncertainties. Although CHIRPS has an mean delay about 3 weeks, it is still capable of providing invaluable information for drought monitoring and climate change with high spatial resolution. The evaluation of temporal and spatial patterns for CHIRPS can better be further improved if more ground stations could be obtained. Investigating characteristics of drought over the past decades in Haihe River basin based on this dataset will be conducted in the future.

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