Calibrating FY4A QPE using CMPA over Yunnan–Kweichow Plateau in summer 2019

Hanyu Lu, Ziyue Huang, Leiding Ding, Tianjian Lu and Yongyi Yuan

ABSTRACT
Accurate satellite-based quantitative precipitation estimates (QPE) with high-quality and fine spatio-temporal resolutions play crucial roles in the meteorological analysis and the research of the global water cycle. The FY-4A is the first satellite of China’s FengYun4 satellite series (FY4 series), the most recent and advanced generation of meteorological satellite operated by China. In this study, China Merged Precipitation Analysis (CMPA, 0.1°/hourly) dataset, generated by combining data of Automatic Weather Stations (AWS) with the Climate precipitation center Morphing (CMORPH), was adopted to calibrating and evaluating the FY-4A QPE (0.04°/half-hourly) by Spatio-Temporal Disaggregation Calibration Algorithm (STDCA), over Yunnan–Kweichow Plateau (YKP). Additionally, we generate new precipitation data called CFY QPE by combining FY4A QPE with CMPA based on STDCA, which has the finer spatio-temporal resolution and higher-quality data. The results indicate that CMPA is suitable in anchoring FY4A QPE, and the systematic biases and random errors of CFY QPE are significantly reduced, especially with a better correlation against gauge in terms of CC (~0.78) and mKGE (~0.7). Besides, the capabilities of capturing precipitation events on CFY QPE significantly improved with POD (~0.82) and FAR (~0.25). Collectively, the significant advantages of STDCA are shown in improving the quality of FY4A QPE.

Introduction
Precipitation is a critical variable in the climate system and plays a crucial role in global water and energy cycles (Z. Q. Ma et al., 2017; Ruhi et al., 2018). High-quality, accurate quantitative precipitation estimates of fine spatio-temporal resolutions are of great significance in various fields, including but not limited to hydrological analysis, water resource management, climate change, and global water cycles (Kling et al., 2012; Hegerl et al., 2015; Ma et al., 2018b). Because precipitation is a complicated atmospheric phenomenon with notable spatio-temporal variations, traditional measurements, such as the rain gauge, which is limited by sparse and uneven distributions, are inadequate for depicting the spatio-temporal patterns of precipitation (Hong et al., 2007; Ma et al., 2017; Ma et al., 2019). Owing to recent years’ frequent heavy rain disasters, satellite-based measurements with their finer resolution have attracted much attention from scientific communities in various fields (Peterson et al., 2012; Tang et al., 2018; Xu et al., 2019).

With the rapid development of satellite-based precipitation measurements in the last few decades, several precipitation estimates, with increasing spatio-temporal resolutions, have been successfully conducted, including the Tropical Rainfall Measurement Mission (TRMM) (Huffman et al., 2007; Kummerow et al., 1998), which is regarded as the stepping stone of satellite-based precipitation measurement, and Global Precipitation Measurement (GPM), GPM resulted in a flexible architecture for precipitation products, such as the TRMM Multi-satellite Precipitation Analysis (TMPA) and the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG), which intercalibrated, merged, and interpolated all MW and IR estimates with gauge data (Ma, Xu et al., 2020a). Subsequently, various calibrated satellite-based precipitation datasets were generated, such as CMAP (Xie & Arkin, 1997), CMORPH (Joyce et al., 2004) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Sorooshian et al., 2000).

The FY series of satellites are the currently operational meteorological satellites of China, comprising two polar orbits and eight geostationary satellites and majorly contributing to monitoring disastrous weather, providing meteorological services and conducting earth system science research. With the increasing influence of the FY series of satellites, calibration for modifying the systematic biases and random errors and evaluation of the quantitative precipitation estimates on the FY series are essential. To anchor the IMERG Final-Run product using the Asian Precipitation – Highly Resolved Observational
Data Integration Towards Evaluation of Water Resources (APHRODITE), Ma et al. proposed a Daily Spatio-Temporal Disaggregation Calibration Algorithm (DSTDCA) which effectively exploited the advantages of satellite-based products and gauge observations. The results demonstrated that the calibrated AIMERG considerably outperformed IMERG at different spatio-temporal scales. In light of the successful application of DSTDCA in generating new, better-quality datasets, the pivotal concept of DSTDCA calibration was used in this study to anchor FY4A QPE calibration using CMPA over the YKP in the summer of 2019.

Materials and Methods

Study Area

The YKP, located in southwestern China with a longitude and latitude range of 100°–111°E and 22°–30°N, was selected as the study area. The YKP includes the eastern Yunnan province, Guizhou province, the northwestern portion of the Guangxi Autonomous Region, and small parts of the Sichuan, Hubei and Hunan provinces. The topography of YKP stepped decreases from northwest to southeast with an elevation ranging from 400 to 3,500 m (shown in Figure 1). Affected by the monsoon of South Asia, the YKP is a humid subtropical area with a subtropical monsoon climate and an uneven distribution of precipitation featuring seasonal variations. Additionally, the heavy and extreme rainfall threshold across the YKP significantly varies, decreasing from southeast to northwest. It is of great significance to research precipitation patterns in the YKP as disasters caused by torrential rain, which indirectly affect the middle and lower reaches of the Yangtze River, occur frequently.

Materials

CMPA

The CMPA is a satellite-gauge merged dataset derived from the conjunction of more than 30,000 hourly AWS data with a strictly quality-controlled CMORPH precipitation product. CMORPH precipitation at 0.1°/hourly is obtained by interpolating and accumulating the original CMORPH with an 8 km/half-hourly scale. An improved PDF-OI method was then applied to reduce the bias and merge it with the rain gauge analysis. CMPA more accurately reflects the actual precipitation event despite the number of gauges and the intensity of precipitation, which is suitable for an area with sparse gauge networks (Shen et al., 2014). The CMPA data could be downloaded from the China Meteorological Data Service Centre (http://data.cma.cn).

FY4A QPE

The FengYun meteorological satellite series is a new generation of geostationary meteorological satellites developed by China. They represent a significant overall improvement over the earlier FengYun2 (FY2) meteorological satellite series in terms of the stability of satellite, ability to scan specific areas with more flexibility, quality and volume of data, and performance of scanning image, among others. The FY4A is the first satellite in the Chinese FY4 series, which was successfully launched on 11 December 2016. The sub-satellite point, located at 104.7°E above the equator and equipped with a 14-channel scanning

Figure 1. The rain gauge network including 323 stations used in this study over the YKP.
radiometer, produced the first regional colourful satellite cloud photograph in 1 min, exceeding the limit of the single visible light channel in FY2. The 0.04° half-hourly precipitation selected in this study results from interpolation based on QPE data derived from FY4A.

Rain gauge data
The rain gauge datasets were collected from the National Meteorological Information Centre of the China Meteorological Administration (http://data.cma.cn). This study used half-hourly gauge precipitation data from 323 strictly quality-controlled rain gauges over the YKP for the summer of 2019. Due to strict data quality control, the rain gauge data are valid and accurate to be employed in related research (Shen et al., 2014). Figure 1 displays the locations of the stations used in this study, indicating the sparse and uneven distribution of these stations. The altitudes of these stations vary from 90 to 3,950 m, with 95.4% of these stations located below 2,000 m.

Methods
Calibration procedure of the Spatio-Temporal Disaggregation Calibration Algorithm
The pivotal concept of calibration used in this study, called STDCA, is based on the DSTDCA proposed by Ma et al. in July 2020, which efficaciously combined advantages both in satellite-based precipitation products and gauge observations. The flowchart of STDCA used in this study is shown in Figure 2, and the main steps are as follows:

1. The FY4A QPE at the hourly scale was obtained by averaging two precipitation intensities in the corresponding hour, which was used to generate the spatial weights to reflect the spatial variations. As the spatial resolution at 0.04°, we selected a 2.5 by 2.5 moving window and obtained the disaggregation weights of spatial variations by calculating the ratios of precipitation estimates at the hourly scale at the centre and the average precipitation estimates in each moving window (Ma et al., 2020b). Afterwards, the temporal weights used in temporally calibrating were obtained by dividing the precipitation at a half-hourly scale by the corresponding precipitation at an hourly scale. It is important to note that the half-hourly temporal weights were set to zero if there is non-precipitation at that period.

2. The CMPA at a spatial and temporal resolution of 0.1°/hourly was geographically matched with the FY4A QPE at 0.04°/hourly scale according to the relationships of geographical positions. Then, the spatially calibrated FY4A QPE data using CMPA at a 0.04°/hourly scale were obtained by multiplying the spatial disaggregation weights in step (1) and the CMPA data at the same scale. Similarly, the process of temporal calibration is multiplying the temporal weights at 0.04°/half-hourly scale with the spatially calibrated FY4A QPE at 0.04°/hourly scale. As a result of a fraction of missing data exist in CMPA data, the grids of those were filling with the nearest effective value. After all steps mentioned above, which take both spatial and temporal variations, the calibration of FY4A QPE using CMPA was completed.

Evaluation
To evaluate the performance of FY4A QPE and the products after calibrating, we selected six metrics, including Correlation Coefficient (CC), BIAS, Root Mean Square Error (RMSE), modified Kring-Gupta Efficiency (mKGE), Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI), as the indicators (Ma et al., 2018b). CC is always used to reflect the degree of correlation among variables, such as the satellite-based data and the gauge observation data; BIAS and RMSE are always used to reflect the error between the satellite-based data and the rain gauge data (Tan et al., 2019); mKGE, a comprehensive relative metric, is suitable for evaluation to balance the contributions of CC, bias and the variability terms (H. Kling et al., 2012); additionally, to indicate the accuracy of satellite-based precipitation products to monitor the rainfall events against the rain gauge observation, POD, FAR, and CSI were
also selected. Specifically, we pre-processed the data of products before evaluating all statistical validation metrics to ensure the validity of the results. The equations of all statistical validation metrics are shown in Table 1.

Results

Spatial Patterns of the Precipitation Over the YKP

The spatial distributions of total precipitation of original FY4A QPE calibrated FY4A QPE data using CMPA, CMPA data, rain gauge data, and rain gauge data generated by using IDW interpolation algorithm in the summer of 2019 (June, July, and August) are demonstrated in Figure 3(a-e), respectively (Ma et al., 2018a). Generally, both distributions of FY4A QPE and CMPA demonstrated a similar trend that the precipitation was decreasing from the northwest to the southeast. The FY4A QPE significantly overestimated and underestimated the precipitation with the CMPA data, especially in the northwest and southeast of the YKP. While compared with CMPA, the calibrated FY4A QPE data using CMPA revealed a great improvement in the distribution and volume of precipitation, which shared a similar pattern. Additionally, compared with the original FY4A QPE data, the calibrated FY4A QPE data using CMPA were closer to the rain gauge data generated using the IDW interpolation algorithm, which means the precipitation estimates of the calibrated product were closer to the true rainfall events.

Table 1. List of the validation statistical metrics for evaluating satellite-based precipitation products in the study.

| Index | Formula |
|-------|---------|
| Correlation coefficient (CC) | \[ CC = \frac{\sum (X_i - \mu_X)(Y_i - \mu_Y)}{\sigma_X \sigma_Y} \] |
| Relative bias (bias) | \[ \text{bias} = \frac{\mu_Y - \mu_X}{\mu_X} \times 100\% \] |
| Root mean square error (RMSE) | \[ \text{RMSE} = \sqrt{\frac{1}{n} \sum (Y_i - X_i)^2} \] |
| Modified Kinger-Guilla efficiency (mKGE) | \[ mKGE = 1 - \sqrt{(CC - 1)^2 + \left(\frac{\mu_X}{\mu_Y} - 1\right)^2 + \left(\frac{\sigma_X}{\sigma_Y} - 1\right)^2} \] |
| Probability of detection (POD) | \[ POD = \frac{TP}{TP + FN} \] |
| False alarm ratio (FAR) | \[ FAR = \frac{FP}{FP + TN} \] |
| Critical success index (CSI) | \[ CSI = \frac{TP}{TP + FN + FP} \] |

Notation: \( X \), the amount of precipitation observed by real data; \( Y \), the estimated values of the satellite-based precipitation product; \( \mu \), the average value of estimated precipitation; \( \sigma \), the standard variance; \( n \), the number of precipitation pairs of real data and the corresponding satellite-based estimates; \( H \), observed precipitation event correctly detected by satellite-based estimates; \( M \), observed precipitation event not detected by satellite-based estimates; \( F \), precipitation event detected by satellite-based estimates but not observed.

![Figure 3](image-url). Spatial distribution of total precipitation in summer of 2019 (June, July, and August) (a) original FY4A QPE, (b) CFY QPE, (c) CMPA, (d) rain gauge data, (e) rain gauge data generated using IDW interpolation algorithm.
**Evaluations on CFY QPE and FY4A QPE Precipitation Products at Daily Scale**

Temporal pattern performance on CFY QPE and FY4A QPE in terms of the CC, bias, RMSE, mKGE, POD, FAR, and CSI against ground observations daily in the summer of 2019 has been depicted in Figure 4, where that of hourly scale accumulated the precipitation at daily scale. Substantially, all statistical validation metrics revealed that CFY QPE was better than FY4A QPE. Most of the CC values on CFY QPE were around 0.8 to 1, significantly improved from FY4A QPE. Regarding bias and RMSE, the values on CFY QPE performed more stable and lower than FY4A QPE. In terms of mKGE, most of the values on CFY QPE are higher than 0.5 in the whole summer, while FY4A QPE performs worse in July and late August with plenty of values below 0. Compared with FY4A QPE, in which a large number of bias values ranged unevenly from 50% to 250%, the bias value of CFY QPE has only one value on July 17 exceeded ~50% and the RMSE on CFY QPE with values ranging from 0 to 15 mm/day performed better than FY4A QPE, especially in July of the summer. As for POD, the values of CFY QPE were above 0.6, and the majority of those were more than 0.8, which were substantially improved from FY4A QPE in June and August. The FAR and CSI on CFY QPE exhibited a similar temporal trend with FY4A QPE in the whole summer. Generally, the FAR values on CFY QPE were lower, and only a few values reached the maximum (~0.5), which were considerably smaller than the maximum on FY4A QPE (~0.85). Similarly, the CSI values on CFY QPE (~0.4) were overall more significant than those on FY4A QPE, which had a fraction of values lower than 0.2.

**Evaluations on CFY QPE and FY4A QPE Precipitation Products at Hourly Scale**

Figure 5 demonstrates scatterplots of the number density of evaluations on FY4A QPE (a) and scatterplots of evaluations on CFY QPE in the summer (b) at an hourly scale over YKP the summer of 2019, which indicated the general comparisons between the FY4A QPE and the CFY QPE (Lu et al., 2020). The CC (~0.78) of CFY QPE significantly outperformed FY4A QPE with CC (~0.25), which validated the CFY QPE was more correlated with rain gauge data than FY4A QPE. The random errors on CFY QPE (~1.11 mm/hour) were also significantly reduced from those on FY4A QPE (~2.02 mm/hour). Additionally, the bias values of FY4A QPE, which showed great overestimation and underestimation, were greatly improved on CFY QPE in each month.

The boxplots illustrated the numerical distributions of evaluation index on FY4A QPE and CFY QPE against the rain gauge data at temporal scale in the summer of 2019 over YKP in Figure 6. Collectively, CFY QPE significantly overwhelmed FY4A QPE in terms of both CC and bias: the CC values of CFY QPE (~0.9) were almost four times larger than those of FY4A QPE (~0.2), and the bias value of CFY QPE in which the median values less than 10% (~8%) were considerably smaller than the FY4A QPE (~70%). In terms of RMSE, the median value of CFY QPE (~0.7) was also reduced from the FY4A QPE (~1.2). Additionally, the POD values of CFY QPE (~0.8) were significantly larger than those of FY4A QPE (~0.3); and the FAR values of CFY QPE (~0.3) were more than twice as small as those of FY4A QPE (~0.7). As a result of which, a better performance was shown on CSI (~0.6), considering both POD and FAR.

The spatial distributions of the difference between statistical validation metrics on CFY QPE and FY4A QPE are shown in Figure 7(a-e). According to the POD difference value, compared with the FY4A QPE, the POD values of CFY QPE were generally improved, especially at the northwest of the study area, in which the values increased more than 0.6; and the significantly increasing with the range of 0.4.

![Figure 4](image-url)  
**Figure 4.** Temporal patterns performance on CFY QPE and FY4A QPE in terms of (a) the CC, (b) bias, (c) RMSE, (d)mKGE, (e) POD, (f) FAR and (g) CSI against ground observations at daily scale in summer of 2019, respectively.
to 0.8 also major distributed at the northwest and slight improvement ranged from 0 to 0.3 occurred over the southeast of YKP. The values of FAR difference indicated that the false alarms were reduced in different degrees on CFY QPE, especially some of those in the north area, which decreased more than 0.55, and the CSI difference obtained by the same parameters also increased mainly from 0.3 to 0.5; These three indicators reflected that the CFY QPE were significantly improved in the capacity of capture precipitation events. The CC difference showed in Figure 7(e) also indicated the CFY QPE were significantly improved with the 0.4–0.8 increase of almost all CC values, even with a fraction of values at the western area more than 0.8–1; and the RMSE difference decreased 0.1 to 1.3 in the northwest and 0.9 to 2.0 in the southeast; both two values mentioned above validated that the relevance and authenticity were improved in CFY QPE. Regarding mKGE difference, CFY QPE generally increased 0.5–1 for mKGE over YKP and increased more than one over north-western of YKP, which also indicated that CFY QPE substantially performed better than FY4A QPE.

Figure 8 displays the spatial distributions of performance in bias values on (a) FY4A QPE and (b) CFY QPE over YKP in the summer of 2019. A large number of bias values on FY4A QPE were lower than −40% in the northwest and larger than 70% in the southeast, indicating that FY4A QPE significantly underestimated and overestimated YKP in the summer of 2019. Regarding the distribution of bias on CFY QPE, the values generally ranged from −20% to 10%, with a fraction of underestimated values (−40% to −20%) in the middle of the study area, which verified that the CFY QPE performed more accurate than FY4A QPE. From what was mentioned above, the CFY QPE outperformed significantly than FY4A QPE in terms of the CC, RMSE, bias, POD, FAR, and CSI.

Figure 9 displays the performance of the temporal pattern between CFY QPE and FY4A QPE in terms of (a) the CC, (b) bias, (c) RMSE, (d) POD, (e) FAR, and (f) CSI against ground observations at hourly scale over YKP in the summer of 2019. Generally, the CC values on CFY QPE (~0.8) were larger about four times than those on FY4A QPE (~0.2) during the entire day. Massive bias values on FY4A QPE (~40%) occurred during the daytime, calibrated to below 25% on CFY QPE. The RMSE of CFY QPE and FY4A QPE showed a similar trend, where the values during the daytime were larger than those in the dark hours, and the values on CFY QPE were overall smaller twice than those on FY4A QPE. In terms of mKGE, CFY QPE improved significantly from FY4A QPE, the values of CFY QPE maintain about 0.5 during the whole day except 4:00. FY4A QPE performed better at the period of 9:00 to 15:00, with the mKGE ranged from −3 to −1. The POD values of FY4A QPE ranging around 0.2 to 0.5 reached their maximum at the period of 11:00 to 12:00 and reached its minimum at the period of 22:00 to 5:00; and the values of CFY QPE were ranged from 0.7 to 0.8 in the entire day, which was more than twice than those of former. The variation of FAR of CFY QPE and FY4A QPE also shared a similar trend that the values at daytime were higher than those at night, and CFY QPE (~0.3) were twice smaller than those of FY4A QPE (~0.65). Additionally, the CSI values of CFY QPE (~0.55) showed a decreased trend at 0 to 7:00 and an increasing trend at 10:00 to 19:00, which were significantly improved from FY4A QPE (~0.15).
Table 2 demonstrates the abilities of CFY QPE and FY4A QPE to detect the rain events for five precipitation intensities for summer in 2019 over YKP. We find that CFY QPE performed better than FY4A QPE for all five precipitations (Shen et al., 2014) intensities, and both two products generally have better performance in terms of POD and CSI with the precipitation increasing. Generally, Especially, POD value of CFY QPE in precipitation of 0.1–1 mm/h is 0.60, which is greatly improved from that of FY4A QPE. As for FAR, the values of CFY QPE reduced half from those of FY4A QPE when precipitation ranged from 0.1 to 8 mm/h. While the precipitation reached 8 mm/hour, the FAR values of CFY QPE reduced to less than 0.1 and those of FY4A QPE were 0.52 and 0.29 in precipitation events of 8–16 mm/h and over 16 mm/h, respectively. Regarding CSI, the values of CFY QPE increased 0.15–0.25 from those of FY4A QPE in all five precipitation intensities. In short, regardless of the precipitation intensity, the CFY QPE has a better performance than FY4A QPE in various degrees.

The summaries of the results for CFY QPE and FY4A QPE at an hourly scale over YK in 2019 were shown in Table 3, which indicated that CFY QPE generally outperformed that of FY4A QPE. According to the CC, the values of CFY QPE (~0.25) were significantly decreased from those of FY4A QPE (~0.78) in the summer. In terms of bias, evident overestimations and underestimations that existed in the values of FY4A QPE were greatly reduced in those of CFY QPE in each month of the summer. The RMSE values of CFY QPE (~1.11 mm/hour) were smaller, nearly twice, than those of FY4A QPE (~2.02 mm/hour). Regarding mKGE, which could balance the contributions of CC, bias and the variability terms, the values of CFY QPE are higher than 0.6 in each month of summer while those of FY4A QPE are smaller than 0.3. As for POD and FAR, the values of CFY QPE (~0.82 and ~0.25) were greatly

Figure 6. The numerical distributions of validation statistical metrics on FY4A QPE and CFY QPE against the rain gauge data in terms of (a) POD, (b) bias, (c) RMSE, (d) POD, (e) FAR and (f) CSI, respectively, at hourly scale over the YKP in 2019.
improved from those of FY4A QPE (~0.38 and ~0.69), and the CSI values of CFY QPE (~0.64) were also larger more than twice than those of FY4A QPE (~0.20). As seen in the results mentioned above, the systematic biases and random errors of CFY QPE were substantially alleviated.

Discussion

The advantages of the STDCA

There are two principal categories of precipitation products derived from ground-based measurement and satellite-based data, respectively. Ground-based measurements such as rain gauges are reliable at the point scale, but these approaches cannot accurately monitor the spatio-temporal variations at large regions (C. Kidd et al., 2017). With the rapid development of satellite-based measurements over the past few decades, those satellite-based precipitation products are capable of monitoring the precipitation with high quality and fine spatio-temporal resolutions (Kidd & Huffman, 2011). In this study, the STDCA comprehensively considered the high spatio-temporal resolution on FY4A QPE and the excellent ability to capture precipitation features on CMPA. After products merging, CFY QPE possesses the high spatio-temporal resolutions on FY4A QPE (0.04°/30 min) and the high-quality data on CMPA. The STDCA

Figure 7. The spatial distributions of difference among validation statistical metrics on CFY QPE and FY4A QPE in terms of (a) POD Difference, (b) FAR Difference, (c) CSI Difference, (d) CC Difference, and (e) RMSE Difference and (f) mKGE Difference at hourly scale over the YKP in summer of 2019, respectively.

Figure 8. The spatial distributions of performance in bias values on (a) FY4A QPE and (b) CFY QPE over YKP in summer of 2019.
significantly reduces the systematic bias and random errors against rain gauges at different temporal scales, and the excellent application of the algorithm in this study could provide references to the calibration of precipitation products.

The advantages and disadvantages of CMPA in anchoring the FY4A QPE

CMPA with hourly and 0.1°×0.1° was generated by merging precipitation product between the gauge and CMORPH using the improved PDF-OI method, which considered the high-frequency features of no-rain events and significantly reduced the systematic biases in the original CMORPH precipitation. Generally, CMPA performs better than CMORPH and TRMM over China with higher quality and stability, which is less affected by the terrain change. Therefore, CMPA has significant advantages in calibrating FY4A QPE at an hourly scale. However, the accuracy of CMPA slightly decreases over the areas with high altitude and slope, which could be further improved by using more real precipitation data. Additionally, the error in the CMPA is also dependent on precipitation intensity, which indirectly impacts the performance of CFY QPE. As the result of the correlation between CMPA and rain gauge data, the evaluation of performance on CFY QPE could be further conducted with other precipitation products (Tang et al., 2020).

Conclusion

Accurate precipitation estimates of satellite-based technology with high-quality and fine spatio-temporal resolutions play crucial roles in meteorological analysis and research of global water cycles. In this study, we evaluated the applicability of calibrating the FY4A by using CMPA with STDCA, and the main conclusions were as follows:

1. The spatial distribution of FY4A QPE and CFY QPE showed a similar trend with ground observations, and the former demonstrated apparent overestimation in the southeast and underestimated in the northwest, over YKP;
2. CMPA was suitable in anchoring FY4A QPE with the STDCA calibration method over YKP;
3. The CFY QPE generated in this study generally outperformed FY4A QPE in terms of the CC, bias,

Table 2. The diagnostic verification for five precipitation intensities for summer of 2019 over YKP.

| Precipitation (mm/h) | POD | FAR | CSI | POD | FAR | CSI |
|----------------------|-----|-----|-----|-----|-----|-----|
| 0.1–1.0              | 0.60| 0.38| 0.47| 0.29| 0.78| 0.14|
| 1.0–2.5              | 0.64| 0.29| 0.50| 0.42| 0.59| 0.26|
| 2.5–8.0              | 0.63| 0.19| 0.55| 0.55| 0.48| 0.36|
| 8.0–16.0             | 0.82| 0.08| 0.76| 0.64| 0.52| 0.38|
| ≥ 16.0               | 0.92| 0.02| 0.91| 0.80| 0.29| 0.60|

Table 3. Summaries of the Results for CFY QPE and FY4A QPE, at hourly scale over YKP in 2019.

| Index | Dataset | June | July | August | Summer |
|-------|---------|------|------|--------|--------|
| CC    | FY4A QPE| 0.29 | 0.25 | 0.22   | 0.25   |
|       | CFY QPE | 0.86 | 0.83 | 0.81   | 0.84   |
| Bias (%) | FY4A QPE | -20.62 | 59.68 | -35.07 | 9.05   |
| RMSE (mm/hour) | CFY QPE | -8.60 | 7.78 | 8.53 | 8.25 |
| mKGE   | FY4A QPE | 2.03 | 2.42 | 1.53 | 2.02 |
| POD    | CFY QPE | 0.24 | 0.05 | -0.01 | 0.20 |
| FAR    | FY4A QPE | 0.74 | 0.69 | 0.66 | 0.70 |
| CSI    | CFY QPE | 0.46 | 0.33 | 0.38 |
|       | FY4A QPE | 0.80 | 0.83 | 0.82 | 0.82 |
|       | CFY QPE | 0.62 | 0.70 | 0.75 | 0.69 |
|       | CFY QPE | 0.23 | 0.23 | 0.32 | 0.25 |
|       | CFY QPE | 0.21 | 0.22 | 0.16 | 0.20 |
|       | CFY QPE | 0.65 | 0.66 | 0.59 | 0.64 |

Figure 9. The temporal patterns performance between CFY QPE and FY4A QPE in terms of (a) the CC, (b) bias, (c) RMSE, (d) mKGE, (e) POD, and (f) FAR and (g) CSI against ground observations at hourly scale over YKP in summer of 2019, respectively.
RMSE and mKGE against rain gauge data both at spatial scales and different temporal scales, over YKP; (4) the capabilities of capturing precipitation events on CFY QPE significantly improved with POD (~0.82), FAR (~0.25), and CSI (~0.64) than FY4A QPE with POD (~0.38), FAR (~0.69), and CSI (~0.20) both at a spatial scale and temporal scale.

In addition, significant advantages of STDCA were shown in this study. These findings above would provide valuable preliminary suggestions for improving the quality of near-real-time satellite-based precipitation products and other fields that would use the precipitation estimates products over YKP.

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Disclosure statement

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Data availability statement

The contribution of the data providers is also greatly appreciated, including the CMPA provider (http://data.cma.cn). Additionally, all data used in this study are all available through the corresponding author.

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