Assessment of Four Satellite-Based Precipitation Products Over the Pearl River Basin, China

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Abstract
Precipitation is a major driven factor in water cycle and hydrological process. Since satellite sensors have been the main sources for acquiring globally continuous precipitation data, inter-comparison between satellite precipitation products (SPPs) from different sensors becomes increasingly significant, especially at daily or sub-daily scale and in regions suffering from frequent heavy rainfall and floods. This paper assessed the performance of four daily SPPs, including data from the Tropical Rainfall Measuring Mission (TRMM), Climate Hazards group Infrared Precipitation with Stations (CHIRPS), Climate prediction center MORMorphism technique (CMORPH) and Advanced SCATterometer (ASCAT) based Soil Moisture to RAINfall algorithm (SM2RAIN-ASCAT), using the ground gauge measurements from 2010 to 2014 over the Pearl River Basin (PRB), China. Accuracy of precipitation estimates and the capability in detecting rainy/non-rainy days and different precipitation categories were evaluated at both basin and station scale. The findings show that: 1) Performance of the SPPs varies temporally and spatially, and better performance can be observed in wet season and south-eastern part of the PRB, when or where precipitation is abundant. 2) All SPPs have poor performance in estimating extreme precipitation in the PRB; 3) Among the four SPPs, TRMM 3B42 exhibits the best performance in the PRB, followed by CMORPH, while CHIRPS performs the worst and is inapt for precipitation estimates in the PRB; SM2RAIN-ASCAT has quite high estimate errors, but it shows advantages against other products in detecting heavy precipitation events. Findings in this study are compared with recent studies conducted in other regions, and some limitations are discussed. This study provides significant reference for understanding the performance of daily SPPs in the PRB as well as areas with similar climate and surface condition.

Index Terms
Accuracy assessment, satellite precipitation product, the Pearl River Basin, extreme precipitation events.

I. INTRODUCTION
Serving as a significant medium for energy exchange between the land surface and the atmosphere, precipitation is essential for modelling water cycle and has important impact on human living environments [1]–[4]. Understanding precipitation patterns is beneficial to improve the utilization rate of water resources and reduce potential negative effects on human society and environment [2], [5], [6]. The Pearl River Basin (PRB), the second largest basin in China, features...
with abundant but unevenly distributed precipitation. In the last few decades, precipitation in the basin has experienced decreasing trends in the upstream area and increasing intensity in the downstream area, and the number of raining days in the whole basin has been much less than before [7], [8]. Increasing number of high-intensity precipitation events in short period are raising the risk of flood and waterlogging disaster [9], [10]. The shortage of water supply caused by the decreased precipitation in the upstream and the excessive rainwater caused by the intense precipitation in the downstream have aggravated the imbalance of water resources and the uncertainty of water supply in this area [11]. Coupled with rapid population growth and social-economic development, water use policy and management issues are facing great challenges in the PRB [12].

Accurate precipitation data is necessary for analyzing the spatiotemporal characteristics and variation of precipitation in the PRB. In-situ rain gauge measurements are the direct sources of real-time and high-quality precipitation data and provide the most reliable baseline for assessment of other precipitation products. The limited representativeness of in-situ measurements makes it difficult to reflect precipitation patterns at regional scales [13]. In contrast, satellite-based precipitation product (SPP) has high spatial and temporal resolution and wide coverage, thus potentially alleviates the limitation of point-scale observations. At present, a series of SPPs are available, such as products derived from the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis [14], Climate Prediction Center morphing technique [15], United States Geological Survey (USGS) and Climate Hazards Group (CHG) [16], Global Satellite Mapping of Precipitation (GSMaP) project [17], and Integrated Multi-satellite Retrievals for the Global Precipitation Measurement [18].

Large amounts of accuracy assessments of various SPPs have been conducted worldwide, for example, in tropic and subtropical areas [19]–[23], or in different parts of China, e.g., the Tibet Plateau [24], Western China [25], [26], the Yellow River Basin [27], and the Yangtze River and Poyang Lake Basin [28], [29]. These studies reveal that there exist significant uncertainties in precipitation estimates of different SPPs, and suggest assessing the data accuracy in capturing the spatial distribution, temporal variations, and frequency of precipitation events before further quantitative applications. In addition, SPPs from diverse sources usually indicate different characteristics in the same region due to the difference in satellite sensor, data processing algorithm, quality control measures, as well as spatial and temporal resolutions [23], [26], [28]. In order to avoid misunderstanding from single data source, inter-comparison of various SPPs is helpful to recognize the real precipitation patterns in a specific region. The comparison can also be a reference to check the temporal and spatial applicability of each SPP.

The PRB faces with frequent flooding and unbalanced water issues. Intelligent scheduling of water resources for residents’ life and urban development requires high-quality SPPs. However, the existing assessments in the PRB mainly focus on the data accuracy of specific product [8], [9], while the consistency of different SPPs still remains unknown. In this study, four widely-used SPPs are chosen and assessed against ground measurements in the PRB with respect to different statistical and categorical metrics. The objective is to find out the reliable SPP data for hydrological related researches and applications in this region.

The remainder of this paper is organized as follows. The data and evaluation metrics are introduced in Section II and III. Section IV presents the results and discussions of the assessments against ground gauge measurements from 2010 to 2014 in the PRB. Conclusions are drawn in Section V.

II. STUDY AREA AND DATA SOURCES

A. THE PEARL RIVER BASIN

The PRB is located in the southern China, with a latitudinal range of 18°39’N –26°51’N and a longitudinal range of 102°15’ E –117°9’ E (Figure 1). The PRB covers an area of 452,000 km2 with complex terrains including plateau (above 500 m), hill (200 m to 500 m) and plain (below 200m) (Figure 2). Precipitation in this area is abundant but unequally distributed in space and time. The seasonal precipitation in this area is mainly influenced by the East Asian summer monsoon [30], and the impacts in space are affected by the distance from the sea. Consequently, extreme precipitation events are more likely to occur in the downstream area that is close to the sea and has low altitudes [31].

B. SATELLITE PRECIPITATION PRODUCTS

Four SPPs (Table 1) are selected and compared in the PRB in this study. All comparisons are conducted at daily scale after resampling the four SPPs to a spatial resolution of 0.05° through bilinear interpolation. A brief description of each SPP is introduced in the following.

The TRMM Multi-satellite Precipitation Analysis (TMPA) is a quasi-global (60°S-60°N) precipitation data set available at 0.25° spatial resolution at three-hourly, daily, and monthly scales. TRMM is a meteorological satellite specially used for quantitative measurement of precipitation in tropical and subtropical regions (e.g. PRB). Herein, the TRMM 3-hourly version 7 product (TRMM 3B42 V7) is selected to provide a baseline for inter-comparison of diverse SPPs. This product benefits from the advantages of infrared and microwave instruments in monitoring precipitation rates, and further adjustment with gauge observations [32]; hence, it has been proven to be one of the best TRMM-era SPP [21].

The Climate Prediction Center MORPHing technique (CMORPH) provides global precipitation estimates available at 0.25° spatial resolution at three-hourly and daily scales. CMORPH takes advantage of the high spatial resolution of microwave observations and the high temporal resolution of geostationary satellites. It applies the cloud motion vectors
inferred from geostationary images to precipitation estimates derived from microwave observations to produce continuous precipitation estimates over the entire globe [15]. The new CMORPH dataset is reprocessed based on the version 1.0 and exhibits improved accuracy because of an additional bias correction using gauge data. Previous studies indicate that the bias-corrected CMORPH has comparable performance with TRMM 3B42 V7 in regions with complex terrain [20], [24], [28]. Therefore, this dataset is chosen as an alternative for the PRB where terrain rainfall is frequent due to the complex terrain.

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) is a quasi-global (50°S-50°N) long-term precipitation data set available at 0.05° spatial resolution at daily, pentad, and monthly scales. CHIRPS combines high resolution precipitation estimates derived from infrared cold cloud duration observations with ground-based rain gauge observations through interpolation techniques [16]. CHIRPS is originally developed for seasonal drought monitoring. The PRB has experienced severe meteorological and hydrological droughts since early 2000s [33], thus evaluation of CHIRPS is of special meaning.

The SM2RAIN–ASCAT is a quasi-global precipitation product obtained from Advanced SCATterometer (ASCAT) soil moisture data through SM2RAIN algorithm [34], [34]. The SM2RAIN algorithm is based on the inverse solution of soil water balance equation [35]. The underlying assumption is that soil can be regarded as a natural rain gauge to measure precipitation. Compared with the SM2RAIN–CCI (Climate Change Initiative) data, the SM2RAIN–ASCAT includes the latest improvements in the pre- and post-processing of soil moisture and precipitation data as well as of the SM2RAIN algorithm. The temporal consistency between estimates in SM2RAIN–ASCAT data is optimized because of the use of the same sensor in ASCAT soil moisture data [34], but the reliability has not been validated in the PRB. The new dataset (in mm/day) is provided over an irregular grid at 0.1° on a global scale.

C. GROUND GAUGE MEASUREMENT

Daily precipitation data measured at 70 meteorological stations in the PRB, as shown in Figure 2, were used as the
TABLE 2. Expressions of statistical and categorical metrics used for assessment.

| Metrics       | Formula                                                                 | Ideal Value |
|---------------|-------------------------------------------------------------------------|-------------|
| CC            | $CC = \frac{\sum_{i=1}^{N}(S_i - \bar{S})(G_i - \bar{G})}{\sqrt{\sum_{i=1}^{N}(S_i - \bar{S})^2 \sum_{i=1}^{N}(G_i - \bar{G})^2}}$ | 1           |
| RMSE          | $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - G_i)^2}$                  | 0           |
| MAE           | $MAE = \frac{1}{N}\sum_{i=1}^{N}|S_i - G_i|$                            | 0           |
| RB            | $RB = \frac{\sum_{i=1}^{N}(S_i - G_i)}{\sum_{i=1}^{N}G_i}$             | 0           |
| POD           | $POD = \frac{H}{H + M}$                                                 | 1           |
| FAR           | $FAR = \frac{F}{H + F}$                                                 | 0           |
| CSI           | $CSI = \frac{H}{H + F + M}$                                             | 1           |
| Fbias         | $Fbias = \frac{H + F}{H + M}$                                           | 1           |

Note: $H$, short for hit, represents the number of precipitation events correctly detected by SPPs; $M$, short for miss, is the number of precipitation events falsely detected by SPPs; and $F$, short for fail, is the number of precipitation events that SPPs fail to detect. The $H/M/F$ are determined following the rules in TABLE 3.

III. METHODS

A. STATISTICAL METRICS

Four generally used statistical metrics are calculated to quantitively evaluate the performance of SPPs against ground gauge measurements, including the correlation coefficient (CC), root mean squared error (RMSE), mean absolute error (MAE) and relative bias (RB). The CC measures the degree of consistency between the SPP and gauge measurement, and has a value ranging from $-1$ to $1$. The RMSE measures the average magnitude of the error between SPP and gauge data, but is sensitive in detecting extra large or small errors. The MAE represents the average difference between SPP and gauge data. The RB characterizes the underestimation or overestimation of SPP estimates against gauge measurement. Generally, an acceptable performance should get a CC value of more than 0.7 and an RB value between $-10\%$ and $10\%$ [36], [37]. All equations and the ideal values of all metrics are listed in Table 2, where $G$ refers to the ground gauge measurement, $S$ is the SPP estimate, and $n$ is the number of all samples. For comparison in different

time periods, the whole year is divided into wet season (from April to September) and dry season (from October to March).

B. CATEGORICAL METRICS

To evaluate the ability of the SPPs to detect the precipitation events, four categorical metrics are adopted, including the probability of detection (POD), false alarm ratio (FAR), critical success index (CSI) and frequency bias (Fbias). As shown in Table 2, all the four metrics are calculated based on three elements, $H$, $M$, and $F$, which are defined in Table 3. According to the classification of precipitation in climatology, 0.1 mm/day, 25 mm/day and 50 mm/day are chosen as the threshold to distinguish precipitation occurrence, heavy and extreme heavy precipitation events [38]. The POD represents the proportion of precipitation events which are accurately detected by the SPP, and the higher the POD, the more proportion of right precipitation detections; FAR is the opposite [39]. The CSI is a balanced score that combines function of both POD and FAR, showing a comprehensive detection capability of SPP for precipitation events [40]. The Fbias indicates the underestimation (less than 1) or overestimation (larger than 1) of precipitation events detected by the SPP. Generally, the closer the value of POD and CSI to 1, or FAR to 0, the higher the accuracy of SPPs in precipitation event detection.

C. PROBABILITY DENSITY FUNCTION

In hydrometeorological studies, accurate information of the frequencies of precipitation with different intensities is as
TABLE 3. Contingency between gauge and SPP.

| G >= T | G < T |
|--------|-------|
| S >= T | H     | F    |
| S < T  | M     | Z    |

Note: G is gauge measurement, S is SPP estimate, T is threshold, and Z represents the number of precipitation events below the threshold T.

TABLE 4. Precipitation class and corresponding daily precipitation range.

| Precipitation class       | Daily precipitation range          |
|---------------------------|------------------------------------|
| No precipitation          | 0 – 0.1 mm/day                     |
| Light precipitation       | 0.1 – 2 mm/day                     |
| Moderate precipitation    | 2 – 5 mm/day                       |
| Heavy precipitation       | 5 – 10 mm/day                      |
| Extreme heavy precipitation| 10 – 25 mm/day                     |
|                           | 25 – 50 mm/day                     |
|                           | 50 – 100 mm/day                    |
|                           | 100 – 250 mm/day                   |
|                           | >250 mm/day                        |

important as spatial/temporal variation patterns precipitation [41], because the same amount of total precipitation that may be attributable to either slight precipitation of extended time period or heavy precipitation of short duration, usually leads to different consequences. To this end probability distribution function (PDF) of precipitation intensity is calculated to examine whether the statistical characteristics of precipitation intensity are properly captured by SPPs. The precipitation is classified into nine categories (Table 4) according to the standard of World Meteorological Organization (WMO) and the precipitation characteristic in the PRB.

In this study, four SPPs and daily gauge measurements at meteorological stations from Jan 1st, 2010 to Oct 30th, 2014 are collected. Values of precipitation were extracted from the four SPPs at the location of each station. The extracted values were then compared with the gauge measurements at the basin and station scale. For assessments at basin scale, the mean precipitation of the whole basin was calculated by averaging over the 68 stations, and the statistical metrics and categorical metrics were calculated based on the mean values to evaluate the overall performance of each SPP. Frequencies of precipitation with different intensities were also evaluated by comparing the PDFs between the gauge measurements and the four SPPs. At station scale, precipitation values extracted at each individual station were used for calculating the statistical metrics and categorical metrics to reveal the spatial pattern of the estimation accuracy for different SPPs.

IV. RESULTS AND DISCUSSIONS

A. ASSESSMENT ON BASIN SCALE

In this section, the whole PRB is treated as one unit to calculate daily precipitation of gauge measurements and four SPPs. The performance of the four SPPs on characterizing the distribution and variation pattern of daily precipitation is assessed from the perspective of the basin scale.

1) BASIN-AVERAGED DAILY PRECIPITATION

Temporal distributions of the basin-averaged daily precipitation values derived from TRMM 3B42, SM2RAIN-ASCAT, CHIRPS, CMORPH and rain gauges in the PRB from 2010 to 2014 are shown in Figure 3. During the study period, daily
TABLE 5. Statistical characteristics of precipitation from rain gauges and four SPPs.

| SPP                     | Mean | Minimum | 25th Quantile | 50th Quantile | 75th Quantile | Maximum |
|-------------------------|------|---------|---------------|---------------|---------------|---------|
| Whole Period            |      |         |               |               |               |         |
| TRMM 3B42              | 45.79| 0       | 1.66          | 16.29         | 69.31         | 564.82  |
| CHIRPS                  | 46.44| 0       | 2.9           | 18.46         | 63.59         | 512.76  |
| CMORPH                  | 42.92| 0.01    | 2.83          | 16.84         | 63.7          | 497.59  |
| SM2RAIN-ASCAT           | 44.68| 1       | 15.14         | 35            | 64.43         | 241.14  |
| Gauge                   | 45.48| 0       | 3.48          | 20.2          | 65.32         | 438.64  |
| Dry Season              |      |         |               |               |               |         |
| TRMM 3B42              | 19.2 | 0       | 0.54          | 2.36          | 11.61         | 564.82  |
| CHIRPS                  | 19.31| 0       | 0.77          | 5.74          | 19.74         | 500.63  |
| CMORPH                  | 19.18| 0.01    | 1.39          | 3.95          | 14.28         | 497.59  |
| SM2RAIN-ASCAT           | 20.67| 1       | 8.57          | 14.86         | 27.29         | 111.86  |
| Gauge                   | 20.95| 0       | 0.69          | 5.07          | 18.6          | 438.64  |
| Wet Season              |      |         |               |               |               |         |
| TRMM 3B42              | 70.46| 0       | 19.38         | 53.65         | 100.14        | 382.33  |
| CHIRPS                  | 71.82| 0       | 14.64         | 49.74         | 102.37        | 512.76  |
| CMORPH                  | 64.92| 0.06    | 17.99         | 47.89         | 90.31         | 414.97  |
| SM2RAIN-ASCAT           | 66.95| 7.57    | 39.29         | 60.86         | 87.57         | 241.14  |
| Gauge                   | 68.22| 0       | 19.7          | 49.73         | 95            | 377.78  |

Note: Colors indicate the absolute value of relative error (RE) between SPPs and gauge measurements according to the following rules:

- RE ≤ 10%
- 10% < RE ≤ 20%
- 20% < RE ≤ 50%
- 50% < RE ≤ 100%
- RE > 10%

precipitation based on the SPPs and rain gauges consistently show similar temporal patterns that precipitation is intensely gathered from April to September. Compared with the gauge measurements, all the four SPPs capture the overall trend of the daily precipitation in the PRB properly. However, obvious distinctions are observed on some days, especially on the days with intense rainfalls. Among the four SPPs, values derived from TRMM 3B42 and CMORPH show more consistent patterns with the gauge measurements, while values from CHIRPS have larger errors on days with intense rainfalls and values from SM2RAIN-ASCAT exhibit significant errors on most of the days during the study period.

According to the statistical characteristics of the basin-averaged daily precipitation in the PRB (Table 5), the precipitation based on the rain gauges has a mean value of 45.48 mm/day, a minimum value of 0 mm/day and a maximum value of 438.64 mm/day. Mean values of the four SPPs are all within a range of relative error from −10% to 10% compared with the gauge measurement in both dry season and wet season, as well as the whole period. However, the quantiles exhibit difference in various degrees. Compared with the gauge measurements, the difference is minimal in wet season for TRMM 3B42 and CMORPH, and in dry season for CHIRPS. SM2RAIN-ASCAT exhibits much larger values in the lower and middle quartiles but much smaller values in the upper quartile than the gauge measurements, implying that SM2RAIN-ASCAT tends to overestimate low intensity precipitation but underestimate extreme high intensity precipitation. Judging from the overall distribution and the statistical characteristics of the basin-averaged daily precipitation, TRMM 3B42 and CMORPH have better performance in the estimation of precipitation amount than the other two SPPs.

TABLE 6. Statistical metrics of SPP estimates in basin scale from 2010 to 2014.

| METRICS   | PERIOD | TRMM 3B42 | CHIRPS | CMORPH | SM2RAIN-ASCAT |
|-----------|--------|-----------|--------|--------|---------------|
| CC        | 0.81   | 0.72      | 0.77   | 0.76   |
| RMSE (mm/day) | All  | 39.28      | 48.52  | 41.45  | 40.84         |
| MAE (mm/day) |        | 22.40      | 28.37  | 23.64  | 25.40         |
| RB (%)    | 1.36   | 2.66      | -5.66  | -1.74  |
| CC        | Dry    | 0.80      | 0.67   | 0.77   | 0.66         |
|           | Wet    | 0.76      | 0.68   | 0.70   | 0.75         |
| RMSE (mm/day) | Dry | 30.27      | 35.21  | 29.76  | 35.04        |
|           | Wet    | 46.13     | 58.22  | 49.90  | 45.57        |
| MAE (mm/day) | Dry | 13.36      | 16.77  | 13.64  | 18.19        |
|           | Wet    | 30.84     | 39.15  | 32.92  | 32.08        |
| RB (%)    | Dry    | -8.02     | -7.02  | -8.22  | -1.15        |
|           | Wet    | 4.03      | 5.42   | -4.93  | -1.91        |

2) PERFORMANCE ASSESSMENT

The performance of the four SPPs on daily precipitation estimation is assessed based on four statistical metrics, as shown in Table 6 and Figure 4. In terms of estimating the daily precipitation for the whole basin, all the four SPPs show good performances with CC values larger than 0.7 and RB values ranged within −10% to 10%. TRMM 3B42 has the highest CC and the lowest RMSE and MAE, with values of 0.81, 39.28 mm/day, and 22.40 mm/day, respectively, followed by CMORPH, SM2RAIN-ASCAT and CHIRPS. TRMM 3B42 and CHIRPS tend to overestimate daily precipitation of the whole basin with RB values of 1.36% and 2.66%, respectively, while CMORPH and SM2RAIN-ASCAT tend...
to underestimate daily precipitation of the whole basin with RB values of $-5.66\%$ and $-1.74\%$, respectively.

Similar assessment is carried out to assess the performance of daily precipitation estimates of the four SPPs in dry season and wet season. Generally, TRMM 3B42 outperforms other three SPPs in both dry and wet season, with higher CC and lower RMSE and MAE. CMORPH outperforms SM2RAIN-ASCAT in dry season while opposite in wet season. CHIRPS performs poorly in both dry and wet season during the study period. In addition, in dry season, all the four SPPs tend to underestimate daily precipitation values of the whole basin; in wet season, TRMM 3B42 and CHIRPS tend to overestimate while CMORPH and SM2RAIN-ASCAT tend to underestimate.

The ability of the four SPPs to detect daily precipitation events is assessed using four categorical metrics, shown in Table 7. A threshold value of 0.1 mm/day is used to determine whether precipitation occurred on one day. Good performances are observed for all the SPPs in detecting precipitation events. Specially, SM2RAIN-ASCAT and CMORPH are able to detect all kinds of precipitation events, and TRMM 3B42 has a POD value as high as 0.98 and all FAR values below 0.1. Correspondingly, CSI values are above 0.90 for the SPPs except CHIRPS. CHIRPS tends to underestimate while other three SPPs tend to overestimate the number of precipitation events.

With respect to the detection ability of heavy (>25 mm/day) and extreme heavy (>50 mm/day) precipitation events, SM2RAIN-ASCAT shows the highest POD values (0.92 for 25 mm/day and 0.83 for 50 mm/day), followed by TRMM 3B42 (0.83 for 25 mm/day and 0.80 for 50 mm/day). SM2RAIN-ASCAT shows the highest FAR of 0.29 for
detecting heavy precipitation events and 0.28 for detecting extreme heavy precipitation events. TRMM 3B42 performs more reliable than SM2RAIN-ASCAT in detecting heavy to extreme heavy precipitation events. However, all the four SPPs show relatively weaker capability in detecting heavy to extreme heavy precipitation events, compared with other events. In addition, SM2RAIN-ASCAT overestimates the frequency of heavy to extreme heavy precipitation events, while the other three SPPs underestimate these events.

3) PRECIPITATION INTENSITY ASSESSMENT

During the study period, frequency of days with light precipitation (0.1–10 mm/day), moderate precipitation (10–25 mm/day), heavy precipitation (25–50 mm/day), and extreme heavy precipitation (>50 mm/day) account for approximately 31%, 15%, 17%, and 31% of the total number of days, respectively. The PDF of gauge measurements and four SPPs in the PRB are presented in Figure 5. As far as different periods are concerned, SPPs show more consistent frequency distributions with the gauge measurements in wet season than in dry season. CHIRPS presents the similar frequency distribution to measurements in both wet and dry season while other three SPPs show significant differences against the measurement in dry season.

In dry season, TRMM 3B42 and CMORPH overestimate the frequency of light precipitation below 2 mm/day by almost 20 percent, while SM2RAIN-ASCAT underestimates the frequency by more than 20 percent. SM2RAIN-ASCAT shows quite large overestimation for the frequency of precipitation ranged from 10 mm/day to 50 mm/day, while TRMM 3B42 and CMORPH slightly underestimate the frequency. In wet season, TRMM 3B42 and CMORPH exhibit nearly consistent frequency distribution with gauge measurements while SM2RAIN-ASCAT notably overestimates the frequency of precipitation between 25 mm/day and 100 mm/day.

B. ASSESSMENT ON STATION SCALE

In this section, mean daily precipitation during the study period on individual station derived from the four SPPs are used for assessment. The performance of four SPPs on estimating precipitation values and identifying precipitation events are assessed from the perspective of a station scale.

1) SPATIAL DISTRIBUTION OF DAILY PRECIPITATION

The spatial distributions daily precipitation in the PRB using the ordinary Kriging interpolation are shown for gauge measurement and the four SPPs in Figure 6. All interpolations are implemented at the spatial resolution of 0.05°. During the study period, more precipitation occurred in the southern and eastern part of the basin, which is highly related with its terrain and geographical location [42], [43]. Except for SM2RAIN-ASCAT, the other three SPPs manage to capture the general spatial trend of daily precipitation in the basin. TRMM 3B42 exhibits the most consistent spatial pattern with the gauge measurement, with a minor overestimation in the middle area of the basin. Both CMORPH and CHIRPS capture the spatial trend of daily precipitation well in the western part of the basin, however, in the southeast coastal of the basin, CMORPH shows underestimation while CHIRPS shows overestimation for the daily precipitation. SM2RAIN-ASCAT overestimates the daily precipitation level in the northern and western parts of the basin where precipitation is insufficient, which may also testify the finding that it tends to overestimate low intensity precipitation.

2) SPATIAL DISTRIBUTION OF STATISTICAL METRICS

As for the basin scale, four statistical metrics are calculated to assess the performance of the four SPPs on daily precipitation estimation at individual station. The boxplots

| METRICS | CLASS | TRMM 3B42 | CHIRPS | CMORPH | SM2RAIN-ASCAT |
|---------|-------|-----------|--------|--------|----------------|
| PDO     | 0.1   | 0.98      | 0.91   | 1.00   | 1.00           |
|         | 25    | 0.83      | 0.79   | 0.82   | 0.92           |
|         | 50    | 0.80      | 0.73   | 0.74   | 0.83           |
| FAR     | 0.1   | 0.06      | 0.04   | 0.07   | 0.07           |
|         | 25    | 0.12      | 0.18   | 0.13   | 0.29           |
|         | 50    | 0.23      | 0.27   | 0.24   | 0.28           |
| Fbias   | 0.1   | 1.04      | 0.95   | 1.07   | 1.08           |
|         | 25    | 0.94      | 0.97   | 0.94   | 1.30           |
|         | 50    | 0.99      | 1.00   | 0.97   | 1.16           |
| CSI     | 0.1   | 0.92      | 0.87   | 0.93   | 0.93           |
|         | 25    | 0.74      | 0.67   | 0.73   | 0.67           |
|         | 50    | 0.64      | 0.57   | 0.60   | 0.63           |
FIGURE 6. Spatial variability in daily precipitation interpolated from (a) TRMM 3B42, (b) CMORPH, (c) CHIRPS, (d) SM2RAIN-ASCAT, and (e) gauge measurement.

in Figure 7 exhibit the distribution of assessment results of the four SPPs concerning four statistical metrics. The mean values and standard deviations (SD) of the statistical metrics are shown in Table 8.

For the whole period, TRMM 3B42 has the highest CC and the lowest MAE, with the mean values of 0.51 and 48.2mm, respectively, followed by CMORPH, SM2RAIN-ASCAT and CHIRPS. TRMM 3B42 has the lowest RB with a mean of 2.98% and a SD of 11.1%, while SM2RAIN-ASCAT has the highest RB with a mean of 7.5% and a SD of 23.03%. Judging from the positive and negative values, TRMM 3B42, CHIRPS, and SM2RAIN-ASCAT tend to overestimate the precipitation while CMORPH tends to underestimate the precipitation at most stations. All SPPs show higher CC and lower RMSE and MAE in dry season than in wet season, while the performance rankings of the four SPPs in two seasons based on the four statistical metrics present nearly identical patterns, similar to that in the whole period.

The spatial distributions of the four statistical metrics for SPPs are shown in Figure 8 and 9. Generally, locations in the south-eastern downstream have higher CC than those in the north-western upstream in both dry and wet season. TRMM 3B42 performs the best among the four SPPs at most locations. However, locations in the western headstream mountainous area present the lowest RMSE and MAE values for all the four SPPs, probably due to the low intensity of the precipitation in this area. In contrast, locations in the eastern downstream area present much higher RMSE and MAE for the four SPPs, especially in wet season when precipitation is abundant in this area. Judging from the spatial distribution of RB values, TRMM 3B42 and CMORPH exhibit better performance at most locations in wet season and at locations in the upstream area in dry season, while CHIRPS and SM2RAIN-ASCAT show better performance at locations in the downstream area in dry season.
3) SPATIAL DISTRIBUTION OF CATEGORICAL METRICS

Four categorical metrics are calculated to evaluate the detection ability of daily precipitation events for the four SPPs at individual station. The boxplots in Figure 10 exhibit the distribution of assessment results of the four SPPs concerning the four categorical metrics. The mean values and standard deviations of the categorical metrics are shown in Table 9. For detecting whether precipitation occurred (larger than 0.1 mm/day), SM2RAIN-ASCAT presents the highest value of POD and CSI with a mean of 0.87 and 0.55, respectively. However, SM2RAIN-ASCAT also shows the highest FAR with a mean of 0.4 for all the locations, generally caused by the limitation in presenting spurious precipitation events due to high frequency soil moisture fluctuations [34]. Meanwhile, TRMM 3B42 shows the second highest CSI with a mean of 0.5, combining high POD values and low FAR values.

For detecting heavy precipitation events (larger than 25 mm/day) and extreme heavy precipitation events (larger than 50 mm/day), the four SPPs exhibit much higher FAR than detecting general precipitation events. SM2RAIN-ASCAT also shows the highest value of POD, followed by TRMM 3B42 and CMORPH. Comprehensively speaking, TRMM 3B42 performs a little better than other three SPPs in detecting heavy and extreme heavy precipitation events. Judging from Fbias, TRMM 3B42, CMORPH and CHIRPS underestimate the occurrence of precipitation events and overestimate heavy and extreme heavy precipitation events; while SM2RAIN-ASCAT tends to overestimate all precipitation.
FIGURE 8. Spatial distribution of CC and RMSE of the four SPPs against gauge measurement over the PRB from 2010 to 2014. (TRMM refers to TRMM 3B42; SM2RAIN refers to SM2RAIN-ASCAT).

C. DISCUSSIONS

Generally, among the four SPPs, TRMM 3B42 is the most reliable daily precipitation product in the PRB. Beyond that, CMORPH also shows good performance in the assessments. Although SM2RAIN-ASCAT shows large errors, it shows superiority in detecting precipitation events in wet season. Nevertheless, CHIRPS exhibits the weakest performance and seems unable to capture daily precipitation pattern in the PRB, thus it would not be discussed below.

To be more specific, in terms of the agreement with ground gauge measurements, TRMM 3B42 shows the highest CC in both basin scale and station scale, followed by CMORPH and SM2RAIN-ASCAT; while in terms of bias and errors, TRMM 3B42 presents the smallest MAE in both basin scale and station scale, followed by CMORPH and SM2RAIN-ASCAT. In addition, the performance is significantly improved in
basin scale compared with that at station scale, which has also been identified in another similar study [38]. Up to now, good performances of TRMM 3B42 with high CC value and low bias have been detected in many comparison studies of SPPs [29], [44], [45].

TRMM 3B42 tends to overestimate precipitation in wet season and underestimate precipitation in dry season in both basin and station scale, which is attributable to the coarse resolution. Because extreme precipitation events occur over a short period and within a small area, using the detected signal at a specific location to express the precipitation of the whole grid will lead to underestimation for heavy precipitation events that usually occurs in wet season and overestimation for light precipitation events that usually occurs in dry season. SM2RAIN-ASCAT tends to underestimate precipitation in basin scale and overestimate precipitation at station scale because the magnitudes of underestimated stations are much larger than that of overestimated stations. Similar patterns have been detected in other studies. A study in Singapore [19] found that TRMM 3B42 overestimated precipitation from June to November while underestimated precipitation from December to March. A similar study in Yangtze River [28] detected that TRMM 3B42 overestimated precipitation in summer and underestimated precipitation in winter, and CMORPH underestimated precipitation in these studies. However, fewer assessment studies on SM2RAIN-ASCAT have been reported so far.

FIGURE 9. Spatial distribution of RB and MAE of the four SPPs against gauge measurement over the PRB from 2010 to 2014. (TRMM refers to TRMM 3B42; SM2RAIN refers to SM2RAIN-ASCAT).
In terms of capacity to detect precipitation events, TRMM 3B42 comprehensively performs more reliable than SM2RAIN-ASCAT with high POD and low FAR. Nevertheless, all the SPPs represent much larger FAR in detecting heavy and extreme heavy precipitations at station scale, which also has been identified in Li’s study [46]. This implies that SPP data is not sensitive to extreme precipitation events. A number of studies have drawn the same conclusion on the weakness of extreme precipitation estimation of SPPs [45], [47]–[49]. The big gap between the spatial resolutions of SPPs and the point nature of gauge measurements is the main causes of the limitation. Moreover, the inability to identify the classification of precipitation type or distinguish between stratiform and convective precipitation can also reduce the sensitiveness of SPPs to extreme precipitation events.

In terms of capturing frequencies of precipitation with different intensities in regional scale, TRMM 3B42 and CMORPH exhibit close agreements with gauge measurement in wet season, while underestimate frequency of precipitation ranged from 0.1 mm/day to 5mm/day in dry season. Different patterns have been detected in other studies. Wang et al. [38] and Tang et al. [29] found that TRMM 3B42 overestimated the frequency of light precipitation (< 1 mm/day) and heavy precipitation (> 25 mm/day). Tan and Duan [19] noticed that TRMM 3B42 overestimated the frequency of precipitation events.
ranged from 1 mm/day to 20 mm/day and underestimated the frequency of precipitation smaller than 1 mm/day or larger than 20 mm/day. The underestimation of TRMM 3B42 on the frequency of low-intensity precipitation events was detected in Qin’s study [44]. SM2RAIN-ASCAT exhibits quite different frequency distribution among different intensities compared with gauge measurements in this study, showing less or even no frequencies of precipitation smaller than 5 mm/day or larger than 100 mm/day and much more frequencies for precipitation ranged from 5 mm/day to 50 mm/day, especially from 10 mm/day to 25 mm/day. This is significantly attributable to the limitation in underestimation of peak precipitation events [34].

In terms of spatial patterns, TRMM 3B42 exhibits a nearly consistent spatial trend with the gauge measurements, same as the study of Shen et al. [50]. As for the spatial patterns of different metrics, TRMM 3B42 represents a trend of better performance in the south-east downstream area, where the elevation is low and precipitation is abundant. Other studies also point out that SPPs perform better in wet climate zones and that topography has certain impacts on the accuracy of satellite-based retrievals of precipitation [44], [45], [51].

In summary, TRMM 3B42 shows good performance at the daily scale in the PRB in this study. To put our study in context, comparison for numerical values of performance metrics is compared with other similar studies (Table 10) that assess the performance of TRMM 3B42 at daily scale. Most of the studies are conducted in Chinese Mainland and similar results have been shown in similar areas. To date, precipitation estimates of TRMM 3B42 have been proved to

**FIGURE 11.** Spatial distribution of POD and FAR of the four SPPs against gauge measurement over the PRB from 2010 to 2014. (TRMM refers to TRMM 3B42; SM2RAIN refers to SM2RAIN-ASCAT).
have a very good correlation with ground-based precipitation in many areas in China, except for the Tibet Plateau, in which the CC values are less than 0.5. The station-based CC value in this study is smaller than other river basins, such as Yangtze River [28], Ganjiang [29], Mishui [48] and downstream of the PRB [38]. It is generally caused by the low correlations (< 0.4) in upstream of the PRB, where the precipitation is scarce. For relative bias, as shown in Table 9, most studies get a value within a range from −10% to 10%, so does this study. However, the relative bias in Tibet Plateau is large (around 50%), which may be related to the topography and climate condition [49], [53]. For precipitation detection ability of TRMM 3B42, studies in Table 9 present similar results, in which CSI is around 0.50 at grid or station scale. In all, assessments in this study show similar results with other studies. Consequently, results present in this study can be considered reliable.

Nevertheless, there are some uncertainties and limitations in this study. The four SPPs are gridded precipitation data, and the gauge data are point-measured at each station. Value of a grid in SPPs stands for the average precipitation level covering an area of approximately 5 to 25 square kilometers while value of a point only stands for the precipitation at a specific location. Therefore, inaccuracies are inevitable when using station-based gauge measurements as reference for SPP assessments. For study area with dense stations, a common way is to upscale point-based precipitation data from gauges to the same grid scale as SPPs by simply averaging or spatial interpolation [19], [54]. However, for study area with sparse stations, such as the case in this study, upscaling...
TABLE 10. Comparison with other studies on TRMM 3B42 assessment at daily scale.

| Research        | Year     | Study Area            | CC    | RB     | POD/FAR | CSI    |
|-----------------|----------|-----------------------|-------|--------|---------|--------|
| Qin et al. [46] | 2003-2006|                       | 0.66  | -      | 0.58/0.34 | -      |
| Shen et al. [52]| 2005-2007| Chinese Mainland      | 0.67  | -      | -       | -      |
| Tang et al. [54]| 2014     |                       | 0.68  | 4.27%  | 0.70/0.36 | 0.50   |
| Prakash et al. [22]| 2000-2010| India                | 0.85  | 2.21%  | -       | -      |
| Tan et al. [20]| 2014-2016| Singapore            | 0.56  | -10.25%| 0.66/0.15 | 0.65   |
| Ren et al. [47]| 2001-2015| China-Beijing        | 0.59  | -1.41% | 0.70/0.42 | 0.46   |
| Xu et al. [51]  | 2014     | China-Tibet Plateau  | 0.45  | 58%    | 0.80/0.39 | 0.53   |
| Ma et al. [55]  | 2014     | Tibet Plateau        | 0.42a | 48.6%a | -       | -      |
| Li et al [29]   | 2008-2012| China-Yangtze River  | 0.96b | 6.01%b | -       | -      |
| Tang et al. [30]| 2014     | China-Ganjiang       | 0.64  | -1.12% | -       | -      |
| Jiang et al [50]| 2005     | China-Mishui         | 0.78d | -4.54%d | 0.71/0.13d | 0.64d |
| Wang et al. [40]| 1998-2006| China-PRB downstream | 0.65  | 5.37%  | -       | -      |
| This study      | 2010-2014| China-PRB            | 0.81d | 1.36%d | 0.98/0.06d | 0.92*  |

Note: All results were obtained for daily precipitation in terms of yearly mean value of grid (station)-based assessment, except for a: 3h; b: in summer; c: in winter; and d: in regional scale.

would be inadvisable since it may induce large interpolation error. Except for directly using the point-based precipitation, an alternative way is to use triple collocation method, which is a preferable way for assessment when reference values are not accessible. The effectiveness of triple collocation in assessing precipitation product has been verified in several studies [55]–[57]. A further work can be conducted for applying a triple collocation method to repeat the same assessment in the PRB and compare the result with this study.

V. CONCLUSION

The analysis presented in this study provides a comprehensive assessment of four SPPs, namely, TRMM 3B42, CMORPH, CHIRPS and SM2RAIN-ASCAT, in estimating daily precipitation over the PRB, using measurements from 68 gauges during 2010-2014. PRB acts as a representative with intensive precipitation, which could provide references on the performance of current SPPs for areas with similar climate and surface condition. The main findings can be summarized as follows:

1. The TRMM 3B42 and CMORPH capture the overall spatial distribution and temporal variation patterns of precipitation and generally have better performance than other two SPPs in the PRB.

2. Performance of the SPPs varies for different time periods and regions, better performances are observed in wet season and south-eastern part of the PRB, where the precipitation is abundant.

3. All SPPs cannot reflect extreme precipitation events in the PRB properly, consistent with the findings in other areas.

4. Although SM2RAIN-ASCAT has notable absolute errors against gauge measurements, it shows advantage in detecting precipitation events. Therefore, it has potential to be used as supplementary data for identifying precipitation events.

In conclusion, among the four assessed SPPs, the TRMM 3B42 shows the best performance in the PRB. Nonetheless, it still has relatively high estimation errors. Meanwhile, for application in a basin scale, current spatial resolution of TRMM 3B42 is insufficient. Consequently, an additional processing is recommended to improve the estimate precision and spatial resolution of the product before further applying it to related research or application. To this end, method for improving satellite-based daily precipitation product should be developed in future work. Finally, there are some uncertainties and limitations in this study due to the different scales of SPPs and gauge measurements. An alternative way is to apply triple collocation method for assessment. In the future, the assessment in the PRB can be conducted using triple collocation and compared with the result in this study.

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