Reply to Reviewer 1

Manuscript ID: essd-2018-150
Title: WHU-SGCC: A novel approach for blending daily satellite (CHIRP) and precipitation observations over Jinsha River Basin
Journal: Earth System Science Data
Type: Article

Dear Reviewer,

Thank you for your insight comments and suggestions. We have modified the manuscript accordingly. We trust that all of your comments have been addressed accordingly in the revised manuscript. If you have further suggestions for changes, please let us know. The detailed corrections are listed below point by point:

All changes in the manuscript are marked with red color.

Minor comments

(1)- Line 14: By mentioning the CHIRP database the University of Santa Barbara needs to be cited as developer. Thus, the sentence has to be changed in: the Climate Hazards Group InfraRed Precipitation (CHIRP, daily 0.05) satellite-derived precipitation developed by the UC Santa Barbara

Answer: Thanks. Done. The University of Santa has been cited when mentioning the CHIRP database.

Change: changed "the Climate Hazards Group Infrared Precipitation (CHIRP, daily, 0.05°) satellite-derived precipitation estimates" to "the Climate Hazards Group Infrared Precipitation (CHIRP, daily, 0.05°) satellite-derived precipitation developed by the UC Santa Barbara over the Jinsha River Basin for the period of June-July-August in 2016"

(2)- Line 52: When the CHIRPS dataset has been mentioned the developer (UC Santa Barbara et al.) has to cited as well.

Answer: Thanks. Done. The University of Santa has been cited when mentioning the CHIRP database.

Change: changed "the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS)" to "the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) developed by the UC Santa Barbara"

(3)- Line 109: Section 2.2 can to be compacted in only 2 subsections for a better reading: 1) precipitation gauged observations and 2) gridded precipitation+CHIRPS

Answer: Thanks. Done. Because the gridded precipitation used here was from China

Meteorological Data Service, interpolated from 2472 rain gauge stations. The interpolated data with some errors was less accurate than the direct measurements from stations, for example, daily precipitation was more than 1000 mm at one interpolated grid point. So only the rain gauge observations were used to the new experiments.

Change: We have only used rain gauge stations to conduct the WHU-SGCC method over the Jinsha River Basin during the summer seasons from 1990 to 2014. So we delete the relative sections (2.2.2 Gridded precipitation observations; 3.1.3 Rule 2 of the WHU-SGCC method). And we changed the classifications of the target pixels from "1) Classify all regional pixels into five types: C1 (pixel including one gauged station in its area), C2 (pixel including one gridded point), C3 (pixel physically similar to C1C2), C4 (pixel physically similar to C3) and C5 (remaining pixels)." to "Classify all regional pixels into four types: C1 (pixel including one gauge station in its area), C2 (pixel statistically similar to C1), C3 (pixel statistically similar to C2) and C4 (remaining pixels). "

(4)- Line 159: what's "SICR approach"?

Answer: Sorry. Thanks. The "SICR" approach must be clerical error.

Change: This sentence has been changed "On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the classification principles of the SICR approach, including five classification and blending rules." to "On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the four classification and blending rules."

(5)- Line 162 "C3 (pixel physically similar to C1C2)". What does it mean "physically"?

Answer: Thanks. Some studies indicate that pixels have similar precipitation features in certain spatial scope. And the size of spatial range can be determined by similar geographical location, elevation and other terrain information with the method of fuzzy c-means (FCM) clustering in this study. Because we deleted the gridded precipitation observations and changed the pixels classifications to "Classify all regional pixels into four types: C1 (pixel including one gauge station in its area), C2 (pixel statistically similar to C1), C3 (pixel statistically similar to C2) and C4 (remaining pixels)." So in the new experiments, we can assume that **the C2 pixels have similar precipitation features (e.g. rainfall distribution) with C1 pixels in the same cluster**, which may be better called **statistically simila**r rather than physically similar.

Change: We changed "C3 (pixel physically similar to C1C2), C4 (pixel physically similar to C3)" to "C2 (pixel statistically similar to C1), C3 (pixel statistically similar to C2)"

(6)- Line 180 ": : :satellite precipitation estimations deviated from observed data : : :". Really satellite precipitation even though retrieved are always measured data. Thus, it is better replacing the above sentence with: "satellite precipitation estimations deviated from ground-based measurements"

Answer: Thanks. Done.

Change: changed “satellite precipitation estimations deviated from observed data” to “satellite precipitation estimations deviated from ground-based measurements”.

(7)- Section 4 – This section is too much subdivided getting quite difficult the reading. Please, let you group the discussion.
Answer: Thanks. Done.
Change: Because of the modification of the WHU-SGCC approach, the section 4 was adjusted accordingly.
Now the section 4 was divided into 3 parts: 4.1 Model performance based on overall accuracy evaluations, 4.2 Model performance based on daily accuracy evaluations and 4.3 Model performance on rain events predictions, which may be simpler for reading.

(8)- Table 6: What’s “wet precipitation?” You mean, probably liquid precipitation, right?
Answer: Yes. Thanks. It is a good idea to state that the paper focus is on liquid precipitation (rainfall) and this term would be used throughout.

Change: changed “wet precipitation” to “liquid precipitation”.

And we stated in the introduction “Here, we will use precipitation to name liquid precipitation throughout the text.”

Major comments to Authors

The proposed manuscript tries to improve the performance of the CHIRP/S datasets by statistically adjusting the original data over complex terrain. The general statistics described in table 5 reveals very light improvements even though WHU-SGCC performs better and CHIRPS dataset seems to be worse also respect to raw data (CHIRP). Skipping to the performance evaluation for rain categories, how do you justify the inversion of BIAS tendency from the category (5,10) to > 40 (see table 6)? The accuracy of WHU-SGCC method seems to be limited to low precipitation (<10, not >20) where the model tends to overestimate. For precipitation greater than 10 the WHU-SGCC starts to underestimate. Please, let u clarify this! Really, the validation of the WHU-SGCC method is only limited to the Jinsha River Basin in summertime 2016 thus new and more accurate validation campaigns have to be done. On that, the challenging efforts to apply and validate a new method over orographically complex terrain have to be supported by new application on similar morphology where the rain-gauges are typically sparse. Furthermore, since during the monsoon season precipitation is typically higher than 20 mm, how the WHU-SGCC will perform? Of course, this question needs to be exhaustively answered by a new validation using the same methodology described in the manuscript.
Answer: The CHIRPS was derived from blending in-suit precipitation observations and the CHIRP data, with a modified inverse-distance weighting algorithm at a quasi-global area (land only, 50° S-50° N). The blended data (CHIRPS) has an effective performance on a large scale region according to existing studies, such as at the national scale, but there are still large discrepancies with ground observations at the sub-regional

level, especially at the river basin scale. The performance and applicability of CHIRPS at the sub-regional level still need to be validated. What's more, the interpolation performance from the limited and sparse rain gauge stations will be affected by more errors which was evaluated with rain gauge stations shown in Table 5.

As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the modified inverse-distance weighting algorithm, the aim of this article is to offer a novel blending approach to improve the precipitation estimated accuracy at the river basin scale.

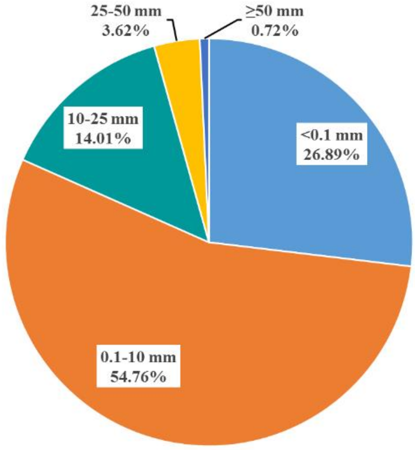
The Jinsha River Basin is a typically study area, with the complex and varied terrains that the range of elevation is from 263 to 6575 m above sea level, which results in significant temporal and spatial weather variation within the basin. What's more, the multi-year (1990-2014) average annual precipitation increases from north to south and the spatial distribution of precipitation is uneven, with an average annual precipitation ranging from less than 250 mm to more than 600 mm during the summer seasons over the Jinsha River Basin. However, the number of rain gauges stations is limited inside the river basin which cause precipitation estimations bias a lot.

In the previous experiment, the rain gauge stations and gridded points were used as the reference precipitation data. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance. And the WHU-SGCC approach was evaluated for the Jinsha River Basin for JJA 2016.

However, the gridded precipitation used here was from China Meteorological Data Service, interpolated from 2472 rain gauge stations, which was less accurate than the rain gauge stations observations, for example, daily precipitation was more than 1000 mm at one interpolated grid point. So only the 30 rain gauge stations were used in the new WHU-SGCC experiments. In the new experiment, selecting 30% of the stations for validation was not an appropriate validation method, while the leave-one-out cross validation was a better instead for using all the stations in WHU-SGCC correction algorithm. What's more, in order to evaluate the model performance more reasonably, the study period was changed from summer of 2016, JJA to a longer study period during June-July-August from 1990 to 2014.

In the results, the days of each class of rain events at the validation gauge station during the JJA from 1990 to 2014 were shown in Table 6 in the paper and the following figure. The major rain events inside the Jinsha River Basin were light rain (0.1-10 mm), accounting for 54.76% of the total days (the average percentage of rain event days in its total days at each gauge station), while the days with daily precipitation over the 50 mm was least, only accounting for 0.72%. And the percentage of the daily precipitation of <0.1, 10-25, and 25-50 mm were 26.89%, 14.01% and 3.62% respectively. The result indicated that the average daily precipitation was less than 10 mm, though in the summer seasons during the multi-year. As well as, the spatial distribution of precipitation was also uneven, with an increase from north to south. In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall less than 25 mm which can represents the mainly precipitation conditions over the

Jinsha River basin.



The WHU-SGCC approach blended daily precipitation gauge data and the CHIRP satellite-derived precipitation, considering the spatial correlation and the historical precipitation characteristics. Therefore, the applicability of the WHU-SGCC method over the complicated mountainous terrain with sparse rain gauge data could be confirmed by the multi-year validation.

It is quite a worthy advice that applying and validating the WHU-SGCC method over the other similar terrain area where the sparse rain-gauges layout. But during the he revision period, our major work was on the study period extension and the method modification, the validation on the other area would be carried on further research.

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Reply to Reviewer 2

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All changes in the manuscript are marked with red color.

General Comments

The manuscript describes a very interesting method to correct random and systematic errors from satellite infrared precipitation estimates based on gauge data and grid points from interpolated precipitation fields. The manuscript is well structured and present links to access all the data that is used in the work. However, I found that the analysis period (summer of 2016, JJA) is too short to make significant conclusions about this precipitation dataset. Also, the manuscript could have explored another ways to analyze and evaluate the dataset other than the very conventional use of statistical metrics, that are definitely needed, but the authors could have explored beyond that. Maybe using a case study or exploring the usefulness of the data for a particular hydrological application would be helpful. The dataset published with the manuscript is of good quality and is stored in a standard and easy to read format. I suggest that the authors make another English revision, especially regarding the use of articles and prepositions.

Answer:

Thank you for your advices on the analysis period, method, validation and the syntax modification.

The WHU-SGCC approach is a promising tool to monitor the summer precipitation over the Jinsha River Basin, considering the spatial correlation and historical precipitation characteristics.

However, in the previous experiment, the analysis period (summer of 2016, JJA) was too short to make significant conclusions. Therefore, in order to evaluate the model performance more reasonably, the study period was changed from summer of 2016, JJA to a longer study period during June-July-August from 1990 to 2014.

What's more, the rain gauge stations and gridded points were used as the reference precipitation data in the previous experiment. Now, due to the gridded precipitation interpolated from 2472 rain gauge stations, which was less accurate than the rain gauge stations observations, for example, daily precipitation was more than 1000 mm at one interpolated grid point (This data can be obtained from the China Meteorological Data Service). In hence, only the 30 rain gauge stations were used in the new WHU-SGCC experiments and the validation method was changed from "selecting 30% of the stations for validation" to leave-one-out cross validation for using all the rain gauge stations. Based on this, the WHU-SGCC was also modified for better precipitation correction.

It is quite a worthy advice that using a case study or exploring the usefulness of the data for a particular hydrological application. But the monitoring data for water level and velocity at the gauge stations are not available online, which limits the input data for hydrological model. Nevertheless, we are applying to hydro-graphic office. The validation on a particular hydrological case would be carried on further research.

In the new experiment, the applicability of the WHU-SGCC method over the complicated mountainous terrain with sparse rain gauge data could be confirmed by the multi-year statistical validation over the Jinsha River Basin.

Specific Comments

(1)- Line 18: It was evaluated not only by categorical indices.

Answer: Thanks. The performance of WHU-SGCC approach was evaluated by multiple error statistics and from different perspectives, such as overall accuracy, daily accuracy and performance on different rain events.

Change: So according to your advice, we changed "which is evaluated by categorical indices" to "which is evaluated by multiple error statistics and from different perspectives".

(2)- Line 28: The number of gauge stations is actually very limited, especially in regions with complex terrain and in the case of gauges that measure solid precipitation. Accuracy of this gauges is also not very good in the case of solid precipitation. It would be a good idea to state that the paper focus is on liquid precipitation (rainfall), and use this term throughout the text.

Answer: Thanks. It is a good idea to state that the paper focus is on liquid precipitation (rainfall) and this term would be used throughout.

Change: We changed "In general, ground-based gauge networks include a substantial number of precipitation observations measured with high accuracy" to "In general, ground-based gauge networks include a substantial number of liquid precipitation observations measured with high accuracy"

Changed "As such, the aim of this article is to offer a novel approach for blending daily precipitation gauge data, gridded precipitation data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates developed by the UC Santa Barbara, over the Jinsha River Basin." to "As such, the aim of this article is to offer a novel approach for blending daily liquid precipitation gauge data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates developed by the UC Santa Barbara, over the Jinsha River Basin."

Added "Here, we will use precipitation to name liquid precipitation throughout the text."

(3)- Line 35: I found this line confusing in the way it is phrased. I think this sentence could be phrased this way: "Satellite estimates are susceptible to systematic biases that can influence hydrological modelling."

Answer: Thanks. Done.

Change: We changed "However, the retrieval algorithms for satellite-based precipitation estimates are susceptible to systematic biases in hydrologic modelling and are relatively insensitive to light rainfall events" to "However, satellite estimates are susceptible to systematic biases that can influence hydrological modelling and the retrieval algorithms are relatively insensitive to light rainfall events".

(4)- In the introduction, I think that a better description of what is available to estimate precipitation from satellites is missing. For example, GOES-R and GPM are missing in the description.

Answer: Thanks. Done. The description of GEOS-R and GPM has been added into introduction.

Change:

Added the description into introduction:

1) The Global Precipitation Measurement (GPM) satellite was launched after the success of the TRMM satellite by the cooperation of National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) on February 27, 2014 (Mahmoud et al., 2018;Ning et al., 2016). The main core observatory satellite (GPM) cooperates with the ten other satellites (partners) to offer the high spatiotemporal resolution products (0.1° × 0.1°- half- hourly) of the global real-time precipitation estimates (Mahmoud et al., 2019).
2) 2) The Geostationary Operational Environmental Satellite (GOES)-R Series is the geostationary weather satellites, which significantly improves the detection and observation of environmental phenomena. The Advanced Baseline Imager (ABI) onboard the GOES-R platform will provide images in 16 spectral bands, spatial resolution of 0.5 to 2 km (2 km in the infrared and 1–0.5 km in the visible), and full-disk scanning every 5 minutes over the continental United States. The GOES-R Series will offer the enhanced capabilities for satellite-based rainfall estimation and nowcasting (Behrangi et al., 2009;Schmit et al., 2005).

Added the relevant references:

Behrangi, A., Hsu, K. L., Imam, B., Sorooshian, S., Huffman, G. J., and Kuligowski, R. J.: PERSIANN-MSA: A Precipitation Estimation Method from Satellite-Based Multispectral Analysis, J. Hydrometeorol., 10, 1414-1429, 10.1175/2009jhm1139.1, 2009.

Mahmoud, M. T., Al-Zahrani, M. A., and Sharif, H. O.: Assessment of global precipitation measurement satellite products over Saudi Arabia, Journal of

Hydrology, 559, 1-12, 10.1016/j.jhydrol.2018.02.015, 2018.
Mahmoud, M. T., Hamouda, M. A., and Mohamed, M. M.: Spatiotemporal evaluation of the GPM satellite precipitation products over the United Arab Emirates, Atmospheric Research, 219, 200-212, 10.1016/j.atmosres.2018.12.029, 2019.
Ning, S., Wang, J., Jin, J., and Ishidaira, H.: Assessment of the Latest GPM-Era High-Resolution Satellite Precipitation Products by Comparison with Observation Gauge Data over the Chinese Mainland, Water, 8, 481-497, doi:10.3390/w8110481,2016.
Schmit, T. J., Gunshor, M. M., Menzel, W. P., Gurka, J. J., Li, J., and Bachmeier, A. S.: Introducing the next-generation Advanced Baseline Imager on goes-R, Bulletin of the American Meteorological Society, 86, 1079-+, 10.1175/bams-86-8-1079, 2005.

(5)- Line 62: That are other sources of uncertainty in the monitoring of rainfall in complex terrain (e.g., orographic enhancement).

Answer: Thanks. Done. In existing studies, they found that topography, seasonality, and climate impacted on the satellite-based precipitation estimations performance.

Change: We changed "estimations over mountainous areas with complex topography often have large uncertainties and systematic errors due to the sparseness of rain gauges (Zambrano-Bigiarini et al., 2017)" to "estimations over mountainous areas with complex topography often have large uncertainties and systematic errors due to the topography, seasonality, climate impact and sparseness of rain gauges (Derin et al., 2016;Maggioni and Massari, 2018;Zambrano-Bigiarini et al., 2017)" and we added the relevant references.

(6)- Line 94: I was not able to understand the average precipitation over the Yangtze River Basin. You could be more specific about what statistic you are presenting here. Usually what is presented is the spatially averaged annual accumulation of precipitation as an indication of precipitation climatology for the region.

Answer: Thanks. Done. We have used the average annual precipitation as an indication of precipitation climatology for the study region.

Change:

1) We changed "The river's catchment proximately covers an area of ~180 × 10^4 km^2.In 2016, the average precipitation in the Yangtze River Basin was 12053 mm and the total precipitation was 21478.7195 billion m3, which is 10.9% higher than the annual average total precipitation" to "The river's catchment proximately covers an area of approximately ~180 × 10^4 km^2 and the average annual precipitation is approximately 1100 mm (Zhang et al., 2019)."

2)We changed "Average annual precipitation in the Jinsha River Basin is approximately 3433.45 mm, the total annual precipitation north of Shigu is 937.25 mm, while south of Shigu annual precipitation is 2496.20 mm." to "The average annual precipitation of the Jinsha River Basin is approximately 710 mm, the average annual precipitation of the lower reaches is approximately 900-1300 mm, while the average annual precipitation of the middle and upper reaches is approximately 600-800 mm (Yuan et al., 2018)."

(7)- Line 98: I was not able to comprehend the units for the area of the basin. It should be presented as km2.

Answer: Thanks. The units for watershed area (the area of the basin) are km^2.

Change: We changed "covering a watershed area of 460 × 103 km^2" to "covering a watershed area of 460×10^3 km^2".

(8)- Line 102: Topography would not exert a temporal variation in climate, since this is not a very dynamic feature of the Earth's surface. It could exert a temporal variation in weather though.

Answer: Thanks. It is indeed that complex and varied terrains would not exert a temporal variation in climate due to relatively stable feature of Earth's surface. However, a temporal variation in weather would be susceptible to topography.

Change: We changed "which results in significant temporal and spatial climate variation within the basin" to "which results in significant temporal and spatial weather variation within the basin"

(9)- Lines 102 and 103: Please try be consistent with the statistics you are using here.

Answer: Thanks. Done. We have been consistent with the statistics and used the average annual precipitation as an indication of precipitation climatology for the study region.

Change:

We changed "Average annual precipitation in the Jinsha River Basin is approximately 3433.45 mm, the total annual precipitation north of Shigu is 937.25 mm, while south of Shigu annual precipitation is 2496.20 mm." to "The average annual precipitation of the Jinsha River Basin is approximately 710 mm, the average annual precipitation of the lower reaches is approximately 900-1300 mm, while the average annual precipitation of the middle and upper reaches is approximately 600-800 mm (Yuan et al., 2018)."

(10)- Line 134: Maybe explain better what is the CHPClim product.

Answer: Thanks. Done. The reference (Funk, C., Verdin, A., Michaelsen, J., Peterson, P., Pedreros, D., and Husak, G.: A global satellite-assisted precipitation climatology, Earth Syst. Sci. Data, 7, 275-287, 10.5194/essd-7-275-2015, 2015) can better explain the CHpClim product. We have added the reference to the sentence (monthly precipitation from CHPClim) and make some changes.

Change: We have changed "monthly precipitation from CHPClim" to "monthly precipitation from CHPClim v.1.0 (Climate Hazards Group's Precipitation Climatology version 1) derived from the combination of the satellite fields, gridded physiographic indicators, and in situ climate normal with the geospatial modelling approach based on moving window regressions and inverse distance weighting interpolation (Funk et al., 2015 b)"

(11)- Line 146: Which CHIRPS data? The data from its stations? Or the blended product? Please make this clear here.

Answer: Thanks. It was stated from section 2.2.2 that CHIRPS data is a blended product interpolating from CHIRP data and in situ precipitation observations obtained from a variety of sources including national and regional meteorological services (Funk et al., 2014).

Change: We changed a more accurate explain for CHIRPS data used for comparisons of precipitation accuracy. Changed "and the corresponding daily CHIRPS data was used for comparisons of precipitation accuracy" to "and the corresponding daily CHIRPS blended data was used for comparisons of precipitation accuracy"

(12)- Line 162: What do you mean about physically similar? Is this means that these pixels are related to others based on its physical attributes (lat, long, elevation, slope, aspect, and curvature)? Or this means that is similar is terms of rainfall distribution? If is in terms of rainfall, I think a better world would be statistically similar rather than physically similar, since this is based on a cluster analysis.

Answer: Thanks. We assumed that the C2 pixels have similar precipitation features (e.g. rainfall distribution) with C1 pixels in the same cluster, which may be better called statistically similar rather than physically similar.

Change: We changed "C3 (pixel physically similar to C1C2), C4 (pixel physically similar to C3)" to "C2 (pixel statistically similar to C1), C3 (pixel statistically similar to C2)"

(13)- Line 170: Please explain why you chose 30% of the stations/grid points for validation. Since the stations and grid points are of limited number, it would not be better to do a Bootstrap validation instead? Then you are able to use all the stations/grid points in your correction algorithm.

Answer: Thanks. The number of rain gauge stations over the Jinsha River Basin is limited. And because the gridded precipitation used here was from China Meteorological Data Service, interpolated from 2472 rain gauge stations, which was less accurate than the rain gauge stations observations, for example, daily precipitation was more than 1000 mm at one interpolated grid point. So only the 30 rain gauge stations were used to the new experiments. In the new experiment, selecting 30% of the stations for validation was not an appropriate validation method, while the leave-one-out cross validation was a better instead for using all the stations in WHU-SGCC correction algorithm. And the analysis period was changed from (summer of 2016, JJA) to "during the JJA from 1990 to 2014".

Change: We changed the validation method from "The proposed approach was evaluated for the Jinsha River Basin for JJA 2016. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance." to "The proposed approach was evaluated over the Jinsha River Basin based on 30 gauge stations and CHIRP satellite-based precipitation estimations during the JJA from 1990 to 2014. The leave-one-out cross validation step was applied to computing the out-of-sample adjusted error with gauge stations."

(14)- Lines 224 and 225: Since your method relies heavily on the cluster algorithm, it would not be better to use some sort of statistical metric to define the number of clusters?
Answer: Thanks. Done. The optimum number of clusters was determined by L(c) which was derived from the inter-distance and inner-distance of samples in the following equation. It is ensured that the distance between the same samples is smaller, while the distance between the different samples is larger.

$$L(c)=\frac{\sum_{i=1}^{c}\sum_{j=1}^{n}w_{ij}^{m}\|c_i-\bar{x}\|^2/(c-1)}{\sum_{i=1}^{c}\sum_{j=1}^{n}w_{ij}^{m}\|x_j-c_i\|^2/(n-c)}$$

In that equation, the denominator is inner-distance and the molecular is inter-distance. The initial value of c is 1 and the maximum value of c is the number of gauge stations in this study area. The optimum number of clusters was optimized to maximize the L(c). For this reason, c value is conducted in the range from 1 to the number of gauge stations with an incremental interval value of 1 in this study. This result was shown in Appendix B.
Change: We added the L(c) metric to determine the optimum number of clusters and the Fig. B1 (The optimum number of clusters determined by the maximum L(c) with the iterative process) was given. Based on this, the optimum number of clusters was set 22 in this study.

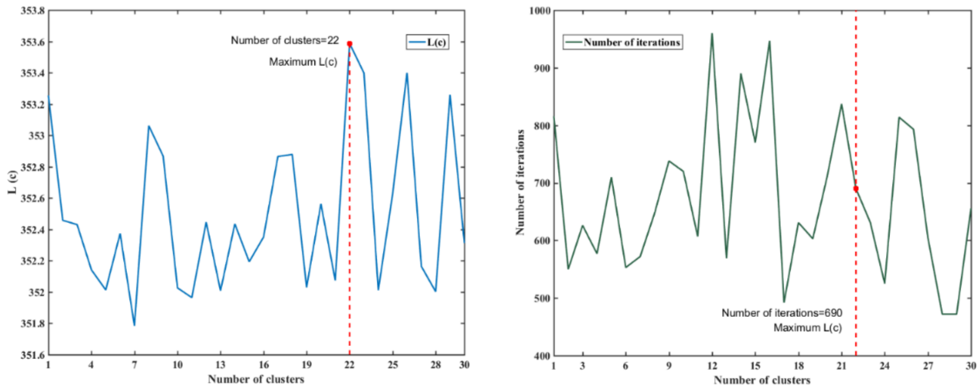


Figure The optimum number of clusters determined by the maximum $L(c)$ with the iterative process.

(15)- Line 234: Pixels should also be similar regarding precipitation characteristics, is that right?
Answer: Thanks. Some studies indicate that pixels have similar precipitation futures in

certain spatial scope. And the size of spatial range can be determined by similar geographical location, elevation and other terrain information with the method of fuzzy c-means (FCM) clustering in this study. Therefore, in each cluster, pixels both have the similar terrain features and precipitation characteristics.

Change: We changed "Pixels in each cluster have similar terrain features" to "Pixels in each cluster have similar terrain features and precipitation characteristics".

(16)- Line 244: I think you should use the word relationship or correlation instead of confidence in this line.

Answer: Thanks. Done.

Change: We changed "confidence is not only determined by the value of the correlation coefficient but also from the correlation test's *p* value" to "correlation is not only determined by the value of the correlation coefficient but also from the correlation test's *p*-value".

(17) Line 259: Why the number of decision trees was set to 500?

Answer: Thanks. Done. The number of decision trees was set to 500, which was determined by out-of-bag (OOB) error (Appendix A). The OOB error reached the minimum value when the number of decision trees was less than 500.

Change: We calculated the OOB-error of Random forest regression with the increase of the number of decision trees from 1 to 500 at each rain gauge station and the Fig. A1 shown the change of out-of-bag (OOB) error with the number of decision trees increase in appendix.

(18)- Line 264: Do C1 and C2 pixels included in the R pixel category?

Answer: No. Thanks. In the previous experiment, C1 and C2 pixels were not included in the R pixels. Now, in the new experiment, we changed the classification of C2, C3 and C4 pixels. Because the gridded precipitation used here was from China Meteorological Data Service, interpolated from 2472 rain gauge stations. The interpolated data with some errors was less accurate than the direct measurements from stations, for example, daily precipitation was more than 1000 mm at one interpolated grid. So only the rain gauge observations were used to the new experiments. And we changed the classifications of the target pixels from "1) Classify all regional pixels into five types: C1 (pixel including one gauged station in its area), C2 (pixel including one gridded point), C3 (pixel physically similar to C1C2), C4 (pixel physically similar to C3) and C5 (remaining pixels)." to "Classify all regional pixels into four types: C1 (pixel including one gauge station in its area), C2 (pixel statistically similar to C1), C3 (pixel statistically similar to C2) and C4 (remaining pixels). "

Change: So with the new experiment, we changed "pixels in each cluster represent potential C3 pixels, with exception of the C1 and C2 pixels and are called R pixels" to "With exception of the C1 pixels, the remaining pixels in each cluster represent potential C2 pixels called R pixels"

(19)- Lines 267 and 280: Are you also considering only SCC values with p-value lower than 0.05 here?

Answer: Yes. Thanks. The correlation coefficient value higher than 0.5 and the p-value lower than 0.05 were considered for C2 pixels selection.

In the new experiment, we changed the statistical metric of SCC to Pearson's correlation coefficient (PCC) because PCC measures the linear correlation between two series better than SCC to evaluate the adjusted precipitation accuracy.

Change: Changed "both the data with a maximum SCC of at least 0.5 and the corresponding index of C1 and C2 pixels" to "both the data with a maximum PCC of at least 0.5 and a p-value lower than 0.05 (Zhang and Chen, 2016)"

(20)- Line 287: Why did you choose the 10 mm value? Could you please explain the meaning of this constant better?

Answer: Thanks. In Eq.(11), the relationship between C2 pixels and the corresponding CGURP grid cells is expressed by the ratio:

$$w_i = \frac{C2_{as_i} + \lambda}{Y_{s_i} + \lambda} \quad i=1,\ldots,n \tag{11}$$

where λ is a positive constant to avoid the denominator value being 0 when CHIRP grid cell value was 0. (Sokol, 2003) tested various λ values indicated that the selected value was not too closely related to the calibration set.

In Rule 3, the values of C3 pixels are derived from Eq. (12):

$$C3_{as} = \max(w \times (Y_s + \lambda) - \lambda, 0) \tag{12}$$

In this equation, the λ set to 10 mm made the calculating simpler, and other values are also available.

(21)- Line 298: Please use the actual percentage here.

Answer: Thanks. In the previous experiment, each C5 pixel value is set to be the same as the CHIRP grid cell value at the corresponding position, because of the few number of the C5 pixels. However, in the new experiment, we abandoned the gridded precipitation observations and only the 30 rain gauge stations with four rules were used to conduct the WHU-SGCC approach. The C5 pixels were changed to C4 pixels for Rule 4 and the percentage of C4 pixels is around 60% of the total number of pixels over the study area. (Due to the leave-one-out cross validation step, the different training samples will have the different number of C2, C3 and C4 pixels respectively inside the Jinsha River Basin). So that, the Inverse Distance Weighted (IDW) method was used to obtain the C4 pixels values.

Change: We added the Table 4 (The number of each class pixels adjusted by each rule using the WHU-SGCC method inside the Jinsha River Basin.) which lists the clearer number and percentage of each class pixels. And the Fig.4 in the previous paper was deleted.

Table 4 The number of each class pixels adjusted by each rule using the WHU-SGCC method inside the Jinsha River Basin.

Validation gauge station	C1 Pixels (%)	C2 Pixels (%)	C3 Pixels (%)	C4 Pixels (%)
52908	29 (0.16%)	3066 (16.59%)	4224 (22.85%)	11163 (60.40%)
56004	29 (0.16%)	2882 (15.59%)	4111 (22.24%)	11460 (62.01%)
56021	29 (0.16%)	3311 (17.91%)	4510 (24.40%)	10632 (57.53%)
56029	29 (0.16%)	3338 (18.06%)	4447 (24.06%)	10668 (57.72%)
56034	29 (0.16%)	3300 (17.86%)	4427 (23.95%)	10726 (58.03%)
56038	29 (0.16%)	3209 (17.36%)	4014 (21.72%)	11230 (60.76%)
56144	29 (0.16%)	3347 (18.11%)	4442 (24.03%)	10664 (57.70%)
56146	29 (0.16%)	3183 (17.22%)	4480 (24.24%)	10790 (58.38%)
56152	29 (0.16%)	3173 (17.17%)	4176 (22.59%)	11104 (60.08%)
56167	29 (0.16%)	3362 (18.19%)	4346 (23.51%)	10745 (58.14%)
56247	29 (0.16%)	3385 (18.32%)	4416 (23.89%)	10652 (57.63%)
56251	29 (0.16%)	3301 (17.86%)	4348 (23.53%)	10804 (58.46%)
56257	29 (0.16%)	3313 (17.93%)	4043 (21.88%)	11097 (60.04%)
56357	29 (0.16%)	3352 (18.14%)	4390 (23.75%)	10711 (57.95%)
56374	29 (0.16%)	3341 (18.08%)	4294 (23.23%)	10818 (58.53%)
56459	29 (0.16%)	3345 (18.10%)	4334 (23.45%)	10774 (58.29%)
56462	29 (0.16%)	3380 (18.29%)	4377 (23.68%)	10696 (57.87%)
56475	29 (0.16%)	3345 (18.10%)	4344 (23.50%)	10764 (58.24%)
56479	29 (0.16%)	3305 (17.88%)	4212 (22.79%)	10936 (59.17%)
56485	29 (0.16%)	3393 (18.36%)	4419 (23.91%)	10641 (57.57%)
56543	29 (0.16%)	3373 (18.25%)	4384 (23.72%)	10696 (57.87%)
56565	29 (0.16%)	3241 (17.54%)	4450 (24.08%)	10762 (58.23%)
56571	29 (0.16%)	3306 (17.89%)	4263 (23.07%)	10884 (58.89%)
56586	29 (0.16%)	3387 (18.33%)	4434 (23.99%)	10632 (57.53%)
56651	29 (0.16%)	3340 (18.07%)	4432 (23.98%)	10681 (57.79%)
56664	29 (0.16%)	3368 (18.22%)	4262 (23.06%)	10823 (58.56%)
56666	29 (0.16%)	3323 (17.98%)	4431 (23.97%)	10699 (57.89%)
56671	29 (0.16%)	3356 (18.16%)	4367 (23.63%)	10730 (58.06%)

(22)Line 326: You should be clearer on what the numbers of pixels are here. Is this the number of pixels inside the basin multiplied by the number of days? It would be a good idea to describe the exact number of pixels for each class along with its actual percentage in the text.

Answer: Thanks. Done.

Change: We added the Table 4 (The number of each class pixels adjusted by each rule using the WHU-SGCC method inside the Jinsha River Basin.) with the exact number of pixels for each class along with its actual percentage. And the Fig.4 in the previous paper was deleted.

The sentence was added into the paper to describe the number and the percentage of each class pixels inside the basin "The number of C1 pixels was the number of training gauge stations accounting 0.16% of the total pixels (18482) inside the basin. Due to the leave-one-out cross validation step, the different training samples will have the different number of C2, C3 and C4 pixels respectively inside the Jinsha River Basin. The number of C4 pixels was approximately 10822 with the percentage around 60%, the number of C3 pixels was approximately 4331 with the percentage ranging from 21.72% to 24.40%, and the number of C2 pixels was approximately 3300 with the percentage ranging from 15.59% to 18.36%."

(23)- Line 341: It would be better to use the same x axis scale in both plots. It seems that the gridded data observation has similar biases as CHIRP and thus their CDFs are more similar, providing less improvement in the adjusted dataset.
Answer: Thanks. According to the new experiment, we changed the Rule 1for the C1 pixels without Adj-QM, so the CDFs were not needed.
Change: We changed the Rule 1 from Adj-QM to establishing the regression relationships between each gauge historical observations and the corresponding CHIRP grid cell value by means of Random Forest Regression. And we deleted the relative sections 4.1 and 4.2 in the previous paper. So the section 4: Results and Discussion only include 4.1 Model performance based on overall accuracy evaluations, 4.2 Model performance based on daily accuracy evaluations, and 4.3 Model performance on rain events predictions.

(24)- Line 355: It would be a good idea to explore and discuss more the statistics presented in Figure 7.
Answer: Because of the multi-year period studied in the new experiment, we modified the WHU-SGCC method. In the new experiment, due to the leave-one-out cross validation step using all the stations, the performance of WHU-SGCC method would be evaluated on the overall accuracy, not on a certain class of pixels. So we didn't evaluate the C3 pixels separately.
Change: The evaluation of C3 pixels and Figure 7 were deleted.

(25)- Line 373: NSE values have increased, but still not very good (i.e., still negative).
Answer: Thanks. The NSE (Nash and Sutcliffe, 1970) determines the relative magnitude of the variance of the residuals compared to the variance of the observations, bounded by minus infinity to 1.
Change: In the new experiment, the NSE of WHU-SGCC method was -0.0137 with an increase of 93.33% and 98.32% to CHIRP and CHIRPS, respectively.
Although the NSE of WHU-SGCC was far less than 1, it was improved to be 0 that indicates the adjusted results were close to the average level of the rain gauge observations, while the NSEs of CHIRP and CHIRPS were much worse.

(26)- Line 376: Is not intuitive that the evaluation metrics are better for CHIRP than CHIRPS, since CHIRPS adds stations data to their dataset. Could you please clarify this? I am seeing here that magnitude evaluation metrics have not changed considerably, probably because the improvement is seem in the low magnitude events. SCC has a considerable increase, but still cannot explain much of the variability of rainfall in the region. POD values are good.

Comments 1): Is not intuitive that the evaluation metrics are better for CHIRP than CHIRPS, since CHIRPS adds stations data to their dataset. Could you please clarify this?

Answer: The CHIRPS was derived from blending in-suit precipitation observations and the CHIRP data, with a modified inverse-distance weighting algorithm at a quasi-global area (land only, 50° S-50° N). The blended data (CHIRPS) has an effective performance on a large scale region, such as at the national scale, but there are still large discrepancies with ground observations at the sub-regional level, especially at the river basin scale. The performance and applicability of CHIRPS at the sub-regional level still need to be validated. What's more, the interpolation performance from the limited and sparse rain gauge stations will be affected by more errors which was evaluated with rain gauge stations shown in Table 5.

As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the modified inverse-distance weighting algorithm, the aim of this article is to offer a novel blending approach to improve the precipitation estimated accuracy at the river basin scale.

Change: We changed the sentence from "As such, the aim of this article is to offer a novel approach for blending daily precipitation gauge data, gridded precipitation data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates over Jinsha River Basin." to "As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the existing blending algorithms, the aim of this article is to offer a novel approach for blending daily liquid precipitation gauge data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates developed by the UC Santa Barbara, over the Jinsha River Basin." for better explanation.

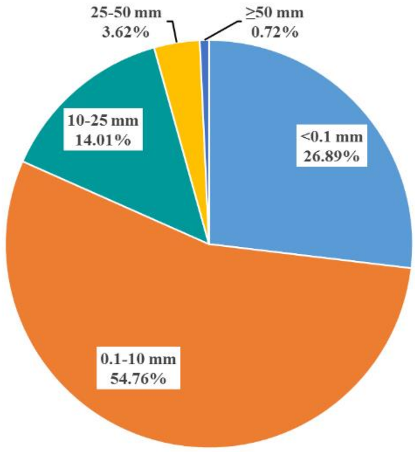
Comments 2): I am seeing here that magnitude evaluation metrics have not changed considerably, probably because the improvement is seem in the low magnitude events. SCC has a considerable increase, but still cannot explain much of the variability of rainfall in the region. POD values are good.

Answer: In the previous experiment, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to test model performance. This validation was not able to use all the rain gauge stations and the same validation set may not fully explain the performance on the Jinsha River Basin. As such, in the presented experiment, the leave-one-out cross validation step was a better instead for using all the stations in WHU-SGCC correction algorithm.

What's more, the analysis period (summer of 2016, JJA) is too short to make significant conclusions about this precipitation dataset, so we changed the period during June-July-August from 1990 to 2014, 92 days per year for 25 years totally.

Change: We use the leave-one-out cross validation to instead the fixed training and testing sets. And we also changed a longer study period during June-July-August from 1990 to 2014, to evaluate the model performance on different rainfall events.

In the results, the days of each class of rain events at the validation gauge station during the JJA from 1990 to 2014 were shown in Table 6 in the paper and the following figure. The major rain events inside the Jinsha River Basin were light rain (0.1-10 mm), accounting for 54.76% of the total days (the average percentage of rain event days in its total days at each gauge station), while the days with daily precipitation over the 50 mm was least, only accounting for 0.72%. And the percentage of the daily precipitation of <0.1, 10-25, and 25-50 mm were 26.89%, 14.01% and 3.62% respectively. The result indicated that the average daily precipitation was less than 10 mm, though in the summer seasons during the multi-year. As well as, the spatial distribution of precipitation was also uneven, with an increase from north to south. In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall less than 25 mm which can represents the precipitation conditions over the Jinsha River basin.



(27)- Line 383: Could this means that because the daily precipitation in the lowland region of the basin is higher, the RMSE values are also higher?

Answer:

In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall lower than and 25 mm, but WHU-SGCC performance for total rainfall higher than 25mm did not improve compared to CHIRP and CHIRPS (Table 7), though it was better than that of CHIRPS. This negative performance on the total rainfall higher than 25 mm was probably caused by the precipitation conditions inside the Jinsha River Basin (Table 6). The average daily precipitation was less than 10 mm inside the basin, during the multi-year summer seasons, which provided a large amount of rain gauge stations data with the values lower than 10 mm, that caused a significantly impact on the statistical relationships establishment for WHU-SGCC. In hence, the approach of WHU-SGCC is applicable for the detection of rainfall events over the Jinsha River Basin, with the average daily precipitation less than 10 mm, or even than 25mm. Due to the 4.34% of summer days with the daily precipitation over the 25 mm, the performance of WHU-SGCC on these rain events was poorer than the results of CHIRP and CHRPS.

(28)- Line 388: The fact that your method performs well in complex terrain is a very positive point in your manuscript, but you will need a longer study period to confirm this finding.

Answer: Thanks. Done.

Change: we changed the study period from summer of 2016, JJA to a longer study period during June-July-August from 1990 to 2014, to evaluate the model performance more reasonably.

(29)- Line 402: The boxplots do not show that the higher reduction is seen in the Bias metric.

Answer: We redraw the boxplots of the statistical analysis of the agreement between daily observations and WHU-SGCC, CHIRP and CHIRPS estimates on leave-one-out cross validation during the JJA from 1990 to 2014.

And now the section 4 was divided into 3 parts: 4.1 Model performance based on overall accuracy evaluations, 4.2 Model performance based on daily accuracy evaluations and 4.3 Model performance on rain events predictions.

Change: Redraw the boxplots.

The slight reduction was reflected in the BIAS, with an 8% to 45% reduction compared to CHIRP and CHIRPS, while all the values were concentrated between -0.5 and 0.5. Therefore, all the precipitation estimations derived from WHU-SGCC, CHIRP, and CHIRPS represented well agreement with the observations in relative bias.

(30)- Line 417: I am still confused about which rainfall value is presented is this figure. It does not seem realistic that the average daily rainfall would be ~ 200 mm. Please be more specific about which rainfall statistic you are using in this figure.

Answer: Thanks. This may the error in gridded precipitation observations.

Because the gridded precipitation used in pervious experiment was from China Meteorological Data Service, interpolated from 2472 rain gauge stations. The interpolated data with some errors was less accurate than the direct measurements from stations, for example, daily precipitation was more than 1000 mm at one interpolated grid.

Change: We have only used 30 rain gauge stations to conduct the WHU-SGCC method over the Jinsha River Basin during the summer seasons from 1990 to 2014.

(31)- Line 430: The evaluation metrics for the threshold values are quite similar among the three precipitation products. Just because the values for WHU-SGCC become slightly worse for precipitation higher than 20 mm/day does not mean they are significantly different from the other products. Since the values are very similar, I would suggest to test their differences statistically before making the assumption that WHU-SGCC works better for low magnitude events. This might also be caused by the limitation of the short study period. There is a tendency to use the word scale for a temporal dimension, better to use period instead. I think it would be interesting to add a map with the accumulated precipitation for the study period. The analysis period of

92 days is too short to make conclusive assumptions about the dataset usefulness in the region, which are made several times throughout the text. I understand why the authors want to focus on the summer months to avoid the higher biases introduced by solid precipitation, but I did not understand why they only performed the evaluation for one summer season. Is there a particular reason for that? I still think that is hard to make the conclusions you made based on 92 days, if you add more seasons to the analysis this can become a very interesting manuscript and dataset.

Answer: Thanks. In the previous experiment, the analysis period (summer of 2016, JJA) is too short to comment about this precipitation dataset.

Changed:

1) We added more summer seasons from 1990 to 2014, 92 days per year for 25 years totally to make a more reasonable conclusive.

2) And we added a map with the multi-year (1990-2014) average annual precipitation (Fig. 2). The multi-year average annual precipitation increases from north to south and the spatial distribution of precipitation is uneven, with an average annual precipitation ranging from less than 250 mm to more than 600 mm during the summer seasons over the Jinsha River Basin.

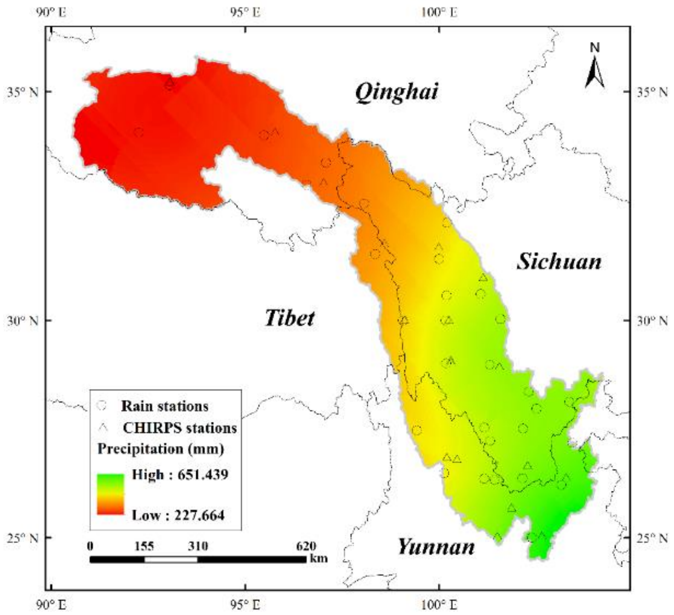


Figure 2 The multi-year (1990-2014) average annual precipitation during JJA over the Jinsha River Basin. 30 rain stations were provided by the China Meteorological Administration stations, the other 18 CHIRPS fusion stations were provided by the Climate Hazards Group UC Santa Barbara online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/global_monthly_station_density/tifs/p05/ (last access: 10 December, 2018).

3) The result indicated that the average daily precipitation was less than 10 mm, though in the summer seasons during the multi-year. As well as, the spatial distribution of precipitation was also uneven, with an increase from north to south. In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall less than 25 mm which can represents the precipitation conditions over the Jinsha River

basin.

According to the comparison, the WHU-SGCC approach achieves error reductions for the RMSE, MAE and BIAS statistics for rain events less than 25 mm. Specifically, compared with CHIRP, the RMSE value was reduced by approximately by 5.92%-39.44%, the MAE value by 4.28%-12.41%, and the absolute BIAS value by 9.15%-44.43%; compared with CHIRPS, the RMSE and MAE values were reduced by 11.04%-56.61%, and the absolute BIAS value by 23.77% -59.58%.

Table 7 Accuracy assessment on liquid precipitation events during the JJA from 1990 to 2014

	RMSE			MAE			BIAS		
Rain Event	WHU-SGCC	CHIRP	CHIRPS	WHU-SGCC	CHIRP	CHIRPS	WHU-SGCC	CHIRP	CHIRPS
<0.1	4.7253	5.0802	7.1643	2.5927	2.9562	2.9145	/	/	/
[0.1,10)	4.1661	6.8684	9.6022	3.9885	4.5534	6.2462	0.8021	1.4435	1.9842
[10,25)	10.4281	11.0848	13.4427	9.2722	9.6866	11.5909	-0.5762	0.6342	0.7559
[25,50)	25.7494	24.5600	25.4975	24.8386	23.0967	23.4927	-0.7784	0.7250	0.7388
≥50	56.6072	54.5037	52.7875	54.4168	52.1557	49.4318	-0.8861	0.8297	0.7852

(32)- The dataset seems to be of good quality. A few comments about it are the following. For a spatial extent of this magnitude I think it would be better to use a geographic coordinate system, rather than a Mercator projection. There is also some artifacts (0 precipitation values) that appear at the same location at multiple days. I was wondering if this is a limitation from the negative values of Rule 4. Is there any way to correct this? This dataset could be very useful if its period is extended to multiple years.
Answer: Thanks. The average annual precipitation of the Jinsha River Basin is less and the spatial distribution of precipitation is uneven, with an average annual precipitation ranging from less than 250 mm to more than 600 mm during the summer seasons. So there are also possible no rain in some locations at multiple days over the north of Jinasha River Basin. The negative values derived from Rule 3 (in the new experiment, the Rule 4 was changed to the Rule 3) were not too closely related to the zero precipitation values appearing at the same location at multiple days.
Change: The results images of the WHU-SGCC method were changed from “Mercator projection” to “geographic coordinate system: WGS_84”

Technical Corrections

(1) Line 2: Change “over Jinsha” for “over the Jinsha”.

Answer: Thanks. Done.

Change: We changed “over Jinsha” to “over the Jinsha”.

(2) Line 31: Change “distributed” for “spatial distribution”.

Answer: Thanks. Done.

Change: We changed “their uneven distributed” to “their uneven spatial distribution”.

(3) Line 37: “without adjustment” is mentioned twice.

Answer: Thanks. Deleted one "without adjustment".

Change: We changed "Without adjustments, inaccurate satellite-based precipitation estimates without adjustment will lead to unreliable assessments of risk and reliability" to "Without adjustments, inaccurate satellite-based precipitation estimates will lead to unreliable assessments of risk and reliability"

(4) Line 68: In table 1, it should be written "PERSIANN-CDR" instead of "PRESSIANN-CDR".

Answer: Thanks. Done.

Change: We changed "PRESSIANN-CDR" to "PERSIANN-CDR"

(5) Line 84: Change "in summer 2016" for "in the summer of 2016".

Answer: Thanks. Done.

Change: We added the seasons in analysis period, so we changed "in summer 2016" to "over the Jinsha River Basin during the summer seasons from 1990 to 2014"

(6) Line 93: Change "proximately covers an area" for "covers an area of approximately".

Answer: Thanks. Done.

Change: We changed "The river's catchment proximately covers an area of ~180 × 10^4 km^2" to "The river's catchment covers an area of approximately ~180 × 10^4 km^2"

(7) Line 95: Change "sub-regions" for "sub-basins".

Answer: Thanks. Done.

Change: We changed "sub-regions" to "sub-basins"

(8) Line 136: Change "precipitation observations" for "surface based precipitation observations".

Answer: Thanks. Done.

Change: We changed "precipitation observations" to "surface based precipitation observations".

(9) Line 157: Change "other pixels" for "the remaining pixels".

Answer: Thanks. Done.

Change: We changed "other pixels" to "the remaining pixels".

(10) Line 159: The acronym "SIRC" meaning was not mentioned before.

Answer: Sorry. Thanks. The "SICR" approach must be clerical error.

Change: This sentence has been changed "On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the classification principles of the SICR approach, including five classification and blending rules." to "On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the five classification and blending rules."

(11) Line 169: The first sentence could be placed before the item 1.

Answer: Thanks. Done.

Change: We changed this sentence into the first phase in section 3.1, as the reference to the overview of items 1-4. And we changed the validation method from "The proposed approach was evaluated for the Jinsha River Basin for JJA 2016. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance." to "The proposed approach was evaluated for over the Jinsha River Basin based on 30 gauge stations and CHIRP satellite-based precipitation estimations during the JJA from 1990 to 2014. The leave-one-out cross validation step was applied to computing the out-of-sample adjusted error with gauge stations."

(12) Line 171: Is the same phrase that is shown in line 163.

Answer: Thanks. Line 171 and line 163 are repeated.

Change: We deleted the repeated phrase in line 163.

(13) Line 172: The flowchart: CHIRP resolution should be 0.05 x 0.05. In the first box of rule 3, change "and gauged" for "with gauged". In the last box of rule 3, change "can derive" for "can be derived". In rule 4, change "ration" for "ratio" (this happens twice here).

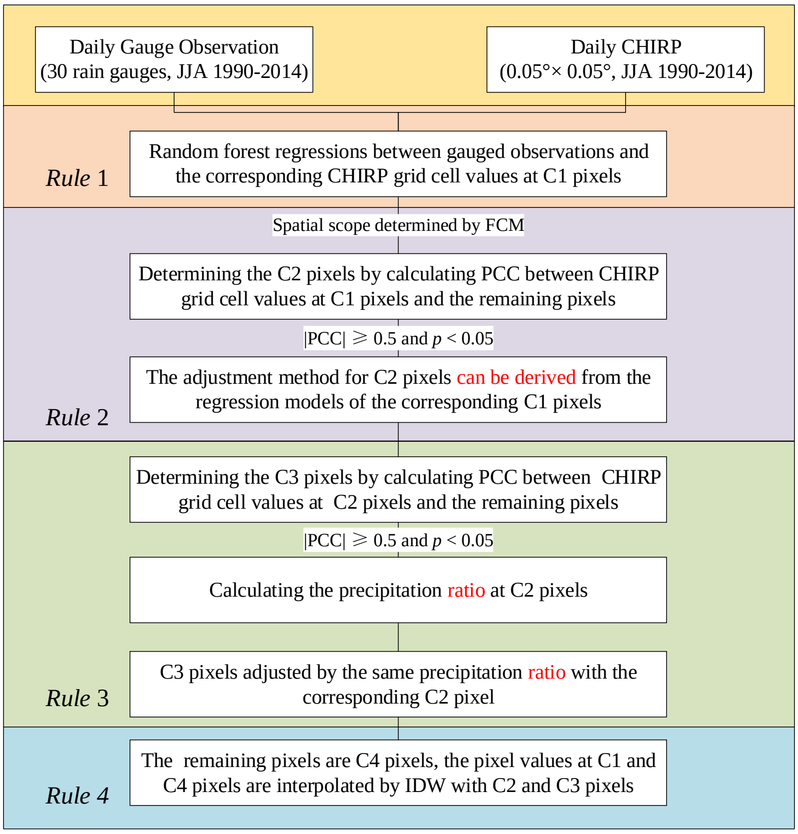
Answer: Thanks. Done. Because we changed the rules of WHU-SGCC, the flowchart was redrawn.

Change: In the flowchart, we changed the CHIRP resolution from "0.5° × 0.5°" into "0.05° × 0.05°"

changed "can derive" to "can be derived"

changed "ration" to "ratio" (two modifications)

The modified flowchart is as follows:



(14) Line 189: Change “as” for “in”.

Answer: Thanks. Done.

Change: We changed the “as Eq. (2)” to “in Eq. (2)”.

(15) Line 246: Change “p” for “p-value”.

Answer: Thanks. Done.

Change: We changed the “*p* value” to “p-value”.

(16) Line 283: The word “method” is repeated twice.

Answer: Thanks. Done.

Change: We deleted the repeated word “method”. Changed “a method for merging method the CHIRP grid cell values” to “a method for merging the CHIRP grid cell values”

(17) Line 300: Change “for summer (JJA) 2016” for “for the summer (JJA) of 2016”.

Answer: Thanks. Done.

Change: We changed the “for summer (JJA) 2016” to “for the summer (JJA) of 2016”.

(18) Line 315: Change “as” for “in”.

Answer: Thanks. Done.

Change: We changed the “All of the accuracy assessment indices are shown as Table 3” to “All of the accuracy assessment indices are shown in Table 3”.

(19) Line 326: Change “to be adjusted” for “adjusted”.
Answer: Thanks. Done.
Change: We changed the “There were 18482 daily pixels to be adjusted” to “There were 18482 daily pixels adjusted”.

(20) Line 340: Change “study” for “studies”.
Answer: Thanks. Done.
Change: We changed the “supports further study” to “supports further studies”.

(21) Line 400: Change “with especially greatly decreases compared to CHIRPS” for “with greater decreases when compared to CHIRPS”.
Answer: Thanks. Done.
Change: We changed the “with especially greatly decreases compared to CHIRPS” to “especially the greater decreases when compared to CHIRPS”.

(22) Line 451: Change “in summer 2016” for “in the summer of 2016”.
Answer: Thanks. Done.
Change: We changed the “in summer 2016” to “in the summer from 1990 to 2014”.

(23) Line 456: Change “over region has” for “over a region that has”.
Answer: Thanks. Done.
Change: We changed the “over region has” to “over a region that has”.

(24) Line 465: Change “of the precipitation region” for “of precipitation events in the region”.
Answer: Thanks. Done.
Change: We changed the “of the precipitation region” to “the large size of light precipitation events with short duration rainstorms in the region resulted in a limited improvement in accuracy”.

(25) Line 466: Change “short” for “short duration”.
Answer: Thanks. Done.
Change: We changed the “during short rainstorms” to “with short duration rainstorms”.

(26) Line 468: Change “complicated mountainous” for “complex terrain”.
Answer: Thanks. Done.
Change: We changed the “complicated mountainous region” to “complex terrain”.

(27) Line 480: Change “topographic and long time series climatic factors” for “topographic factors and longer time series”.
Answer: Thanks. Done. Due to the longer time series data has been taken into the new experiment, the future development was changed.
Change: We changed the “topographic and long time series climatic factors” to “more climatic factors and mulit-model ensemble”.

Reply to Reviewer 3

Manuscript ID: essd-2018-150

Title: WHU-SGCC: A novel approach for blending daily satellite (CHIRP) and precipitation observations over Jinsha River Basin

Journal: Earth System Science Data

Type: Article

Dear Reviewer,

Thank you for your insight comments and suggestions. We have modified the manuscript accordingly. We trust that all of your comments have been addressed accordingly in the revised manuscript. If you have further suggestions for changes, please let us know. The detailed corrections are listed below point by point:

All changes in the manuscript are marked with red color.

The manuscript presents a new method for combining high-resolution daily satellite precipitation estimates with rain gauge observations. The method is applied and evaluated over the Jinsha River Basin for the summer period in 2016 (June, July August). The performance of the method is compared to already existing satellite datasets CHIRP, which is also the base for the new dataset, and CHIRPS. The evaluation reveals an improvement in accuracy of precipitation estimates with rain rates of less than 20 mm per day compared to CHIRP and CHIRPS, however, the chosen time period of just 3 months seems to be rather short for this somewhat general conclusion. For heavy precipitation, however, no improvement could be found. The dataset and the blending method are described and the data is available for free.

The manuscript fits in the scope of ESSD, but some issues need to be addressed. I recommend taking the following suggestions and comments into account:

1.

(1)- It is not quite clear to me what exactly is the reference dataset in this study. On page 6, line 170 the authors state that 70% of the total gauged stations and gridded points were used as the training dataset and the remaining 30% serve as reference dataset. How was decided which station / grid point was used for training and which station / grid point was used for evaluation? As I understand it is a mixture between actual station measurements and gridded, i.e. interpolated, station data. Is the ratio for both data types also 70% training and 30% reference data points? Is there a difference in performance metrics when only one of the two datasets is used for evaluation? Direct measurements from stations might be even more accurate than the interpolated data.

Answer: In the previous experiment, the 30 rain gauge stations and 170 gridded points were used as the “true” precipitation values. However, the gridded precipitation data was from China Meteorological Data Service, interpolated from 2472 rain gauge stations, which was less accurate than the direct measurements from stations, for example, daily precipitation was more than 1000 mm at one interpolated grid point. So only the rain gauge observations were used to the new experiments. What’s more, selecting 30% of the stations for validation was not an appropriate validation method, while the leave-one-out cross validation step was a better instead for using all the stations in WHU-SGCC correction algorithm

Change: We have only used 30 rain gauge stations as the reference precipitation values to conduct the WHU-SGCC method. We changed from “The proposed approach was evaluated for the Jinsha River Basin for JJA 2016. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance.” to “The proposed approach was evaluated over the Jinsha River Basin based on 30 gauge stations and CHIRP satellite-based precipitation estimations during the JJA from 1990 to 2014. The leave-one-out cross validation step was applied to computing the out-of-sample adjusted error with gauge stations.”

(2)- A more detailed description of the reference dataset and decision making process is desirable, e.g. a map with the mean or the sum of precipitation during the observation period at the reference grid points and stations.

Answer: Thanks. Done.

Changed: We added a map with the multi-year (1990-2014) average annual precipitation (Fig. 2). The multi-year average annual precipitation increases from north to south and the spatial distribution of precipitation is uneven, with an average annual precipitation ranging from less than 250 mm to more than 600 mm during the summer seasons over the Jinsha River Basin.

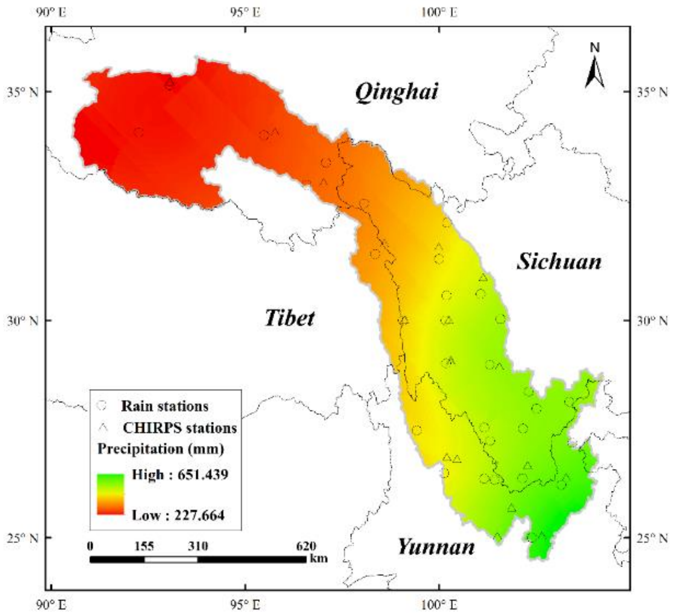


Figure 2 The multi-year (1990-2014) average annual precipitation during JJA over the Jinsha River Basin. 30 rain stations were provided by the China Meteorological Administration stations, the other 18 CHIRPS fusion stations were provided by the Climate Hazards Group UC Santa Barbara online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/global_monthly_station_density/tifs/p05/ (last access: 10 December, 2018).

(3)- As far as I understand, using this evaluation dataset implies that only C1 and C2 grid points are evaluated, because they contain either a rain gauge station or a grid point of the interpolated station data. Is that correct? Can the authors give an assessment on the quality of the method at C3 and C4 pixels?

Does the selection of the stations and grid points for training have an influence on the model performance? Depending on the location of the points for adjustment the quality of the blended dataset may vary. An ensemble study using different compositions of the pool of training stations / grid points would give statistically more robust results.

Answer: Thanks. In the new experiment, the leave-one-out cross validation step using all the stations was used to evaluate the performance of the WHU-SGCC algorithm. The training set was used to establish statically relationships when conducting the WHU-SGCC method, and the remaining one gauge station was used to evaluate. The adjusted process shown that the adjustment method for C2 pixels was derived from C1 pixels, the adjustment method for C3 pixels was derived from C2 pixels, and the adjusted values for C1 and C4 pixels were interpolated by IDW with C2 and C3 pixels. There were statistically relationship among C1, C2, C3 and C4 pixels. Thus, the performance of WHU-SGCC method would be evaluated on the overall accuracy, not on a certain class of pixels.

2.

(1)- CHIRP data is used as basis for the WHU-SGCC dataset and it is shown that the blending approach leads to better (light and moderate rainfall) or similar (heavy precipitation) results compared to measurements. CHIRPS, however, seems to perform much worse than the original CHIRP dataset although it is also adjusted to rain gauges. Can the authors give an explanation for that?

Answer: The CHIRPS was derived from blending in-suit precipitation observations and the CHIRP data, with a modified inverse-distance weighting algorithm at a quasi-global area (land only, 50° S-50° N). The blended data (CHIRPS) has an effective performance on a large scale region according to existing studies, such as at the national scale, but there are still large discrepancies with ground observations at the sub-regional level, especially at the river basin scale. The performance and applicability of CHIRPS at the sub-regional level still need to be validated. What's more, the interpolation performance from the limited and sparse rain gauge stations will be affected by more errors which was evaluated with rain gauge stations shown in Table 5.

As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the modified inverse-distance weighting algorithm, the aim of this article is to offer a novel blending approach to improve the precipitation estimated accuracy at the river basin scale.

Change: We changed the sentence from "As such, the aim of this article is to offer a novel approach for blending daily precipitation gauge data, gridded precipitation data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates over Jinsha River Basin." to "As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the existing blending algorithms, the aim of this article is to offer a novel approach for blending daily liquid precipitation gauge data, gridded precipitation data and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates developed by the UC Santa Barbara, over the Jinsha River Basin." for better explanation.

(2)- It would also be desirable to expand the investigated period to get more robust results, e.g. add more summer seasons from other years.

Answer: Thanks. Done.

Change: we changed the study period from summer of 2016, JJA to a longer study period during June-July-August from 1990 to 2014, to evaluate the model performance more reasonably.

Specific comments

(1) - P.1, L.37: There is twice "without adjustment" in the sentence

Answer: Thanks. Deleted one "without adjustment".

Change: We changed "Without adjustments, inaccurate satellite-based precipitation estimates without adjustment will lead to unreliable assessments of risk and reliability" to "Without adjustments, inaccurate satellite-based precipitation estimates will lead to unreliable assessments of risk and reliability".

(2) - P.2, L.63 and 65: Remove the brackets at Bai et al. and Trejo et al.

Answer: Thanks. Done.

Change: We removed the brackets at Bai et al. and Trejo et al.

(3) - P.3, L.89: Section 5 is about data availability. Section 6 presents conclusions

Answer: Thanks. Done.

Change: changed from "The results and discussion are analysed in Section 4, and conclusions and future work are presented in Section 5." to "The results and discussion are analysed in Section 4, the data available is described in Section 5, and conclusions and future work are presented in Section 6."

(4) - P.3, L.102-103: I'm a bit confused here. Does "average annual precipitation", "annual precipitation" and "total annual precipitation" mean the same thing? Or is the total (for me this refers to the sum) of the precipitation north of Shigu almost four times smaller than the mean annual precipitation in the whole Jinsha River Basin?

Answer: Thanks. Done. We have used the spatially averaged annual accumulation of precipitation as an indication of precipitation climatology for the study region. The reference (Yuan, Z., Xu, J. J., and Wang, Y. Q.: Projection of Future Extreme Precipitation and Flood Changes of the Jinsha River Basin in China Based on CMIP5 Climate Models, Int. J. Environ. Res. Public Health, 15, 17, 10.3390/ijerph15112491, 2018.) can support the average annual precipitation statistic.

Change: We changed "Average annual precipitation in the Jinsha River Basin is approximately 3433.45 mm, the total annual precipitation north of Shigu is 937.25 mm, while south of Shigu annual precipitation is 2496.20 mm." to "The average annual precipitation of the Jinsha River Basin is approximately 710 mm, the average annual precipitation of the lower reaches is approximately 900-1300 mm, while the average annual precipitation of the middle and upper reaches is approximately 600-800 mm (Yuan et al., 2018)."

(5) - P.6, L169: I would remove the numbering here, as it doesn't seem to be another part of the method, but refers to the overview of steps 1-4.

Answer: Thanks. Done.

Change: We added this sentence into the first phase in section 3.1, as the reference to the overview of steps 1-4.

(6) - P.11, L.309: Nash and Sutcliffe(1970) is missing in the references

Answer: Thanks. Done.

Change: We have added the Nash and Sutcliffe (1970) in the references.

(Nash, J. E., Sutcliffe, J. V.: River flow forecasting through conceptual models, Part I - A discussion of principles, Journal of Hydrology, 10, 282–290, doi.org/10.1016/0022-1694(70)90255-6, 1970.)

(7) - P.14, Table 4: How is the accuracy assessment of C3 pixels done? What is the reference here? Why is SCC < 0.5?

Answer: Thanks. In the previous experiment, the number of C3 pixels accounted for 62.18% of the total pixels inside the river basin and the major of the C3 pixels had the same location with the 30% testing data. So we evaluated the C3 pixels with part of testing set (rain gauge stations and gridded points). While, in the new experiment, due to the leave-one-out cross validation step using all the stations, the performance of WHU-SGCC method would be evaluated on the overall accuracy, not on a certain class of pixels. So we didn't evaluate the C3 pixels separately.

Change: Deleted the statistical analysis about the C3 pixels.

(8) - P.17, Fig.10: It might be helpful to present the percentage deviation from the observations for clarification of the model performance. It seems that at some days, all three datasets deviate more than 70% from the observations.

Answer: Thanks. Because the daily precipitation of rain stations may be no rain, the percentage deviation from the observations cannot be obtained (the denominator is 0). The statistical analysis of the agreement between daily observations and WHU-SGCC, CHIRP and CHIRPS estimates on leave-one-out cross validation: a) Pearson's correlation coefficient b) root mean square error c) mean absolute error d) relative bias e) Nash-Sutcliffe efficiency coefficient f) probability of detection g) false alarm ratio, and h) critical success index was shown in Fig. 5.

Change: We redraw the boxplots of the statistical analysis of the agreement between daily observations and WHU-SGCC, CHIRP and CHIRPS estimates on leave-one-out cross validation.

And now the section 4 was divided into 3 parts: 4.1 Model performance based on overall accuracy evaluations, 4.2 Model performance based on daily accuracy evaluations and 4.3 Model performance on rain events predictions.

WHU-SGCC：A novel approach for blending daily satellite (CHIRP) and precipitation observations over the Jinsha River Basin

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Abstract. Accurate and consistent satellite-based precipitation estimates blended with rain gauge data are important for regional precipitation monitoring and hydrological applications, especially in regions with limited rain gauges. However, existing fusion precipitation estimates often have large uncertainties over mountainous areas with complex topography and sparse rain gauges, and the existing data blending algorithms are very bad at removing the day-by-day random errors. Therefore, the development of effective methods for high-accuracy precipitation estimates over complex terrain and on a daily scale is of vital importance for mountainous hydrological applications. This study aims to offer a novel approach for blending daily precipitation gauge data and the Climate Hazards Group Infrared Precipitation (CHIRP, daily, 0.05°) satellite-derived precipitation developed by the UC Santa Barbara ~~estimates~~ over the Jinsha River Basin for the period of June-July-August ~~in~~ from 1994 to 2014~~6~~. This method is named the Wuhan University Satellite and Gauge precipitation Collaborated Correction (WHU-SGCC). The results show that the WHU-SGCC method is effective in liquid precipitation bias adjustments from point to surface, which is evaluated by multiple error statistics and from different perspectives~~categorical indices~~. Moreover, the accuracy of the spatial distribution of the precipitation estimates derived from the WHU-SGCC method is related to the complexity of the topography. The validation also verifies that the proposed approach is effective in the detection of the major precipitation events inside the Jinsha River Basin with the daily precipitation less than 25 mm~~that are less than 20 mm~~. This study indicates that the WHU-SGCC approach is a promising tool to monitor monsoon precipitation over the Jinsha River Basin, the complicated mountainous terrain with sparse rain gauge data, considering the spatial correlation and the historical precipitation characteristics. The daily precipitation estimations at 0.05° resolution over the Jinsha River Basin during the summer seasons from 1990 to 2014~~in summer 2016~~, derived from WHU-SGCC are available at the PANGAEA Data Publisher for Earth & Environmental Science portal (https://doi.pangaea.de/10.1594/PANGAEA.900620)~~https://doi.pangaea.de/10.1594/PANGAEA.896615)~~

1 Introduction

Accurate and consistent estimates of precipitation are vital for hydrological modelling, flood forecasting and climatological studies in support of better planning and decision making (Agutu et al., 2017;Cattani et al., 2018;Roy et al., 2017). In general, ground-based gauge networks include a substantial number of liquid precipitation observations measured with high accuracy, high temporal resolution, and long historical records. However, sparse distribution and point measurements limit the accurate estimation of spatially gridded rainfall (Martens et al., 2013).

Due to the sparseness of rain gauges and their uneven spatial distribution~~distributed~~ and high proportion of missing data, satellite-derived precipitation data are an attractive supplement offering the advantage of plentiful information with high spatio-temporal resolution over widespread regions, particularly over oceans, high elevation mountainous regions, and other remote regions where gauge networks are difficult to deploy. However, ~~the retrieval algorithms for satellite-based precipitation estimates are susceptible to systematic biases in hydrologic modelling~~ satellite estimates are susceptible to systematic biases that can influence hydrological modelling and the retrieval algorithms are relatively insensitive to light rainfall events, especially in complex terrain, resulting in underestimation of the magnitude of precipitation events (Behrangi et al., 2014;Thiemig et al., 2013;Yang et al., 2017). Without adjustments, inaccurate satellite-based precipitation estimates ~~without adjustment~~ will lead to unreliable assessments of risk and reliability (AghaKouchak et al., 2011).

Accordingly, there are many kinds of precipitation estimates combining multiple sources datasets. Since 1997, the Tropical Rainfall Measurement Mission (TRMM) has improved satellite-based rainfall retrievals over tropical regions (Kummerow et al., 1998;Simpson et al., 1988), and then applies a stepwise method for blending daily TRMM Multisatellite Precipitation Analysis (TMPA) output with rain gauges in South America (Vila et al., 2009). The Global Precipitation Measurement (GPM) satellite was launched after the success of the TRMM satellite by the cooperation of National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) on February 27, 2014 (Mahmoud et al., 2018;Ning et al., 2016). The main core observatory satellite (GPM) cooperates with the ten other satellites (partners) to offer the high spatiotemporal resolution products (0.1° × 0.1°- half- hourly) of the global real-time precipitation estimates (Mahmoud et al., 2019). The Geostationary Operational Environmental Satellite (GOES)-R Series is the geostationary weather satellites, which significantly improves the detection and observation of environmental phenomena. The Advanced Baseline Imager (ABI) onboard the GOES-R platform will provide images in 16 spectral bands, spatial resolution of 0.5 to 2 km (2 km in the infrared and 1–0.5 km in the visible), and full-disk scanning every 5 minutes over the continental United States. The GOES-R Series will offer the enhanced capabilities for satellite-based rainfall estimation and nowcasting (Behrangi et al., 2009;Schmit et al., 2005). The Global Precipitation Climatology Project (GPCP) is one of the successful projects for blending rain gauge analysis and multiple satellite-based precipitation estimates, and constructed a relatively coarse-resolution (monthly, 2.5° × 2.5°) global precipitation dataset (Adler et al., 2003;Huffman et al., 1997). To improve the resolution of this satellite-based dataset, the GPCC network data was incorporated into remote sensing information with Artificial Neural Networks (PERSIANN) rainfall estimates, which provides finer temporal and spatial resolutions (daily, 0.25° × 0.25°) (Ashouri et al., 2015). The CPC Merged Analysis of Precipitation (CMAP) product is a data blending and fusion analysis of gauge data and satellite-based precipitation estimates (Xie and Arkin, 1996). CMAP has a long-term dataset series from 1979, while the resolution is relatively coarse. Although the aforementioned products are widely used and have performed well, the data resolution cannot achieve high accuracy in precipitation monitoring over the Jinsha River Basin, China.

Currently, the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) developed by the UC Santa Barbara, which has a higher spatial resolution (0.05°), can solve the scale problem. CHIRPS is a long-term precipitation data series, which merges three types of information: global climatology, satellite estimates and in situ observations. Table 1 shows the temporal and spatial resolution of current major satellite-based precipitation datasets. The CHIRPS precipitation dataset with several temporal and spatial scales has been evaluated in Brazil (Nogueira et al., 2018;Paredes-Trejo et al., 2017), Chile (Yang et al., 2016;Zambrano-Bigiarini et al., 2017), China (Bai et al., 2018), Cyprus (Katsanos et al., 2016b;Katsanos et al., 2016a), India (Ali and Mishra, 2017) and Italy (Duan et al., 2016). Nevertheless, the temporal resolutions of the aforementioned applications were mainly at seasonal and monthly scales, lacking the evaluation of daily precipitation. Additionally, despite the great potential of gauge-satellite fusing products for large-scale environmental monitoring, there are still large discrepancies with ground observations at the sub-regional level where these data are applied. Furthermore, the CHIRPS product reliability has not been analysed in detail ~~for~~ over the Jinsha River Basin, China, particularly on a daily scale. The existing research indicates that estimations over mountainous areas with complex topography often have large uncertainties and systematic errors due to the topography, seasonality, climate impact and sparseness of rain gauges (Derin et al., 2016;Maggioni and Massari, 2018;Zambrano-Bigiarini et al., 2017)~~(Zambrano-Bigiarini et al., 2017).~~ Moreover, ~~(~~Bai et al., 2018~~)~~ evaluates CHIRPS over mainland China and indicates that the performance of CHIRPS is poor over the Sichuan Basin and the Northern China Plain, which have complex terrains with substantial variations in elevation. Additionally, ~~(~~Trejo et al., 2016~~)~~ shows that CHIRPS overestimates low monthly rainfall and underestimates high monthly rainfall using several numerical metrics, and rainfall event frequency is overestimated excluding the rainy season.

Table 1 Coverage and spatiotemporal resolutions of major satellite precipitation datasets

Product	Temporal resolution	Spatial resolution	Period	Coverage
TRMM 3B42	3hours	0.25°	1998-present	50°S-50°N
GPM	30min/Hourly/ 3hours/Daily/3Day/7 Day/Monthly	0.1°/0.25°/0.05°/5°	2014-present	60°S-60°N 70°N-70°S 90°N-90°S
GOES-R	5min/15min	0.5-2 km	2016-present	the continental United States/ western hemisphere
GPCP	Monthly/Pentad	2.5°	1979-(delayed) present	90°S-90°N
P~~R~~ERS~~S~~SIANN-CDR	Daily	0.25°	1983-(delayed) present	60°S-60°N
CMAP	Monthly	2.5°	1979- present	90°S-90°N
CHIRPS	Annual/Monthly/ Dekad/Pentad/Daily	0.05°/0.25°	1981- present	50°S-50°N

To overcome these limitations, many studies have focused on proposing effective methodologies for blending rain gauge observations and satellite-based precipitation estimates, and sometimes radar data to take advantage of each dataset. Many numerical models are established among these datasets for high-accuracy precipitation estimations, such as bias adjustment by a quantile mapping (QM) approach (Yang et al., 2016), Bayesian kriging (BK) (Verdin et al., 2015) and a conditional merging technique (Berndt et al., 2014). Among aforementioned methods, the QM approach is a distribution-based approach, which works with historical data for bias adjustment and is effective in reducing the systematic bias of regional climate model precipitation estimates at monthly or seasonal scales (Chen et al., 2013). However, the QM approach offers very limited improvement in removing day-by-day random errors. The BK approach shows very good model fit with precipitation observations. Unfortunately, the Gaussian assumption of the BK model is invalid for daily scales. Overall, there is a lack of effective methods for high-accuracy precipitation estimates over complex terrain on a daily scale.

As such, due to the poor performance of CHIRPS data at the sub-regional scale and the shortcomings of the existing blending algorithms, the aim of this article is to offer a novel approach for blending daily liquid precipitation gauge data~~, gridded precipitation data~~ and the Climate Hazards Group Infrared Precipitation (CHIRP) satellite-derived precipitation estimates developed by the UC Santa Barbara, over the Jinsha River Basin. Here, we will use precipitation to name liquid precipitation throughout the text. The CHIRP is the raw data of CHIRPS before blending in rain gauge data. The objective is to build corresponding precipitation models that consider terrain factors and precipitation characteristics to produce high-quality precipitation estimates. This novel method is named the Wuhan University Satellite and Gauge precipitation Collaborated Correction (WHU-SGCC) method. We demonstrate this method by applying it to daily precipitation over the Jinsha River Basin during the summer seasons from 1990 to 2014~~in summer 2016~~. The results support the validity of the proposed approach for producing refined satellite-gauge precipitation estimates over mountainous areas.

The remainder of this paper is organized as follows: Section 2 describes the study region and ~~precipitation~~ rain gauges~~, gridded observations~~ and CHIRPS dataset used in this study. Section 3 presents the principle of the WHU-SGCC approach for high-accuracy precipitation estimates. The results and discussion are analysed in Section 4, the data available is described in Section 5, and conclusions and future work are presented in Section ~~5~~6.

2 Study Region and Data

2.1 Study Region

The Yangtze River, one of the largest and most important rivers in Southeast Asia, originates on the Tibetan Plateau and extends approximately 6300 km eastward to the East China Sea. The river's catchment ~~proximately~~ covers an area of approximately ~180 × 10^4 km^2 and the average annual precipitation is approximately 1100 mm (Zhang et al., 2019)~~. In 2016, the average precipitation in the Yangtze River Basin was 12053 mm and the total precipitation was 21478.71 billion m^3, which is 10.9% higher than the annual average total precipitation.~~ Yangtze River is divided into nine sub-~~regions~~basins, the upper drainage basin is the Jinsha River Basin, which flows through the provinces of Qinghai, Sichuan, and Yunnan in western China. The total river length is 3486 km, accounting for 77% of the length of the upper Yangtze River, and covering a watershed area of 460 × 10^3 km^2. The location of the Jinsha River Basin is shown in Fig. 1, and covers the eastern part of the Tibetan Plateau and the part of the Hengduan Mountains. The southern portion of the river basin is the Northern Yunnan Plateau and the eastern portion includes a wide area of the southwestern margin of the Sichuan basin. Crossing complex and varied terrains, the elevation of the Jinsha River ranges from 263 to 6575 m above sea level, which results in significant temporal and spatial ~~climate~~ weather variation within the basin. The average annual precipitation of the Jinsha River Basin is approximately 710 mm, the average annual precipitation of the lower reaches is approximately 900-1300 mm, while the average annual precipitation of the middle and upper reaches is approximately 600-800 mm (Yuan et al., 2018). ~~Average annual precipitation in the Jinsha River Basin is approximately 3433.45 mm, the total annual precipitation north of Shigu is 937.25 mm, while south of Shigu annual precipitation is 2496.20 mm.~~ The climate of the Jinsha River Basin has more precipitation during the ~~warm~~ summer season (June-July-August, JJA), which is affected by oceanic southwest and southeast monsoons ~~and is drier in cold season (December to February)~~. Therefore, the blending of satellite estimations with gauged observations during the ~~summer (~~JJA~~)~~ is the main focus of this research.

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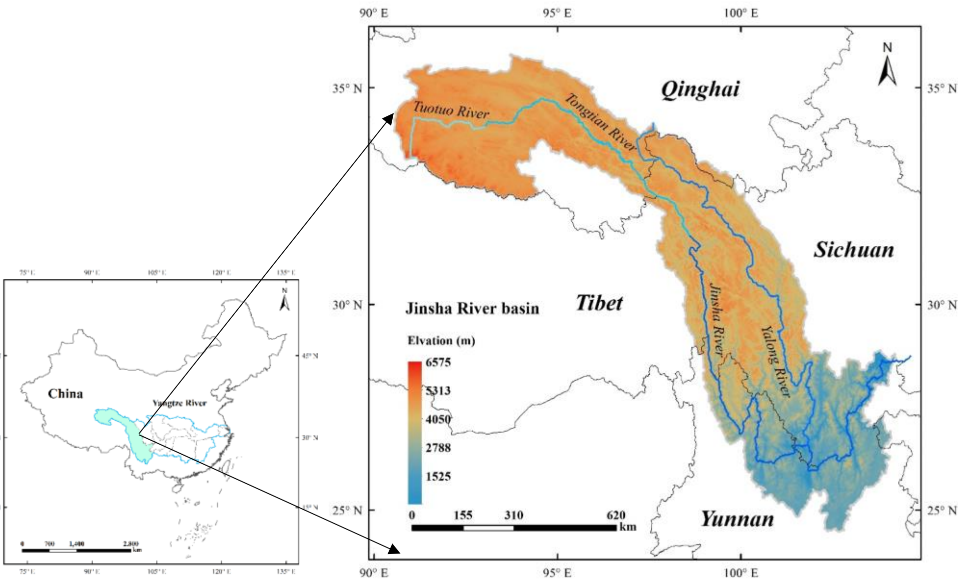


Figure 1 Location of the study area with key topographic features.

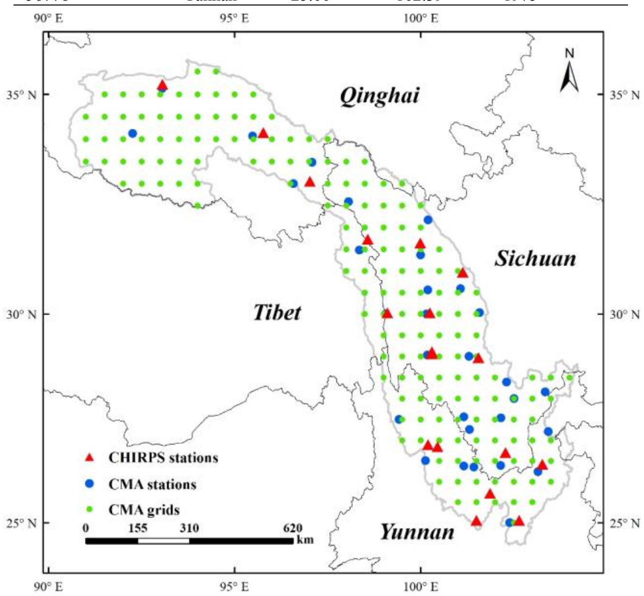
2.2 Study Data

2.2.1 Precipitation gauge~~d~~ observations

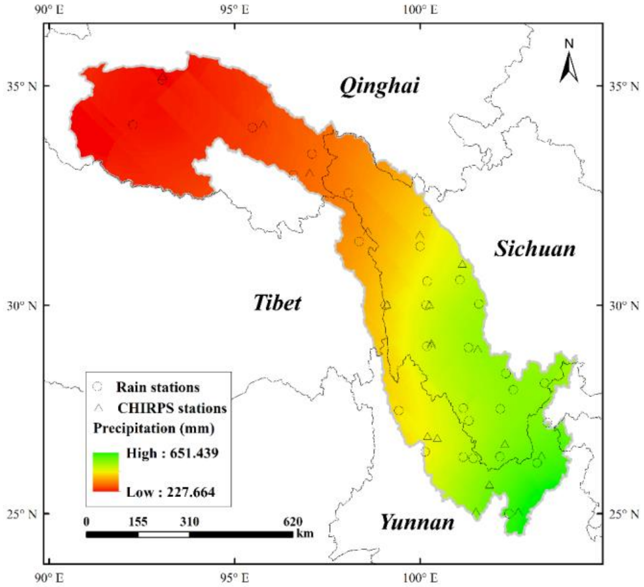
Daily rain gauge observations at 30 national standard rain stations in the Jinsha River Basin ~~for~~ during the JJA from 1990 to 2014~~6~~ were provided by the National Climate Centre (NCC) of the China Meteorological Administration (CMA) （http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html, last access: 10 December, 2018）, which imposes a strict quality control at station-provincial-state levels. Station identification numbers and relevant geographical characteristics are shown in Table 2, and their uneven spatial distribution is shown in Fig. 2. The selected rain gauges are located in Qinghai, Tibet, Sichuan and Yunnan Provinces but are mainly scattered in Sichuan Province, and the number of rain gauges in the northern river basin is less than in the southern river basin. In this study, the gauge observations were used as the reference data in bias adjustment of satellite precipitation estimations.

Table 2 Geographical characteristics of rain stations.

Station number	Province	Lat (°N)	Lon (°E)	Elevation (m)
52908	Qinghai	35.13	93.05	4823
56004	Qinghai	34.13	92.26	4744
56021	Qinghai	34.07	95.48	5049
56029	Qinghai	33.00	96.58	4510
56034	Qinghai	33.48	97.08	4503
56144	Tibet	31.48	98.35	4743
56038	Sichuan	32.59	98.06	4285
56146	Sichuan	31.37	100.00	4703
56152	Sichuan	32.17	100.20	4401
56167	Sichuan	30.59	101.07	3374
56247	Sichuan	30.00	99.06	2948
56251	Sichuan	30.56	100.19	4284
56257	Sichuan	30.00	100.16	3971
56357	Sichuan	29.03	100.18	4280
56374	Sichuan	30.03	101.58	3902
56459	Sichuan	27.56	101.16	3002
56462	Sichuan	29.00	101.30	4019
56475	Sichuan	28.39	102.31	1850
56479	Sichuan	28.00	102.51	2470
56485	Sichuan	28.16	103.35	2060
56565	Sichuan	27.26	101.31	2578
56571	Sichuan	27.54	102.16	1503
56666	Sichuan	26.35	101.43	1567
56671	Sichuan	26.39	102.15	1125
56543	Yunnan	27.50	99.42	3216
56586	Yunnan	27.21	103.43	2349
56651	Yunnan	26.51	100.13	2449
56664	Yunnan	26.38	101.16	1540
56684	Yunnan	26.24	103.15	2184
56778	Yunnan	25.00	102.39	1975



The multi-year (1990-2014) average annual precipitation during the JJA over the Jinsha River Basin increases from north to south (Fig. 2). The spatial distribution of precipitation is uneven, with an average annual precipitation ranging from less than 250 mm to more than 600 mm during the summer seasons. Figure. 2 also shows the multi-year average daily precipitation during the JJA is no more than 10mm.



~~**Figure 2** Jinsha River Basin with 18 CHIRPS fusion stations, 30 gauge stations and 170 grid points provided by the China Meteorological Administration stations.~~

Figure 2 The multi-year (1990-2014) average annual precipitation during JJA over the Jinsha River Basin. ~~Jinsha River Basin with~~ 30 rain stations were provided by the China Meteorological Administration stations, the other 18~~18~~ CHIRPS fusion stations were provided by the Climate Hazards Group UC Santa Barbara online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/diagnostics/global_monthly_station_density/tifs/p05/ (last access: 10 December, 2018).

~~, 30 gauge stations and 170 grid points provided by the China Meteorological Administration stations.~~

~~2.2.2 Gridded precipitation observations~~

~~The gridded precipitation data developed by CMA with 0.5°× 0.5° resolution on a daily scale, was interpolated from 2472 gauge observations with a thin plate spline algorithm from 1961 to the present. Over the Jinsha River Basin, a total of 170 gridded points were selected as the supplementary data for observations in JJA 2016, due to the 2472 gauged station data that were not shared on CMA (http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_PRE_DAY_GRID_0.5.html, last access: 10 December, 2018). The even distribution of daily gridded precipitation observations is shown in Fig. 2.~~

2.2.~~3~~ 2 CHIRPS satellite-gauge fusion precipitation estimates

The CHIRPS v.2 dataset, a satellite-based daily rainfall product, is available online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_daily/tifs/p05/ (last access: 10 December, 2018). It covers a quasi-global area (land only, 50° S-50° N) with several temporal scales (daily, 3-day, 6-day or monthly time steps) and high spatial resolution (0.05°) (Rivera et al., 2018). This dataset contains a wide variety of satellite-based rainfall products derived from multiple data sources and incorporates four data types: monthly precipitation from CHPClim v.1.0 (Climate Hazards Group's Precipitation Climatology version 1) derived from the combination of the satellite fields, gridded physiographic indicators, and in situ climate normal with the geospatial modelling approach based on moving window regressions and inverse distance weighting interpolation (Funk et al., 2015 b), quasi-global geostationary thermal infrared satellite observations

(TRMM 3B42 version 7), atmospheric model rainfall fields CFS (Climate Forecast System) from NOAA, and surface based precipitation observations from various sources including national or regional meteorological services. The differences from other frequently used precipitation products are the higher resolution of 0.05° and the longer-term data series from 1981 to the present (Funk et al., 2015 a).

CHIRPS is the blended product of a two-part process. First, IR precipitation (IRP) pentad rainfall estimates are fused with corresponding CHPClim pentad data to produce an unbiased gridded estimate, called the Climate Hazards Group IR Precipitation (CHIRP), which is available online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRP/daily/ (last access: 10 December, 2018). In the second part of the process, CHIRP data is blended with in situ precipitation observations obtained from a variety of sources including national and regional meteorological services by means of a modified inverse-distance weighting algorithm to create the final blended product, CHIRPS (Funk et al., 2014). The daily CHIRP satellite-based data over the Jinsha River Basin during the summer seasons from 1990 to 2014~~over Jinsha River Basin in JJA 2016~~ was selected as the input for WHU-SGCC blending with rain observations, and the corresponding daily CHIRPS blended data was used for comparisons of precipitation accuracy.

The blended in situ daily precipitation observations come from a variety of sources such as: the daily GHCN archive (Durre et al., 2010), the Global Summary of the Day dataset (GSOD) provided by NOAA's National Climatic Data Center, the World Meteorological Organization's Global Telecommunication System (GTS) daily archive provided by NOAA CPC, and over a dozen national and regional meteorological services. The number of daily ~~CHIRP~~ observation stations used for CHIRPS data ~~in~~over the Jinsha River Basin was only 18, compared to the 30 rain gauge stations~~ and 170 grid points~~ provided by CMA~~; hence, the number of CHIRP stations limited the accuracy of spatial rainfall estimates~~ (Fig. 2).

3 Methods

3.1 The WHU-SGCC approach

In this study, the approach of the WHU-SGCC is to estimate the precipitation for every pixel by blending satellite estimates and rain gauge observations considering the terrain factors and precipitation characteristics. There were ~~five~~ four steps to establish the numerical relationship between gauge~~d~~ stations and the corresponding satellite pixels, and interpolation for the remaining pixels~~other pixels~~. On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the four classification and blending rules. A flowchart of the WHU-SGCC method is shown in Fig. 3. The proposed approach was evaluated over the Jinsha River Basin based on 30 gauge stations and CHIRP satellite-based precipitation estimations during the JJA from 1990 to 2014. The leave-one-out cross validation step was applied to computing the out-of-sample adjusted error with gauge stations.

~~On this basis, the WHU-SGCC method identifies the geographical locations and topographical features of each pixel and applies the classification principles of the SICR approach, including five classification and blending rules.~~ The basic description of the WHU-SGCC method is given below, with details illustrated separately in later sections:~~.~~

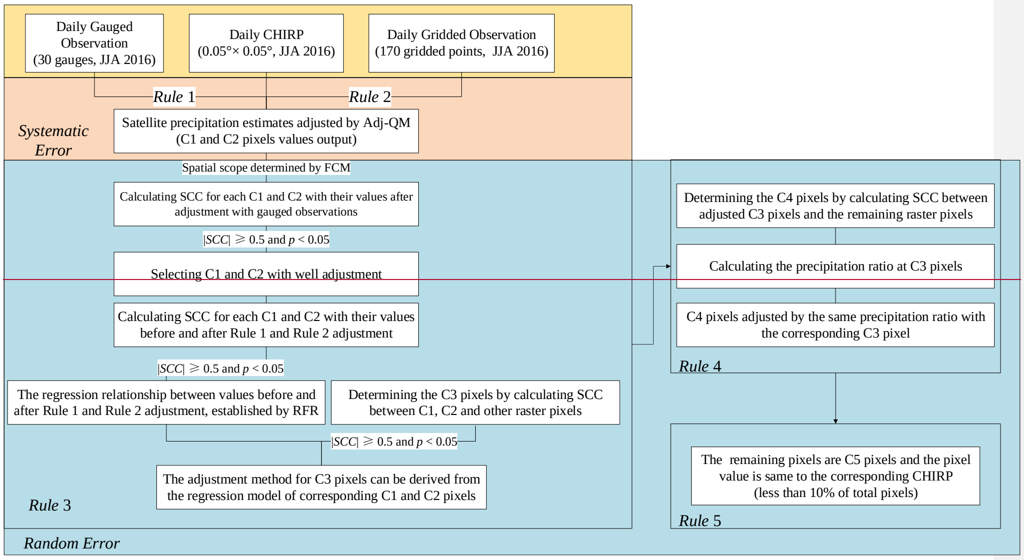
1) ~~A flowchart of the WHU-SGCC method is shown in Fig. 3. The proposed approach was evaluated for the Jinsha River Basin for JJA 2016. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance. The proposed approach was evaluated for the Jinsha River Basin for theJJA 2016.~~ Classify all regional pixels into ~~five~~ four types: C1 (pixel including one gauge~~d~~ station in its area), ~~C2 (pixel including one gridded point), C3~~ C2 (pixel statistically ~~physically~~ similar to C1~~C2~~), ~~C4~~ C3 (pixel statistically ~~physically~~ similar to ~~C3~~C2) and ~~C5~~ C4 (remaining pixels).

2) Analyse the relationships between precipitation observations and the C1, C2, and C3 pixel types, and interpolated for ~~with~~ the C4 ~~and C5~~ pixels. These relationships are described by ~~five~~ four rules, detailed below as Rules 1 through ~~5~~4.

3) ~~Bias-adjust, establish~~ Establish regression models and screen target pixels based on the ~~five~~ four aforementioned rules.

4) Correct all precipitation pixels in daily regional precipitation images.

~~5) A flowchart of the WHU-SGCC method is shown in Fig. 3. The proposed approach was evaluated for the Jinsha River Basin for JJA 2016. From that data, the training samples represented 70% of total gauged stations and gridded points, and the remaining data were used to verify the model performance.~~



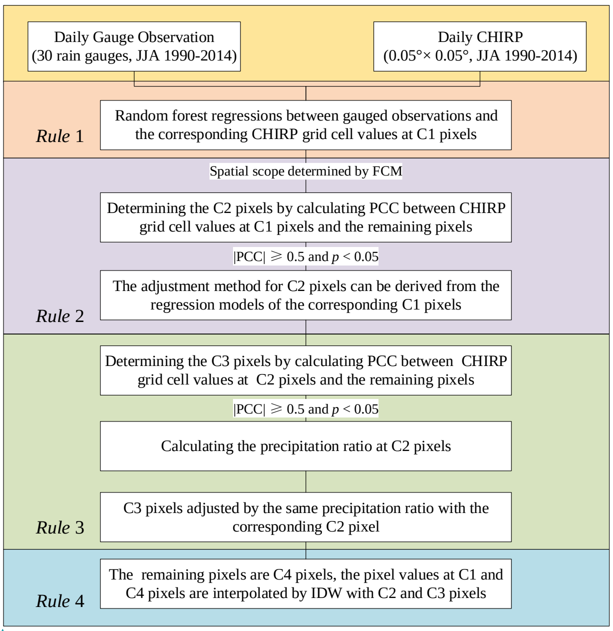


Figure 3 Flowchart of the WHU-SGCC approach with the ~~five~~ four rules applied in this study.

3.1.1 Assumptions

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1) Gauge ~~and gridded point~~ observations are the most accurate, or “true”, values for reference purposes.

2) No major terrain change occurred during the twenty years.

3) ~~Spearman’s~~ Pearson’s Correlation Coefficient (~~SCC~~PCC) can indicate the statistically similarity of rainfall characteristics among pixels over a seasonal scale.

3.1.2 Rule 1 of the WHU-SGCC method

~~In general, satellite precipitation estimations deviated from ground-based measurements, which were assumed to be the true values. Rule 1 adjusts the biases in the satellite estimations. For every C1, its precipitation value was derived from a quantile mapping (QM) approach. It has been shown that the QM method is the best for reducing systematic biases of regional satellite precipitation estimates because of its independence from predetermined functions (Themessl et al., 2011;Chen et al., 2013).~~

~~QM is a nonparametric empirical approach that considers a time-dependent correction function. This approach is designed to transform the cumulative distribution function (CDF) of satellite data into the CDF of data at each station.~~

$$\cancel{Y_o = \mathrm{h}(Y_s)} \qquad \cancel{(1)}$$

~~where the variable~~ $\cancel{Y_s}$ ~~is the distribution of the observed variable~~ $\cancel{Y_o}$~~. In this study~~ $\cancel{Y_o}$ ~~denotes each gauge or gridded precipitation data point location from CMA and~~ $\cancel{Y_s}$ ~~denotes the corresponding CHIRP grid cell value. The objective of QM is to correct the daily precipitation amount from a climate simulation and the transformation~~ $\cancel{h}$ ~~is defined in Eq. (2):~~

$$\cancel{Y_o = H_o^{-1}(H_s(Y_s))} \qquad \cancel{(2)}$$

~~where the~~ $\cancel{H_s}$ ~~is the CDF of~~ $\cancel{Y_s}$ ~~and~~ $\cancel{H_o^{-1}}$ ~~is the inverse CDF (or quantile function) corresponding to~~ $\cancel{Y_o}$ ~~(Gudmundsson et al., 2012).~~

~~Notably, we separately calculate CDFs at each gauge and gridded pixel using the historical daily rainfall from the JJA in 2016.~~

~~The result of a QM adjustment is~~ $\cancel{\overline{Y}_{Qm}}$~~, which is approximately the same as the CDF of the gauge observations on a seasonal scale, which is distinct from daily data. The suitable scale of the CDF is seasonal because the QM cannot effectively remove the day-by-day random errors in CHIRP estimates. Therefore, on the basis of~~ $\cancel{\overline{Y}_{Qm}}$~~, the adjustment result,~~ $\cancel{\widehat{C1}_{as}}$~~, for each C1 pixel is derived from the minimum absolute value of the difference between the gauge observations and satellite estimations before and after applying the QM adjustment, referred to as the adjusted QM (Adj-QM) method, as shown in Eq. (3) - Eq. (5).~~

$$\cancel{D_{QM} = |\overline{Y}_{QM} - Y_o|} \qquad \cancel{(3)}$$

$$\cancel{D_s = |Y_s - Y_o|} \qquad \cancel{(4)}$$

$$\cancel{\widehat{C1}_{as} = \begin{cases} \overline{Y}_{QM}, & D_{QM} \le D_s \\ Y_s, & D_s \le D_{QM} \end{cases}} \qquad \cancel{(5)}$$

~~where~~ $\cancel{D_{QM}}$ ~~is the absolute value of the difference between~~ $\cancel{\overline{Y}_{Qm}}$ ~~and~~ $\cancel{Y_o}$~~, and~~ $\cancel{D_s}$ ~~is the absolute value of difference between~~ $\cancel{\overline{Y}_s}$ ~~and~~ $\cancel{Y_o}$~~.~~

In general, satellite precipitation estimations deviated from ground-based measurements~~observed data~~, which were assumed to be the true values. Rule 1 aims to establish a regression model between each gauge historical observations and the corresponding CHIRP grid cell values. The regression relationship was derived by random forest regression (RFR) at each gauge station. RFR is a machine-learning algorithm for a predictive model with a large set of regression trees in which each tree in the ensemble is grown from a bootstrap (Johnson, 1998) sample drawn with replacement from the training set. The final prediction is obtained by combining the results of the prediction methods applied to each bootstrap sample (Genuer et al., 2017). The predicted value is calculated by the mean of all trees.

$$Y_o = f_{RFR}(Y_s) \qquad (1)$$

where Y_o denotes each gauge historical observations and Y_s denotes the corresponding CHIRP grid cell values at C1 pixels, f_{RFR} is constructed from the time series Y_o (dependent variable) and Y_s (independent variable) by means of RFR. The number of decision trees was set to 500, which was determined by out-of-bag (OOB) error (Appendix A). The OOB error reached the minimum value when the number of decision trees was less than 500.

The Rule 1 builds the statistical relationships between gauge observations and the corresponding CHIRP grid cell values, which is the key idea in correcting the satellite-based precipitation estimations in the whole study area. As there are 30 gauge stations in the study area, 30 regression relationships at C1 pixels were derived from Rule1. The values of C1 pixels are not corrected in Rule 1, but interpolated in Rule 4.

~~3.1.3 Rule 2 of the WHU-SGCC method~~

~~Commonly, a few of the national standard stations have free access, and these stations are unevenly distributed and do not satisfied the accuracy needed for regional precipitation estimation. Under these circumstances, the gridded precipitation data developed by CMA are applied as the supplementary data for observations with uniform spatial distribution. Therefore, Rule 2 is same as Rule 1 with different input data.~~ $\cancel{\widehat{C2}_{as}}$ ~~is the adjusted target precipitation of one C2 pixel.~~

3.1.~~4~~ 3 Rule ~~3~~2 of the WHU-SGCC method

It is reasonable to assume that there are some pixels that are statistically ~~physically~~ similar to the precipitation characteristics of C1 pixels in a certain spatial scope. Therefore, it is feasible to adjust the satellite estimation bias of ~~C3~~ C2 pixels by referring to the appropriate regression relationships at corresponding C1 pixels based on Rule 1.

First, the spatial scope in which pixels may have highly similar characteristics is established. Some studies indicate that geographical location, elevation and other terrain information influences the spatial distribution of rainfall, especially in mountainous areas with complex topography (Anders et al., 2006;Long and Singh, 2013). The size of the spatial range is an important parameter to distinguish spatial similarity and heterogeneity. In the WHU-SGCC method, the approach of fuzzy c-means (FCM) clustering was explored to determine the spatial range considered as each pixel's terrain factors including longitude, latitude, elevation, slope, aspect and curvature. FCM method was developed by J.C. Dunn in 1973 (Dunn, 1973), and improved in 1983 (Wang, 1983). It is an unsupervised fuzzy clustering method and the steps are as follows (Pessoa et al., 2018):

1) Choose the number of clusters ~~t~~c. The optimum number of clusters was determined by $L(c)$ which was derived from the inter-distance and inner-distance of ~~elements~~samples in Eq. (2). It is ensured that the distance between the same samples is smaller, while the distance between the different samples is larger.

$$L(c)=\frac{\sum_{i=1}^{c}\sum_{j=1}^{n} w_{ij}^{m}\,\|c_i-\bar{x}\|^2/(c-1)}{\sum_{i=1}^{c}\sum_{j=1}^{n} w_{ij}^{m}\,\|x_j-c_i\|^2/(n-c)} \tag{2}$$

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In Eq. (2), the denominator is inner-distance and the molecular is inter-distance. The initial value of c is 1 and the maximum value of c is the number of gauge stations in this study area. The optimum number of clusters was optimized to maximize the L(c). For this reason, c value is conducted in the range of 1 to the number of gauge stations with an incremental interval value of 1 in this study.

2) Assign coefficients randomly to each data point x_i for the degree to which it belongs in the ~~j~~i th cluster $w_{ij}(x_i)$:

$$c_i^{(t)} = \frac{\sum_{j=1}^{n} w_{ij}^m x_i}{\sum_{j=1}^{n} w_{ij}^m} \quad (\cancel{6}3), \qquad w_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| x_i - c_i \|}{\| x_i - c_k \|} \right)^{\frac{2}{m-1}}} \quad (\cancel{7}4), \qquad \bar{x} = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n} w_{ij}^m x_j}{n} \quad (5)$$

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where x is a finite collection of n elements that will be partitioned into a collection of c fuzzy clusters, c_i is the centre of each cluster, m is the hyper-parameter that controls the level of cluster fuzziness and w_{ij} is the degree to which element x_i belongs to c_i and $\bar{x}$ is the centre vector of collection. In Eq. (~~6~~3), $c_j^{(t)}$ represents the cluster centre in iteration t. If the minimum improvement in objective function between two consecutive iterations satisfies the following equation, the algorithm terminates in iteration t (Eq. (6)):

$$\| c_i^{(t)} - c_i^{(t+1)} \| < \varepsilon \qquad (6)$$

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~~1)~~3) Minimize the objective function F_c to achieve data partitioning.

$$F_c = \sum_{j=1}^{n}\sum_{i=1}^{c} w_{ij}^m \| x_j - c_i \|^2 \qquad (\cancel{8}7)$$

The results of FCM are the degree of membership of each pixel to the cluster centre as represented by numerical value. Pixels in each cluster have similar terrain features and precipitation characteristics.

~~Second, the adjusted C1 and C2 are employed. SCC was used as the evaluation index for each C1 and C2 with their values after adjustment and gauge observations in JJA:~~

$$\cancel{SCC = \frac{\sum_{i=1}^{n}(rgx_i - rg\bar{x})(rgy_i - rg\bar{y})}{\sqrt{\sum_{i=1}^{n}(rgx_i - rg\bar{x})^2}\sqrt{\sum_{i=1}^{n}(rgy_i - rg\bar{y})^2}}} \qquad \cancel{(9)}$$

~~Spearman's correlation coefficient is defined as Pearson's correlation coefficient between the ranked variables, and it assesses monotonic relationships (whether linear or not) where *n* is the number of data points in each set, which was the number of each C1 or C2 in the historical JJA dataset. x_i is the *i*th data value in the first data set (satellite estimations after Rule 1 and Rule 2 adjustment, $\widehat{C1}_{as}$ and $\widehat{C2}_{as}$), x_i is converted to its rank rgx_i, and $rg\bar{x}$ is its average value. Similar definitions exist for rgy_i and $rg\bar{y}$ (gauge and gridded observations at C1 and C2 pixels, Y_o). The value range of the *SCC* is between -1 and +1. If there are no repeated data values, a perfect *SCC* of +1 or −1 occurs when each of the variables is a perfect monotone function of the other. However, if the value is close to zero, there is zero correlation. In addition, correlation is not only determined by the value of the correlation coefficient but also from the correlation test's *p*-value. The critical value is 0.05, thus a *p* lower than 0.05 indicates the data are significantly correlated. Therefore, the C1 and C2 pixels selected for Rule 3 must meet the following criteria:~~

$$\cancel{|SCC| \geq 0.5 \quad and \quad p < 0.05} \qquad \cancel{(10)}$$

~~Third, the filtered C1 and C2 pixels after adjustment is used to establish a regression model between the historical $\widehat{C1}_{as}$, $\widehat{C2}_{as}$ and Y_s. To ensure high accuracy, it is necessary to calculate the *SCC* and *p* values between $\widehat{C1}_{as}$, $\widehat{C2}_{as}$ and Y_s, and complete the filtering criteria described above in Eq. (7) before building the regression model. The regression relationship was~~

~~derived by random forest regression (RFR). RFR is a machine-learning algorithm for a predictive model with a large set of regression trees in which each tree in the ensemble is grown from a bootstrap (Johnson, 1998) sample drawn with replacement from the training set. The final prediction is obtained by combining the results of the prediction methods applied to each bootstrap sample (Genuer et al., 2017). The predicted value is calculated by the mean of all trees.~~

$$\cancel{\widehat{C1}_{as} \text{ or } \widehat{C2}_{as} = f_{RFR}(Y_s)} \qquad \cancel{(11)}$$

~~where f_{RFR} is constructed from the time series $\widehat{C1}_{as}$ or $\widehat{C2}_{as}$ (dependent variable) and the corresponding Y_s data (independent variable) at filtered C1 and C2 pixels in JJA by means of RFR. The number of decision trees was set at the default value of 500.~~

~~Fourth, as mentioned above, the aim of Rule 3 is to derive an adjustment method for C3 pixels based on learning from Rule 1 and Rule 2. With the establishment of a regression relationship between values before and after adjustment of the C1 and C2 pixels by RFR method, the determination of C3 pixels follows a considerable procedure. Pixels in each cluster represent potential C3 pixels, with exception of the C1 and C2 pixels and are called R pixels. Spearman's *r* and *p* values between the satellite estimations (CHIRP grid cell values) at R pixels and the C1 and C2 pixels are the criteria for final determination of C3 pixels. Each R pixel has *m SCC* and *p* values (the number of C1 and C2 pixels in the cluster), and the subset of C3 pixels is identified by excluding the data that failed the correlation test and retaining both the data with a maximum *SCC* of at least 0.5 and the corresponding index of C1 and C2 pixels. The selected C3 pixels are statistically similar to the precipitation characteristics of corresponding C1 and C2 pixels in their defined spatial scope.~~

~~After identifying the C3 pixels and their corresponding C1 and C2 pixels, the adjustment method for C3 pixels is derived from the regression model for the C1 and C2 pixels.~~

$$\cancel{\widehat{C3}_{as} = f_{RFRc}(Y_s)} \qquad \cancel{(12)}$$

~~where $\widehat{C3}_{as}$ is the adjusted satellite precipitation estimate and Y_s is the CHIRP grid cell value for the C3 pixels, and f_{RFRc} is the f_{RFR} of corresponding C1 and C2 pixels.~~

Second, as mentioned above, the aim of Rule 2 is to derive an adjustment method for C2 pixels based on learning from Rule 1. With the establishment of a regression relationship between gauge observations and the corresponding CHIRP grid cell values of the C1 pixels by RFR method, the determination of C2 pixels follows a considerable procedure. With exception of the C1 pixels, the remaining pixels in each cluster represent potential C2 pixels called R pixels. Pearson's correlation coefficient (PCC) and *p*-values between the satellite estimations (CHIRP grid cell values) at R pixels and the C1 pixels are the criteria for final determination of C2 pixels. The PCC is defined as follows:

$$PCC_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (8)$$

where *n* is the number of samples, x_i and y_i are individual samples (CHIRP grid cell values at C1 and C2 pixels), $\bar{x}$ is the arithmetic mean of *x* calculated by $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, $\bar{y}$ is the arithmetic mean of *y* calculated by $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

The value range of the PCC is between -1 and +1. If there are no repeated data values, a perfect PCC of +1 or −1 occurs when each of the variables is a perfect monotone function of the other. However, if the value is close to zero, there is zero correlation. In addition, correlation is not only determined by the value of the correlation coefficient but also from the correlation test's *p*-value. The critical values for PCC and *p*-value are 0.5 and 0.05, thus a PCC value higher than 0.5 and a *p*-value lower than 0.05 indicate the data are significantly correlated (Zhang and Chen, 2016). Therefore, the final determination

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of C2 pixels must meet the following criteria:

$$|\mathrm{PCC}| \geq 0.5 \quad and \quad p < 0.05 \qquad (9)$$

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Each R pixel has m PCC and p-values (the number of C1 pixels in the cluster), and the subset of C2 pixels is identified by excluding the data that failed the correlation test and retaining both the data with a maximum PCC of at least 0.5 and a p-value lower than 0.05, and the corresponding index of C1 pixels. The selected C2 pixels are statistically similar to the precipitation characteristics of corresponding C1 pixels in their defined spatial scope.

After identifying the C2 pixels and their corresponding C1 pixels, the adjustment method for C2 pixels is derived from the regression model for the C1 pixels.

$$C2_{as} = f_{RFRc}(Y_s) \qquad (10)$$

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where $C2_{as}$ is the adjusted satellite precipitation estimate and Y_s is the CHIRP grid cell value at the C2 pixels, and f_{RFRc} is the f_{RFR} of corresponding C1 pixel.

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3.1.~~5~~ 4 Rule ~~4~~ 3 of the WHU-SGCC method

Recognizing that precipitation has a spatial distribution, the assumption that ~~C4~~ C3 pixels are statistically ~~physically~~ similar to the precipitation characteristics of ~~C3~~ C2 pixels ~~was~~ is adopted to establish the adjustment method for ~~C4~~ C3 pixels.

First, the determination of ~~C4~~ C3 pixels in each spatial cluster is based on the selection of ~~C3~~ C2 pixels. The satellite-based estimation values ~~for~~ at the remaining ~~regional~~ pixels with exception of the C1and ~~,~~C2 pixels are used to calculate the ~~SCC~~ PCC and p~~-~~values with the satellite-based estimation values~~Y_s~~ ~~for~~ at the ~~C3~~ C2 pixels in the same cluster~~ of the JJA dataset~~. The results of each pixel's k ~~SCC~~ PCC and p~~-~~value (the number of ~~C3~~ C2 pixels in the cluster) are evaluated based on the correlation test (Eq. (9))~~,~~ ~~and~~ that the pixels with a maximum ~~SCC~~ PCC ~~of~~ is at least 0.5 and the p-value is no more than 0.05, ~~as well as~~and then –the corresponding index of ~~C3~~ C2 pixels~~,~~ are retained. The selected pixels called ~~C4~~ C3 pixels, which are statistically ~~physically~~ similar to the precipitation characteristics of the corresponding ~~C3~~ C2 pixels in the defined spatial scope.

After identifying the ~~C4~~ C3 pixels, a method for ~~merging method the~~merging the CHIRP grid cell values at ~~C4~~ C3 pixels (Y_s) and the target reference values of $\cancel{\hat{C3}_{as}}$ $C2_{as}$ at the corresponding ~~C3~~ C2 pixels ~~was~~ is applied to estimate the adjusted precipitation values ~~for~~ at ~~C4~~ C3 pixels. This method combines Y_s and $\cancel{\hat{C3}_{as}}$ $C2_{as}$ values in one variable, as shown in Eq. (~~13~~11):

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$$w_i = \frac{C2_{as_i}+\lambda}{Y_{s_i}+\lambda} \quad i=1,\ldots,\ n \qquad (\cancel{13}11)$$

where λ is a positive constant set to 10 mm (Sokol, 2003), $\cancel{\hat{C3}_{as}}$ $C2_{as}$ is the adjusted precipitation values ~~for~~ at the ~~C3~~ C2 pixels, Y_{s_i} is extracted from the CHIRP grid cell values at~~for~~ the ~~pixel~~ corresponding location of ~~with~~ the ~~C3~~ C2 pixel, and n is the number of ~~C3~~ C2 pixels in each spatial cluster.

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Each w of the ~~C4~~ C3 pixels is assigned the same value as the corresponding ~~C3~~ C2 pixel. Therefore, the values of ~~C4~~ C3 pixels are~~is~~ derived from Eq. (~~14~~12):

$$C3_{as} = \max(w \times (Y_s + \lambda) - \lambda, 0) \qquad (\cancel{14}12)$$

where $\cancel{\hat{C4}_{as}}$ $C3_{as}$ is the adjusted target precipitation value at one ~~C4~~ C3 pixel and Y_s is the corresponding CHIRP grid cell value. To avoid precipitation estimates below 0, Eq. (~~14~~12) sets these negative values to 0.

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~~If there is no C3 pixels in a spatial cluster, the C4 pixels are assumed to be physically similar to the precipitation characteristics of the C1 and C2 pixels and adjusted by the above method in Rule 4.~~

~~**3.1.6 Rule 5 of the WHU-SGCC method**~~

~~Excluding the C1, C2, C3 and C4 pixels, the number of remaining pixels, called C5 pixels, is less than 10% of the total number of pixels, and each C5 pixel value ($\hat{C5}_{as}$) is set to be the same as the CHIRP grid cell value at the corresponding position.~~

~~In the end, after applying these five rules, we obtained complete daily adjusted regional precipitation maps for the summer (JJA) 2016.~~

3.1.~~6~~ 5 Rule ~~5~~ 4 of the WHU-SGCC method

Excluding the C1~~,~~ C2~~, C3~~ and ~~C4~~ C3 pixels, the number of remaining pixels, called ~~C5~~ C4 pixels which are adjusted by Inverse Distance Weighted (IDW). IDW is based on the concept of the first law of geography from 1970. It was defined as *everything is related to everything else, but near things are more related than distant things*. Therefore, the attribute value of an unsampled point is the weighted average of known values within the neighbourhood, and the distance weighting can be determined by IDW (Lu and Wong, 2008). In Rule 4, IDW is used to interpolate the unknown spatial precipitation data from the adjusted precipitation values at the C2 and C3 pixels. The IDW formulas are given as Eq. (13) and Eq. (14).

$$R_{as} = \sum_{i=1}^{n} w_i R_i \tag{13}$$

$$w_i = \frac{d_i^{-\alpha}}{\sum_{i=1}^{n} d_i^{-\alpha}} \quad \text{with} \quad \sum_{i=1}^{n} w_i = 1 \tag{14}$$

where R_{as} is the unknown spatial precipitation data, R_i is the adjusted precipitation values at C2 and C3 pixels, n is the number of C2 and C3 pixels, d_i is the distance from each C2 or C3 pixel to be unknown grid cell, α is the power which is generally specified as a geometric form for the weight. Several researches (Simanton and Osborn 1980; Tung 1983) have experimented with variations in a power, the small α tends to estimate values with the averages of sampled grids in the neighbourhood, while large α tends to give larger weights to the nearest points and increasingly down-weights points farther away (Chen and Liu, 2012;Lu and Wong, 2008). The value of α has an influence on the spatial distribution of information from precipitation observations. For this reason, α value is conducted in the range of 0.1 to three (0.1, 0.3, 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0) in this study.

It is noted that the unknown spatial precipitation data including C1 and C4 pixels, because C1 pixels values were not adjusted in Rule 1.

~~, is less than 10% of the total number of pixels, and each C5 pixel value ($\hat{C5}_{as}$) is set to be the same as the CHIRP grid cell value at the corresponding position.~~

In the end, after applying these ~~five~~ four rules, we obtained complete daily adjusted regional precipitation maps for the summer (JJA) ~~2016~~over the Jinsha River basin.

3.2 Accuracy assessment

The performance of the WHU-SGCC adjusted precipitation estimates was evaluated by eight statistical ~~indicators~~metrics: ~~Spearman's correlation coefficient (SCC)~~ Pearson's correlation coefficient (PCC), root mean square error (RMSE), mean absolute error (MAE), relative bias (BIAS), the Nash-Sutcliffe efficiency coefficient (NSE), probability of detection (POD) and false alarm ratio (FAR) and critical success index (CSI). ~~SCC~~PCC, RMSE, MAE and BIAS were used to evaluate how well the WHU-SGCC method adjusted satellite estimation bias, while POD, FAR and CSI were used to evaluate the precipitation event predictions (Su et al., 2011). ~~S~~PCC measures strength of the ~~nonlinear~~ correlation relationship between the satellite estimations and observations. RMSE is an absolute measurement used to compare the difference between the satellite estimations and observations. MAE represents the average magnitude of error estimations, considering both systematic and random errors. The NSE (Nash and Sutcliffe, 1970) determines the relative magnitude of the variance of the residuals compared to the variance of the observations, bounded by minus infinity to 1. A negative value indicates a poor precipitation estimate and the value of an optimal estimate is equal to 1. BIAS measures the mean tendency of the estimated precipitation to be larger (positive values) or smaller (negative values) than the observed precipitation, with an optimal value of 0. POD, also known as the hit rate, represents the probability of rainfall detection. FAR is defined as the ratio of the false alarm ~~detection~~ of rainfall to the total number of rainfall events. All of the accuracy assessment metrics ~~indices~~ are shown ~~as~~ in Table 3.

Table 3 Accuracy assessment metrics~~indices~~.

Accuracy assessment Index	Unit	Formula	Range	Optimal value
~~Spearman's~~ Pearson's Correlation Coefficient (*SCC*)	NA	$\mathrm{P\cancel{S}CC} = \frac{\sum_{i=1}^{n}(Y_{oi}-\bar{Y}_o)(C_i-\bar{C})}{\sqrt{\sum_{i=1}^{n}(Y_{oi}-\bar{Y}_o)^2}\cdot\sqrt{\sum_{i=1}^{n}(C_i-\bar{C})^2}}$	[-1,1]	1
Root Mean Square Error (RMSE)	m~~M~~m	$\mathrm{RMSE} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(C_i-Y_{oi})^2}$	[0,+∞)	0
Mean Absolute Error (MAE)	m~~M~~m	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert C_i-Y_{oi}\rvert$	[0, +∞)	0
Relative Bias (BIAS)	NA	$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(C_i-Y_{oi})}{\sum_{i=1}^{n}Y_{oi}}$	(-∞, +∞)	0
Nash-Sutcliffe Efficiency Coefficient (*NSE*)	NA	$\mathrm{NSE} = 1-\frac{\sum_{i=1}^{N}(C_i-Y_{oi})^2}{\sum_{i=1}^{N}(C_i-\bar{Y}_o)^2}$	(-∞,1]	1
Probability of Detection (POD)	NA	*POD=H/(H+M)*	[0,1]	1
False Alarm Ratio (FAR)	NA	*FAR=F/(H+F)*	[0,1]	0
Critical Success Index (CSI)	NA	*CSI=H/(H+M+F)*	[0,1]	1

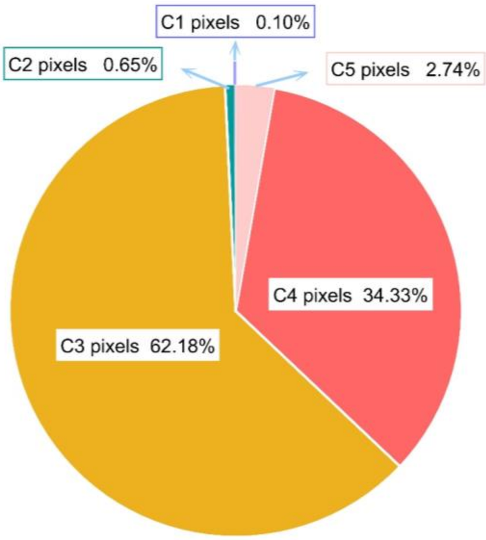
Note: Y_{oi} is the observation data and C_i is the adjusted value using the WHU-SGCC method for test sample pixel; $\bar{Y}_o$ is the arithmetic mean of Y_o and is given by $\bar{Y}_o = \frac{1}{n}\sum_{i=1}^{n}Y_{oi}$; $\bar{C}$ is the arithmetic mean of *C* and is given by $\bar{C} = \frac{1}{n}\sum_{i=1}^{n}C_i$; H represents the number of both observed and estimated precipitation events (successfully forecasted), and F is the number of false alarms when observed precipitation was below the threshold and estimated precipitation was above threshold (false alarms). M is the number of events in which the estimated precipitation was below the threshold and observed precipitation was above the threshold (missed forecasts). POD and FAR values are dimensionless numbers ranging from 0 to 1. The precipitation threshold (event/no event) was set to 0.1 mm/day.

4 Results and Discussion

There were 18482 daily pixels ~~to be~~ adjusted by blending satellite estimations (CHIRP) and observations (rain gauge stations ~~and gridded points~~) using the WHU-SGCC approach over the Jinsha River Basin during the~~for the 92 days of~~ JJA from 1990 to 2014~~2016~~. The number ~~of pixels~~of pixels adjusted by each rule in the WHU-SGCC method is shown in ~~Fig~~Table~~.~~ 4. The number of C1 pixels was the number of training gauge stations accounting 0.16% of the total pixels (18482) inside the basin. Due to the leave-one-out cross validation step, the different training samples will have the different number of C2, C3 and C4 pixels respectively inside the Jinsha River Basin. The number of C4 pixels was approximately 10822 with the percentage around 60%, the number of C3 pixels was approximately 4331 with the percentage ranging from 21.72% to 24.40%, and the number of C2 pixels was approximately 3300 with the percentage ranging from 15.59% to 18.36%. ~~The number of C1 and C2 was nearly 140, as well as 11493 C3 pixels, approximately 6344 C4 pixels, and the number of remaining C5 pixels was no more than 5%.~~

Table 4 The number of each class pixels adjusted by each rule using the WHU-SGCC method inside the Jinsha River Basin.

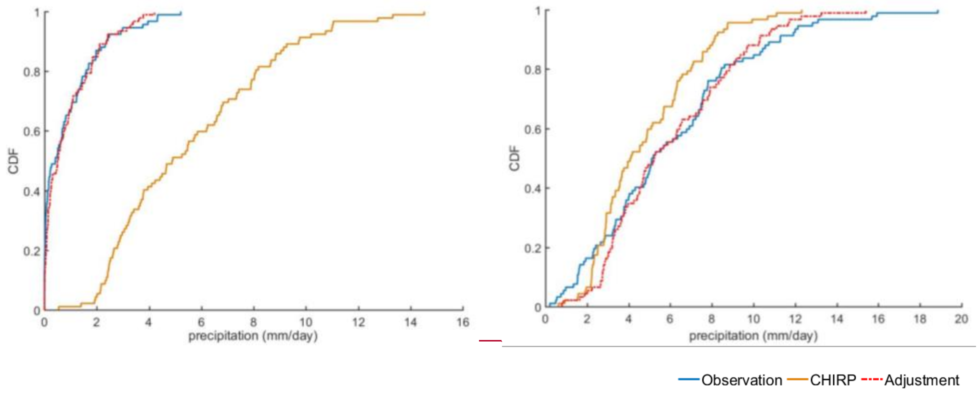
Validation gauge station	**C1 Pixels (%)**	**C2 Pixels (%)**	**C3 Pixels (%)**	**C4 Pixels (%)**
52908	29 (0.16%)	3066 (16.59%)	4224 (22.85%)	11163 (60.40%)
56004	29 (0.16%)	2882 (15.59%)	4111 (22.24%)	11460 (62.01%)
56021	29 (0.16%)	3311 (17.91%)	4510 (24.40%)	10632 (57.53%)
56029	29 (0.16%)	3338 (18.06%)	4447 (24.06%)	10668 (57.72%)
56034	29 (0.16%)	3300 (17.86%)	4427 (23.95%)	10726 (58.03%)
56038	29 (0.16%)	3209 (17.36%)	4014 (21.72%)	11230 (60.76%)
56144	29 (0.16%)	3347 (18.11%)	4442 (24.03%)	10664 (57.70%)
56146	29 (0.16%)	3183 (17.22%)	4480 (24.24%)	10790 (58.38%)
56152	29 (0.16%)	3173 (17.17%)	4176 (22.59%)	11104 (60.08%)
56167	29 (0.16%)	3362 (18.19%)	4346 (23.51%)	10745 (58.14%)
56247	29 (0.16%)	3385 (18.32%)	4416 (23.89%)	10652 (57.63%)
56251	29 (0.16%)	3301 (17.86%)	4348 (23.53%)	10804 (58.46%)
56257	29 (0.16%)	3313 (17.93%)	4043 (21.88%)	11097 (60.04%)
56357	29 (0.16%)	3352 (18.14%)	4390 (23.75%)	10711 (57.95%)
56374	29 (0.16%)	3341 (18.08%)	4294 (23.23%)	10818 (58.53%)
56459	29 (0.16%)	3345 (18.10%)	4334 (23.45%)	10774 (58.29%)
56462	29 (0.16%)	3380 (18.29%)	4377 (23.68%)	10696 (57.87%)
56475	29 (0.16%)	3345 (18.10%)	4344 (23.50%)	10764 (58.24%)
56479	29 (0.16%)	3305 (17.88%)	4212 (22.79%)	10936 (59.17%)
56485	29 (0.16%)	3393 (18.36%)	4419 (23.91%)	10641 (57.57%)
56543	29 (0.16%)	3373 (18.25%)	4384 (23.72%)	10696 (57.87%)
56565	29 (0.16%)	3241 (17.54%)	4450 (24.08%)	10762 (58.23%)
56571	29 (0.16%)	3306 (17.89%)	4263 (23.07%)	10884 (58.89%)
56586	29 (0.16%)	3387 (18.33%)	4434 (23.99%)	10632 (57.53%)
56651	29 (0.16%)	3340 (18.07%)	4432 (23.98%)	10681 (57.79%)
56664	29 (0.16%)	3368 (18.22%)	4262 (23.06%)	10823 (58.56%)
56666	29 (0.16%)	3323 (17.98%)	4431 (23.97%)	10699 (57.89%)
56671	29 (0.16%)	3356 (18.16%)	4367 (23.63%)	10730 (58.06%)
56684	29 (0.16%)	3335 (18.04%)	4278 (23.15%)	10840 (58.65%)
56778	29 (0.16%)	3347 (18.11%)	4277 (23.14%)	10829 (58.59%)



~~Figure 4~~ ~~The number of pixels adjusted by each rule using the WHU-SGCC method.~~

~~4.1 CDFs of Rule 1 and Rule 2 results~~

~~Figure 5 shows the daily average precipitation for observations, CHIRP, C1 (Fig. 5 (a)) and C2 (Fig. 5 (b)) in JJA 2016. Compared to the gauge or grid observations, CHIRP estimations deviated from the observations in Jinsha River Basin. However, the adjusted values for the C1 and C2 pixels improved the estimates and approximated the observations with application of Rule 1 and Rule 2 of the WHU-SGCC method. This result demonstrates that Rule 1 and Rule 2 of WHU-SGCC method are effective in correcting consistent biases and considerably reduce the systematic biases of CHIRP. These improvements not only adjust the bias of satellite estimations but also preserve the original CHIRP pixel values which are close to the corresponding observed data. These adjustments provide reliable precipitation estimates for the C1 and C2 pixels, which supports further study using the WHU-SGCC method, especially for areas in which rain gauges are limited.~~

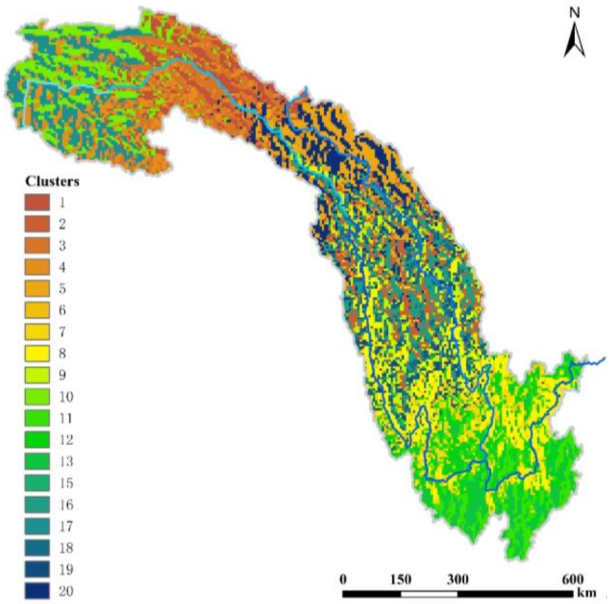


~~(a)~~ ~~(b)~~

~~Figure 5~~ ~~CDFs of seasonal mean daily observations, CHIRP, C1 and C2 estimations for the Jinsha River Basin in JJA 2016~~

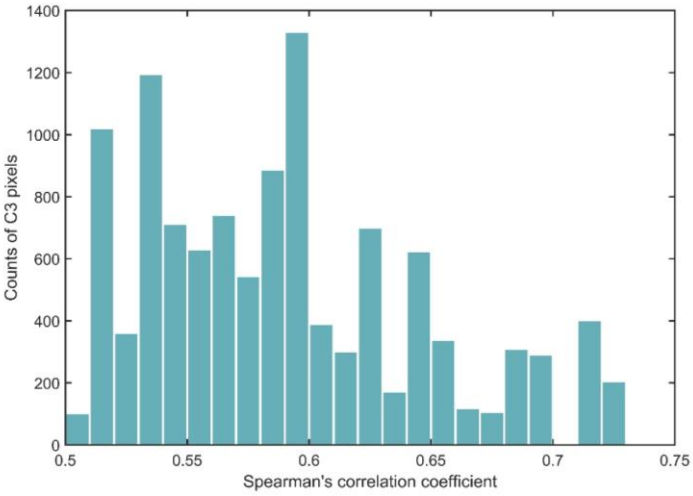
~~4.2 Spatial Clustering of Rule 3 results~~

~~To adjust the pixels other than for the gauged and gridded points, the pixels physically similar to the C1 and C2 pixels were selected. According to Rule 3, C3 pixels were identified in a spatial scope defined by the FCM method. Figure 6 shows the twenty spatial clusters with consideration of the terrain factors. Overall, the spatial results of FCM have many of the same characteristics as spatial areas defined by terrain changes, especially with respect to slope and runoff directions, which may influence regional rainfall to some extent.~~



~~**Figure 6** Spatial clustering as defined by FCM for the Jinsha River Basin.~~

~~After Rule 3, each C3 pixel has a good SCC with a C1 or C2 pixel in its cluster; the statistical analysis is shown in Fig. 7. It was found that the average SCC value was 0.6. Therefore, the regression model established in Rule 3 for C1 and C2 before and after adjustment is applicable for each corresponding C3 pixel.~~



~~**Figure 7** Frequency distribution histogram for Spearman's correlation coefficient (SCC) for C3 pixels and their corresponding C1 and C2 pixels using Rule 3.~~

~~It is important to note that 62.18% of the pixels satellite precipitation estimates were adjusted by Rule 3 of the WHU-SGCC method. The accuracy assessment of C3 pixels is shown in Table 4. Validation statistics indicate that compared with the CHIRP and CHIRPS satellite estimations, the WHU-SGCC approach provides best adjustments based on all the statistical indicators at C3 pixels. With the improvement of precipitation accuracy by WHU-SGCC of C3 pixels, the adjustments of C4 pixels, which mainly rely on C3 pixel corrections, are reasonable.~~

~~**Table 4** Accuracy assessment of C3 pixels for JJA 2016.~~

~~Statistic~~	~~WHU-SGCC~~	~~CHIRP~~	~~CHIRPS~~
~~SCC~~	~~0.3518~~	~~0.3176~~	~~0.2476~~
~~RMSE~~	~~5.1776~~	~~5.6686~~	~~7.0311~~
~~MAE~~	~~3.5226~~	~~3.7353~~	~~4.6909~~
~~BIAS~~	~~-0.0831~~	~~-0.2366~~	~~-0.2404~~
~~NSE~~	~~-0.0590~~	~~-0.2693~~	~~-0.9528~~
~~POD~~	~~1.0000~~	~~0.8900~~	~~0.3396~~
~~FAR~~	~~0.0687~~	~~0.0749~~	~~0.0763~~
~~CSI~~	~~0.9313~~	~~0.8302~~	~~0.3304~~

4.~~3~~ 1 Model performance based on overall accuracy evaluations

To test the performance of the WHU-SGCC method for precipitation estimates, the statistical analyses of ~~SCC~~PCC, RMSE, BAE, BIAS, NSE, POD, FAR, and CSI were calculated and are presented in Table 5 (The results were derived from the 22 clusters for FCM in Rule 2 shown in Appendix B, and α =0.1 for IDW in Rule 4 after the comparison of RMSEs). Compared with the satellite images of CHIRP and CHIRPS, the results of the WHU-SGCC provide the greatest improvements for regional daily precipitation estimates over the Jinsha River Basin during the~~in~~ JJA from 1990 to 201~~6~~4. After bias adjustment of the WHU-SGCC, ~~SCC~~ PCC was improved by ~~17.38~~3.34% and ~~39.62~~31.81% compared to CHIRP and CHIRPS, respectively. Meanwhile, the RMSE and~~,~~ MAE ~~and BIAS~~ of the WHU-SGCC was decreased by ~~4.20~~6.91% and~~,~~ ~~6.23~~6.59% ~~and 11.83%~~ compared to CHIRP, and by ~~19.10~~22.71% and~~,~~ ~~24.47~~22.15%~~ and 41.93%~~ compared to CHIRPS. Although, the absolute value of BIAS of WHU-SGCC was no significant improvement than CHIRP and slightly higher than CHIRPS, all of the values were

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approximately to 0. This results of BIAS indicates that all the three kinds of data were much the same on the performance of relative bias. Nevertheless, ~~T~~the NSE of the WHU-SGCC reached -0.0137~~0.0864~~, an increase of ~~0.10~~ 93.33% and ~~0.60~~98.32% compared to CHIRP and CHIRPS, respectively. The NSE of WHU-SGCC was still negative, but it was improved to be zero that indicates the adjusted results are close to the average level of the rain gauge observations, while the NSEs of CHIRP and CHIRPS were much worse. It is noted that the POD of WHU-SGCC was approximate to 1, better than CHIRP and CHIRPS, and the FAR of WHU-SGCC was 0.11, lower than CHIRP and CHIRPS, which represents the better ability on precipitation event predictions of the WHU-SGCC.

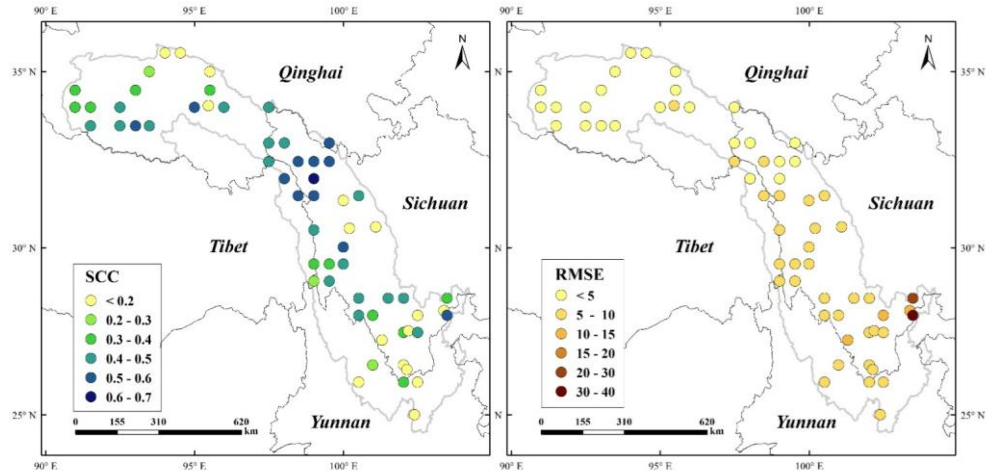
~~not only was the POD improved to over 0.95, but the CSI was also improved to over 0.85, and all the FARs were approximately 0.11.~~

Table 5 Overall accuracy assessment during the JJA from 1990 to 2014~~Overall accuracy assessment in JJA 2016~~.

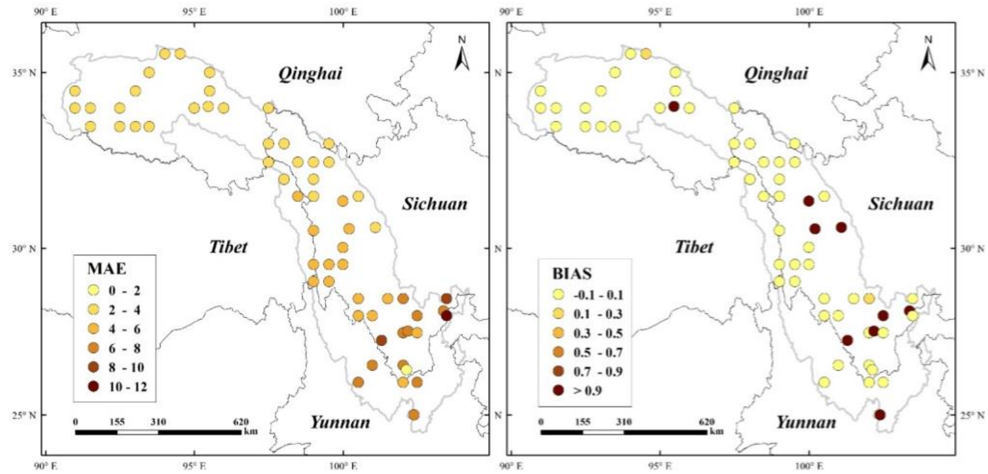
~~Statistic~~	~~WHU-SGCC~~	~~CHIRP~~	~~CHIRPS~~
~~SCC~~	~~0.3006~~	~~0.2561~~	~~0.2153~~
~~RMSE~~	~~8.3349~~	~~8.7003~~	~~10.3026~~
~~MAE~~	~~4.4671~~	~~4.7641~~	~~5.9146~~
~~BIAS~~	~~-0.0529~~	~~-0.0600~~	~~-0.0911~~
~~NSE~~	~~-0.0864~~	~~-0.1838~~	~~-0.6599~~
~~POD~~	~~0.9822~~	~~0.9230~~	~~0.3686~~
~~FAR~~	~~0.1023~~	~~0.1122~~	~~0.1125~~
~~CSI~~	~~0.8833~~	~~0.8266~~	~~0.3522~~

Statistic	WHU-SGCC	CHIRP	CHIRPS
PCC	0.2536	0.2454	0.1924
RMSE	8.7608	9.4108	11.3354
MAE	5.4564	5.8415	7.0088
BIAS	-0.0167	-0.0443	-0.0134
NSE	-0.0139	-0.2083	-0.8293
POD	0.9932	0.9578	0.4351
FAR	0.1146	0.2323	0.1601
CSI	0.8799	0.7405	0.4010

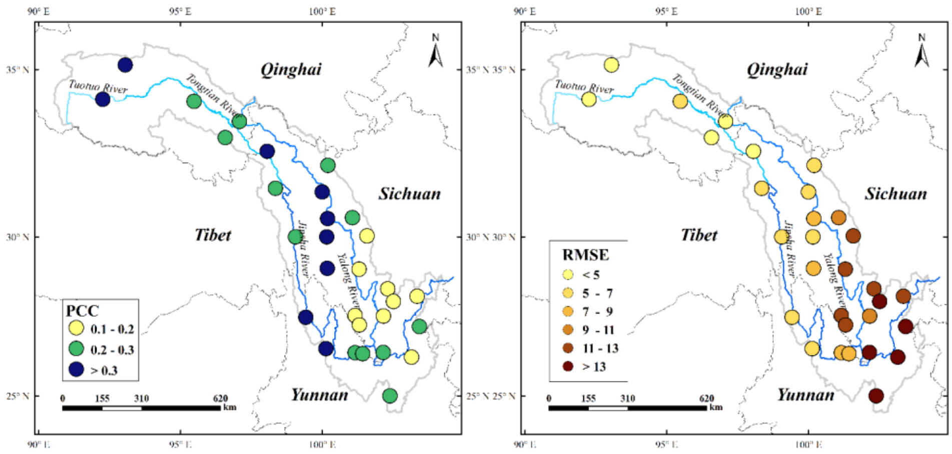
The spatial distributions of the statistical comparisons between observations and WHU-SGCC precipitation estimations are shown in Fig. ~~8~~4. The variation of ~~SCC~~ PCC as seen in Fig. ~~8~~4 (a) shows that low correlations are observed in areas with lower elevation, particularly in the southern Jinsha River Basin where there is higher precipitation and a greater density of rain gauges. This result is in contrast to the result in (Rivera et al., 2018), because of the few days for heavy rains in this study area. ~~However,~~ ~~t~~The higher correlations noted over the north central area of the river basin are in a drier region with complex terrain and sparse rain gauges. With respect to the spatial distribution of RMSE, Fig. ~~8~~ 4 (b) indicates that smaller errors are scattered in the northwest area of the river basin, with values lower than 5 mm, while the highest errors, which are over ~~20~~ 10 mm, are located over the border between the lower reaches of the Jinsha Jiang River and the river basin. All the values of MAE are below 10~~2~~ mm and the spatial behaviour is similar to that of the RMSE. Fig. ~~8~~ 4 (c) shows that the lower MAE values ~~are~~ were located over the mountainous region southwest of Qinghai and west of Sichuan, with values below 6 mm. The spatial distribution of the BIAS (Fig. 4 (d)) indicates that the WHU-SGCC has good agreement with the observations, with the most values ranging from -~~10~~-0.1~~%~~-0.1~~10%~~. All the spatial distribution statistics indicate that the statistical relationships established during the process of the WHU-SGCC method is susceptible to the mode values of the rain gauge stations data. Although the average annual precipitation in the southern Jinsha River Basin was more than 600 mm (Fig.2), the days of light rain were still in the great percentage that caused the large biases and limited the performance over the south area, while there were sufficient data with similar precipitation features for WHU-SGCC over the north area. Nevertheless, the WHU-SGCC approach is still~~All the spatial distribution statistics indicate that the WHU-SGCC is~~ effective in adjusting the satellite biases by blending with the observations, particularly in the complicated mountainous region where there ~~are~~ were higher ~~SCC~~ PCC corresponding to lower values of RMSE, MAE and BIAS. ~~The lower SCC and higher errors located over the area southeast of the river basin showed very limited improvement in precipitation estimates.~~



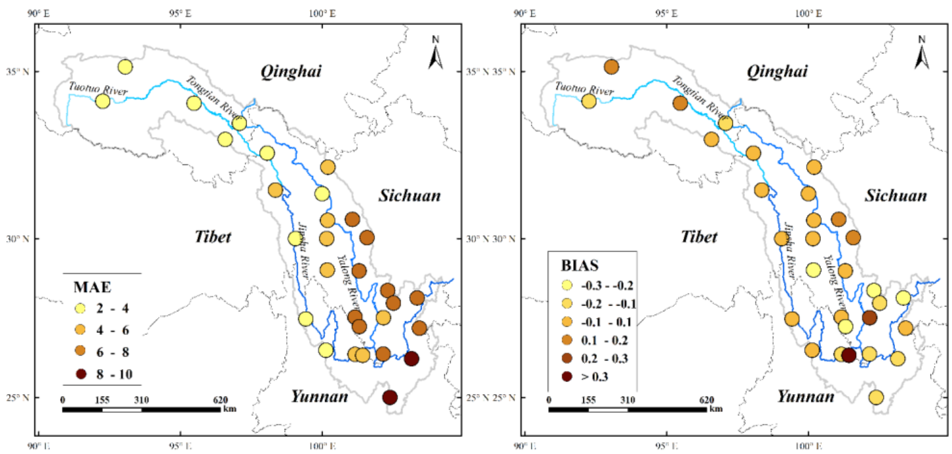
(a) (b)



(c) (d)



(a) (b)

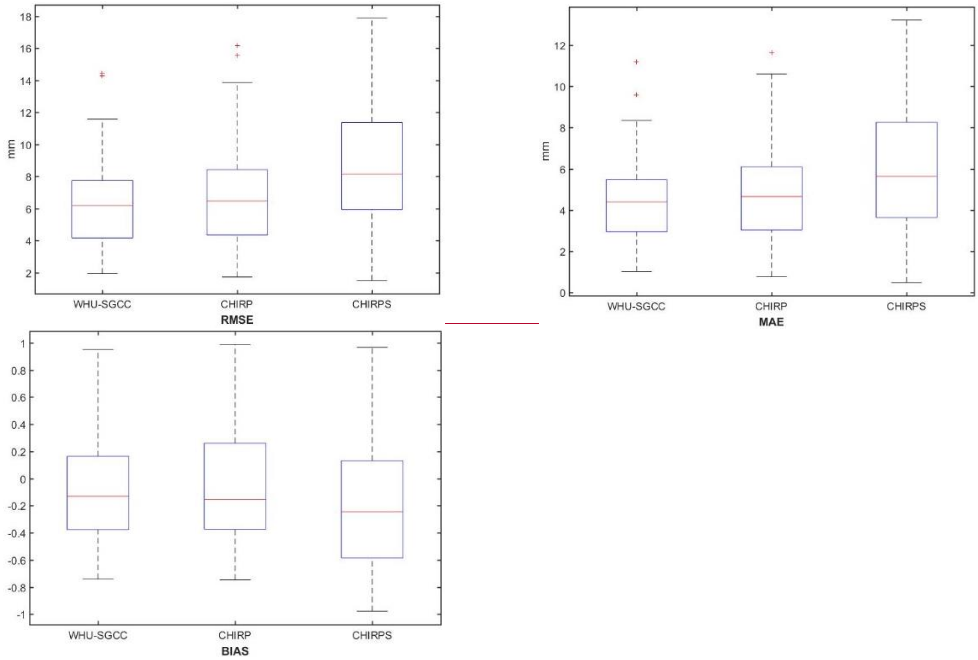


(c) (d)

Figure ~~8~~ 4 Spatial distribution of the statistical analyses of the overall agreement between observations and the WHU-SGCC estimations on leave-one-out cross validation ~~30% validation for~~ during the JJA from 1990 to 2014 ~~2016~~: a) ~~Spearman's~~ Pearson's correlation coefficient, b) root mean square error c) mean absolute error, and d) relative bias.

~~**4.4 Model performance based on daily accuracy evaluations**~~

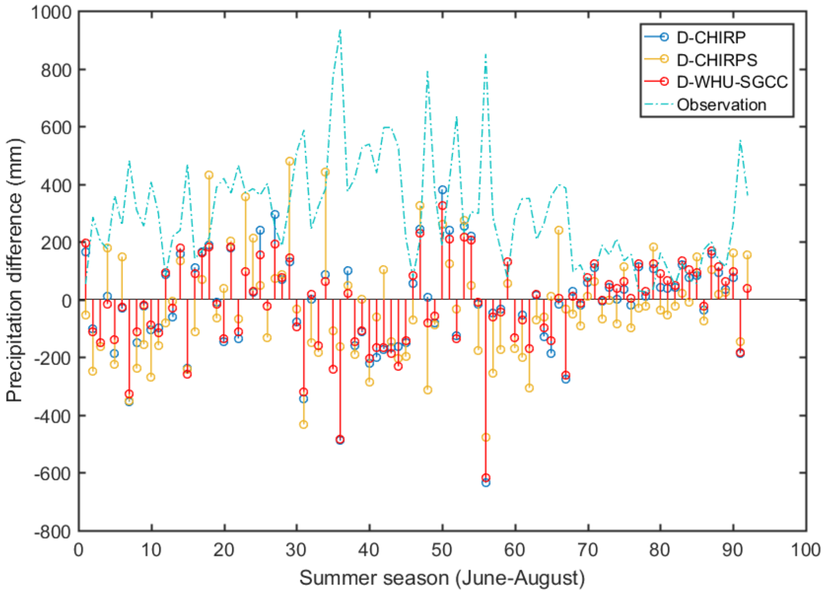
~~After overall accuracy evaluations for JJA were conducted, further evaluations of daily accuracy were undertaken and the results are shown in Fig. 9. The evaluation of daily accuracy indicates that the WHU-SGCC reduces errors and biases compared to CHIRP and CHIRPS, with especially greatly decreases compared to CHIRPS. The RMSE and MAE derived from the WHU-SFCC were reduced by approximately 5% and 30% compared to CHIRP and CHIRPS, respectively. However, the greatest reduction was reflected in the BIAS, with at least an 18% and 30% reduction compared to CHIRP and CHIRPS, respectively. Therefore, the WHU-SGCC approach is effective for adjustments of daily precipitation estimates, and improves estimate performance.~~



~~**Figure 9** The statistical analysis of the agreement between daily observations and WHU-SGCC, CHIRP and CHIRPS estimates on 30% validation: a) root mean square error b) mean absolute error, and c) relative bias.~~

~~The series of daily precipitation differences between WHU-SGCC, CHIRP, CHIRPS and observations is presented in Fig. 10. In this comparison, the WHU-SGCC has the best agreement with the observations, and provides a certain improvement compared to CHIRP, while CHIRPS shows the greatest inconsistencies with the observations.indicates that short heavy rainstorms (Katsanos et al., 2016b;Herold et al., 2017).~~ In general, the precipitation estimated using the WHU-SGCC method are superior to other products.

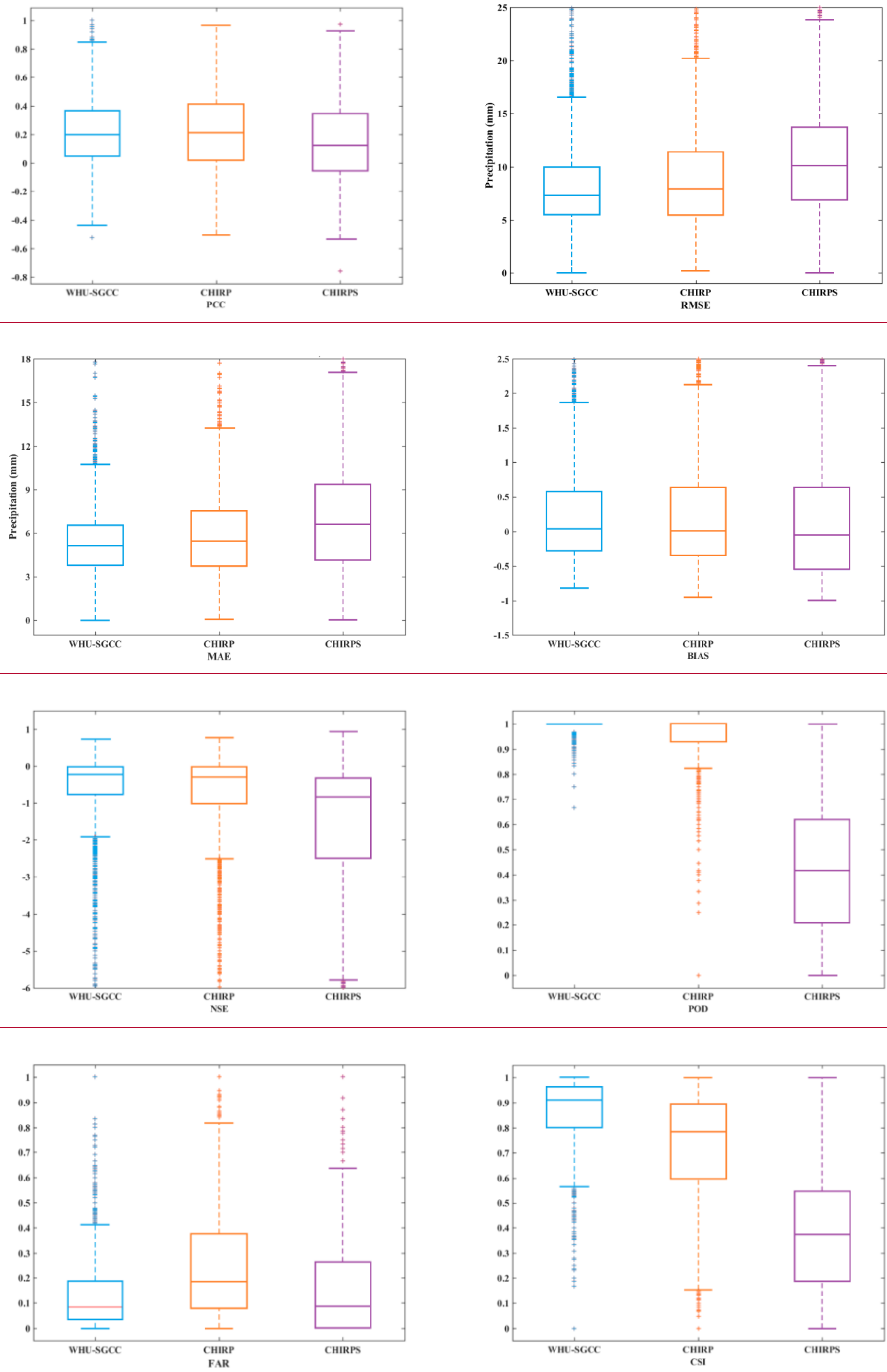
~~Furthermore, it is noted that differences in precipitation estimates and observations are reduced gradually as the season progresses, especially in August when rainfall is decreased. But at days 36 and 56, short heavy rain events occurred in conjunction with the largest differences in observed WHU-SGCC values. This However, in general, the precipitation estimated using the WHU-SGCC method are superior to other products.~~



~~**Figure 10** The daily precipitation difference between WHU-SGCC, CHIRP, CHIRPS and observations; D-CHIRP is the difference between CHIRP and observations, D-CHIRPS is the difference between CHIRPS and observations, and D-WHU-SGCC is the difference between WHU-SGCC and observations.~~

4.2 Model performance based on daily accuracy evaluations

After overall accuracy evaluations for JJA were conducted, further evaluations of daily accuracy were investigated and the results were shown in Fig. 5. The evaluation of daily accuracy indicates that the PCCs of WHU-SGCC, CHIRP and CHIRPS were roughly the same, while WHU-SGCC has the reduction of errors and biases compared to CHIRP and CHIRPS, especially the greater decreases when compared to CHIRPS. Figure. 5 indicates that there was no significant increase in PCC, however, PCC is a relative metric about the magnitude of the association between paired variables, and a relative consistency may not mean absolute proximity. Thus, the absolute measure indicated by RMSE may be more reasonable. In this study, the RMSE and MAE derived from the WHU-SGCC were reduced by approximately 15% and 30% compared to CHIRP and CHIRPS, respectively. The slight reduction was reflected in the BIAS, with an 8% to 45% reduction compared to CHIRP and CHIRPS, while all the values were concentrated between -0.5 and 0.5. All the precipitation estimations derived from WHU-SGCC, CHIRP, and CHIRPS represented well agreement with the observations in relative bias. The WHU-SGCC method shown obvious improvement in the NSE relative to CHIRP and CHIRPS, while the values were still less than 0 which may be due to the inherent uncertainty in the CHIRP. Moreover, in terms of POD, FAR and CSI, the WHU-SGCC method seems to be more promising in detecting precipitation than CHIRP and CHIRPS, although it performs poorly on FAR relative to CHIRPS in some days. However, the POD and CSI of WHU-SGCC were closest to 1. Overall, the WHU-SGCC approach is effective for adjustments of daily precipitation estimates, and improves estimate performance.



WHU-SGCC
CHIRP
CHIRPS
PCC
Precipitation (mm)
RMSE
MAE
BIAS
NSE
POD
FAR
CSI

Figure 5 The statistical analysis of the agreement between daily observations and WHU-SGCC, CHIRP and CHIRPS estimates on leave-one-out cross validation: a) Pearson's correlation coefficient b) root mean square error c) mean absolute error d) relative bias e) Nash-Sutcliffe efficiency coefficient f) probability of detection g) false alarm ratio, and h) critical success index.

4.~~5~~ 3 Model performance on rain events predictions~~Model performance for rain events~~

To measure the WHU-SGCC performance ~~for~~ on different rain events predictions, the daily precipitation thresholds of 0.1, 10, 25, and ~~5~~50~~5, 10, 20, and 40~~ mm were considered, and the result ~~is~~ was shown in Table 6 and Table ~~6~~7 ~~and Fig. 11~~. The days of each class of rain events at the validation gauge station during the JJA from 1990 to 2014 were shown in Table 5. The major rain events inside the Jinsha River Basin were light rain (0.1-10 mm), accounting for 54.76% of the total days (the average percentage of rain event days in its total days at each gauge station), while the days with daily precipitation over the 50 mm was least, only accounting for 0.72%. And the percentage of the daily precipitation of <0.1, 10-25, and 25-50 mm were 26.89%, 14.01% and 3.62% respectively. The result indicated that the average daily precipitation was less than 10 mm, though in the summer seasons during the multi-year. As well as, the spatial distribution of precipitation was also uneven, with an increase from north to south.

~~In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall between 1 and 20 mm, but WHU-SGCC performance for heavy rain (20-40 mm) events did not improve compared to CHIRP, though it was better than that of CHIRPS. Although the WHU-SGCC approach improved accuracy for light rain events, its behaviour for heavy rain (≥40 mm) events was not as good as CHIRP and CHIRPS, as shown in Fig. 11. These results indicate that WHU-SGCC is applicable for the detection of rainfall events with less than 20 mm precipitation, while there is insufficient observational data for the validation of WHU-SGCC performance during heavy rain events, which represented less than 4% of all observational data and were not sufficient to fully test performance of the model.~~

Table 6 The days of each class of rain events at the validation gauge station during the JJA from 1990 to 2014 inside the Jinsha River

Validation gauge station \ Rain event (mm)	<0.1	[0.1,10)	[10,25)	[25,50)	>=50	Total days
52908	637	1186	134	9	0	1966
56004	628	1243	128	3	0	2002
56021	535	1305	166	9	0	2015
56029	556	1328	190	5	0	2079
56034	558	1351	185	17	0	2111
56038	459	1329	222	16	0	2026
56144	562	1153	321	25	0	2061
56146	467	1278	267	19	0	2031
56152	466	1255	307	35	1	2064
56167	565	1234	278	20	0	2097
56247	591	1089	246	34	0	1960
56251	466	1247	320	30	0	2063
56257	336	1212	429	59	0	2036
56357	313	1247	373	63	1	1997
56374	393	1191	351	47	0	1982
56459	487	1080	377	102	13	2059
56462	185	1315	430	86	2	2018
56475	544	983	352	148	20	2047
56479	667	931	298	156	28	2080
56485	588	905	232	100	37	1862
56543	332	1200	289	41	1	1863

56565	526	1020	349	120	13	2028
56571	674	819	301	159	49	2002
56586	730	950	223	79	9	1991
56651	402	1056	391	137	31	2017
56664	727	797	306	166	56	2052
56666	858	791	226	128	44	2047
56671	616	886	289	148	70	2009
56684	768	899	246	114	19	2046
56778	682	930	274	119	43	2048

In terms of performance with respect to different daily rain events, the WHU-SGCC approach had the lowest error, as indicated by RMSE, MAE and BIAS for events with total rainfall ~~between 1~~lower than ~~–and 20~~25 mm, but the performance of WHU-SGCC ~~performance~~ for total rainfall higher than 25mm ~~heavy rain (20-40 mm) events~~ did not improve compared to CHIRP and CHIRPS (Table 6)~~, though it was better than that of CHIRPS~~. This negative performance on the total rainfall higher than 25 mm was probably caused by the precipitation conditions inside the Jinsha River Basin (Table 6). The average daily precipitation was less than 10 mm inside the basin, during the multi-year summer seasons, which provided a large amount of rain gauge stations data with the values lower than 10 mm, that caused a significantly impact on the statistical relationships establishment for WHU-SGCC. In hence, the approach of WHU-SGCC is applicable for the detection of rainfall events over the Jinsha River Basin, with the average daily precipitation less than 10 mm, or even than 25mm. Due to the 4.34% of summer days with the daily precipitation over the 25 mm, the performance of WHU-SGCC on these rain events was poorer than the results of CHIRP and CHRPS.

~~Although the WHU-SGCC approach improved accuracy for light rain events, its behaviour for heavy rain (≥40 mm) events was not as good as CHIRP and CHIRPS, as shown in Fig. 9. These results indicate that WHU-SGCC is applicable for the detection of rainfall events with less than 20 mm precipitation, while there is insufficient observational data for the validation of WHU-SGCC performance during heavy rain events, which represented less than 4% of all observational data and were not sufficient to fully test performance of the model.~~

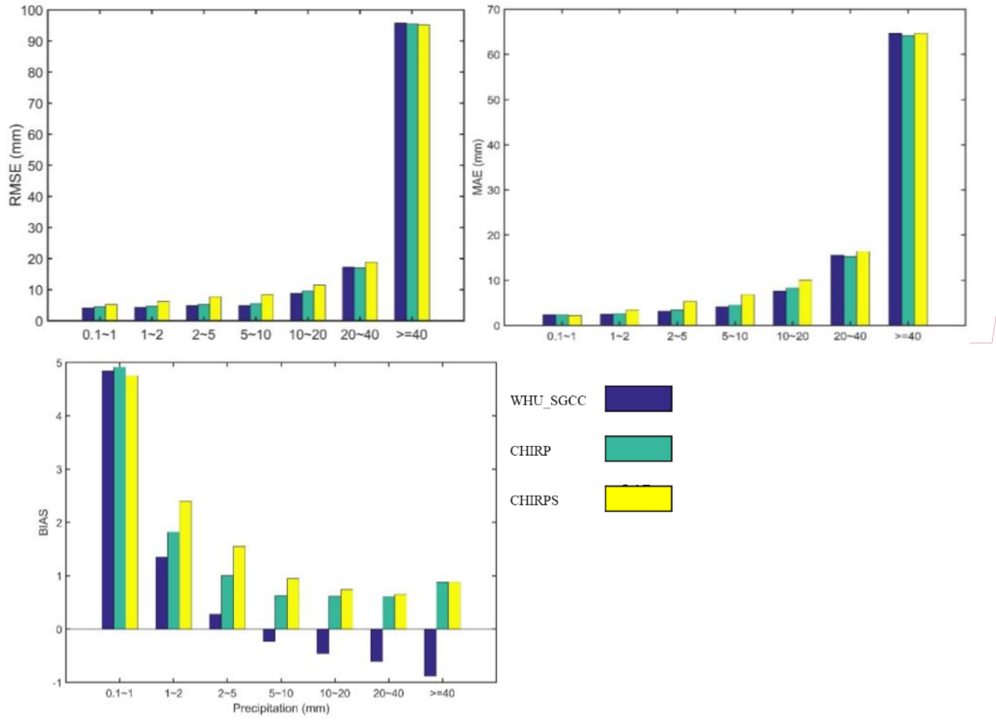
~~**Table 6** Accuracy assessment on wet precipitation events for JJA 2016~~

	~~RMSE~~			~~MAE~~			~~BIAS~~		
~~Rain Event~~	~~WHU-SGCC~~	~~CHIRP~~	~~CHIRPS~~	~~WHU-SGCC~~	~~CHIRP~~	~~CHIRPS~~	~~WHU-SGCC~~	~~CHIRP~~	~~CHIRPS~~
~~[0.1,1)~~	~~4.1609~~	~~4.5077~~	~~5.2762~~	~~2.3569~~	~~2.2940~~	~~2.2187~~	~~4.8423~~	~~4.9153~~	~~4.7541~~
~~[1 , 2)~~	~~4.2658~~	~~4.7385~~	~~6.2943~~	~~2.4820~~	~~2.5563~~	~~3.3707~~	~~1.3491~~	~~1.8199~~	~~2.3996~~
~~[2 , 5)~~	~~4.8378~~	~~5.2392~~	~~7.7315~~	~~3.2026~~	~~3.4011~~	~~5.2681~~	~~0.2808~~	~~1.0023~~	~~1.5525~~
~~[5 , 10)~~	~~4.8765~~	~~5.5616~~	~~8.4619~~	~~4.0646~~	~~4.5505~~	~~6.8346~~	~~-0.2292~~	~~0.6315~~	~~0.9485~~
~~[10,20)~~	~~8.8240~~	~~9.5254~~	~~11.5381~~	~~7.5957~~	~~8.3153~~	~~10.0287~~	~~-0.4627~~	~~0.6142~~	~~0.7408~~
~~[20,40)~~	~~17.3305~~	~~17.0107~~	~~18.8758~~	~~15.5649~~	~~15.2646~~	~~16.4080~~	~~-0.6035~~	~~0.6011~~	~~0.6461~~
~~≥40~~	~~95.8157~~	~~95.5185~~	~~95.2107~~	~~64.6789~~	~~64.1252~~	~~64.6337~~	~~-0.8850~~	~~0.8774~~	~~0.8844~~

Table 7 Accuracy assessment on liquid precipitation events during the JJA from 1990 to 2014

	RMSE			MAE			BIAS		
Rain Event	WHU-SGCC	CHIRP	CHIRPS	WHU-SGCC	CHIRP	CHIRPS	WHU-SGCC	CHIRP	CHIRPS
<0.1	4.7253	5.0802	7.1643	2.5927	2.9562	2.9145	/	/	/
[0.1,10)	4.1661	6.8684	9.6022	3.9885	4.5534	6.2462	0.8021	1.4435	1.9842
[10,25)	10.4281	11.0848	13.4427	9.2722	9.6866	11.5909	-0.5762	0.6342	0.7559
[25,50)	25.7494	24.5600	25.4975	24.8386	23.0967	23.4927	-0.7784	0.7250	0.7388

≥50	56.6072	54.5037	52.7875	54.4168	52.1557	49.4318	-0.8861	0.8297	0.7852



~~**Figure 11** Accuracy assessment based on daily observations for the estimations of WHU-SGCC, CHIRP and CHIRPS for wet precipitation events in JJA 2016: a) root mean square error b) mean absolute error, and c) relative bias.~~

批注 [S1]: This figure was same to the table 7, so we deleted it.

~~**5 Data availability**~~

~~All the resulting dataset derived from the WHU-SGCC approach is available on PANGAEA, with the following DOI: https://doi.pangaea.de/10.1594/PANGAEA.896615 (Shen et al., 2018). The high-resolution (0.05°) daily precipitation estimation data over Jinsha River Basin in summer 2016 can be downloaded in TIFF format.~~

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All the resulting dataset derived from the WHU-SGCC approach is available on PANGAEA, with the following DOI: https://doi.pangaea.de/10.1594/PANGAEA.896615 (Shen et al., 2018). The high-resolution (0.05°) daily precipitation estimation data over the Jinsha River Basin in the summer from 1990 to 2014 can be downloaded in TIFF format.

6 Conclusions

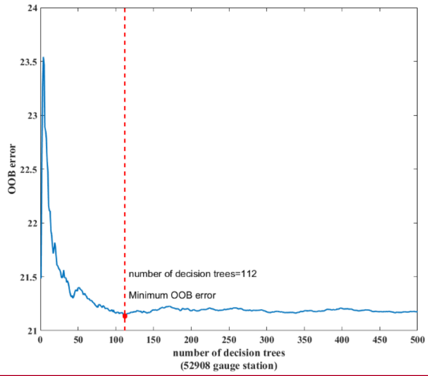
This study provides~~d~~ a novel approach in the WHU-SGCC method for merging daily satellite-based precipitation estimates with observations. A case study of Jinsha River Basin was conducted to verify the effectiveness of the WHU-SGCC approach during the ~~in~~ JJA from 1990 to 2014~~2016~~, and the adjusted precipitation estimates were compared to CHIRP and CHIRPS.

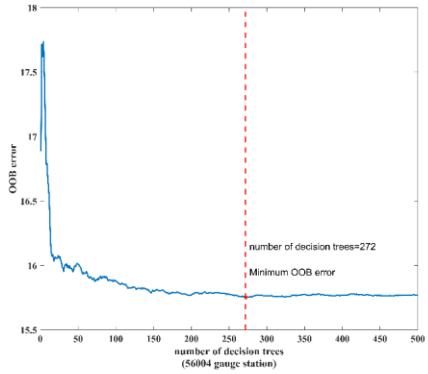
WHU-SGCC aims to reduce systematic and random errors in CHIRP over ~~the~~ a region that has complicated mountainous terrain and sparse rain gauges. To the best of the authors' knowledge, this study is the first to use daily CHIRP and CHIRPS data in this area.

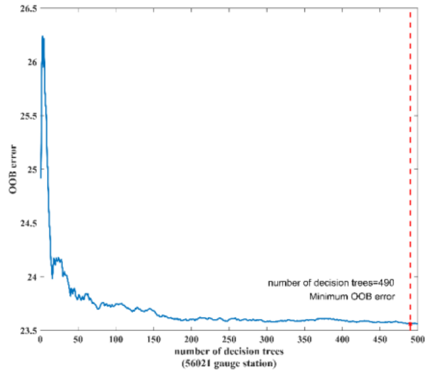
According to our findings, the following conclusions can be drawn: (1) The WHU-SGCC method is effective for the adjustment of precipitation biases from point to surface. The precipitation estimated by the WHU-SGCC method can achieve greater accuracy, which was evaluated with ~~SCC~~PCC, RMSE, MAE, BIAS, NSE, POD, FAR and CSI. Particularly, the ~~SCC~~ NSE statistic was improved by ~~17.38~~93.33% and ~~39.62~~98.32% compared to CHIRP and CHIRPS, respectively, and all measured errors were reduced except the BIAS with no significant improvement, but approximately to 0. The results show that compared to CHIRPS, the WHU-SGCC approach can achieve substantial improvements in precipitation estimate accuracy. (2) Moreover, the spatial distribution of precipitation estimate accuracy derived from the WHU-SGCC method is related to the complexity of the topography. These random errors over the lower evaluations and the large size of ~~the~~ light precipitation events with short duration rainstorms in the region resulted in a limited improvement in accuracy, with ~~SCC~~ PCC values less than 0.3, ~~especially during short rainstorms.~~ However, higher ~~SCC~~ PCC and lower errors were observed over the north central area of the river basin, which is a drier region with complex terrain and sparse rain gauges. All the spatial distribution statistics indicate that the WHU-SGCC method is promising ~~superior~~ for adjustment of satellite biases by blending with the observations over the complex terrain~~complicated mountainous~~ region. (3) The leave-one-out cross validation of WHU-SGCC on daily rain events confirmed~~The WHU-SGCC validations for daily rain events confirmed~~ that the model was effective in the detection of precipitation events less than ~~20~~ 25 mm due to the less average annual precipitation inside the Jinsha River Basin. According to the comparison, the WHU-SGCC approach achieves error reductions for the RMSE, MAE and BIAS statistics for rain events within the range of 1-~~20~~ 25 mm. Specifically, compared with CHIRP, the RMSE value was reduced by approximately by 5.92%-39.44%~~9%~~, the MAE value by ~~2.91~~4.28% ~~∼~~ - ~~10.68~~12.41%, and the absoulte BIAS value by ~~1.49~~9.15% ~~∼~~ - ~~175.33~~44.43%; compared with CHIRPS, the RMSE and MAE values were reduced by ~~20~~11.04% ~~∼~~ - ~~40~~56.61%, and the absolute BIAS value by ~~43.78~~23.77% ~~∼~~ - ~~162.46~~59.58%.

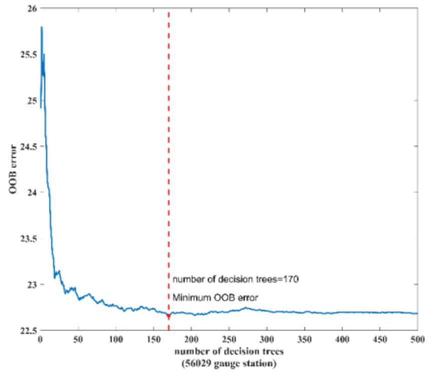
In conclusion~~Therefore~~, the WHU-SGCC approach can help adjust the biases of daily satellite-based precipitation estimates over the Jinsha River Basin, the complicated mountainous terrains with sparse rain gauges, particularly on the daily~~f~~ ~~or~~ precipitation events with less than ~~20~~ 25 mm in the summer. This approach is a promising tool to monitor monsoon precipitation over the Jinsha River Basin, considering the spatial correlation and historical precipitation characteristics between raster pixels located in regions with similar topographic features. Future development of the WHU-SGCC approach will focus on the following three aspects: (1) improvement of the adjusted precipitation quality by blending in different rain ~~reducing random errors~~events and applying in all seasons; (2) introduction of more climatic factors and mulit-model ensemble ~~introduction of more topographic and long time series climatic factors~~ to achieve a more accurate spatial distribution of precipitation; and (3) investigation of the performance over the other areas and on the particular hydrological case to validate the WHU-SGCC approach.

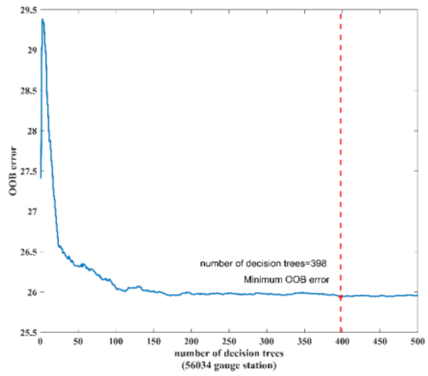
Appendix A: The selection of decision trees for random forest regression

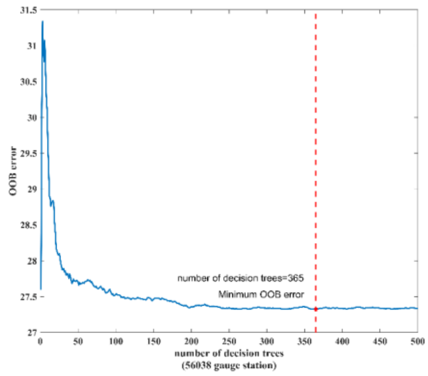

OOB error
number of decision trees=112
Minimum OOB error
number of decision trees
(52908 gauge station)

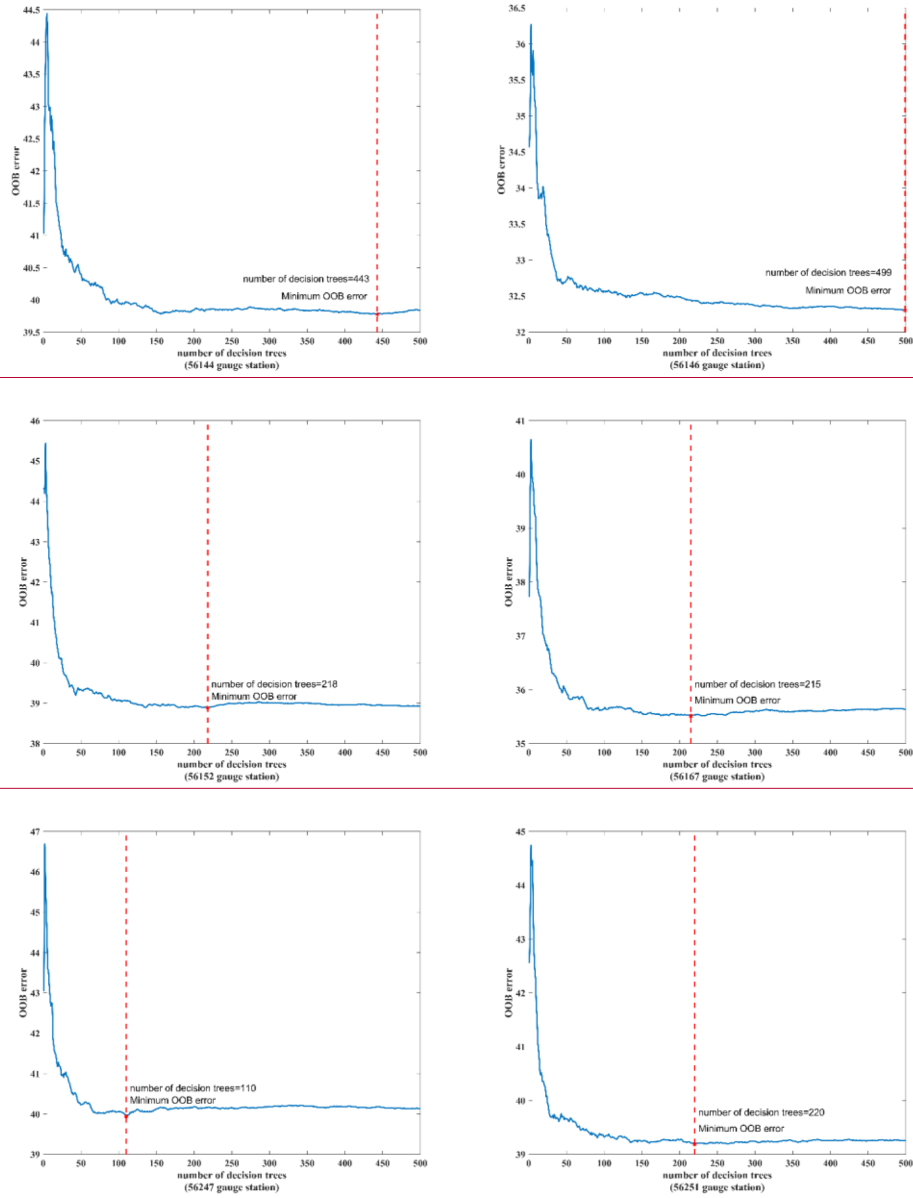

OOB error
number of decision trees=272
Minimum OOB error
number of decision trees
(56004 gauge station)

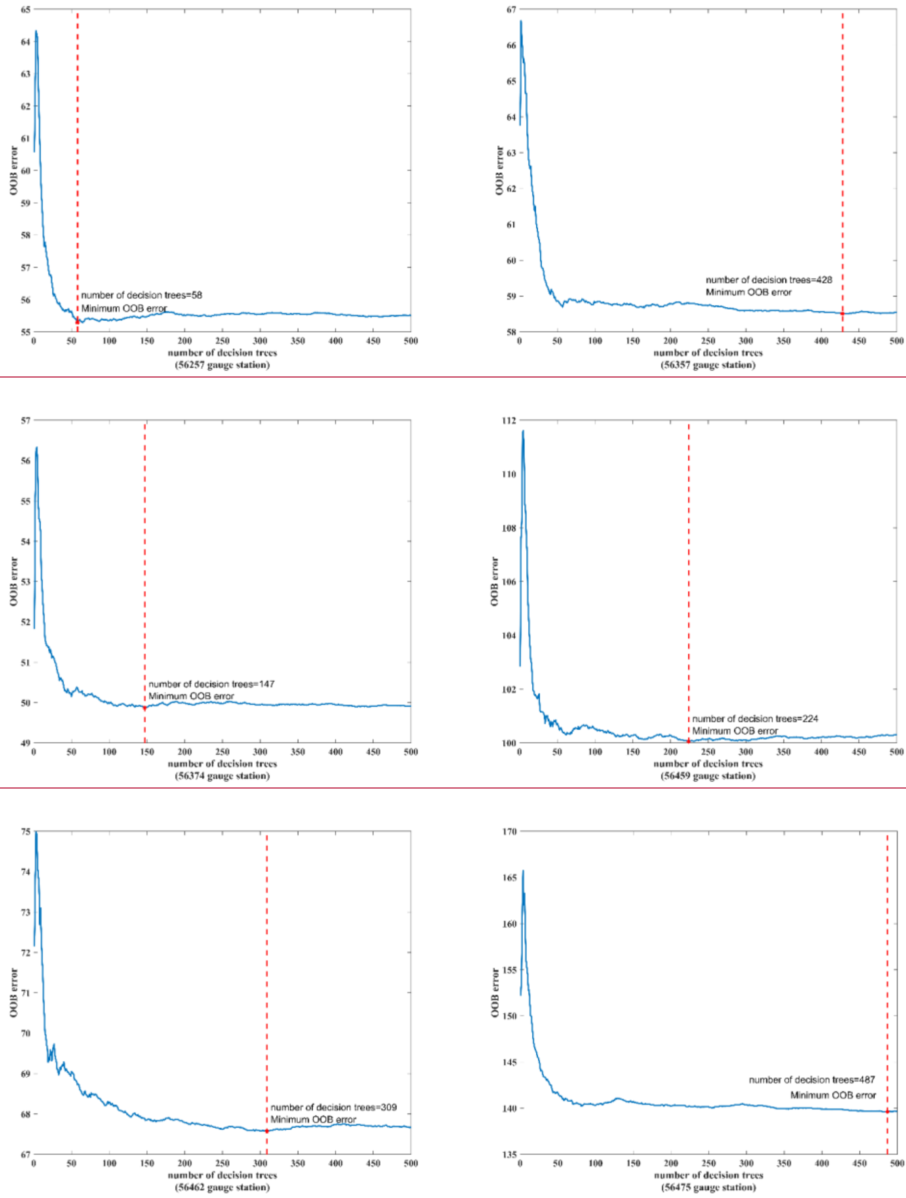

OOB error
number of decision trees=490
Minimum OOB error
number of decision trees
(56021 gauge station)

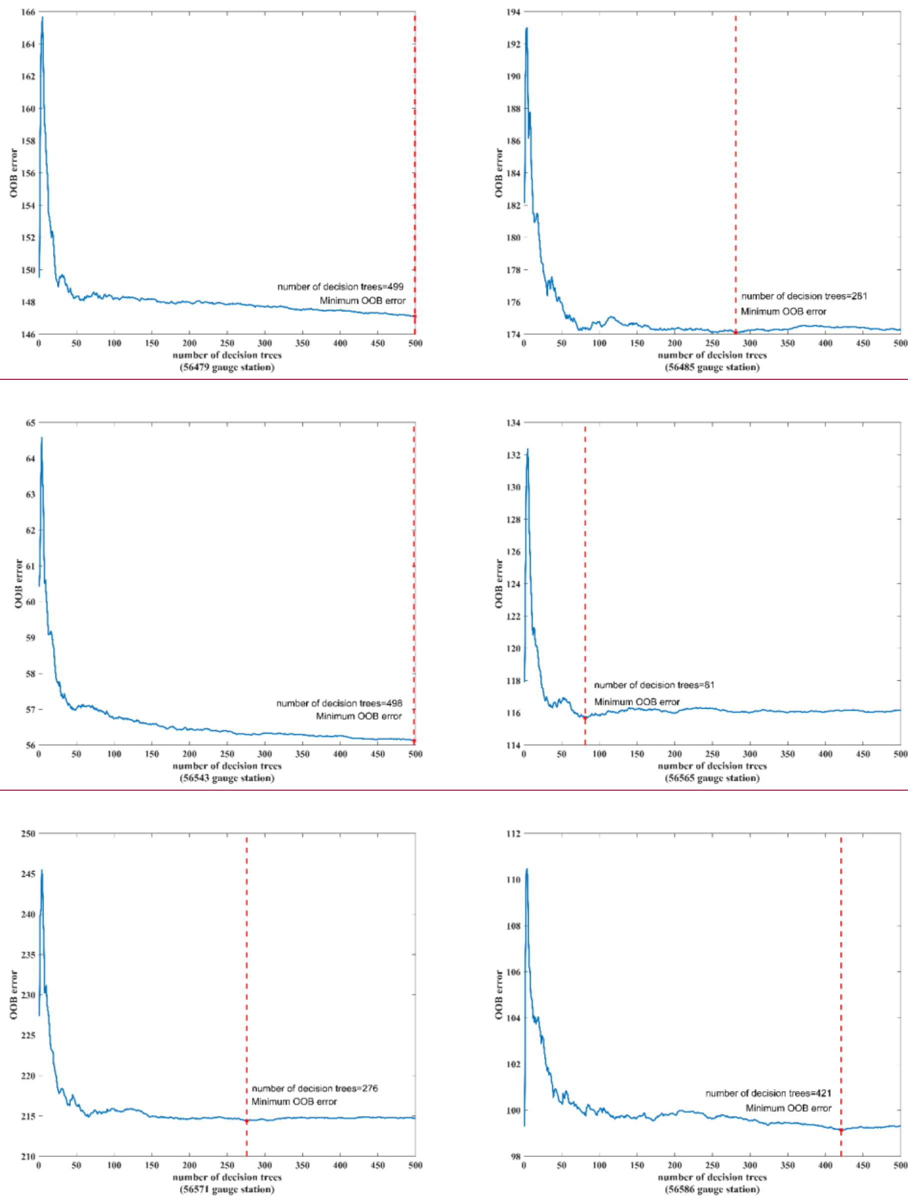

OOB error
number of decision trees=170
Minimum OOB error
number of decision trees
(56029 gauge station)


OOB error
number of decision trees=398
Minimum OOB error
number of decision trees
(56034 gauge station)


OOB error
number of decision trees=365
Minimum OOB error
number of decision trees
(56038 gauge station)


OOB error
number of decision trees
number of decision trees=443
Minimum OOB error
(56144 gauge station)
number of decision trees=499
Minimum OOB error
(56146 gauge station)
number of decision trees=218
Minimum OOB error
(56152 gauge station)
number of decision trees=215
Minimum OOB error
(56167 gauge station)
number of decision trees=110
Minimum OOB error
(56247 gauge station)
number of decision trees=220
Minimum OOB error
(56251 gauge station)


OOB error
number of decision trees=58
Minimum OOB error
number of decision trees
(56257 gauge station)
OOB error
number of decision trees=428
Minimum OOB error
number of decision trees
(56357 gauge station)
OOB error
number of decision trees=147
Minimum OOB error
number of decision trees
(56374 gauge station)
OOB error
number of decision trees=224
Minimum OOB error
number of decision trees
(56459 gauge station)
OOB error
number of decision trees=309
Minimum OOB error
number of decision trees
(56462 gauge station)
OOB error
number of decision trees=487
Minimum OOB error
number of decision trees
(56475 gauge station)


OOB error
number of decision trees=499
Minimum OOB error
number of decision trees
(56479 gauge station)
OOB error
number of decision trees=281
Minimum OOB error
number of decision trees
(56485 gauge station)
OOB error
number of decision trees=498
Minimum OOB error
number of decision trees
(56543 gauge station)
OOB error
number of decision trees=81
Minimum OOB error
number of decision trees
(56565 gauge station)
OOB error
number of decision trees=276
Minimum OOB error
number of decision trees
(56571 gauge station)
OOB error
number of decision trees=421
Minimum OOB error
number of decision trees
(56586 gauge station)

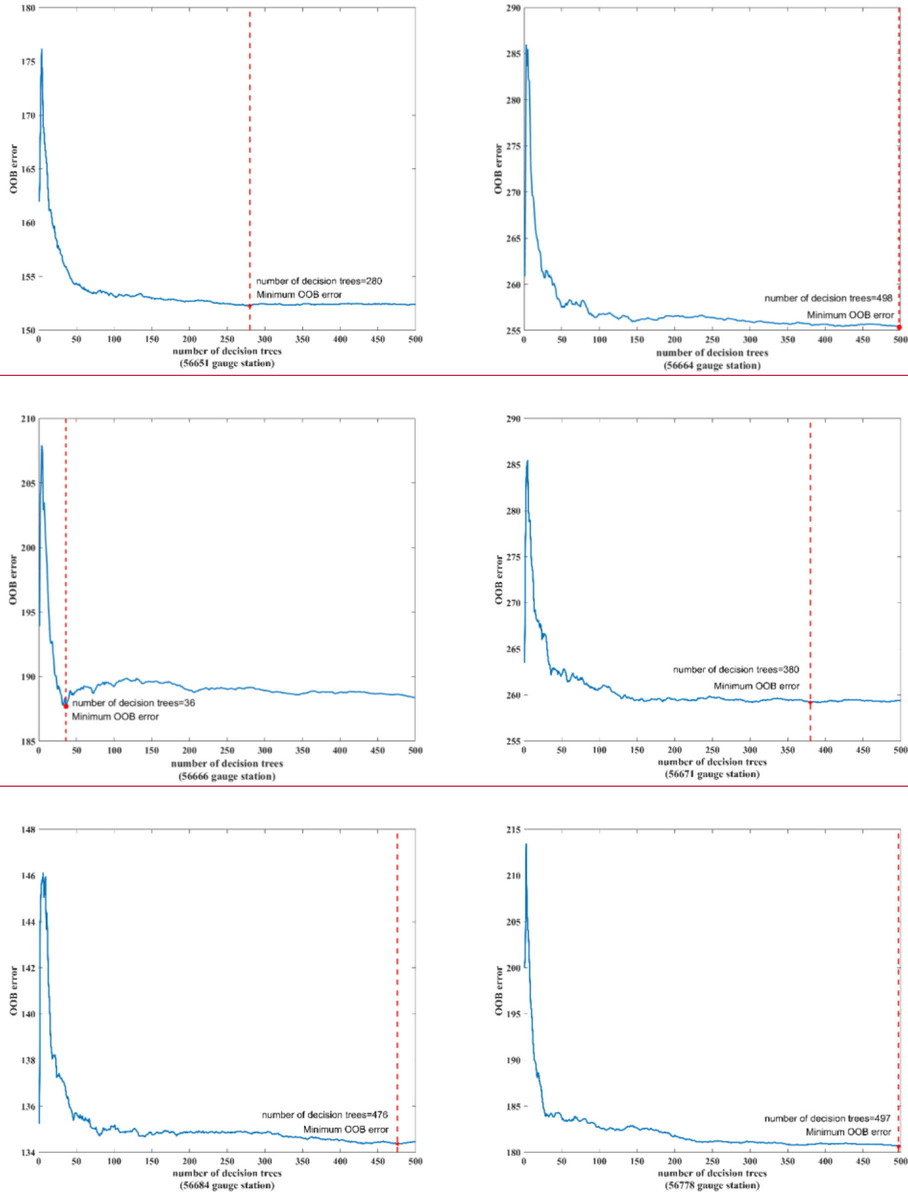


Figure A1 The change of out-of-bag (OOB) error with the number of decision trees increase by means of random forest regression at each gauge station.

Appendix B: Spatial Clustering from the FCM method

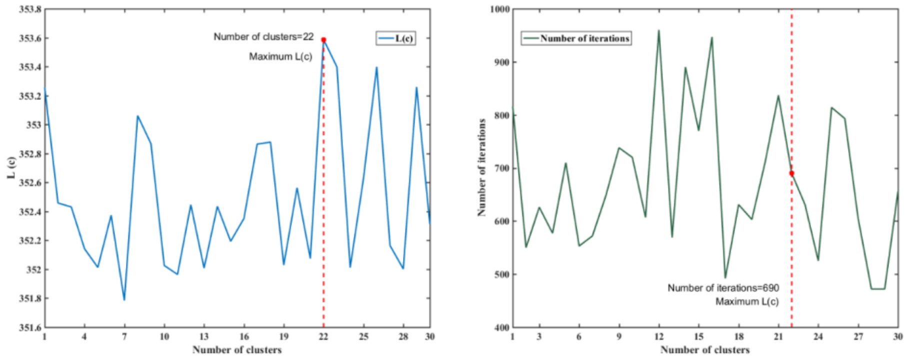


Figure B1 The optimum number of clusters determined by the maximum $L(c)$ with the iterative process.

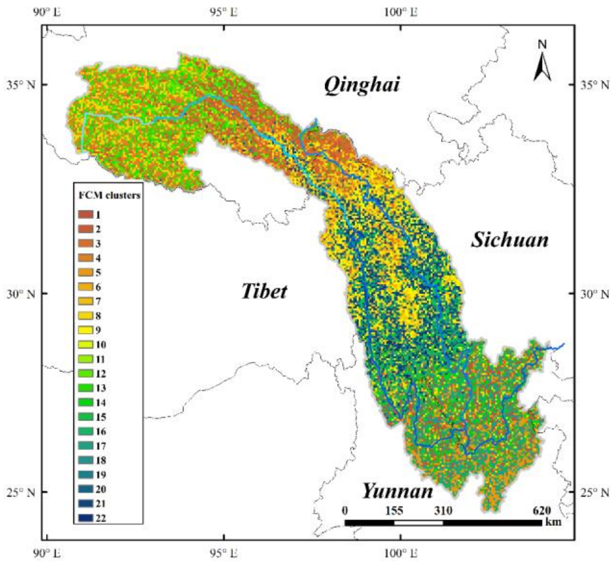


Figure B2 Spatial clustering as defined by FCM for the Jinsha River Basin.

This appendix demonstrates how to set the number of clusters in the FCM method.

To adjust the pixels other than for the gauged stations, the pixels statistically similar to the C1 were selected. According to Rule 2, C2 pixels were identified in a spatial scope defined by the FCM method. In the following experiments of Rule 2, we set the parameters $m = 2, \varepsilon = 0.00001$ and the maximum number of iterations was set 1000 (an enough large value with the consideration of the algorithm efficiency). In order to determine the optimal numbers of clusters, c value was conducted in the range from 1 to 30 with an incremental interval value of 1 in this study. During the running of FCM approach, the values of $L(c)$ were shown in Fig B1. The optimum number of clusters was 22, with the number of iterations was 690 less than the maximum number of iterations.

Therefore, the number of clusters was set to 22 and the number of iterations was still set to 1000 for fully operations by means of FCM. The spatial clusters results with consideration of the terrain factors was shown in Fig. B2. Overall, the spatial

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results of FCM have many of the same characteristics as spatial areas defined by terrain changes, especially with respect to slope and runoff directions, which may influence regional rainfall to some extent.

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