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SUPER v2: A 3-Hourly Global Precipitation Dataset Optimized for Sparse Data Challenges

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Abstract. The Statistical Uncertainty analysis-based Precipitation mERging (SUPER) methodology can optimally merge different precipitation datasets with minimal use of ground-based information and is therefore better suited for data-sparse regions. Although a proof-of-concept SUPER framework has already been introduced previously, it contains substantial uncertainties and is only available at a daily timescale, which is inadequate for land surface modeling. In response, we present here a new 3-hourly, 0.1-degree, global SUPER version 2 (v2) dataset, spanning 2000–2023. SUPER v2 is unique in three key aspects: i) it optimizes the number of input precipitation datasets, which reduces data redundancy and mitigates negative biases in extreme precipitation events; ii) it optimally evaluates its internal merging weights and filters out false-alarmed events without reliance on extensive gauge networks; and iii) it employs a multi-scale (i.e., monthly–daily–3-hourly) temporal correction/merging procedure that enhances the robustness of precipitation estimates. The SUPER v2 product is comprehensively evaluated using 5,972 independent gauges. Results show that it has a root-mean-squared-error of 3.64 mm d^{-1} and correlation coefficient of 0.68 [-] for daily precipitation estimates. These error metrics outperform traditional approaches over 81% to 86% of the validation gauges. The superiority of SUPER v2 with regards to rain/no-rain classification skill is even more evident, with Heidke's Skill Score 22% higher than commonly used datasets. Similar findings are also demonstrated in the 3-hourly SUPER v2 precipitation dataset. As such, SUPER v2 provides a unique opportunity for enhancing global-scale hydrology and land surface modeling — particularly for data sparse regions.

1 Introduction

Precipitation is the primary driver of the terrestrial hydrological cycle (Hu et al., 2025; Tang et al., 2025; Tian et al., 2013; Wu et al., 2023). While remote sensing (RS) and reanalysis techniques provide global precipitation estimates (Ma et al., 2025; Maggioni et al., 2016; Maina & Kumar, 2025), they often contain substantial errors due to uncertainties in their ancillary data and retrieval algorithms (Maggioni & Massari, 2018; Maggioni et al., 2016; L. Y. Wei et al., 2023). Data merging methods can improve large-scale precipitation estimates by integrating multiple datasets (Baez-Villanueva et al., 2020; Chao et al.,

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

2018; Gavahi et al., 2023; Shen, 2010). Numerous merging techniques have been developed, e.g., optimal interpolation (Shen et al., 2022; Shen et al., 2014), Bayesian estimation (Ma et al., 2018), geographically weighted regression (Chao et al., 2018; Chen et al., 2020; Shen et al., 2022), and neural network approaches (Jiao et al., 2025; Wu et al., 2020; You et al., 2025). However, these merging frameworks typically require high-quality gauge networks. As such, their reliability is undermined in data-sparse or ungauged regions where high-quality observations are unavailable (Baez-Villanueva et al., 2020; Dong, Lei, et al., 2020).

In light of these limitations, statistical approaches for uncertainty analysis have been introduced for precipitation error estimation without using gauge data. A prominent example is triple collocation (TC), which applies a linear model to three independent datasets to resolve their individual error variances (Stoffelen, 1998). TC has been successfully employed for precipitation error estimation (Li et al., 2018; Paul & Alemohammad, 2025; Tang et al., 2020; L. Wei et al., 2023) and precipitation data merging (Chen et al., 2022; Lyu et al., 2021; L. Wei et al., 2023; L. Y. Wei et al., 2024). Since TC-based approaches do not require gauge observations for calculating precipitation merging weights, they are theoretically better suited for data-sparse regions (Ding et al., 2024; Dong et al., 2022; Duan et al., 2021).

However, these TC-based merging frameworks typically neglect the interdependence of different precipitation datasets (Gu et al., 2025; Lyu et al., 2021; Park et al., 2023). As a result, the merging results may overfit the noise from a particular data source. Additionally, traditional merging studies also fail to address rain/no-rain classification errors, leading to substantial false-alarm events (Dong, Lei, et al., 2020; Yang et al., 2017).

To address this limitation, recent studies further leverage multiple uncertainty analysis tools suitable for interdependent datasets (e.g., quadruple collocation, or QC, Gruber et al., 2016b) and binary variables (e.g., categorical triple collocation, CTC, McColl et al., 2016). Based on these advances, the statistical uncertainty analysis-based precipitation merging framework, SUPER v1, was developed (Dong et al., 2022). Comprehensive evaluations have shown that SUPER v1 outperforms leading satellite-based and reanalysis products across multiple dimensions in both precipitation intensity and rain/no-rain classification performance (Dong et al., 2022; Kang et al., 2024; Songyan et al., 2024). Due to its demonstrated effectiveness, similar merging strategies have been adopted in recent data-merging studies (Li et al., 2024; L. Wei et al., 2024; L. Wei et al., 2023).

Although SUPER v1 can enhance precipitation estimation accuracy with reduced reliance on gauge observations, several key concerns remain. First, like most data-merging approaches, SUPER v1 ingests nearly all publicly available precipitation datasets. While this may, in theory, increase the amount of precipitation information available for its merged estimates, it can also introduce numerical instability problems — particularly when the parent datasets are noisy or strongly cross-correlated (Alvarez-Garreton et al., 2016). More importantly, increasing the number of parent precipitation datasets may also intensify the negative biases in extreme precipitation events (EP) (Kang et al., 2024; Xia & Wang, 2025). Likewise, SUPER v1 implicitly assumes that the rain/no-rain time series of the parent precipitation datasets are unbiased. This assumption can be violated in practice and yield substantially increased false-alarmed events (Dong, Crow, et al., 2020). Finally, SUPER v1, and other statistical analysis-based merging approaches are generally limited to daily timescales. This is because applying statistical uncertainty analysis at finer temporal resolutions suffers from numerical instability problems, largely due to the reduced signal-

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

to-noise ratio of sub-daily precipitation inputs (Hirpa et al., 2010; Xu et al., 2023; Zhang et al., 2024). As a result, these datasets remain inadequate for land surface and hydrological modeling applications that require a higher temporal resolution.

In response, this study develops an enhanced precipitation merging framework and produces a corresponding global precipitation dataset at 0.1-degree spatial and 3-hourly temporal resolutions. Specifically, we identify the optimal set of parent datasets that balances precipitation information content and EP accuracy. We then introduce strategies to reduce rain/no-rain classification errors and further disaggregate daily precipitation estimates into 3-hourly datasets. This new version, SUPER v2, is evaluated using 5,972 independent gauge observations and demonstrates substantial improvements over the SUPER v1 datasets and other similar state-of-the-art precipitation products.

2 Data

In this study, commonly used RS and reanalysis precipitation datasets are systematically compiled and summarized in Table 1. These datasets are used to illustrate the SUPER v2 strategy for selecting optimal inputs. All the precipitation datasets are spatially aligned to a 0.1° grid using nearest-neighbor resampling. Detailed descriptions of these datasets are available in Sect. S1 of the Supplement.

Table 1. Datasets involved in the construction and verification of SUPER v2.

Name	Purpose	Spatiotemporal Resolution	Spatial Coverage	Type	Reference
ERA5	Input/ comparison	0.25° / 1h	90° N–90° N	Reanalysis	(Hersbach et al., 2020)
CPC	Input	0.5° / 1 day	90° N–90° N	Gauge-based	(Chen et al., 2008; Xie et al., 2007)
IMERG V07 Final Run	Input/ comparison	0.1° / 30 min	60° N–60° N	RS: MW+IR	(Huffman, 2023; Yong et al., 2015)
CMORPH CDR	Input/ comparison	8 km / 30 min	60° N–60° N	RS: MW+IR	(Joyce et al., 2004; Xie et al., 2017)

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

Open Access Earth System Science Data Discussions

PERSIANN CDR	Auxiliary	0.25° / 1 day	60° N–60° N	RS: IR	(Ashouri et al., 2015)
CHIRPS-2.0	Auxiliary	0.05° / 1 day	50° N–50° N	RS: IR	(Funk et al., 2015)
MSWEP V2	Comparison	0.1° / 3 h	90° N–90° N	merged	(Beck, van Dijk, et al., 2017; Beck, Wood, et al., 2019)
Gauge	Validation	Point/ 1 day, 1 h	-	Gauge	-

3 Methods

3.1 SUPER v2 framework

SUPER v2 is an updated global precipitation merging system designed to minimize reliance on ground-based gauge observations. It integrates false-alarmed precipitation filtering, bias correction, uncertainty-based merging, and temporal downscaling. Specifically, the precipitation merging procedure consists of four key steps:

1) Rain/no-rain correction

In this step, we first filter out false-alarmed events within the input precipitation datasets using a categorical triple collocation merging (CTC-M) algorithm (Dong, Crow, et al., 2020). This algorithm integrates precipitation estimates from three independent categories, i.e., ERA5 (reanalysis), CPC (gauge-interpolated), and IMERG (remote sensing). For each grid cell, CTC-M constructs an optimized rain/no-rain classification time series based on pixel-level agreement. This optimized time series is then used to filter out false-alarm events across all input datasets in SUPER v2. Notably, compared to SUPER v1, SUPER v2 replaces the soil-moisture-derived precipitation dataset with CPC, which leads to a significantly reduced false alarms (see Table 3 and Appendix A).

2) Monthly correction

After rain/no-rain filtering, all input datasets are adjusted to match a pre-selected, reference monthly precipitation climatology. Specifically, for each grid and month, daily values are proportionally scaled to match the monthly totals from the pre-selected reference dataset. We selected the monthly IMERG dataset as the reference standard for this step owing to its superior accuracy

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

and consistency (see Appendix B for further details). Such adjustment corrects systematic bias while maintaining the original daily variability. The correction follows:

$$P_i^{corrected} = P_i \times \frac{P_{ref}^{month}}{P_i^{month}} \tag{1}$$

where P_{ref}^{month} is the monthly precipitation from the reference datasets (i.e., IMERG); P_i^{month} is the total monthly precipitation estimated by product i; P_i and $P_i^{corrected}$ refer to the original and bias-corrected time series of daily precipitation from product i. No correction is applied when P_i^{month} is less than 5 mm to avoid numerical instability problems.

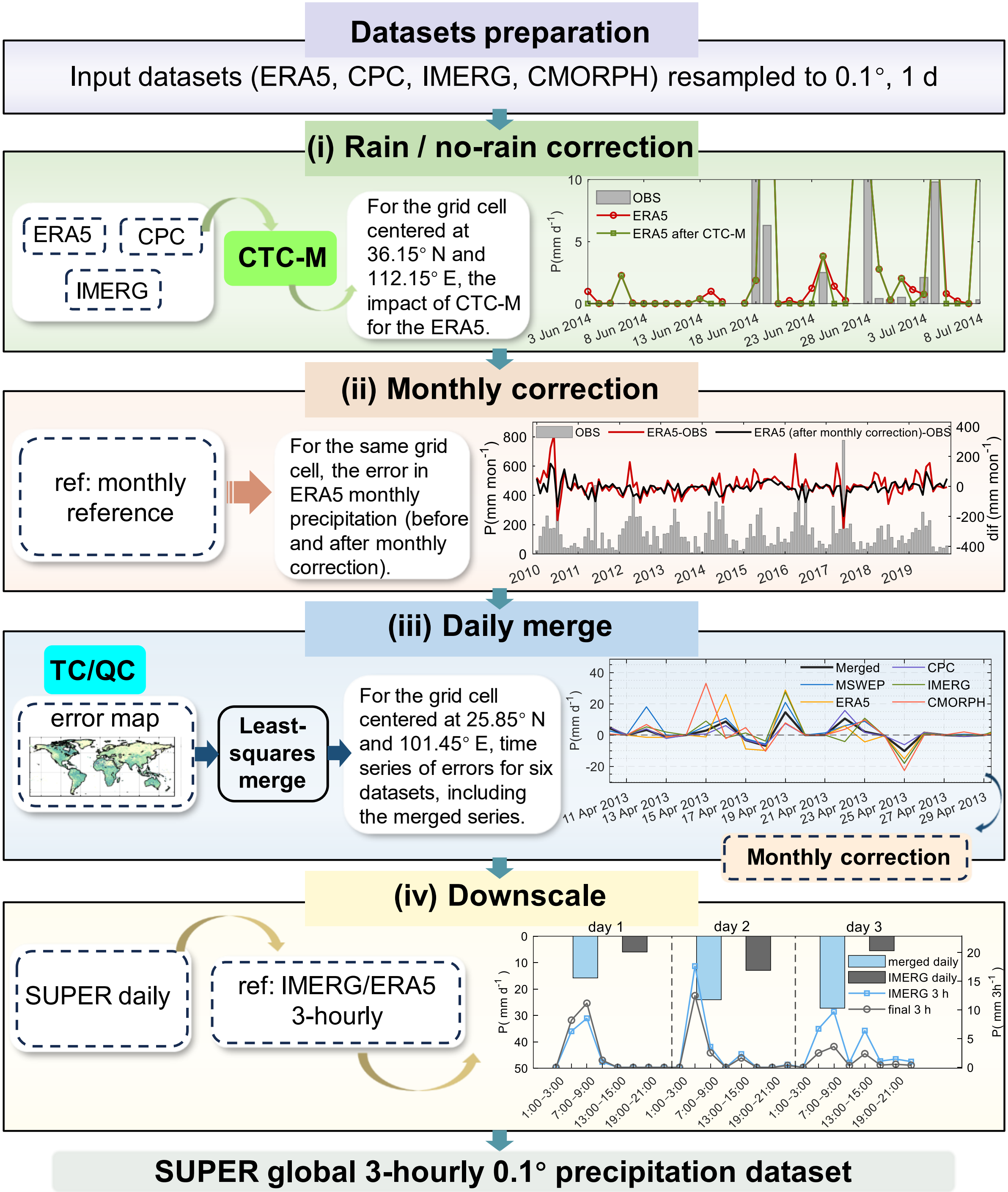
3) Daily Merging Based on Statistical Uncertainty

The monthly-corrected datasets are then merged into daily precipitation estimates using a least-squares framework, with weights determined by error variances estimated via quadruple collocation (QC) (Gruber et al., 2016a). Note that QC estimates both the error variance and inter-product error covariance across all input datasets using four datasets. If fewer than four datasets are available for a given grid cell, such as in high-latitude regions, the TC method is used instead. Details of the QC and CTC algorithms are provided in Sect. S2 of the Supplement. Unlike SUPER v1, SUPER v2 does not merge all available datasets, as many of them are interdependent and can degrade merging accuracy. Instead, it selects an optimal subset to reduce redundancy and enhance precipitation estimation accuracy (see Sect. 4.1.)

4) Downscaling Daily Precipitation to 3-Hourly Resolution

Due to the limited availability and generally lower accuracy of sub-daily precipitation products, directly merging 3-hourly datasets may be affected by numerical instability problems. Therefore, we adopt a simple yet robust approach to enhance the temporal resolution of SUPER v2. Specifically, we select IMERG as the primary reference for disaggregating the daily SUPER v2 precipitation estimates due to its superior ability in capturing sub-daily precipitation variability (see Appendix C for further details). The daily precipitation totals from SUPER v2 are then redistributed into 3-hourly intervals based on the temporal distribution provided by IMERG. On days when IMERG reports zero precipitation, ERA5 is used as an alternative reference. This procedure produces the final global 3-hourly SUPER v2 precipitation dataset.

In summary, SUPER v2 incorporates several key improvements: i) a refined selection of the monthly reference dataset to minimize systematic precipitation biases; ii) incorporation of CPC into the CTC-M framework for improved global rain/no-rain classification performance; iii) an optimized input dataset strategy that reduces data redundancy while improving precipitation estimation accuracy; and iv) temporal downscaling from daily to 3-hourly resolution — thus providing higher-frequency precipitation estimates suitable for hydrological and land surface modeling.



130 **Figure 1.** Overview of the SUPER v2 processing framework: **(i)** Rain/no-rain correction using the CTCM-M algorithm; **(ii)** Monthly precipitation bias correction; **(iii)** Daily precipitation merging via least-squares optimization; and **(iv)** Downscaling the merged daily precipitation to 3-hourly intervals using IMERG/ERA5 as the reference dataset.

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

Open Access Earth System Science Data Discussions

3.1 Validation

We employed seven evaluation metrics to assess the general accuracy of precipitation products, along with an additional metric for evaluating extreme precipitation (EP) performance.

For daily precipitation intensity, we used the Pearson correlation coefficient (CC), the root-mean-square-error (RMSE), and mean error (ME) — see Table 2. Regarding rain/no-rain detection skills, we calculated binary classification metrics derived from the contingency table components — see Table 3. Specifically, the probability of detection (POD) quantifies a product's ability to correctly identify precipitation events, while the false alarm ratio (FAR) assesses its tendency to falsely report them (Tang et al., 2020). The overall classification performance was assessed using the Heidke's Skill Score (HSS) (Munchak & Skofronick-Jackson, 2013).

We also assess how well each dataset captures EP events. Here, we use R95p for demonstration, which defines EP as events with daily precipitation intensity exceeding the 95th percentile threshold of all wet days (Duan et al., 2022). This study only focuses on R95p for brevity, but our findings remain robust when a different percentile threshold is used.

Table 2. Error metrics for precipitation assessment. N denotes the total sample size; M_i and G_i refer to the precipitation estimates from the merged product and the gauge observations, respectively; σ_G and σ_M correspond to the standard deviations of the gauge and merged datasets; P_i stands for the precipitation value (either merged or observed). $P95$ indicates daily precipitation exceeding the 95th percentile threshold of the wet days; W is the total number of observed wet days. A wet day is defined as daily precipitation >= 0.5 mm.

Statistic metrics	Equation	Perfect value
Correlation Coefficient (CC)	$CC = \frac{\frac{1}{N}\sum_{i=1}^{N}(M_i - \bar{M})(G_i - \bar{G})}{\sigma_M \sigma_G}$	1
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - G_i)^2}$	0
Mean Error (ME)	$ME = \frac{1}{N}\sum_{i=1}^{N}(M_i - G_i)$	0
Probability Of Detection (POD)	$POD = \frac{h}{h+m}$	1
False Alarm Ratio (FAR)	$FAR = \frac{f}{h+f}$	0

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

Heidke's Skill Score (HSS)	$HSS = \frac{2(hc - fm)}{(h+m)(m+c)+(h+f)(f+c)}$	1
R95p	$R95p = \frac{1}{W}\sum_{w=1}^{W} P95_w$	Same as OBS

Table 3. Contingency table for daily precipitation classification assessment based on a 0.5 mm d^{-1} rain/no-rain threshold.

	OBS: rain	OBS: no-rain
Product: rain	hits (h)	false alarms (f)
Product: no-rain	misses (m)	correct negatives (c)

4 Results

4.1 Optimal number and combination of datasets for precipitation merging

RS precipitation datasets often rely on similar ancillary inputs and retrieval algorithms, leading to strong error cross-correlations (ECC, Fig. 2). For example, the ECC between IMERG and CMORPH exceed 0.5 [-] for most land pixels (Fig. 2b). Similarly, CHIRPS and PERSIANN exhibit strong mutual error correlations (Fig. 2e). As a result, merging all RS inputs, as done in SUPER v1 and many other data merging studies, can introduce data redundancy and degrade precipitation estimation accuracy.

To address this, we first assess how precipitation merging accuracy varies across different combinations of RS datasets (Fig. 3). In all experiments, ERA5 (reanalysis-based) and CPC (gauge-interpolated) are consistently included, as they rely on fundamentally different data sources and estimation strategies and are credibly independent of RS datasets (Dong, Crow, et al., 2020; Dong, Lei, et al., 2020; Dong, Wei, et al., 2020). Precipitation merging accuracy is then evaluated using daily independent gauge observations listed in Sect. S1 of the Supplement.

When only three datasets are used, merging performance is relatively low and highly sensitive to the inclusion of specific datasets (Fig. 3a). Incorporating four datasets improves precipitation estimation accuracy by approximately 10% and significantly stabilizes the merging performance. However, adding a fifth or sixth dataset offers only marginal benefits. Moreover, increasing the number of input datasets tends to amplify biases in EP, as measured by R95p (Fig. 3b). This is because excessively increasing datasets during merging tend to dampen precipitation variability (Kang et al., 2024). Although overall accuracy is similar across our different four-dataset combinations, the set using ERA5, CPC, IMERG, and CMORPH performs best in capturing EP events (Fig. 3c). Accordingly, these four datasets are selected as the final inputs for SUPER v2.

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

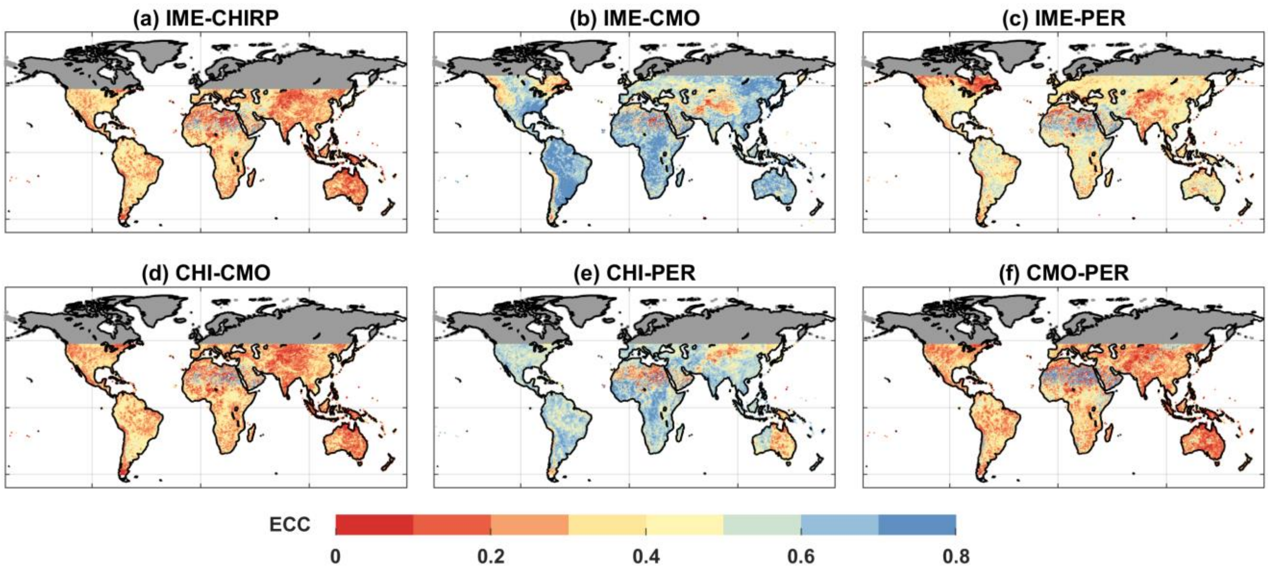


Figure 2. Global distribution of QC-based error cross-correlation (ECC) among the four satellite precipitation products used in SUPER v1. Grey regions in (**d**) to (**f**) indicate areas where QC analysis was not feasible due to insufficient data coverage.

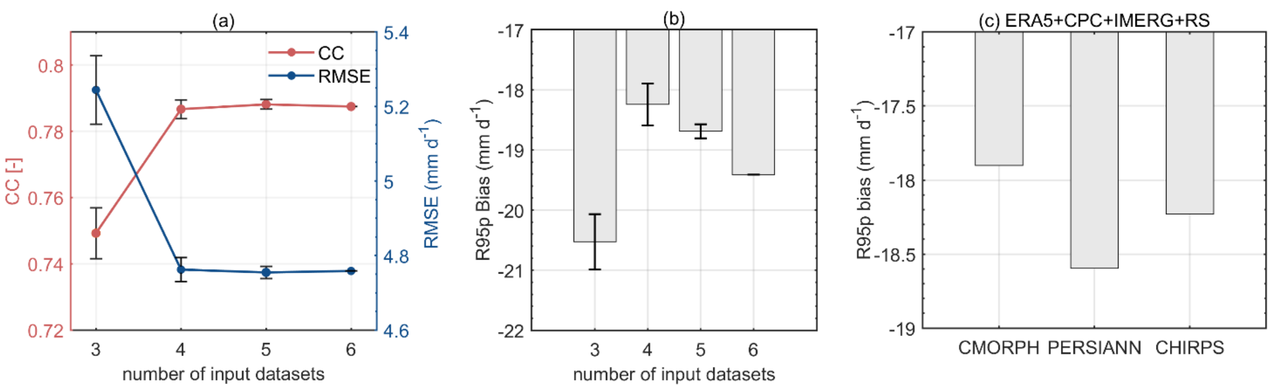


Figure 3. (**a**) Sensitivity of precipitation merging accuracy to the number of input data sources. Error bars represent the variability across dataset combinations when the total number of inputs is fixed. (**b**) The impact of input dataset count on merged R95p, with error bars indicating standard deviation across combinations. (**c**) The effect of substituting the fourth dataset (RS) with CMORPH, PERSIANN, or CHIRPS on merged R95p, while keeping ERA5, CPC, and IMERG fixed. The y-axis (ΔR95p) indicates deviation from gauge-based R95p; values closer to zero reflect better performance.

4.2 Merging weights of the four parent datasets in SUPER v2

Figure 4 illustrates the weights assigned to each input dataset merged in SUPER v2 (i.e., ERA5, CPC, IMERG, and CMORPH). These weights are estimated using QC/TC-based uncertainty estimates (Gruber et al., 2016a; Stoffelen, 1998) and the least-squares merging approach (Avery, 1991). ERA5 receives the highest weights globally due to its superior performance (Fig.

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

4c). IMERG also contributes substantially to the merging process, particularly over regions such as eastern CONUS and China, where its weights exceed 0.3 (Fig. 4a). In contrast, CMORPH and CPC receive relatively low weights, with values generally below 0.3 for most land pixels (Fig. 4b and d).

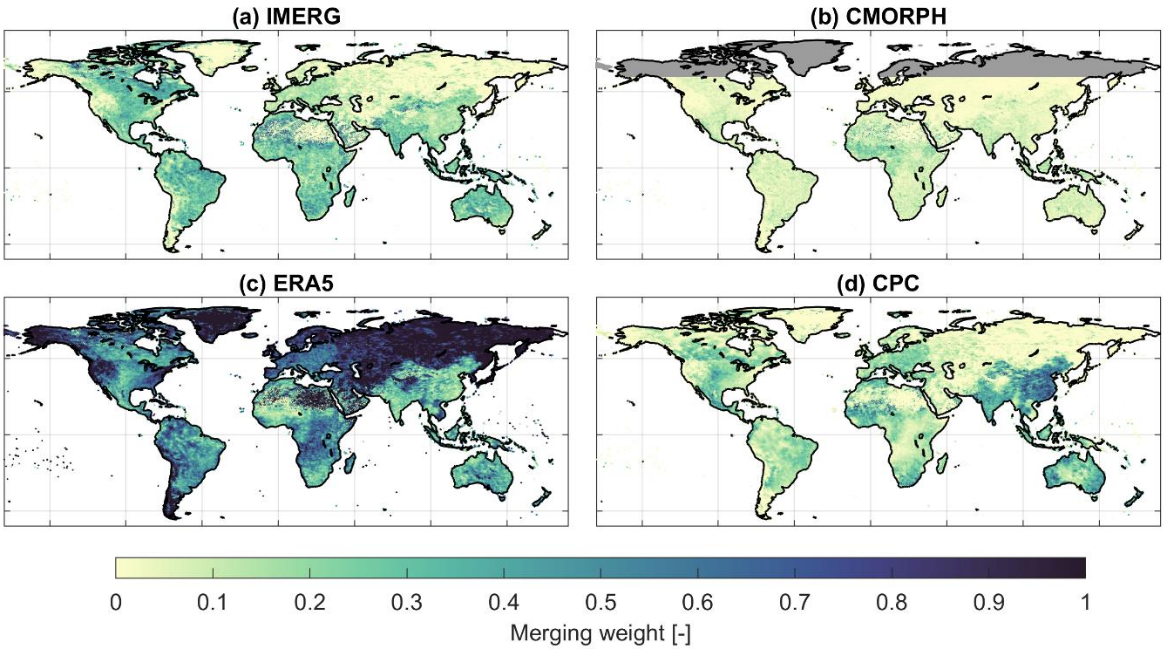


Figure 4. Precipitation merging weights of the four parent RS/Reanalysis precipitation datasets used in SUPER v2. The merging weights are calculated based on error statistics evaluated using QC/TC and a least-square algorithm. Grey regions in (**b**) indicate describes areas where CMORPH is not available.

4.3 Comparison of SUPER v2 with RS/reanalysis datasets

Based on the refined merging procedure, SUPER v2 reduces the RMSE of precipitation estimates by approximately 10%, and increases HSS by 16%, compared to SUPER v1 (Table 4). These results highlight the effectiveness and added value of the SUPER v2 approach. Therefore, subsequent analyses focus primarily on SUPER v2 and other widely used datasets for brevity. As shown in Fig. 5, SUPER v2 outperforms conventional RS and reanalysis datasets at approximately 86% and 81% of the validation gauges in terms of CC and RMSE, respectively (Fig. 5, columns 2 and 3; Table 4). Likewise, the mean error (i.e., bias) of SUPER v2 is 0.34±0.43 mm d^{-1}, which is substantially lower than that of ERA5 (0.54±0.42 mm d^{-1}). Notably, the superiority of SUPER v2 to IMERG and CMORPH is even more evident (Fig. 5, columns 2 and 3 and Table 4).

In addition to precipitation intensity, SUPER v2 also demonstrates robustness in detecting daily precipitation occurrence (Fig.6 and Table 4). Specifically, the RS and reanalysis datasets are prone to false alarm events, with FAR ranging from 0.45 to 0.50 (Table 4). Based on the CTC-M procedure, SUPER v2 reduces the FAR to 0.38. As such, the general performance in identifying precipitation events (captured by HSS) of SUPER v2 is approximately 22% higher than that of the abovementioned

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

datasets, with superior performance observed at more than 75% of the validation sites. The improvement can be largely attributed to false alarm filtering using CTC-M with optimized precipitation inputs (see Appendix A for further details). Likewise, the performance of SUPER v2 is also demonstrated at the 3-hourly time scale (Table 4 and Fig. 7).

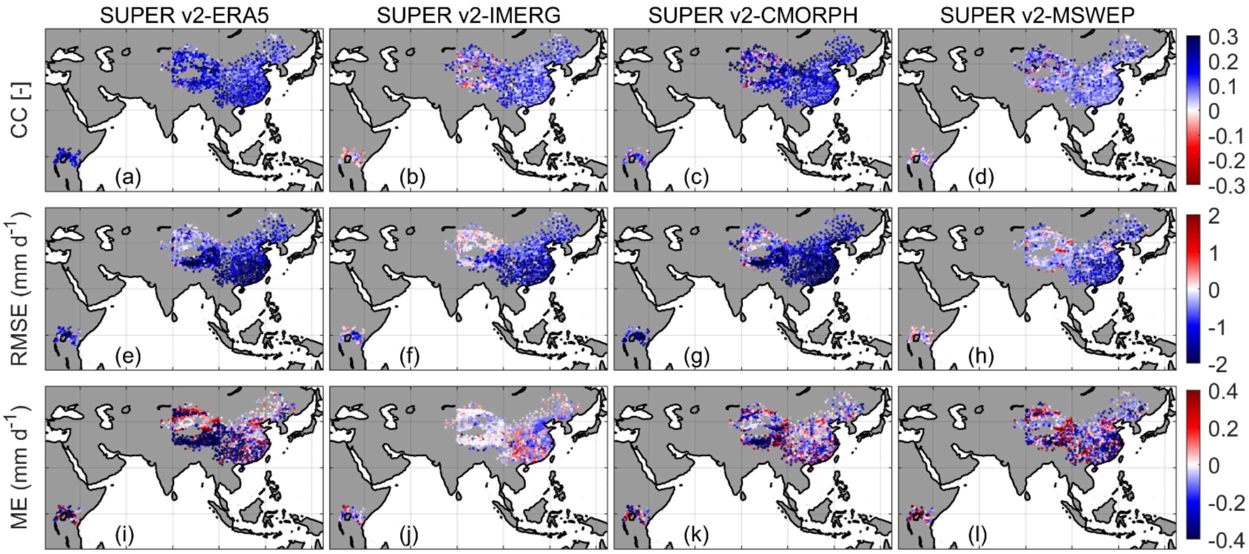


Figure 5. The relative performance of different error metrics for SUPER v2, ERA5, IMERG, CMORPH, and MSWEP at the daily scale (first to third row, respectively). Note that the differences in ME are based on absolute values (e.g., ME differences are calculated as $|ME_{SUPER}|-|ME_{MSWEP}|$). Grey regions denotes areas lacking a sufficiently dense network of independent gauge observations..

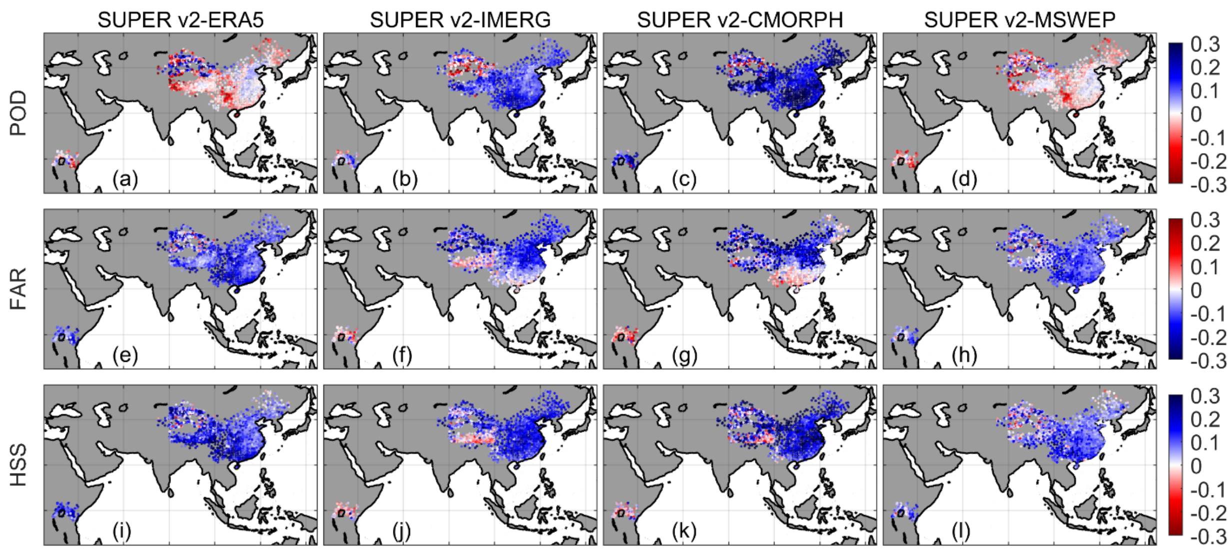


Figure 6. Comparative assessment of daily precipitation occurrence detection capabilities among SUPER v2, ERA5, IMERG, CMORPH and MSWEP. Evaluation results for POD, FAR, and HSS are shown in the first to the third rows, respectively.

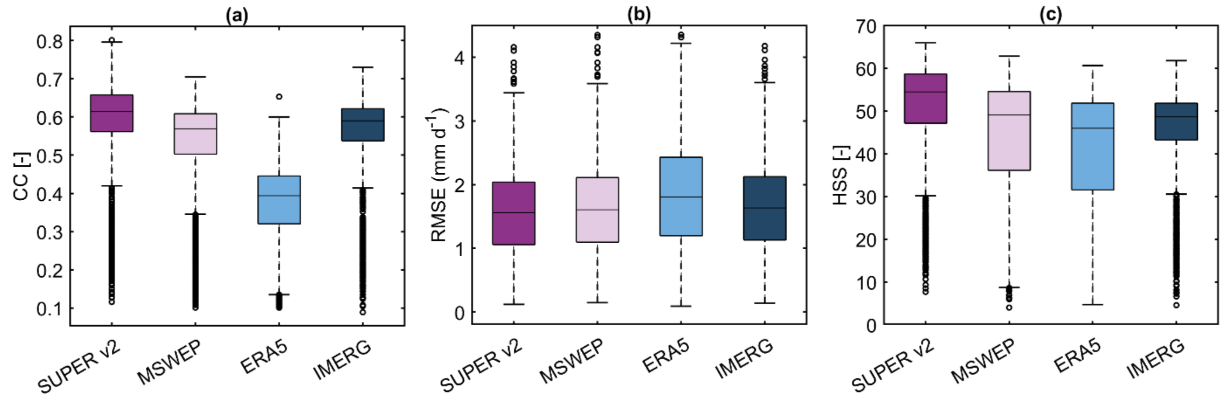


Figure 7. Boxplots of CC (**a**), RMSE (**b**), and HSS (**c**) of SUPER v2, ERA5, IMERG, and MSWEP precipitation estimates evaluated on a 3-hourly time scale. The error metrics are sampled across independent hourly gauge observations located in China mainland.

4.4 Comparison of SUPER v2 with gauge-merged datasets

In addition to comparisons with RS and reanalysis datasets, the performance of SUPER v2 is also evaluated against a widely used gauge-based merging product, MSWEP. Although SUPER v2 and MSWEP rely on similar parent precipitation datasets, SUPER v2 achieves a lower areal mean RMSE (3.98 mm d^{-1} vs. 4.27 mm d^{-1}) and a higher CC (0.67 vs. 0.61 [−]) than MSWEP (Fig.5 column 4). This could be attributed to the overall benefit of SUPER v2 in the strategy of precipitation error estimation. Specifically, SUPER v2 solves for the error statistics at the individual grid-cell level, while MSWEP applies spatially interpolated weights derived from nearby gauge observations. Additionally, SUPER v2 accounts for inter-product cross-correlated errors to avoid overfitting (Dong et al., 2022). These detailed considerations directly enhance the accuracy of SUPER v2 precipitation intensity estimates. Moreover, SUPER v2 also exhibits stronger rain/no-rain detection skill than MSWEP, as evidenced by its lower FAR and higher HSS — see the fourth column of Fig. 6. Similar advantages in SUPER v2 in precipitation estimates are also seen at the 3-hourly time scale (Table 4 and Fig. 7).

Table 4. Daily and 3-hourly performance of different error metrics for all evaluated datasets. The dataset with optimal performance is shown in bold. Values are reported as mean ± standard deviation based on a 95% confidence level.

		SUPER v1	SUPER v2	ERA5	IMERG	CMORPH	MSWEP
daily	CC	0.64±0.14	**0.68±0.18**	0.56±0.17	0.61±0.16	0.53±0.18	0.62±0.17
	RMSE (mm d^{-1})	4.01±2.33	**3.64±2.83**	5.00±3.65	4.66±3.29	5.41±3.48	4.27±3.07
	ME (mm d^{-1})	0.37±0.63	**0.34±0.33**	0.54±0.42	0.34±0.82	0.35±0.83	0.35±0.43

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

	POD	0.86±0.21	0.85±0.14	0.84±0.17	0.77±0.12	0.70±0.15	**0.87±0.13**
	FAR	0.45±0.17	**0.38±0.18**	0.50±0.17	0.46±0.19	0.46±0.21	0.45±0.16
	HSS	0.50±0.19	**0.58±0.17**	0.44±0.18	0.48±0.14	0.44±0.15	0.51±0.16
	R95P (mm d^{-1})	15.21±14.11	16.19±13.90	13.95±11.59	**16.50±14.34**	16.01±14.02	14.05±12.63
3h	CC	-	**0.60±0.16**	0.38±0.18	0.57±0.18	-	0.53±0.18
	RMSE (mm $3h^{-1}$)	-	**1.56±0.78**	1.82±0.97	1.63±0.69	-	1.60±0.98
	POD	-	0.68±0.14	0.84±0.11	0.63±0.16	-	**0.86±0.14**
	FAR	-	**0.49±0.17**	0.64±0.18	0.53±0.16	-	0.62±0.17
	HSS	-	**0.51±0.13**	0.41±0.16	0.45±0.13	-	0.44±0.14

4.5 Bias in extreme precipitation (EP)

Data merging tends to attenuate EP intensity (Abdelmoaty et al., 2021; Beck, Pan, et al., 2019; Kang et al., 2024). To determine how well different datasets capture extreme events, we analyse their relative performance using R95p. Note that evaluations based on other EP statistics yield similar results (Kang et al., 2024) and are therefore not included here for brevity. Additionally, although SUPER v2 is available at the global scale, we restrict the presentation of R95p over regions where independent gauge observations are available (Fig. 8). Generally, all the datasets can capture the large-scale variations in climate aridity, e.g., R95p shows a decreasing trend from the southeast to the northwest part of China. Across all the RS and reanalyzed datasets, IMERG-based R95p is closer to gauge observations (16.54 mm d^{-1} vs. 27.16 mm d^{-1}, see Fig. 8e). Such improvement is likely facilitated by the adoption of localized CDF matching and the dual-frequency precipitation radar during precipitation retrieval (Tan et al., 2021).

Interestingly, the R95p of MSWEP is only 14.43 mm d^{-1}, with a negative bias up to −109.86 mm d^{-1} in humid regions (Fig. 8c). Although SUPER v2 also employs a least-squares-based merging strategy, its R95p more closely aligns with IMERG and significantly outperforms MSWEP (Fig. 8b). This is because nearly all RS and reanalyzed precipitation data are biased for EP,

https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

which cannot be entirely corrected by monthly scaling or CDF matching. In addition, RS/reanalyzed datasets can also contain substantial timing errors, and increasing the number of datasets tends to amplify EP biases (Kang et al., 2024). For instance, if one dataset correctly captures EP while another entirely misses it, merging the two will underestimate the EP intensity. As noted above, MSWEP and SUPER v2 are based on the merger of 7 and 4 different datasets, respectively. Therefore, by reducing the number of parent inputs, SUPER v2 can mitigate R95p bias that is a by-product of merging.

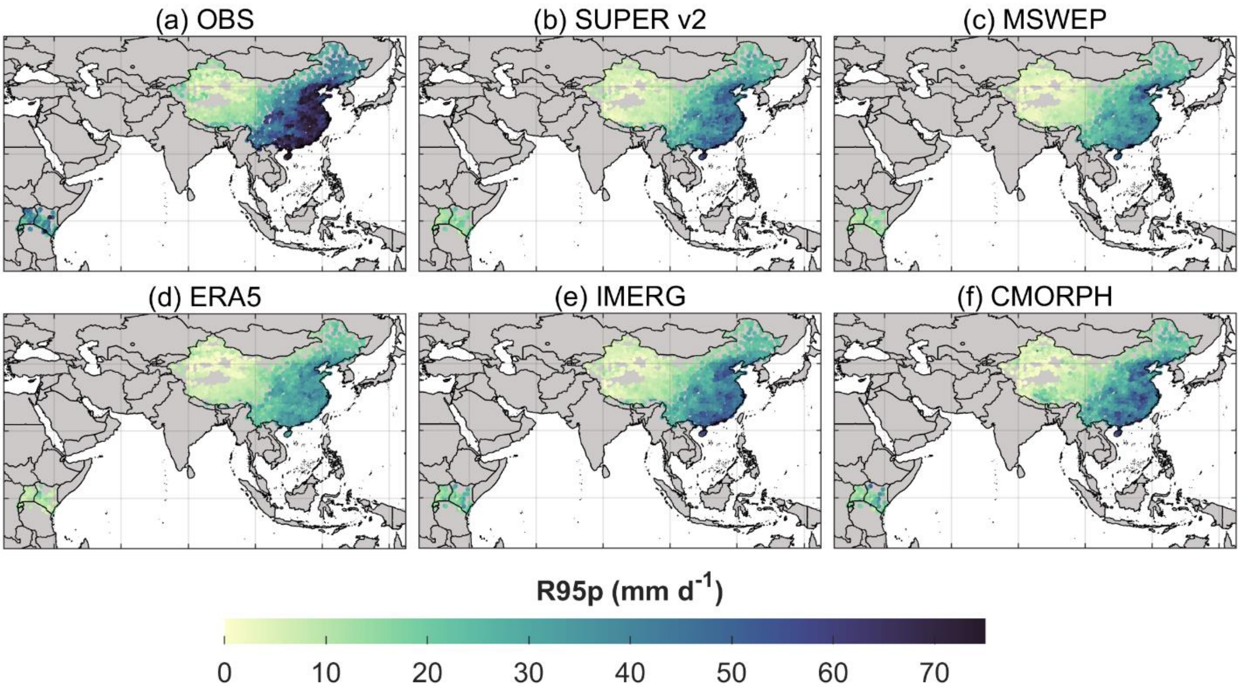


Figure 8. The spatial distribution of mean R95P for (**a**) SUPER v2, (**b**) MSWEP, (**c**) and four RS/Reanalysis products (**d–f**). All values are based on comparisons against daily rain-gauge data.

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Preprint. Discussion started: 23 January 2026

5 Discussion and Conclusions

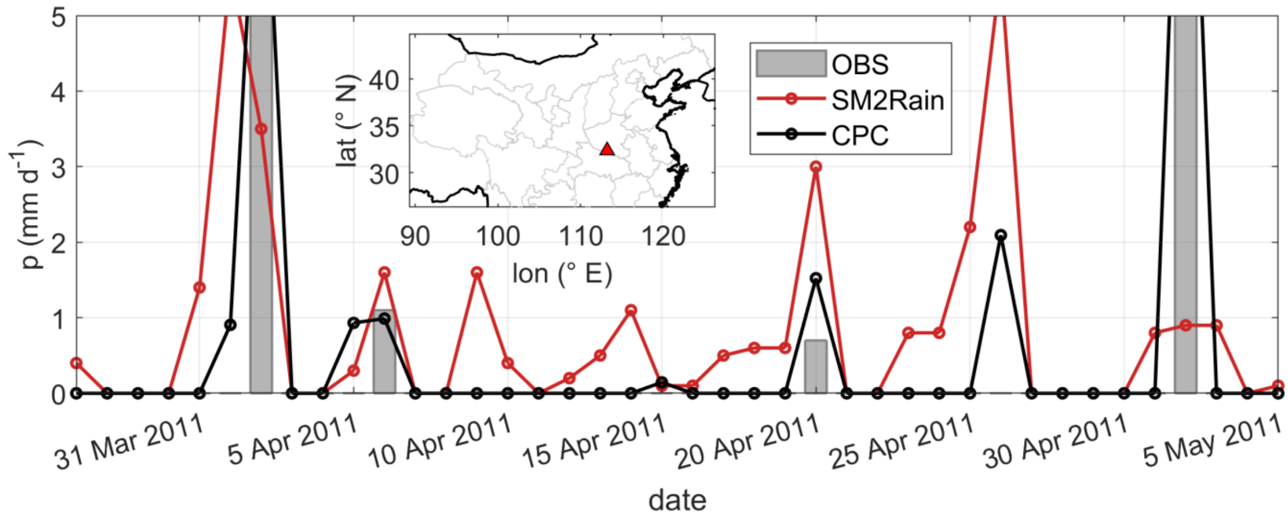
This study presents the SUPER v2, a 3-hourly, 0.1-degree global precipitation dataset spanning 2000–2023, designed to enhance large-scale precipitation estimation. The primary advantage of SUPER v2 is its use of statistical uncertainty-based merging framework with optimized inputs. As such, it preserves sufficient precipitation information without excessively attenuating extreme precipitation (EP) intensity. Critically, SUPER v2 suppresses random and rain/no-rain classification error without requiring high-quality gauges — making it better suited for data-sparse regions. Validation using 5,972 independent rain gauges demonstrates that SUPER v2 achieves a daily RMSE of 3.64 mm d^{-1}, CC of 0.68 and HSS of 0.58. These metrics outperform traditional RS, reanalysis, and gauge-merged products at 81%, 86%, and 75% of our independent validation sites, respectively.

A key finding of our analysis is that indiscriminately increasing the number of input precipitation datasets, as done in many previous studies, can inadvertently degrade merging accuracy. This counterintuitive outcome arises because typical merging approaches prioritize the overall estimation accuracy (variance-minimized), which inadvertently suppress natural precipitation variability, especially in extremes (Abdelmoaty et al., 2021; Beck, Vergopolan, et al., 2017). Furthermore, RS-based precipitation products often exhibit substantial intensity and timing errors, particularly for EP events. The combination of these factors leads to a systematic underestimation of EP intensity, a risk that escalates with the inclusion of additional, error-prone datasets (Kang et al., 2024). Therefore, SUPER v2 employs a selective strategy, incorporating only four representative datasets. This ensures a balance between overall precipitation accuracy and realistic EP estimates.

It is important to note that SUPER v2 also incorporates gauge-based information, such as the CPC product. However, it fundamentally differs from traditional gauge-based frameworks, which often assume gauge observations to provide an error-free reference. This assumption introduces significant uncertainties, particularly in data-sparse regions with limited gauge coverage. In contrast, SUPER v2 integrates CPC as a standard gridded input, explicitly quantifying and incorporating its uncertainties during the merging process. For example, the contribution of CPC is minimal in data-sparse regions, with an assigned weight of less than 0.05, while greater reliance is placed on RS and reanalysis datasets (Fig. 4) in these areas. This allows SUPER v2 to implicitly account for observational errors and effectively leverage multi-source precipitation information, resulting in a more balanced and robust performance across regions with varying gauge densities. As such, SUPER v2 will provide valuable support for global-scale hydrological and land surface modeling.

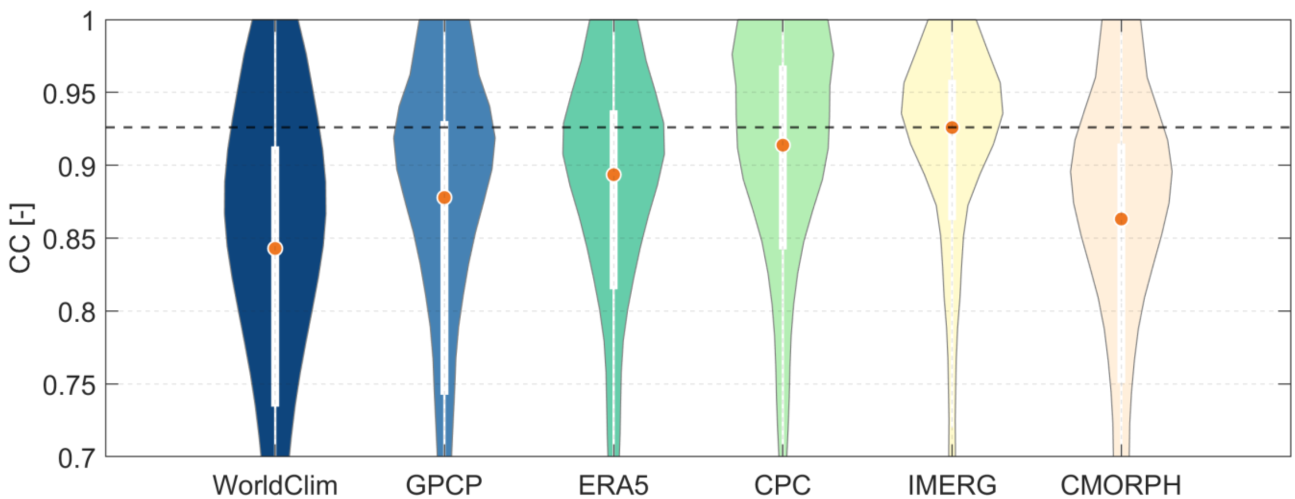
https://doi.org/10.5194/essd-2025-792
Preprint. Discussion started: 23 January 2026

Appendix A: Selection of CTC-M input datasets



295 **Figure A1.** Comparison of observed daily precipitation (OBS) with SM2Rain and CPC estimates for a selected site. The geolocation of this illustrative grid cell is shown in the inset. SM2Rain falsely detects precipitation events for 19 out of 40 days, resulting in a higher false alarm rate. In contrast, CPC shows better agreement with observations, with false alarms on only 4 out of 40 days.

Appendix B: Selection of reference precipitation climatology



300 **Figure B1.** Pearson correlation coefficients (CC) of six precipitation datasets evaluated against daily gauge observations (based on monthly total precipitation). Among the evaluated datasets, IMERG shows the highest consistency with gauge observations.

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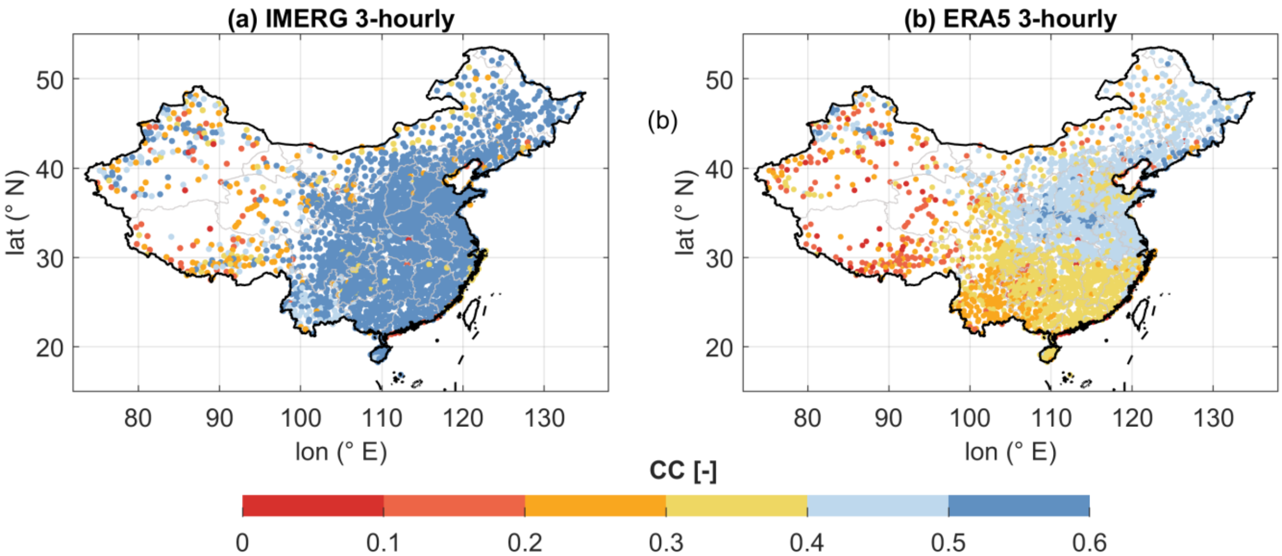
Preprint. Discussion started: 23 January 2026

Appendix C: Evaluation of IMERG 3-hourly precipitation accuracy



305 **Figure C1.** Spatial distribution of correlation coefficients (CC) between hourly observations from 2,674 national stations in China and (**a**) IMERG 3-hourly and (**b**) ERA5 3-hourly precipitation estimates. IMERG exhibits generally higher correlations across most regions, particularly in southern and eastern China, indicating its superior capability in capturing sub-daily precipitation variability.

Data availability

The SUPER v2 (3-hourly, 0.1°, global, 2000–2023) dataset is openly available at:
310 https://doi.org/10.6084/m9.figshare.30899792 (Zhang & Dong, 2025a). Daily precipitation data are also supplied to support diverse user needs: https://doi.org/10.6084/m9.figshare.29206313 (Zhang & Dong, 2025b). All data are provided in NetCDF format.

Author contributions

Research design was initiated by HZ and JD. HZ led the data analysis and drafted the initial manuscript under the supervision
315 of JD. The gauge datasets essential for validation were supplied by LW and YZ. The final manuscript was revised and approved by all co-authors.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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