Accounting for spatiotemporal errors of gauges: A critical step to evaluate
gridded precipitation products

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Abstract: Rain gauge observations are commonly used to evaluate the quality of satellite precipitation products. However, the inherent difference between point-scale gauge measurements and areal satellite precipitation, i.e. a point of space in time accumulation v.s. a snapshot of time in space aggregation, has an important effect on the accuracy and precision of qualitative and quantitative evaluation results. This study aims to quantify the uncertainty caused by various combinations of spatiotemporal scales (0.1° – 0.8° and 1–24h) of gauge network designs in the densely gauged and relatively flat Ganjiang River basin, South China, in order to evaluate the state-of-the-art satellite precipitation, the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG). For comparison with the dense gauge network serving as “ground truth”, 500 sparse gauge networks are generated through random combinations of gauge numbers at each set of spatiotemporal scales. Results show that all sparse gauge networks persistently underestimate the performance of IMERG according to most metrics. However, the probability of detection is overestimated because hit and miss events are more likely fewer than the reference numbers derived from dense gauge networks. A nonlinear error function of spatiotemporal scales and the number of gauges in each grid pixel is developed to estimate the errors of using gauges to evaluate satellite precipitation. Coefficients of determination of the fitting are above 0.9 for most metrics. The error function can also be used to estimate the required minimum number of gauges in each

39 grid pixel to meet a predefined error level. This study suggests that the actual quality of
40 satellite precipitation products could be better than conventionally evaluated or expected,
41 and hopefully enables non-subject-matter-expert researchers to have better understanding
42 of the explicit uncertainties when using point-scale gauge observations to evaluate areal
43 products.

44 **Key terms:** Precipitation; IMERG; rain gauge; gauge density; evaluation; error function

1. Introduction

Precipitation is one of the most critical components in the global water and energy cycles. However, accurate measurement of precipitation has been challenging due to its high spatiotemporal variations. In general, there are three main approaches to observing precipitation, i.e., rain gauges, weather radars, and satellite sensors (Li et al., 2013). Novel approaches to precipitation estimation are also being developed and provide more alternatives based on various data sources, such as soil moisture and water storage changes (Behrangi et al., 2017; Ciabatta et al., 2015). Nevertheless, only satellite remote sensing provides global coverage of precipitation estimation (Tian and Peters-Lidard, 2010).

Various multi-satellite precipitation products have been made available in recent years, such as the Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (IMERG) (Huffman et al., 2017), Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) (Huffman et al., 2007), Climate Prediction Center (CPC) MORPHing technique (CMORPH) (Joyce et al., 2004), and Global Satellite Mapping of Precipitation (GSMaP) (Kubota et al., 2007). However, satellite precipitation products are also subject to various systematic and random error sources, including deficiencies in algorithms, inadequate spatiotemporal sampling, and instrument limitations (Xie and Arkin, 1997). These errors are characterized by regional and seasonal variations and could be propagated into studies that use the data (Hong et al., 2006). A

65 large number of studies have been conducted to quantify errors of satellite precipitation
66 products for better applications and further improvements (Behrangi et al., 2011; Shen et
67 al., 2010; Tang et al., 2016b; Tang et al., 2016c; Yong et al., 2013).

68 Rain gauges are commonly employed to evaluate the performance of satellite
69 precipitation products because of the advantages of direct and accurate measurement,
70 sizeable spatial coverage, long time span, and simple data acquisition and processing.
71 However, rain gauges are also subject to errors such as the wind-induced undercatch,
72 trace amount, wetting and evaporation loss (Adam and Lettenmaier, 2003; Ma et al., 2015;
73 Yang and Ohata, 2001). In addition, accumulated precipitation of rain gauges is different
74 with satellite precipitation with temporal sampling errors resulting from repeated
75 temporal gaps, which contributes to uncertainties in the evaluation. Furthermore,
76 point-scale gauge observations can deviate far from true areal precipitation. For example,
77 Wood et al. (2000) indicated that the standard error of precipitation based on a single
78 gauge is around 33% in a 2×2 km grid pixel. Jensen and Pedersen (2005) found that
79 variation in accumulated precipitation from 9 gauges in a 500×500 m pixel is even up to
80 100% between neighboring gauges over a 4-day period. Villarini et al. (2008) suggested
81 that over 25 gauges are needed to make the error of average rainfall within 20% of the
82 actual rainfall in a pixel of ~200 km² at the 15 min scale. Therefore, the mismatch
83 between continuously accumulating point-scale gauge observations and snapshot areal
84 satellite precipitation has a marked impact on evaluation results.

85 However, currently there seems to be no better alternatives compared to rain gauges for
86 the evaluation of satellite precipitation products. Unfortunately, publicly accessible rain
87 gauges are very sparse in most regions of the world, especially mountainous areas such as
88 the Tibetan Plateau (Gao and Liu, 2013). Interpolation methods such as inverse distance
89 weighting, nearest neighbor, and kriging can be employed to transfer point-scale
90 observations to areal estimates (Vicente-Serrano et al., 2003). However, interpolation also
91 brings additional uncertainties and the quality of interpolated precipitation in grid pixels
92 without gauges is typically lower than that in grid pixels with gauges (Tang et al., 2016b).

93 To ensure the reliability of results, assessment of satellite products is often conducted in
94 grid pixels containing at least one gauge or close to gauges (Asong et al., 2017; Cohen
95 Liechti et al., 2012; Salio et al., 2015; Shen et al., 2010; Tang et al., 2016b; Xu et al.,
96 2017). To acquire more representative areal precipitation using rain gauges, some studies
97 set a minimum number (> 1) of gauges contained in each grid pixel (Tan and Duan, 2017;
98 Xue et al., 2013; Yong et al., 2014; Yong et al., 2010; Yong et al., 2013). For instance,
99 Yong et al. (2014; 2010; 2013) only selected grid pixels containing at least two gauges to
100 evaluate the performance of TMPA 3B42 and 3B42RT products in two basins at 0.25°
101 and daily scales. Some studies are conducted in regions with highly dense rain gauges
102 and can achieve more reliable results (Tan et al., 2016; Tan and Duan, 2017). However,
103 such regions are universally small in area, and similar studies are typically not possible in
104 most regions of the world.

105 Despite these efforts to involve as many gauges as possible, only a few studies
106 investigate the uncertainties of using rain gauges to evaluate satellite or radar
107 precipitation (Mandapaka et al., 2009; Rudolf et al., 1994). For radar rainfall evaluation,
108 some studies use highly dense gauge networks to evaluate errors and spatial correlation in
109 small experimental regions, and explore the effect of gauge configuration (Mandapaka et
110 al., 2010; Villarini et al., 2008). In addition to radar estimation errors, gauge sampling
111 errors also contribute to difference between radar and rain gauge rainfall, and generally
112 decrease with increasing time scales (Peleg et al., 2013). Similarly, for satellite
113 precipitation evaluation, it is important to investigate the reliability of evaluation results
114 based on rain gauges, and understand the accuracy of metrics used to indicate the quality
115 of evaluated objects.

116 Therefore, the objectives of this study are twofold: (1) comparing the metrics of satellite
117 precipitation products based on sparse and highly dense gauge networks at 0.1° – 0.8° and
118 1–24 h scales from June to August 2014 in the Ganjiang River basin in South China; and
119 (2) proposing an error function of spatial scales, temporal scales, and gauge numbers to
120 characterize the errors of using rain gauges to evaluate satellite precipitation products.

121

2. Study area, data sets, and methods

2.1 Study area

The study area covers 24° N–29.4° N and 113° N–117° N, which is centered by the Ganjiang River basin, China, with a highly dense rain gauge network (Figure 1). For simplicity, the entire study area is referred to as the Ganjiang River basin. The topography of this region is characterized by hills in the southern part and alluvial plains in the northwestern part with elevations ranging from 7 m to 1997 m. The climate is dominated by the East Asian monsoon (Tang et al., 2016c). Previous studies indicated that satellite precipitation products including TMPA and IMERG perform well in the Ganjiang River basin from statistical and hydrological perspectives (Hu et al., 2014; Tang et al., 2016c).

Figure 1. (a) Spatial distribution of rain gauges, and DEM of the study area which is centered by the Ganjiang River basin. (b) Location of the study area in China.

2.2 Data sets

2.2.1 Rain gauges

Hourly rain gauge data were acquired from the China Meteorological Administration (CMA) (Shen et al., 2014). The total number of gauges is 3032, which is large for the study area with a latitude span of 5.4° and longitude span of 4° . The study period is from June to August 2014, corresponding to the warm season in the Ganjiang River basin, because rain gauges are less reliable in cold seasons. The hourly gauge observations have undergone preliminary quality control such as extreme rainfall intensity check (Shen et al., 2014). However, due to various unpredictable instrument problems, further quality control is performed to ensure persuasive validation of satellite products (refer to Section 2.3.1).

2.2.2 IMERG products

The Global Precipitation Measurement (GPM) mission aims at providing the next generation of global precipitation products after the TRMM satellite was decommissioned in 2015. IMERG provides combined-satellite Level 3 products at 0.1° and 30 min resolutions. Compared with TMPA 3B42 and 3B42RT, by and large, IMERG improves the accuracy of precipitation estimation (Ma et al., 2016; Tang et al., 2016a).

IMERG has three products: the near-real-time Early and Late run, and the post-real-time Final run. The Final run incorporates gauge data from the Global Precipitation Climatology Centre (GPCC) and is characterized by high accuracy but large latency. We used the IMERG Late run product (referred as IMERG-L for simplicity) to avoid the problem of gauge dependence. GPCC and CMA have overlapping gauges although the number is minimal compared to the CMA gauge number. However, at coarse spatial scales (e.g., 0.8°), many grid pixels could contain a few GPCC gauges and affect the evaluation results.

2.3 Methods

2.3.1 Rain gauge quality control

Three quality control strategies were used, including missing data check, zero value check, and correlation check. For missing data check, if the proportion of missing data in the hourly data series exceeds 10%, the rain gauge is excluded. To conduct zero value check and correlation check, rain gauges within each $0.2^\circ \times 0.2^\circ$ grid pixel are grouped into pairs. Note that the 0.2° scale is only used for quality control. It is reasonably assumed that the hourly precipitation observations of all gauges in the same pair should not exhibit distinct climatological differences. For zero value check, we calculated ratios of zero values to the number of all samples for all the gauges and the mean ratio for each data pair. For each pair, a gauge is removed if its zero ratio is larger than 1.5 times or smaller than 0.5 times that of the mean zero ratio. This problem arises probably due to (1)

173 some missing values being recorded as zero, and (2) format issues in some data records.
174 For correlation check, we first calculated the correlation coefficient (CC) between each
175 gauge and all the other gauges belonging to the same pair. Then, the mean CC was
176 acquired for each gauge. A gauge is excluded if its mean CC is lower than the predefined
177 threshold (0.4) determined by trial and error. The correlation problem could be attributed
178 to less-obvious instrument anomalies.

179 As a result, 347 gauges which account for ~11.5% of the total number, were excluded
180 after the three steps of quality control. We also validated the effectiveness of the quality
181 control strategies by manually checking the hourly data series of those excluded gauges.
182 Results indicate that most of these gauges were indeed subject to quality problems, and
183 could cause nonnegligible errors in the study.

184 **2.3.2 Metrics**

185 To comprehensively assess the performance of satellite precipitation products, we utilized
186 six metrics. CC denotes the correlation between rain gauges and satellite products.
187 Normalized root mean square error (NRMSE) and relative bias (BIAS) denote the error
188 characteristics of satellite products. Instead of RMSE, NRMSE is adopted because it
189 avoids increasing values with increasing temporal scales. Their formulas are

$$190 \quad CC = \frac{\sum_{i=1}^n (S_i - \bar{S}) \cdot (G_i - \bar{G})}{\sqrt{\sum_{i=1}^n (S_i - \bar{S})^2 \cdot (G_i - \bar{G})^2}} \quad (1)$$

$$191 \quad \text{BIAS} = \frac{\sum_{i=1}^n (S_i - G_i)}{\sum_{i=1}^n G_i} \quad (2)$$

$$192 \quad \text{NRMSE} = \frac{\sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (S_i - G_i)^2}}{\bar{G}} \quad (3)$$

193 where n is the number of samples, S_i is satellite estimated precipitation, G_i is gauge
 194 observed precipitation, and $\bar{S}$ and $\bar{G}$ are their mean values, respectively. The perfect
 195 values are 1 for CC, and 0 for BIAS and NRMSE, respectively.

196 In addition, three contingency metrics were used, including probability of detection (POD)
 197 representing the ratio of events correctly detected by satellite products, false alarm ratio
 198 (FAR) representing the ratio of events falsely reported by satellite products, and critical
 199 success index (CSI) as a function of POD and FAR providing more balanced judgement
 200 of satellite products. To calculate the three contingency metrics, we used a threshold to
 201 determine rain or no rain (RN) which was defined as 0.1 mm for 1 h. Thresholds for other
 202 temporal scales (3–24 h) were accumulated from the hourly threshold. For example, the
 203 threshold is 0.3 mm at the 3 h scale. Uniform thresholds for all temporal scales are also
 204 tested in Section 3.3.3. Formulas of POD, FAR, and CSI are given as follows:

$$205 \quad \text{POD} = \frac{H}{H + M} \quad (4)$$

$$206 \quad \text{FAR} = \frac{F}{H + F} \quad (5)$$

$$207 \quad \text{CSI} = \frac{H}{H + M + F} = \frac{1}{1/(1 - \text{FAR}) + 1/\text{POD} - 1} \quad (6)$$

208 where H is the number of hits, M is the number of misses, and F is the number of false

alarms. A hit occurs when both gauge and satellite precipitation is larger than RN . A miss occurs when gauge precipitation is larger than RN while satellite precipitation is smaller than RN . A false alarm occurs when gauge precipitation is smaller than RN while satellite precipitation is larger than RN . The perfect values are 1 for POD and CSI, and 0 for FAR, respectively.

2.3.3 Quantifying the uncertainties in evaluation

(1) Generating sparse gauge networks

In this study, a sparse gauge network is defined as the one that the number of gauges in each grid pixel is small such that it cannot well represent areal precipitation. For example, if a 0.25° grid pixel only contains one gauge, it is definitely sparse. A dense gauge network is the one that can be taken as the closest to true precipitation. However, the dense networks in this study could also contain uncertainties caused by insufficient densities and instrument errors (e.g., undercatch). Like many previous studies (Tang et al., 2016c; Yong et al., 2014; Yong et al., 2013), we did not correct undercatch by gauges which has small effect in the study region.

Sparse gauge networks are generated from the dense gauge network in the Ganjiang River basin. The spatial scales (s) are from 0.1° to 0.8° , and the temporal scales (t) are from 1 h to 24 h. Although the s of most satellite precipitation products is not larger than 0.25° , the resolution of some reanalysis products such as ERA-Interim can be coarser. For an arbitrary combination of s and t , only grid pixels (G_{st}) containing more gauges

than a predefined threshold (TH_{st}) are involved in the evaluation to represent the dense network. TH_{st} should be as large as possible so that the average precipitation of all gauges in each grid pixel can approximate true areal precipitation. TH_{st} is determined through sensitive analysis in Section 3.2.

The spatial distribution of G_{st} in the study area is not necessarily even, which does not affect the results because we focus only on the differences between sparse and dense networks. A sparse gauge network (G'_{st}) was generated by randomly selecting a certain number (N_{st}) of gauges in each grid pixel of G_{st} . Therefore, G'_{st} has the same grid pixels as G_{st} , whereas the number of gauges in each grid pixel is N_{st} which is much smaller than TH_{st} . The locations of the N_{st} gauges at the sub-grid scale could also be uneven. For example, if these gauges are all located at the corner of the pixel, the mean precipitation of N_{st} gauges could deviate far from true areal precipitation. To reduce such uncertainties, we randomly generated 500 independent sparse gauge networks (referred to as G_{st}^{500}). The number 500 was determined through sensitivity analysis. We found that the results remain almost the same as the number of independent sparse gauge networks changes from 100 to 1000. Finally, 500 was selected for the balance between sample numbers and computational efficiency.

(2) Estimating the error of metrics based on sparse gauge networks

For each combination of s and t , satellite precipitation was resampled from the IMERG-L product at the original 0.1° and 30 min resolutions. Specifically, precipitation at coarser

spatial scales is averaged from 0.1° scale, and precipitation at various temporal scales was accumulated from 30 min. Satellite precipitation was evaluated using G_{st} as benchmark. We presume that the six metrics (Met_T) were close to the true metric values due to the large number of gauges in each grid pixel. Then, metrics based on sparse gauge networks (Met_S) were derived through evaluation of satellite precipitation using G'_{st} . The error of Met_S is calculated as

$$\Delta\text{MET} = \frac{\text{Met}_S - \text{Met}_T}{\text{Met}_T} \times 100\% \quad (7)$$

where Met represents CC, BIAS, NRMSE, POD, FAR and CSI. For example, CC_T and CC_S represent the CC based on dense gauge networks (G_{st}) and sparse gauge networks (G'_{st}), respectively. The error of CC_S benchmarked by CC_T is ΔCC . For G_{st}^{500} comprising 500 G'_{st} , ΔMET^{500} is acquired. ΔMET is the mean of ΔMET^{500} , and represents the bias of using sparse gauge networks to evaluate satellite products.

(3) *Error function*

Hong et al. (2006) proposed a power-law function of s , t , rain intensity, and sampling frequency to express the error of precipitation estimates. This study aims at expressing the error of metrics, which nonlinearly changes with s , t , and N_{st} . Following the form of Hong et al. (2006) which shares some similarities with this study, a nonlinear error function of s , t and N is developed to estimate ΔMET .

$$\Delta\text{MET} = a \cdot s^b \cdot t^c \cdot N_{st}^d \quad (8)$$

where a , b , c , and d are parameters. Different metrics exhibit different error patterns and thus different signs of the parameters. Eq. (8) can also be used to determine the density of gauges that delivers a predefined accuracy level. To control the errors of metrics within a specific range (ΔMET^s , e.g., $\pm 5\%$), the minimum number of gauges (N_{st}^s) required in each grid pixel can be calculated using Eq. (9). An example of application is given in Section 3.4.

$$N_{st}^s = \left(\frac{\Delta\text{MET}^s}{a \cdot s^b \cdot t^c} \right)^{1/d} \quad (9)$$

3. Results

3.1 Spatial distribution of precipitation

Figure 2 compares the IMERG-L mean precipitation map with gauge observations in the Ganjiang River basin. There is a notable precipitation band in the central area and a hotspot in the southwest region, which is captured by both gauges and IMERG-L. However, IMERG-L overestimates precipitation in the northwest area. The mean IMERG-L and gauge precipitation is 5.68 mm/d and 6.51 mm/d, respectively, indicating that overall IMERG-L underestimates precipitation by -12.67%. The CC between IMERG-L and gauge precipitation is 0.46 at the 0.1° and 1 h scale, which is much higher than that in western and northern China (Tang et al., 2016b).

Figure 2. Precipitation distributions of (a) Gauge and (b) IMERG-L from June to August 2014 in the Ganjiang River basin.

3.2 Evaluating satellite products using highly dense gauges

3.2.1 Determining the number of gauges in each grid pixel

A sensitivity analysis of TH_{st} was conducted to determine the minimum number of gauges that can be taken as the closest to true areal precipitation in each grid pixel. The spatial scales were from 0.1° to 0.8° . The temporal scale was chosen to be 1 h because TH_{st} at coarser temporal scales should be smaller than that at the hourly scale. As TH_{st} increases, the number of qualified grid pixels in the basin decreases. We first determine the maximum TH_{st} at each spatial scale which is termed as Threshold 4 (T4). T4 is set

as large as possible, but also keeps the number of qualified grid pixels within a reasonable range. The process was completed by continued trial. Then, we obtained the numbers of Thresholds 1–3 (T1–T3) by reducing the number of T4 gradually as shown in Table 1. T1–T3 had smaller numbers of gauges in each grid pixel but larger number of qualified pixels, which could be beneficial to acquiring comprehensive evaluation results. Table 1 shows the numbers corresponding to T1–T4. G_{st} was acquired using T4 as TH_{st} at all spatial scales. Then, G_{st}^{500} was acquired from G_{st} using T1, T2, and T3 as N_{st} , respectively, according to the method in Section 2.3.3. Finally, ΔMET was obtained by comparing G_{st} and G_{st}^{500} , which represents the gap between T1–T3 and T4.

The smaller ΔMET , the closer the threshold to the “ideal” density, because marginal benefits of increasing TH_{st} gradually decrease. Therefore, appropriate TH_{st} can be determined according to the magnitude of ΔMET . If ΔMET stabilizes, the corresponding threshold can be regarded as dense enough. CC, NRMSE, and CSI were selected to analyze ΔMET . Other metrics also have similar error characteristics although they are not included in this section. The advantage of this method is that scenarios close to actual evaluation studies are created, and both temporal and spatial variations of the data series are considered. The method is better than just comparing mean areal precipitation of gauges which cannot reflect the temporal variations of data series.

Table 1 Four sets of thresholds used to determine the minimum number of gauges that can approximate true areal precipitation in each grid pixel at 0.1°–0.8° and 1 h scales.

Spatial Scale	0.1°	0.2°	0.3°	0.4°	0.5°	0.6°	0.7°	0.8°
Threshold 1 (T1)	4	8	18	27	35	45	62	90
Threshold 2 (T2)	5	10	20	30	40	50	70	100
Threshold 3 (T3)	6	12	22	33	45	55	78	110
Threshold 4 (T4)	7	14	24	36	50	60	86	120

316 Figure 3 shows that metrics based on T1–T3 are all slightly worse than those based on T4,
 317 indicating that IMERG-L agrees better with denser gauge networks compared with sparse
 318 gauge networks. ΔMET decreases as the number increases from T1 to T3. Overall, the
 319 errors of all the three metrics are very small, particularly at 0.3°–0.8° scales with the
 320 absolute values of ΔMET generally smaller than 1%. At 0.1°–0.2° scales, ΔMET
 321 values are slightly larger, especially for T1, indicating that the numbers of gauges are
 322 relatively insufficient. Although T3 and T4 are the closest to the ideal situation, we chose
 323 T2 (see Table 1) as the TH_{st} because of its small ΔMET within $\pm 1.5\%$ benchmarked
 324 by T4. More importantly, the number of qualified grid pixels based on T3 or T4 is too
 325 small compared with that based on T2, which is undesirable when assessing satellite
 326 precipitation.

327 We also used the variance reduction factor (VRF) to assess the accuracy of pixel-average
 328 precipitation provided by T2 (Peleg et al., 2013; Villarini et al., 2008). Small VRF
 329 indicates that the uncertainties of using pixel-average precipitation to represent true areal
 330 precipitation are small. VRF values are generally smaller than 2% at 0.3°–0.8° and 3–24

h scales (supplemental file: Figure S1). However, VRF is much larger at the 0.1° scale with values ranging between 5% and 7.6%, indicating that the gauge network is still not dense enough. This problem is inevitable because it is impractical to deploy a sufficient dense network at the 0.1° scale in a region as large as the Ganjiang River basin. Therefore, the estimated metrics based on the dense gauge network can only approach but never reach true metrics. ΔMET calculated in this study is actually slightly smaller than the actual errors, particularly at small spatial scales.

Figure 3. (a) Number of gauges corresponding to the four sets of thresholds (T1–T4) at 0.1°–0.8° scales. (b) The relative bias of CC based on T1–T3 benchmarked by that based on T4 at 0.1°–0.8° and 1 h scales. (c) and (d) are similar to (b) but for NRMSE and CSI, respectively.

3.2.2 Metrics based on dense gauge networks

Locations of G_{st} based on T2 at 0.1° – 0.8° scales are shown in Figure 4. The spatial distributions are uneven, with more pixels in the western and central parts and fewer pixels in the eastern and southern parts. Therefore, the metrics derived in this study may not represent the average situation in the Ganjiang River basin. Nevertheless, we focus on the difference between sparse and dense gauge networks, which is not affected by this problem.

Figure 4. Locations of grid pixels (blue boxes) at 0.1° – 0.8° scales in the study area. Only grid pixels that contain a specific number of gauges as shown in the bottom of each subfigure are included.

As the spatial scale increases from 0.1° to 0.8° and the temporal scale increases from 1 h to 24 h, most metrics are notably improved, i.e., increasing CC, POD, and CSI, and

decreasing FAR and NRMSE (Figure 5). This result is consistent with previous studies on the scale effect of the performance of satellite precipitation products (Hong et al., 2006; Tang et al., 2016b). Note that we used NRMSE in this study (Figure 5b). RMSE will exhibit a different trend with better performance (smaller values) as the spatial scale decreases and the temporal scale increases because accumulated precipitation is used to calculate the metric. Despite the difference, RMSE and NRMSE lead to similar errors of metrics.

Different from the other metrics with clear and regular changing patterns, BIAS remains almost the same when the temporal scale changes, and is irregular at different spatial scales (Figure 5c) chiefly due to the shifting positions of the grid pixels that qualify at each spatial scale (Figure 4). BIAS has strong spatial variation resulting in different values at the eight spatial scales. Further comparison shows that grid pixels at different scales exhibit similar BIAS values if these pixels are close to each other in location, indicating that BIAS will remain consistent if calculated in the same regions. It should also be noted that although the color contrast is conspicuous in Figure 5c, the extent of BIAS is narrow ranging between -8% and -12%.

Figure 5. (a) CC, (b) NRMSE, (c) BIAS, (d) POD, (e) FAR, and (f) CSI based on highly dense gauge networks at 0.1° – 0.8° and 1–24 h scales from June to August 2014 in the Ganjiang River basin. The threshold used for rain/no rain determination is 0.1–2.4 mm at 1–24 h scales, respectively.

3.3 Errors of metrics based on sparse gauge networks

3.3.1 Histograms of metrics

Figure 6 compares CCs based on 500 sparse gauge networks (G_{st}^{500} , refer to Section 2.3.3) and CC_T based on highly dense gauge networks (G_{st}). CCs was calculated in the same grid pixels with CC_T (Figure 4), while each grid pixel only contains one gauge. This density of gauges is common in the evaluation of satellite precipitation products at 0.1° or 0.25° scales, although in reality grid pixels with larger sizes such as 0.8° generally contain more gauges.

CC_T is much higher than CCs at all the temporal and spatial scales. As the temporal scale

decreases and the spatial scale increases, the gap between CC_T and CC_S becomes larger. Even at the 0.1° and 1 h scales for which the gap is smallest, CC_T is 0.46 while the mean of CC_S is only 0.39 with a negative ΔCC up to -15%. Moreover, each of the 500 CC_S is smaller than CC_T at all spatiotemporal scales, indicating that the performance of satellite products is always underestimated by a sparse gauge network without exception. Increasing gauge numbers contained in each grid pixel can narrow but not eliminate the gap. NRMSE, POD, FAR and CSI all exhibit similar phenomena (not shown).

Figure 6. Histograms of CC between satellite precipitation estimates and rain gauge observations based on 500 sparse gauge networks at $0.1^\circ/0.3^\circ/0.8^\circ$ and 1/3/24 h scales. Each grid pixel contains one gauge. Red lines represent CC based on highly dense gauge networks.

BIAS is different from the other metrics as shown in Figure 7. $BIAS_T$ is located within the extent of $BIAS_S$. However, the mean of $BIAS_S$ is closer to zero compared to $BIAS_T$

at all spatial scales. For example, at the 0.1° and 1 h scale, BIAS_T is -10.45% while the mean of BIAS_S is -6.22%. Furthermore, the BIAS_S of 198 networks among all the 500 sparse networks is positive, which means that evaluation based on ~40% of the sparse gauge networks will draw an opposite conclusion with the dense gauge network concerning BIAS. Therefore, one should be cautioned with the nominal BIAS of satellite products if the gauge network is relatively sparse. It is not certain whether satellite products overestimate or underestimate precipitation if the BIAS value is close to zero.

Figure 7. Same as Figure 6 but for BIAS.

3.3.2 Errors of metrics at different spatiotemporal scales

ΔMET of all the six metrics was calculated according to Eq. (7) at 0.1° – 0.8° and 1–24 h scales as shown in Figure 8. Each grid pixel contains only one gauge. For CC, CSI and

NRMSE, ΔMET becomes larger as the spatial scale increases and temporal scale decreases (Figure 8a, b, and f). Overall, ΔCC and ΔCSI are moderate ranging between -6% and -50%. ΔNRMSE is much larger, indicating that NRMSE is more prone to the effect of gauge densities. For example, the overestimation of NRMSE ranges between 13.43% at the 0.1° and 24 h scale and 134% at the 0.8° and 1 h scale. ΔBIAS keeps almost consistent for different temporal scales as expected, and is almost irregular as the spatial scale increases from 0.1° to 0.8° (Figure 7c), which could be attributed to the inconsistent locations of grid pixels at different spatial scales.

POD is insensitive to the number of gauges in each grid pixel. ΔPOD is very small ranging between -5% and 11%. The pattern of ΔPOD is elusive (Figure 8d). At 0.1° – 0.7° and 3–24 h scales, the pattern of ΔPOD is similar with that of ΔCC , ΔNRMSE , and ΔCSI . However, the values of ΔPOD are positive, indicating that POD based on sparse networks is better than that based on dense networks. This is because a single gauge only captures point-scale precipitation events which are far less than sufficient to represent true areal events. Hit and miss events are fewer than the situation benchmarked by the sparse gauge networks, leading to smaller H and M in Eq. (4). At 3–24 h scales, the effect of the underestimation of M is larger, resulting in the overestimation of POD. In contrast, the effect of the underestimation of H dominates at 1 h and $0.1^\circ/0.2^\circ$ scales and POD is slightly underestimated with negative ΔPOD . At the 0.8° scale, the pattern of ΔPOD is not clear, probably because one gauge is too few for such a large scale and the calculated

428 H and M contain large uncertainties.

429 In contrast to POD, FAR is the most sensitive metric, and is always overestimated by
 430 sparse gauge networks with ΔFAR ranging between 9% and 410%. For example, at the
 431 0.1° and 24 h scale which is common in the evaluation of IMERG-L products, FARs is
 432 0.28 while FAR_T is only 0.20 with a ΔFAR up to 40%. ΔFAR gets larger as the
 433 temporal scale increases, which is contrary to ΔCC , ΔNRMSE , and ΔCSI . FAR is
 434 positively correlated with F and negatively correlated with H . Because a single gauge
 435 tends to capture fewer precipitation events in each grid pixel, false alarms are much larger
 436 than the actual situation leading to a much larger F . The large F and small H jointly
 437 contribute to the large FAR and ΔFAR based on sparse gauge networks. As the temporal
 438 scale increases, the ratio between H and F becomes smaller, leading to larger ΔFAR .

440 **Figure 8.** Errors of the six metrics based on sparse gauge networks at 0.1° – 0.8° and 1–24 h scales

relative to the dense gauge networks. Each grid pixel contains one gauge. Metrics based on highly dense networks are utilized as a benchmark. The threshold used for rain/no rain determination is 0.1–2.4 mm at 1–24 h scales, respectively.

3.3.3 Effect of rain/no rain thresholds and gauge numbers

RN values used to determine rain or no rain have a marked effect on contingency metrics, including POD, FAR, and CSI. Figure 9 shows Δ POD, Δ FAR, and Δ CSI at various spatiotemporal scales using different *RN* values from 0.05 mm/h to 0.3 mm/h. Thresholds at 3–24 h scales are accumulated from the hourly threshold. The patterns of Δ POD show notable variation, indicating that POD is more sensitive to *RN* compared with FAR and CSI. The patterns of Δ FAR remain consistent at different *RN* values, except for the largest *RN* (0.3 mm/h) for which the peak of Δ FAR shifts slightly. Δ CSI exhibits stable patterns due to the advantage of combining POD and FAR.

In addition, we also checked the errors of metrics under the situation that all the temporal scales adopted the same *RN* as shown in Figure 10 (i.e., 0.1 and 0.2 mm for 1–24 h). Results indicate that the patterns of Δ FAR and Δ CSI change little, while the pattern of Δ POD shows more variation. Overall, FAR and CSI are less sensitive to the *RN* threshold values than POD.

Figure 9. Same as Figure 8, but only for the three contingency metrics including POD, FAR and CSI. The numbers behind metric names are thresholds (0.05, 0.1, 0.2, 0.3 mm/h) used to determine rain or no rain. The thresholds for other time scales (3–24 h) are accumulated from the thresholds for 1 h.

Figure 10. Same as Figure 9, but the thresholds are fixed at 1–24 h scales, i.e., 0.1 mm for the upper row and 0.2 mm for the lower row.

In addition to RN , the effect of the number of gauges (N_{st}) contained in each grid pixel was also investigated (Figure 11). N_{st} increases from one to 80% of TH_{st} (T2 in Table 1) to generate sparse gauge networks with different densities. BIAS is not included because of its irregularities (Section 3.3.1 and 3.3.2). The combinations of $0.1^\circ/0.8^\circ$ and 1/24 h scales were selected as representative examples. It is notable that ΔMET of all metrics decreases and tends to be zero as N_{st} increases. The curves of CC and CSI almost overlap at large temporal or spatial scales (Figure 11b–d), indicating that the two metrics have a similar sensitivity to gauge densities. $\Delta NRMSE$ and ΔFAR are positive and increase rapidly as the temporal or spatial scales increase. POD always exhibits the smallest difference. On the whole, the curves are smooth, which proves that it is feasible

475 to use a nonlinear error function to estimate ΔMET based on sparse gauge networks.

476

477 **Figure 11.** Errors of CC, NRMSE, POD, FAR and CSI with different numbers of gauges contained in
 478 each grid pixel at 0.1°/0.8° and 1/24 h scales. The numbers increase from one to 80% of T2 in Table 1.

479 The second Y-axis on the right in (d) is for the biases of NRMSE and FAR.

480 3.4 Error function of spatiotemporal scales and gauge numbers

481 ΔMET of all metrics except BIAS can be estimated using Eq. (8). Inputs were acquired
 482 with the spatial scale changing from 0.1° to 0.8°, the temporal scale changing from 1 h to
 483 24 h, and the number of gauges in each grid pixel changing from one to 80% of T2.
 484 Parameters were derived using the least square method (Table 2). Coefficients of
 485 determination (R^2) of CC, NRMSE, FAR and CSI are above 0.9, indicating that the error

function fits well for the four metrics. However, POD exhibits much lower R^2 , which is as expected because of its irregular patterns in Section 3.2 and 3.3.

The sign of parameter a represents whether the metric is underestimated or overestimated. The signs of parameter b , c , and d represent whether the magnitude of ΔMET is positively or negatively correlated with s , t , and N_{st} , respectively. ΔMET based on sparse gauge networks can be estimated by combining Eq. (8) and parameters in Table 2 at arbitrarily spatiotemporal scales. For example, in the evaluation of the TMPA products at the 0.25° scale with each grid pixel only containing one gauge, ΔCC could be around -26% and -14% at 3 h and 24 h scales, respectively. At the IMERG-L resolution (0.1° and 0.5 h), ΔCC decreases from -16% to -5% as the gauge number in each pixel increases from one to three. At the reanalysis resolution (e.g., 0.5° and 6 h), ΔCC decreases from -46% to -8% as the gauge number in each pixel increases from one to five.

Table 2 Parameters of the nonlinear error function used to estimate the errors of metrics and the coefficients of determination (R^2) for the fitting.

Parameters	CC	NRMSE	POD	FAR	CSI
a	-161.45	256.95	52.82	521.90	-99.59
b	1.08	1.19	1.36	1.52	1.08
c	-0.29	-0.16	-0.48	0.20	-0.15
d	-1.09	-1.13	-0.98	-1.07	-1.07

R^2	0.97	0.95	0.45	0.91	0.92
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Eq. (9) can be used to calculate the gauge density at different spatiotemporal scales to achieve metrics within a predefined error level. Figure 12 shows the minimum number of gauges in each grid pixel to control ΔMET within $\pm 5\%$. For CC, NRMSE, and CSI, the number increases as the temporal scale decreases and the spatial scale increases. For example, to control ΔCC within $\pm 5\%$, the minimum gauge number is 2.5 at the 0.1° and 1 h scale corresponding to products such as IMERG-L and GSMaP. The number increases to 4.6 at the 0.25° and 3 h scale corresponding to products such as TMPA and CMORPH. For FAR, the number increases as the temporal scale decreases and the spatial scale increases (Figure 12c). It is noted that the minimum required gauge number of FAR is much larger than that of other metrics.

510

Figure 12. Minimum numbers of gauges in each grid pixel at different spatiotemporal scales to control the biases of (a) CC, (b) NRMSE, (c) FAR, and (d) CSI within $\pm 5\%$.

4. Discussion

4.1 Applicability of the error function

The error function fits quite well with CC, NRMSE, FAR, and CSI, worse for POD, and is not suitable for BIAS. Fortunately, CSI is a more comprehensive contingency metric combining the advantages of both POD and FAR. BIAS is a unique metric which suffers little from sparse gauges. However, it should be noted that if the BIAS is relatively small in the evaluation, the reliability of its sign (i.e., negative or positive) should be checked by considering the locations and density of gauges. There are other metrics such as the frequency of hit (FOH) and Heidke skill score (HSS), which are not included in this study. We believe that most metrics used to indicate the performance of satellite precipitation products tend to be worse based on sparse gauge networks. However, the applicability of the error function (Eq. (8)) for other metrics still needs validation.

Although the study was conducted in the Ganjiang River basin, the error function could also be applicable in other regions, particularly for those with similar topography and climate. For regions where precipitation has a stronger variability in space and time at the sub-grid scale, the errors of metrics based on sparse gauge networks would be larger, and vice versa. Therefore, it is possible to add a parameter (such as coefficient of variation) in the error function to represent regional variability and to make the function applicable in

various regions. Furthermore, cold seasons are different from warm seasons concerning precipitation characteristics, particularly in high latitude and high altitude regions where snowfall dominates in winter. Gauge undercatch is particularly important for snowfall. Meanwhile, satellite retrievals are more difficult over regions with snow cover and not good enough at snowfall estimation. Finally, the current study period is relatively short. The general conclusion should be consistent even for a longer period because the limitation of gauge observations is inherent. However, more robust parameters of the error function could be acquired if longer data series are employed. Further studies are needed to explore the effect of gauge densities on the evaluation of rainfall/snowfall using long series of gauge or radar observations.

For all remote sensing technologies and models providing areal estimates (e.g., evapotranspiration, soil moisture, and snow cover), their performance could also be underestimated if the evaluation is conducted using point-scale measurements. The degree of underestimation depends on the spatiotemporal scales and the number of gauges in each grid pixel.

4.2 Error variation and uneven gauge distributions

The error function estimates the mean error of metrics based on combinations of random sparse gauge networks in this study. As shown in Figure 6, overall CC values based on sparse gauge networks follow the normal distribution. Other metrics are similar with CC respecting the distribution. The error function approximates the mean or expectation of

the normal distribution. However, in actual situations it is hard to know the actual performance of a sparse gauge network. Errors of metrics calculated using the error function can act as the reference but are not entirely the same as the actual numbers. Therefore, the variance of metrics should be estimated in future studies to enable estimation of bias range.

Another issue is that the number of gauges in each grid pixel is not the same for a specific gauge network, which is different from the ideal situation in this study. However, the uneven distribution of gauges is not beneficial to reducing the biases of gauges. Metrics based on uneven gauge networks are generally worse than even gauge networks with the same total gauges. We experimented by generating gauge networks with half grid pixels containing one gauge and half grid pixels containing three gauges. ΔMET based on such gauge networks is larger than that based on a gauge network with all grid pixels containing two gauges. For example, the mean ΔNRMSE is 35% based on the uneven gauge network, and 29% based on the even gauge network. The reason is that marginal benefits become smaller as the gauge number increases. The adverse effect of pixels with fewer gauges overwhelms the favorable effect of pixels containing more gauges.

5. Conclusion

Gauge networks with limited numbers of gauges in each grid pixel generally underestimate the quality of satellite products because point-scale observations of scarce gauges cannot perfectly represent areal precipitation. This study focuses on the errors of

six metrics based on sparse networks which exhibit different spatiotemporal patterns. Errors of CC, NRMSE, and CSI become larger as the spatial scale increases and temporal scale decreases, while the error of FAR becomes larger as the temporal scale increases. In contrast to other metrics, POD is overestimated by sparse gauge networks compared to highly dense networks at 3–24 h scales because point-scale gauge observations cause substantial uncertainties in calculating hit and miss event numbers. As a whole, among the three contingency metrics, CSI is the most robust. Particularly, BIAS values based on sparse gauge networks fluctuate around the value based on dense gauge network. Therefore, it could be difficult to judge whether satellite products overestimate or underestimate precipitation in a domain if BIAS values are not very large and gauges are sparse.

We propose a nonlinear error function which expresses the spatiotemporal errors of CC, NRMSE, FAR, and CSI pretty well with R^2 around or above 0.9. The function can also be used to estimate the required number of gauges in each grid pixel to deliver a predefined error level. For example, to control the bias of CC within $\pm 5\%$, the minimum gauge number in each grid pixel is 2.5 at the 0.1° and 1 h scale. The quantitative analysis in this study is helpful to obtain more reliable information on the quality of satellite products. The concept can also guide the design of optimized gauge networks for field studies. As the results could depend on region and season, future studies should explore the sensitivity of the results to variations in topography, climate conditions, and precipitation

phase. The formula of the error function can potentially be improved to include more metrics and to account for regional and seasonal variations.

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