Improving daily spatial precipitation estimates by merging gauge observation with multiple satellite-based precipitation products based on the geographically weighted ridge regression method

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Abstract

Merging gauge observation with a single original satellite-based precipitation product (SPP) is a common approach to generate spatial precipitation estimates. For the generation of high-quality precipitation maps, however, this common method has two drawbacks: (1) the spatial resolutions of original SPPs are still too coarse; and (2) a single SPP can’t capture the spatial pattern of precipitation well. To overcome these drawbacks, a two-step scheme consisting of downscaling and fusion was proposed to merge gauge observation with multiple SPPs. In both downscaling and fusion steps, the geographically weighted ridge regression (GWRR) method, which is a combination of the geographically weighted regression (GWR) method and the ridge regression method, is proposed and implemented to generate improved spatial precipitation estimates by overcoming the collinearity problem of the pure GWR method. The proposed two-step merging scheme was applied to Xijiang Basin of China deriving daily precipitation estimates from the data of both gauge observation and four near real-time SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) during the period of 2010-2017. The results showed that: (1) the collinearity problem caused by GWR was not serious in downscaling but serious enough to prevent GWR from being directly used in the fusion; and (2) the proposed two-step merging scheme significantly improved the spatial resolution and accuracy of precipitation estimates over the original SPPs. Comparisons also showed that, in the second step (fusion) of the merging scheme, the use of multiple SPPs provided more reliable spatial precipitation estimates than using a single SPP.

KEYWORDS: two-step merging scheme, multiple satellite-based precipitation products, gauge observation, geographically weighted ridge regression, collinearity problem

1. Introduction

Spatial precipitation estimates, the essential input for hydrological models, is one of the
atmospheric research issues most difficult to solve due to the high spatio-temporal variability of precipitation (Golding 2009; Gourley and Vieux 2006; Sorooshian et al. 2011; Zhao et al. 2015). In the current rapid development of remote sensing techniques, satellite-based precipitation product (SPP) provides an attractive source for precipitation estimates characterized with extensive spatial coverage, especially for regions with complex terrain and clustered in valleys where the gauge network is generally sparse (Verdin et al. 2015). However, SPP inevitably contains large error because of the indirect derivation. To reduce the errors of SPP, merging gauge observation that provides accurate precipitation data at point locations with SPP becomes a common approach for spatial precipitation estimation (AghaKouchak et al. 2009; Gebremichael et al. 2010; Yang et al. 2016; Nerini et al. 2015).

Great efforts have been made to develop and evaluate many different algorithms of gauge-satellite precipitation merging, e.g., mean field bias correction (Huffman et al. 2007), additive/multiplicative bias correction (Vila et al. 2009), statistical bias correction (Beck et al. 2019; Ma et al. 2019), inverse-root-mean-square-error (IRMSE) weighting (Yang et al. 2017), random forest (Baez-Villanueva et al. 2020), Geographic Differential/ Ratio Analysis (GDA/GRA; Cheema and Bastiaanssen 2012; Jongjin et al. 2016; Chao et al. 2018), global regression models (Almazroui 2011; Cheema and Bastiaanssen 2012), Barnes objective analysis (Rozante et al. 2010), Bayesian combination (BC; Nerini et al. 2015), conditional merging (CM; Jongjin et al. 2016), cokriging (CK), kriging with external drift (KED; Grimes et al. 1999; Manz et al. 2016), and double kernel smoothing (DS; Li and Shao 2010).

Most of the algorithms were developed for the merging of gauge observation and only a single SPP. Although the outcomes are encouraging, it is quite a challenging job to generate high-quality precipitation maps because the spatial pattern of precipitation cannot be well captured by a single SPP. Derived from the signals of satellite sensors with specific retrieval algorithm, the spatial pattern of precipitation in SPP is susceptible to the retrieval algorithm,
satellite sensors and sampling frequency, the imperfections of which will cause considerable system errors in the complicated derivation process (Bharti and Singh 2015; Dinku et al. 2010). The marked difference in algorithm, sensors and sampling frequency for the available SPPs, such as the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA; Huffman et al. 2007), Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Hsu et al. 1997 1999), Global Satellite Mapping of Precipitation (GSMaP; Ushio et al. 2009), Integrated MultisatelliteE Retrievals for Global Precipitation Measurement (IMERG; Huffman et al. 2017), Soil Moisture to Rain (SM2RAIN; Ciabatta et al. 2018) and Multi-Source Weighted-Ensemble Precipitation (MSWEP; Beck et al. 2017), causes the performance of merging varies from region to region, time to time, and product to product (Sun et al. 2018; Hussain et al. 2018). Each product has its own strengths and weaknesses in the capture of precipitation spatial pattern, and no product has been shown to be superior to others for all time and regions (Maggioni et al. 2016; Sun et al. 2018). To exploit the strength of each SPP, some researchers have attempted to combine multiple SPPs together and they have found that the combined product provides more reliable spatial pattern estimates of precipitation compared with the individual SPPs (Golian et al. 2015; Ma et al. 2017). It seems, therefore, that merging gauge observation with multiple SPPs instead of a single SPP could be more conducive to the improvement of spatial precipitation estimates.

Another restriction for estimating high-quality precipitation originates from the coarse spatial resolution of SPPs released to public, which generally ranges from 0.25° to 0.05° at present. Remaining the same as the SPP involved in the merging, the spatial resolution of the merged precipitation product (MPP), derived from direct merging of gauge observation and the original SPP performed in most previous studies, is still too coarse for local hydrological
and meteorological applications, as the meso- and micro-scale variability of precipitation cannot be presented (Tao and Barros 2010; Xu et al. 2015). In addition, the significant discrepancy in the spatial scale between coarse satellite pixels and point-based rain gauges adversely affects the accuracy of the MPP (Duan and Bastiaanssen 2013). Thus, a procedure spatially downscaling the original SPP will benefit to improve both the spatial resolution and accuracy of the merged precipitation product. The key for spatial downscaling is to construct the regression relationship between precipitation and environmental variables. By using the Normalized Difference Vegetation Index (NDVI) alone as explanatory variable, Immerzeel et al. (2009) successfully downscaled TRMM data on an annual scale for the first time. Taking both NDVI and elevation into consideration, Jia et al. (2011) improved the downscaling results of annual TRMM data. In the spatial downscaling of TRMM during six rainstorm events (lasting 1-3 days per event) for the Xiao River basin, Fang et al. (2013) indicated that the influence of slope, aspect and terrain roughness should not be neglected. Thereafter, various environmental factors such as vegetation (e.g., NDVI), topography (e.g., elevation, slope, aspect), geographical location (longitude and latitude), and land surface temperature (LST) were widely used in the spatial downscaling of SPP at annual or monthly scale (Xu et al. 2015; Chen et al. 2015; Jing et al. 2016; Ma et al. 2017; Zhan et al. 2018; Zhang et al. 2018). Due to the low correlation relationship between precipitation and environmental variables at daily scale, Chen et al. (2019) and Ma et al. (2019) tried to downscale the annual SPP accumulated from daily precipitation with regression model first and then disaggregate the result into daily scale to generate the downscaled daily SPP.

To improve spatial estimates of MPP, a two-step scheme consisting of downscaling and fusion for merging gauge observation with multiple SPPs is proposed in this study. Geographically weighted regression (GWR, Brunsdon et al. 1996; Fotheringham et al. 2002), a local form of linear regression, provides a potential method for both the spatial downscaling
and fusion, but probably cannot be directly used because of the collinearity problem. The collinearity problem, leading to unstable and inflated parameter estimates and in extreme cases even making the parameter not solvable, has been widely acknowledged as a critical concern for general multivariate regression (Belsley et al. 1980; O’Brien 2007; Shieh 2011). In GWR, collinearity is potentially more of a problem because of two possible reasons: (1) the adverse effects can be more pronounced with smaller localized samples and (2) if the data are spatially heterogeneous in terms of their correlation structure, some localities may exhibit collinearity while others do not (Brunsdon et al. 2012). In both cases, GWR may be highly susceptible to collinearity problem even when the problem does not exist in global datasets (Wheeler and Tiefesdorf 2005). The topographic variables (e.g., elevation, slope and aspect) derived from the DEM data may be related to each other, and each topographic variable may also be related to the vegetation variable (e.g., NDVI). When retrieving the same precipitation event, different SPPs might also have similar estimates in some areas on the condition that the precipitation is well captured. Therefore, collinearity is very likely to be a problem for the GWR-based downscaling-fusion scheme. One remedy for collinearity problem is to penalize the size of regression coefficients with ridge regression (Hoerl and Kennard 1970; Muniz and Kibria 2009). To deal with the local collinearity problems in GWR, Wheeler (2007) attempted to integrate ridge regression into the GWR framework by introducing a global-compensated ridge term. Then, Gollini et al. (2015) revealed that integration of ridge regression and GWR is better performed using space-varying ridge parameter, thus ridge regressions can only be fitted at locations in which the collinearity problem is diagnosed. Despite these encouraging ideas, their tentative integration method is still inadequate for practical application, as the method to remove the intercept term is not applicable to the GWR frame and the criteria adopted for collinearity diagnosis gives misleading results in particular cases (Lazaridis 2007; Salmeron et al. 2018). Considering these factors, the
geographically weighted ridge regression method (GWRR) was established by re-combining ridge regression with GWR to overcome the local collinearity problem in the two-step merging scheme for spatial precipitation estimation.

In this paper, the proposed GWRR-based two-step merging scheme was used to estimate the spatial distribution of daily precipitation in the Xijiang Basin of China for the period of 2010 to 2017. The rest of this paper is organized as follows. Section 2 describes the study area and datasets, Section 3 presents both the proposed GWRR-based two-step merging scheme and some performance evaluation indices, and Section 4-6 present the results, discussion and concluding remarks, respectively.

2. Study Area and Datasets

2.1. Study Area

The Xijiang Basin is located in South China and has an area of 353,100 km$^2$, accounting for 77.8% of the total area of the Pearl River Basin. As main stream of the Pearl River Basin, the Xijiang River, originates from Maxiong Mountain of Yunnan Province and flows through the Yunnan, Guizhou, Guangxi and Guangdong Provinces. The landform, with small and scattered plains, consists mainly of mountains and hills. The basin has sub-tropical and tropical monsoon climates. The mean annual temperature and precipitation are 14-22 °C and 1200-1900 mm, respectively. The precipitation decreases from east to west in general, and numerous high and low precipitation areas are formed due to the topographic change. With 70%-80% of the annual precipitation occurring from April-September, precipitation is unevenly distributed over a year. In this paper, the Wuzhou upstream region of Xijiang Basin (Figure 1), with an area of 329,700 km$^2$, was selected as the study area.
2.2. Datasets

2.2.1 Rain gauge data

Daily time series of 42 rain gauges (Figure 1) used in this study were provided by the National Meteorological Information Center of China Meteorological Administration (http://data.cma.cn). All the data were subjected to strict quality control at three levels: (1) extreme values check, (2) internal consistency check, and (3) spatial consistency check (Feng et al. 2004; Ma et al. 2017). The daily observation was interpreted as the 24-h accumulated rainfall up to 8 p.m. Beijing time for a given day. Attributable to terrain difficulties, the rain gauge network in the study area is sparse, with an average of one station for every 9,420 km², in which situation the spatial representativeness of precipitation estimates obtained through the spatial interpolation of rain gauge data is quite poor. Thus, for this study area, SPPs can be attractive due to the well spatial representativeness, and the merging conducted to improve the spatial precipitation estimates of SPPs seems meaningful.

2.2.2 Satellite-based precipitation products (SPPs)

Four level-3 near real-time SPPs, i.e., TRMM Multisatellite Precipitation Analysis 3B42 in Real-Time (TMPA-3B42RT), CMORPH, PERSIANN, and GSMaP in Near Real Time (GSMaP_NRT), were used in the GWRR-based two-step merging scheme. The former three provide 3-hourly precipitation data at 0.25° spatial resolution, and the last one provides hourly precipitation at 0.1° spatial resolution. The signal inputs adopted in these products come from geosynchronous infrared (IR) sensors on geostationary (GEO) satellites and passive microwave (PMW) sensors on low-Earth-orbiting (LEO) satellites. IR observations enable a high sampling frequency but are limited to cloud-top temperature measurements and cloud height, which are not directly related to lower-level rainfall rates, while PMW imagers
and sounders provide more direct information about precipitation despite the poor temporal
sampling. The signal sources adopted in the four SPPs, especially the PMW observations,
 exhibit large difference. In addition, different algorithms are used to retrieve spatially
continuous distribution information for precipitation from signal sources for the four SPPs,
i.e., the histogram matching method for TMPA-3B42RT, morphing technique for CMORPH,
adaptive artificial neural network for PERSIANN, and Kalman filter model for GSMaP_NRT.
The detailed information for the four products is summarized in Table 1. The daily
accumulations of SPPs were computed from 12 a.m. to 12 a.m. UTC to match the 8 p.m. to 8
p.m. Beijing time (UTC+8 time zone) of the gauge data.

| Table 1 here |

### 2.2.3 Explanatory variables

The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) monthly NDVI
products (MOD13A3) were downloaded from the NASA Land Processes Distributed Active
Archive Center (https://lpdaac.usgs.gov/dataset_discovery/modis) and used in this study. As
vegetation growth can be suppressed by water areas, urban and rural construction land, and
unused land, the NDVI data for these land uses no longer dominated by precipitation were
excluded from the original MOD13A3 and then filled with interpolated values using the
moving window method. Land-Use and Land-Cover Change (LUCC) with 5-year temporal
resolution and 1km spatial resolution, downloaded from the Resource and Environment Data
Cloud Platform (http://www.resdc.cn), were used to detect the excluded pixels of MOD13A3.
The DEM data with a 3 arc-second (~90 m) resolution was obtained from the Shuttle
Radar Topographic Mission (SRTM, http://srtm.csi.cgiar.org/) and resampled to 1km
resolution using the bilinear interpolation technique (Blue et al., 2004). Then, the variables of
longitude, latitude, elevation and slope data were further extracted from the resampled
1km-resolution DEM data with ArcGIS software.

3. Methodology

A flowchart of the proposed GWRR-based two-step scheme consisting of downscaling and fusion is presented in Figure 2 to illustrate the procedures of merging the gauge observation with multiple SPPs. In the first step, each of four SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) was downscaled to 1 km resolution separately by employing the relationships between precipitation and the explanatory variables such as NDVI, elevation, slope, longitude and latitude. In the second step, gauge observation was fused with the four downscaled SPPs. Both the downscaling and fusion algorithm are based on the geographically weighted ridge regression (GWRR) method, which was established by combining ridge regression with geographically weighted regression (GWR) to overcome the local collinearity problem in GWR. Collinearity refers to the strong or near to strong linear correlation between the explanatory variables of linear regression model, which will lead to unstable and inflated parameter estimates. In the following sections of 3.1-3.4, GWR, GWRR, downscaling by GWRR, and fusion by GWRR will be introduced in detail. Section 3.5 presents some statistical indices for the performance evaluation of the two-step merging scheme.

3.1. Geographically weighted regression (GWR)

GWR is a local form of linear regression that can be used to investigate the non-stationary and scale-dependent characteristics of the relationship between the dependent variable and explanatory variables (Brunsdon et al. 1996; Fotheringham et al. 2002). Compared with a global regression, the coefficients in GWR are functions of spatial location. The GWR model can be expressed as follows:
\[ y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i \]  

where \( y_i \) is the dependent variable at location \( i \); \( x_{ik} \) is the \( k \)th independent variable at location \( i \); \( p \) is the number of independent variables; \( \beta_{i0} \) and \( \beta_{ik} (k = 1, 2, \ldots, p) \) are the intercept and slopes to be estimated at location \( i \), respectively; and \( \varepsilon_i \) is the regression residual at location \( i \).

In the calibration of GWR, observations around a prediction point are weighted using a distance decay function, assuming the observation closer to the location of the prediction point has a greater impact on the local parameter estimates for the location. The regression coefficients, including intercept \( \beta_{i0} \) and slopes \( \beta_{ik} (k = 1, 2, \ldots, p) \) at location \( i \), are estimated by minimizing the weighted residual sum of squares:

\[
\hat{\beta}(i) = \arg \min_{\beta} \left\{ \sum_{j=1}^{n} w_j(i) \left( y_j - \beta_{i0} - \sum_{k=1}^{p} x_{jk} \beta_{ik} \right)^2 \right\} 
\]

(2)

Where \( \hat{\beta}_i = (\hat{\beta}_{i0}, \hat{\beta}_{i1}, \ldots, \hat{\beta}_{ip})^T \) is the vector of estimated coefficients of GWR at location \( i \), \( w_j(i) \) denotes the geographical weight of \( j \)-th observation data for location \( i \), and \( n \) is the total number of observation points.

Equation (2) is solved by the weighted least square method, and then the regression coefficients \( \beta_{0}(u_i,v_i) \) and \( \beta_{k}(u_i,v_i) \) can be estimated with the following matrix form:

\[
\hat{\beta}(i) = \left( X'^\top W(i) X \right)^{-1} X'^\top W(i) y
\]

(3)

where \( X \) is the matrix of independent variables with a column of 1s for the intercept, \( W(i) = \text{diag} \left[ w_1(i), w_2(i), \ldots, w_n(i) \right] \) is the diagonal weights matrix denoting the geographical weighting of each observed data for prediction location \( i \), \( y \) is the vector of the dependent variable, and superscript \( T \) indicates the matrix transpose.
In the GWR model, it should be emphasized, the column vectors in $\mathbf{X}$ are assumed to not be linearly related to each other, which is not true in many practical applications. The linear correlation between these column vectors, known as collinearity in regression, causes the solution to Equation (3) to be highly problematic or even unobtainable, because in this situation, the determinant of matrix $(\mathbf{X}^T \mathbf{W}(i) \mathbf{X})$ is close or equal to 0.

3.2. Geographically weighted ridge regression (GWRR)

To overcome the collinearity problem in GWR, GWRR is established by integrating ridge regression into the GWR framework. Each local GWRR model works by “shrinking” the effect of the redundant variables with constrained slopes. The solution to GWRR is actually a constrained minimization problem, which can be formulated as

$$
\hat{\beta}^R(i) = \arg \min_{\beta} \left\{ \sum_{j=1}^{n} w_j(i) \left( y_j - \beta_{i0} - \sum_{k=1}^{p} x_{jk} \beta_{ik} \right)^2 \right\} 
$$

subject to $\sum_{k=1}^{p} \beta_{ik}^2 \leq M(i)$ (4)

where $\hat{\beta}^R(i) = (\hat{\beta}^R_{i0}, \hat{\beta}^R_{i1}, \ldots, \hat{\beta}^R_{ip})^T$ is the vector of estimated coefficients of GWRR at location $i$.

Using a Lagrange multiplier, Equation (4) can also be expressed as

$$
\hat{\beta}^R(i) = \arg \min_{\beta} \left\{ \sum_{j=1}^{n} w_j(i) \left( y_j - \beta_{i0} - \sum_{k=1}^{p} x_{jk} \beta_{ik} \right)^2 + \lambda(i) \sum_{k=1}^{p} \beta_{ik}^2 \right\} 
$$

where $\lambda(i)$ is the ridge parameter that controls the amount of shrinkage in the slopes at location $i$, and there is a one-to-one correspondence between the ridge parameter $\lambda(i)$ and parameter $M(i)$.

The intercept term $\beta_{i0}$ is not constrained by the ridge parameter $\lambda(i)$ and thus should be removed prior to the estimation of ridge parameter $\lambda(i)$. In addition, variables need to be scaled to shake off the effects of different dimensions, as the ridge regression solution is scale
dependent. In the studies of Wheeler (2007) and Gollini et al. (2015), variables $x$ and $y$ were centered to remove the intercept and standardized to eliminate the effects of different dimensions. Their method stemming from general ridge regression, however, is not applicable to the GWR frame. Thus, a different method is presented as follows to obtain a better ridge regression solution.

Based on Equation (5) above, the intercept can be estimated by Equation (6) and removed through a simple transformation for local $x$ and $y$ variables shown in Equation (7):

$$\hat{\beta}_{10} = \frac{\sum_{j=1}^{n} w_j(i) y_j}{\sum_{j=1}^{n} w_j(i)} - \sum_{k=1}^{p} \hat{\beta}_{jk} \left( \frac{\sum_{j=1}^{n} w_j(i) x_{jk}}{\sum_{j=1}^{n} w_j(i)} \right)$$  \hspace{1cm} (6)

$$\bar{x}_{jk} = x_{jk} - \frac{\sum_{j=1}^{n} w_j(i) x_{jk}}{\sum_{j=1}^{n} w_j(i)}, \quad \bar{y}_j = y_j - \frac{\sum_{j=1}^{n} w_j(i) y_j}{\sum_{j=1}^{n} w_j(i)}, \quad (j = 1,2,...,n; k = 1,2,...,p)$$  \hspace{1cm} (7)

where $\hat{\beta}_{10}$ and $\hat{\beta}_{jk}(k = 1,2,\cdots, p)$ are the estimated intercept and slopes of GWRR for location $i$, respectively.

Then, to eliminate the effects of the different dimensions, variables $\bar{x}$ are scaled with the following equation:

$$x^*_{jk} = \frac{\bar{x}_{jk}}{\sqrt{\sum_{j=1}^{n} w_j(i) (\bar{x}_{jk})^2}} \quad (j = 1,2,...,n; \quad k = 1,2,...,p)$$  \hspace{1cm} (8)

The vector of scaled slopes $\hat{\beta}^* (i) = (\hat{\beta}_{11}^*, \hat{\beta}_{12}^*, \ldots, \hat{\beta}_{1p}^*)^T$ in GWRR model is obtained as

$$\hat{\beta}^* (i) = (X_w^T X_w^* + \lambda(i) I_p)^{-1} X_w^T y_w$$  \hspace{1cm} (9)

where $X_w^*$ is the matrix of weighted $x^*$ variables $\sqrt{w}x^*$, $y_w$ is the vector of weighted $y$ variable $\sqrt{w}y$, and $I_p$ is the $(p \times p)$ identity matrix.
The original slopes used for estimating the dependent variable are

\[ \hat{\beta}_{ik}^R = \hat{\beta}_{ik}^R \times \sqrt{\sum_{j=1}^{n} w_j(i)(x_{jk} - \bar{x}_k)^2} \quad (k = 1,2,\ldots,p) \]  

(10)

With the estimated intercept \( \hat{\beta}_{i0}^R \) and slopes \( \hat{\beta}_{ik}^R (k = 1,2,\ldots,p) \), the dependent variable at location \( i \) can be estimated as

\[ \hat{y}_i^R = \hat{\beta}_{i0}^R + \sum_{k=1}^{p} \hat{\beta}_{ik}^R x_{ik} \quad (k = 1,2,\ldots,p) \]  

(11)

Note that if the ridge parameter \( \lambda(i) \) is 0, the GWRR estimator coincides with the GWR estimator. In our integration framework, ridge regression was only fitted at locations where collinearity was strong enough to be a problem. To achieve this goal, the local ridge parameter was initially set as 0 and re-estimated when collinearity problem was diagnosed. Condition number (CN), a very stable procedure in comparison to other tests, was preferred as the diagnosis indicator of collinearity problem in this study. For a column-scaled matrix \( X \) (each column has unit length), the CN is defined as

\[ \text{CN}(X) = \frac{\mu_{\text{max}}}{\mu_{\text{min}}} \]  

(12)

where \( \mu_{\text{max}} \) and \( \mu_{\text{min}} \) are the maximum and minimum singular values of matrix \( X \), respectively, which can be obtained by applying singular value decomposition (SVD) to matrix \( X \).

The larger the CN value, the stronger is the collinearity among the columns of matrix \( X \). Collinearity has almost no effect on estimation results with a low CN value and is strong enough to be a problem when the CN of the design matrix exceeds a certain threshold level. In extreme cases where the CN of the design matrix tends to be infinite, perfect collinearity, which makes the regression equation unsolvable, is produced. The threshold CN of 30 for the intercept-included and column-scaled design matrix, used in most previous collinearity
diagnosis, has already proved to give misleading results in particular cases and should be
replaced by the threshold CN of 5.42 for the intercept-excluded and column-scaled design
matrix $X^*$ to achieve a better diagnosis (Lazaridis. 2007; Salmeron et al. 2018).

To test the presence of the collinearity problem after the constraint of slopes, the CN in
ridge regression must also be estimated. Unlike the CN in general linear regression, the CN in
ridge regression cannot be directly estimated because the design matrix $X^R = \left( \frac{X^*}{\sqrt{\lambda I_p}} \right)$ does
not have vectors of unit length. To extend the diagnosis to ridge regression, Salmeron et al
(2018) compared two extensions of the CN in ridge regression: one accessible but unnatural
(given the definition of CN) and one natural but inaccessible, and they found that the two
extensions led to very similar results. Being able to present an algebraic closed-form
expression for the CN in ridge regression, the unnatural extension is easier to apply and can
be used to determine the ridge parameter. Suppose the intercept-excluded and column-scaled
design matrix $X^*$ has singular values of $\mu_1, \mu_2, \ldots, \mu_p (\mu_1 < \mu_2 < \cdots < \mu_p)$, then the singular
values of matrix $X^R = \left( \frac{X^*}{\sqrt{\lambda I_p}} \right)$ are $\sqrt{\mu_1^2 + \lambda}, \sqrt{\mu_2^2 + \lambda}, \ldots, \sqrt{\mu_p^2 + \lambda}$, and thus the close-form
expression of the CN in ridge regression can be given by $CN(X^R) = \frac{\mu_p^2 + \lambda}{\mu_1^2 + \lambda}$. By setting
$CN(X^R)$ as the threshold of 5.42 to protect the ridge regression from collinearity problem,
the ridge parameter can be determined as:

$$\hat{\lambda} = \frac{\mu_p^2 - 5.42^2 \cdot \mu_1^2}{5.42^2 - 1} \quad (13)$$

Taking matrix $X_w^*$ mentioned above instead of matrix $X^*$ as the design matrix, the
method for collinearity diagnosis and elimination can be migrated from general linear
regression to GWR.

Solving the GWR or GWRR equations first requires an estimation of the spatial weights matrix \( W(i) = \text{diag}[w_1(i), w_2(i), \ldots, w_n(i)] \). A kernel that is commonly used to calculate the weights matrix is the bi-square function, where the weight of observation at location \( j \) for estimating the dependent variable at location \( i \) is given by

\[
w_j(i) = \begin{cases} 
[1-(d_{ij}/b)^2]^2 & d_{ij} \leq b \\
0 & d_{ij} > b 
\end{cases}
\]  \( (14) \)

where \( d_{ij} \) is the Euclidean distance between prediction location \( i \) and observation location \( j \); and \( b \) is the kernel bandwidth. An optimum bandwidth can be found by minimizing the cross-validation (CV) score (Bowman. 1984), given as:

\[
CV = \sum_{j=1}^{n} \left[ y_j - \hat{y}_{x_j}(b) \right]^2
\]  \( (15) \)

where \( \hat{y}_{x_j}(b) \) is the estimated value of \( y_j \) with the observation for location \( j \) omitted from the calibration process.

3.3. Downscaling by GWRR

The downscaling algorithm is based on the assumption that the GWRR relationship between precipitation and explanatory variables (i.e., NDVI, elevation, slope, longitude and latitude) constructed at original coarse resolution can be used to predict precipitation with the explanatory variables at a finer resolution. The residuals of GWRR model were considered to have some spatial correlation (Kumar et al. 2012, Harris et al. 2010; Ye et al. 2017) and thus were interpolated using ordinary Kriging to improve the prediction accuracy. Since the relationship between precipitation and environmental variables at daily scale is far less statistically significant than that at annual and monthly scale (Chen et al. 2019; Ma et al 2019), we constructed the GWRR model at monthly scale and then disaggregated the
downscaled monthly result into daily precipitation to generate the downscaled daily SPP. It is noted that precipitation and NDVI of the same period were used to construct the GWRR model for downscaling monthly SPP, as vegetation conditions can disturb the spatial distribution of precipitation nearly without time lag (Brunsell 2006; Xu et al. 2015). The specific steps of the downscaling algorithm based on GWRR are as follows:

(1) Resample the original NDVI, elevation, slope, longitude and latitude data of 1km resolution to 0.25° and 0.1° resolutions respectively by pixel averaging. The original 1km-resolution NDVI of month \(m\), and the elevation, slope, longitude and latitude for location \(i\) are denoted by \(NDVI_{i,m}^{1\text{km}}\), \(Elevation_{i,m}^{1\text{km}}\), \(Slope_{i,m}^{1\text{km}}\), \(Longitude_{i,m}^{1\text{km}}\), and \(Latitude_{i,m}^{1\text{km}}\), respectively; and the corresponding resampled results with 0.25° resolution and 0.1° resolution are denoted as \(NDVI_{i,m}^{0.25^\circ}\), \(Elevation_{i,m}^{0.25^\circ}\), \(Slope_{i,m}^{0.25^\circ}\), \(Longitude_{i,m}^{0.25^\circ}\), \(Latitude_{i,m}^{0.25^\circ}\), \(NDVI_{i,m}^{0.1^\circ}\), \(Elevation_{i,m}^{0.1^\circ}\), \(Slope_{i,m}^{0.1^\circ}\), \(Longitude_{i,m}^{0.1^\circ}\), \(Latitude_{i,m}^{0.1^\circ}\), respectively.

(2) Accumulate original satellite daily precipitation to generate monthly precipitation, and construct the GWRR model for downscaling the satellite monthly precipitation with the resampled NDVI, elevation, slope, longitude and latitude generated by step (1) as independent variables. The original 0.25° and 0.1°-resolution satellite daily precipitation for location \(i\) and day \(d\) are denoted by \(P_{i,d}^{0.25^\circ,\text{SAT}}\) (\(P_{i,d}^{0.25^\circ,\text{TMP}}\) for TMPA-3B42RT, \(P_{i,d}^{0.25^\circ,\text{CMO}}\) for CMORPH and \(P_{i,d}^{0.25^\circ,\text{PER}}\) for PERSIANN) and \(P_{i,d}^{0.1^\circ,\text{SAT}}\) (i.e. \(P_{i,d}^{0.1^\circ,\text{GSM}}\) for GSMaP_NRT), respectively; and the corresponding accumulated satellite monthly precipitation for location \(i\) and month \(m\) are denoted by \(P_{i,m}^{0.25^\circ,\text{SAT}}\) (\(P_{i,m}^{0.25^\circ,\text{TMP}}\) for TMPA-3B42RT, \(P_{i,m}^{0.25^\circ,\text{CMO}}\) for CMORPH, and \(P_{i,m}^{0.25^\circ,\text{PER}}\) for PERSIANN) and \(P_{i,m}^{0.1^\circ,\text{SAT}}\) (i.e. \(P_{i,m}^{0.1^\circ,\text{GSM}}\) for GSMaP_NRT), respectively.
For the 0.25°-resolution satellite monthly precipitation $P_{i,m}^{0.25,SAT}$, the constructed GWRR model for downscaling is expressed as:

$$
P_{i,m}^{0.25,SAT} = \alpha_{i,m}^{SAT,0} + \alpha_{i,m}^{SAT,1} NDVI_{i,m}^{0.25} + \alpha_{i,m}^{SAT,2} Elevation_{i,m}^{0.25} + \alpha_{i,m}^{SAT,3} Slope_{i,m}^{0.25} + \alpha_{i,m}^{SAT,4} Longitude_{i,m}^{0.25} + \varepsilon_{i,m}^{0.25,SAT}
$$

(16a)

And for the 0.1°-resolution satellite monthly precipitation $P_{i,m}^{0.1,SAT}$, the constructed GWRR model for downscaling is expressed as:

$$
P_{i,m}^{0.1,SAT} = \alpha_{i,m}^{SAT,0} + \alpha_{i,m}^{SAT,1} NDVI_{i,m}^{0.1} + \alpha_{i,m}^{SAT,2} Elevation_{i,m}^{0.1} + \alpha_{i,m}^{SAT,3} Slope_{i,m}^{0.1} + \alpha_{i,m}^{SAT,4} Longitude_{i,m}^{0.1} + \varepsilon_{i,m}^{0.1,SAT}
$$

(16b)

where $\alpha_{i,m}^{SAT,0}$, $\alpha_{i,m}^{SAT,1}$, $\alpha_{i,m}^{SAT,2}$, $\alpha_{i,m}^{SAT,3}$, $\alpha_{i,m}^{SAT,4}$ and $\alpha_{i,m}^{SAT,5}$ are regression coefficients for location $i$ and month $m$ ($m = 1, 2, \ldots, 96$ for the period of 2010 to 2017), and $\varepsilon_{i,m}^{0.25,SAT}$ and $\varepsilon_{i,m}^{0.1,SAT}$ are the residual with 0.25° resolution and 0.1° resolution for location $i$ and month $m$, respectively, which can be interpreted as the amount of satellite precipitation that is not be explained by the constructed GWRR model for downscaling. The regression coefficients and residual are estimated in this step.

(3) Resample the regression coefficients $\alpha_{i,m}^{SAT,0}$, $\alpha_{i,m}^{SAT,1}$, $\alpha_{i,m}^{SAT,2}$, $\alpha_{i,m}^{SAT,3}$, $\alpha_{i,m}^{SAT,4}$ and $\alpha_{i,m}^{SAT,5}$ obtained by step (2) to acquire the 1km-resolution regression coefficients $\alpha_{i,m}^{1km,SAT,0}$, $\alpha_{i,m}^{1km,SAT,1}$, $\alpha_{i,m}^{1km,SAT,2}$, $\alpha_{i,m}^{1km,SAT,3}$, $\alpha_{i,m}^{1km,SAT,4}$ and $\alpha_{i,m}^{1km,SAT,5}$ with the bilinear interpolation technique.

(4) Estimate the 1km-resolution satellite monthly precipitation $\hat{P}_{i,m}^{1km,SAT}$ from $NDVI_{i,m}^{1km}$, $Elevation_{i,m}^{1km}$, $Slope_{i,m}^{1km}$, $Longitude_{i,m}^{1km}$, and $Latitude_{i,m}^{1km}$ using the resampled 1km-resolution regression coefficients:

$$
\hat{P}_{i,m}^{1km,SAT} = \alpha_{i,m}^{1km,SAT,0} + \alpha_{i,m}^{1km,SAT,1} NDVI_{i,m}^{1km} + \alpha_{i,m}^{1km,SAT,2} Elevation_{i,m}^{1km} + \alpha_{i,m}^{1km,SAT,3} Slope_{i,m}^{1km} + \alpha_{i,m}^{1km,SAT,4} Longitude_{i,m}^{1km} + \alpha_{i,m}^{1km,SAT,5} Latitude_{i,m}^{1km}
$$

(17)
As the resampling process in step (1) smooths the extreme values, the obtained regression coefficients and $\hat{P}_{1km,SAT}$ over the high-resolution grid-cells with extreme NDVI or elevation values may have poor performance.

(5) Interpolate the 0.25° or 0.1°-resolution residuals $\varepsilon_{i,m}^{0.25°,SAT}$ or $\varepsilon_{i,m}^{0.1°,SAT}$ to obtain the 1km-resolution residuals $\varepsilon_{i,m}^{1km,SAT}$ using ordinary kriging method, and then add the interpolated residuals $\varepsilon_{i,m}^{1km,SAT}$ to the estimated satellite monthly precipitation $\hat{P}_{1km,SAT}^{i,m}$ by equation (17) to generate the GWRR-downscaled satellite monthly precipitation $P_{1km,SAT}^{i,m}$, which is denoted as $P_{1km,TMP}^{i,m}$ for TMPA-3B42RT, as $P_{1km,CMO}^{i,m}$ for CMORPH, as $P_{1km,PER}^{i,m}$ for PERSIANN, and as $P_{1km,GSM}^{i,m}$ for GSMaP_NRT, namely:

$$P_{1km,SAT}^{i,m} = \hat{P}_{1km,SAT}^{i,m} + \varepsilon_{i,m}^{1km,SAT} \quad (18)$$

(6) Disaggregate the downscaled satellite monthly precipitation into daily precipitation. Assuming that the occurrence of rainfall events is correctly detected, the fraction of each daily precipitation to the monthly total precipitation at original 0.25° or 0.1° resolution, denoted by $F_{i,d}^{0.25°,SAT}$ or $F_{i,d}^{0.1°,SAT}$, can be obtained from the original SPP data ($P_{i,d}^{0.25°,SAT}$ or $P_{i,d}^{0.1°,SAT}$). The $F_{i,d}^{0.25°,SAT}$, for example, is expressed with the following equation:

$$F_{i,d}^{0.25°,SAT} = \frac{P_{i,d}^{0.25°,SAT}}{P_{i,m}^{0.25°,SAT}} \quad (19)$$

Then, $F_{i,d}^{0.25°,SAT}$ or $F_{i,d}^{0.1°,SAT}$ was further resampled to 1km resolution with the bilinear interpolation technique, denoted by $F_{i,d}^{1km,SAT}$.

(7) The downscaled satellite daily precipitation $P_{i,d}^{1km,SAT}$, which is denoted as $P_{i,d}^{1km,TMP}$ for TMPA-3B42RT, $P_{i,d}^{1km,CMO}$ for CMORPH, $P_{i,d}^{1km,PER}$ for PERSIANN, $P_{i,d}^{1km,GSM}$ for GSMaP_NRT, can be acquired by multiplying the 1km-resolution daily fractions by the
downscaled satellite monthly precipitation:
\[
P_{i,d}^{1km, SAT} = F_{i,d}^{1km, SAT} \cdot P_{i,m}^{1km, SAT}
\] (20)

### 3.4. Fusion by GWRR

Regarding gauge precipitation as the actual and neglecting the influence of scaling gaps between gauge precipitation and satellite precipitation, the fusion can be performed with the functional relationship between gauge precipitation and multiple satellites precipitation constructed with the GWRR method. Given that the model validity will be undermined by the spatially intermittency of daily precipitation, the Box-Cox transformed precipitation data are used in the GWRR model construction. The constructed GWRR model for fusion can be expressed with the following equation:

\[
\frac{(P_{i,d}^{Gauge})^\delta - 1}{\delta} = \beta_{i,d}^0 + \beta_{i,d}^1 \frac{(P_{i,d}^{1km,TMP})^\delta - 1}{\delta} + \beta_{i,d}^2 \frac{(P_{i,d}^{1km,CMO})^\delta - 1}{\delta} + \beta_{i,d}^3 \frac{(P_{i,d}^{1km,PER})^\delta - 1}{\delta} + \epsilon_{i,d}
\] (21)

where \(P_{i,d}^{Gauge}\) is the gauge precipitation at location \(i\) for day \(d\); \(\beta_{i,d}^0, \beta_{i,d}^1, \beta_{i,d}^2, \beta_{i,d}^3\) and \(\beta_{i,d}^4\) are regression coefficients at location \(i\) for day \(d\); \(\epsilon_{i,d}\) is the residual at location \(i\) for day \(d\); \(\delta\) is the parameter in Box-Cox transformation. As indicated by Erdin et al. (2012), the optimal \(\delta\) value varies slightly with the days, with 87% ranging from 0.2 to 0.3 and a mean close to 0.25 over one year. This explains why the results of a fixed \(\delta\) value of 0.25 (Cecinati et al., 2017; Gurung 2017) or 0.2 (Delrieu et al., 2014) are satisfactory and very similar with that of the optimal and time-variant \(\delta\) value. In this paper, a fixed value of 0.25 is set for \(\delta\).

The fusion regression coefficients in equation (21) at any 1km grid cell can be obtained from gauge observation and the four downscaled SPPs, i.e., \(P_{i,d}^{1km,TMP}, P_{i,d}^{1km,CMO}, P_{i,d}^{1km,PER}\).
and $P_{i,d}^{1km,GSM}$, with which the daily precipitation at any 1km grid cell, denoted by $\hat{P}_{i,d}^{1km,GWRR}$ for location $i$ and day $d$, can be estimated by the following equation:

$$
\frac{(\hat{P}_{i,d}^{1km,GWRR})^{\delta} - 1}{\delta} = \beta_{i,d}^0 + \beta_{i,d}^1 \left( \frac{(P_{i,d}^{1km,TMP})^{\delta} - 1}{\delta} \right) + \beta_{i,d}^2 \left( \frac{(P_{i,d}^{1km,CMO})^{\delta} - 1}{\delta} \right) + \beta_{i,d}^3 \left( \frac{(P_{i,d}^{1km,PER})^{\delta} - 1}{\delta} \right)
$$

(22)

The residuals obtained only at gauge sites from equation (21) are interpolated to obtain the residuals for all 1km grid cells, denoted by $\varepsilon_{i,d}^{1km}$ for location $i$ and day $d$, using ordinary Kriging method. Finally, the daily estimates of the merged precipitation product (MPP) for 1km resolution by the two-step scheme (downscaling and fusion) using the GWRR method, which is denoted by $P_{i,d}^{1km,MPP}$, can be calculated as:

$$
P_{i,d}^{1km,MPP} = \hat{P}_{i,d}^{1km,GWRR} + \varepsilon_{i,d}^{1km}
$$

(23)

3.5. Performance evaluation indices

A set of statistical indices, including continuous indices and categorical indices, were examined to evaluate the leave-one-out cross validation results of the GWRR-based two-step merging scheme. The statistical metrics used in this study are listed in Table 2.

[Table 2 here]

3.5.1 Continuous indices

The correlation coefficient (CC) reflects the degree of linear correlation between the estimations and observations; the mean error (ME) simply scales the general deviation of estimations from the observations, the relative bias (rBIAS) describes the systematic bias of estimations, and the modified Kling-Gupta efficiency (KGE; Kling et al., 2012) incorporates three components, i.e., the correlation coefficient, the bias ratio, and the variability ratio to compare observations with estimations. Moreover, centered root-mean square difference
(RMSD) was also calculated for the Taylor diagram (Taylor 2001), which is drawn to visually show how closely the retrieved precipitation match the gauge observation and can be beneficial for evaluating the relative accuracy of various SPPs.

### 3.5.2 Categorical indices

To quantitatively evaluate the precipitation detection ability of SPP against the gauge observation over different precipitation intensities, four categorical statistical indices, including probability of detection (POD), false alarm ratio (FAR), the frequency bias index (FBI) and critical success index (CSI) were also calculated. POD, also known as the hit rate, describes how often the SPP correctly detects the precipitation event. FAR measures the proportion of cases in which the satellite identify the event when rain gauges do not. FBI compares the number of events identified by the SPP to the number of events registered by the gauge station. If FBI > 1, the number of occurrences of the respective precipitation event is overestimated by the SPP, while FBI < 1 indicates underestimation. CSI shows the overall ability of SPP to correctly diagnose different precipitation events.

### 4. Results

#### 4.1. The collinearity problem in the GWR-based merging scheme

The collinearity problem, which appears when CN reaches the threshold CN value of 5.42, leads to unstable and inflated parameter estimates. The collinearity problem in extreme cases where CN tends to be infinite, which is termed as perfect collinearity problem, even makes the parameter of GWR unsolvable. To quantity the overall occurrence of these two problems, collinearity rate (CR) and perfect collinearity rate (PCR) were defined as the ratio of the number of times the collinearity problem and perfect collinearity problem occurred to the total number of times the GWR model was fitted during a certain period, respectively.
Figure 3 presents the spatial distribution of CR in the GWR model for downscaling monthly SPP (without integration of ridge regression) from 2010-2017. It can be seen that GWR models for downscaling 0.25°-resolution TMPA-3B42RT, CMORPH and PERSIANN were more likely to suffer from collinearity problem than those for downscaling 0.1°-resolution GSMaP_NRT. Furthermore, the GWR models for downscaling developed at the same resolution had similar collinearity problem, with CR values less than 30% in depression areas and greater than 70% in many other areas. The small difference in CR of GWR model for downscaling TMPA-3B42RT, CMORPH and PERSIANN could be attributed to the different optimal bandwidth selected to fit the GWR model, which depended on the data quality of SPP. The PCR of GWR model for downscaling was zero for all the regions, indicating that the perfect collinearity problem will never trouble the GWR model for downscaling. In addition, apart from adopting GWRR method, the collinearity problem existed in the GWR model for downscaling can be alternatively addressed by enlarging the sample size, since there are so many samples (satellite precipitation pixels) can be used. With respect to the GWR model for fusion (without integration of ridge regression), the PCR ranged from 30% to 48% at 42 gauge locations, which was approximately 20% less than CR (Figure 5). Such a high PCR value indicated that it was urgent to overcome the collinearity problem in the GWR model for fusion to achieve stable parameter estimates. High values of CR and PCR in the GWR model for fusion also occurred in regions close to the border where few samples were used for model fitting. Excluding the effect of sample size, CR and PCR of the GWR model for fusion in the eastern plains had higher values than in the middle hills and western mountains. Limited by few gauge observations, the collinearity problem in the GWR model for fusion cannot be addressed by simply enlarging the sample size, which is different from the GWR model for downscaling.

[Figure 3 here]
4.2. Assessment of the GWRR-based merging scheme

4.2.1 Local regression analysis

The GWRR model for fusion exploits the strength and minimizes the weakness of each SPP member with time-varying and space-varying regression coefficients, which are determined by the performance of SPPs. The well performing SPP member will receive a positive and large coefficient, the ordinarily performing SPP member will receive a negative coefficient, and the poorly performing SPP member will receive a coefficient close to 0. In particular cases presenting collinearity problem, some SPP members will also receive a coefficient that is arbitrarily close to zero, regardless of the performance. The GWRR-based proceeding dealing with perfect collinearity problem can be regarded as a process of variable selection, in which the redundant SPP members are removed from the regression.

Figure 5 displays the spatial pattern of the regression coefficients of the GWRR model for fusion on two typical days: June 21 and September 30, 2014. All the regression coefficients for the Box-Cox transformed downscaled SPP had numerous values that were far away from 0, indicating that none of the four SPPs was useless and that using multiple SPPs seemed to benefit the fusion result. In addition, all the regression coefficients unevenly distributed in space were markedly different between the two days. In terms of the area average of the regression coefficients for Box-Cox transformed downscaled SPPs, the order was \( \beta^4 (1.04) > \beta^2 (0.30) > \beta^3 (-0.03) > \beta^1 (-0.31) \) on June 21, 2014, and was \( \beta^4 (1.21) > \beta^2 (0.39) > \beta^1 (0.08) > \beta^3 (-0.18) \) on September 30, 2014. The area average of \( \beta^0 \) was 0.73 mm on June 21, 2014 and was 0.93 mm on September 30, 2014. As for the spatial pattern of the regression coefficients, the differences between the two days were manifested in the northern region for \( \beta^1, \beta^3 \) and \( \beta^4 \), as well as in the central region for \( \beta^2 \). This
result suggested the presence of spatiotemporal non-stationarity in the relationship between
gauge observation and the four downscaled SPPs, which was consistent with the findings of
Hussain et al (2018). Therefore, as a local form of linear regression, GWRR provided an
effective way to fuse gauge observation with multiple SPPs.

[Figure 5 here]

Figure 6 shows the scatterplots with color density between the original satellite
precipitation and the estimated precipitation by GWRR model for downscaling at monthly
and original spatial scale (0.25° for TMPA-3B42RT, CMORPH and PERSIANN, and 0.1° for
GSMaP_NRT) from 2010-2017. The GWRR model for downscaling performed well for all
the four SPPs, with CC values ranging from 0.98 to 0.99. The model performance varied little
with SPP, indicating that the local regression relationship between satellite monthly
precipitation and monthly NDVI, elevation, slope, longitude and latitude was relative steady
at different resolutions (0.25° resolution and 0.1° resolution in this study), which will benefit
the spatial downscaling. As shown in Figure 7, the estimated precipitation by GWRR model
for fusion corresponded well with the rain gauge observation, with CC of 0.86. This good
agreement indicated that both the constructed GWRR model for downscaling and that for
fusion had good performance in spatial precipitation estimates.

[Figure 6 here]

[Figure 7 here]

4.2.2 Kriging-based residual correction

Some researchers believe that the residuals generated by the GWR-related model have a
spatial correlation structure and thus can be interpolated to help explain the variation of the
target variable across space (Kumar et al. 2012; Harris et al. 2010; Ye et al. 2017). In our
merging scheme, the residuals generated by the GWRR model for downscaling and the
GWRR model for fusion were interpolated using ordinary Kriging and added to the model estimations (termed as residual correction) to improve the prediction accuracy. To assess the necessity of kriging-based residual correction, CC, ME, rBIAS and KGE for the four downscaled daily SPPs and MPP before and after residual correction with reference to gauge observation were calculated and compared (Table 3). For the downscaled daily SPPs, the residual correction resulted in small changes in all the four indices. CC of the downscaled SPP, which reflects the spatial representativeness of precipitation, increased by 0.01 for TMPA-3B42RT and remained basically unchanged for CMORPH, PERSIANN, GSMaP_NRT after residual correction, indicating that the residual correction contributed little to the spatial downscaling step which mainly aimed to derive the spatial pattern of precipitation for the fusion step. If not followed by a fusion step, residual correction isn’t necessary for the spatial downscaling of the four SPPs, since the KGE values kept unchanged or even declined. With regard to MPP, CC and KGE increased by 0.09 (from 0.86 to 0.95) and 0.18 (from 0.70 to 0.88), respectively, and ME and rBIAS decreased by half after residual correction. In conclusion, kriging-based residual correction benefitted the spatial representativeness of all the four downscaled SPPs and both the spatial representativeness and accuracy of the Merged precipitation product (MPP); thus, it was necessary for the GWRR-based two-step merging scheme.

4.3. **Performance of the merged precipitation product**

4.3.1 **Merged precipitation product**

Figure 8 displays the precipitation maps of the original SPPs, the downscaled SPPs, the gauge observation and the final merged precipitation product (MPP) on June 21, 2014. The spatial pattern of the original TMPA-3B42RT was similar to the original CMORPH (except in
the southern region of the study area), and significantly different from the original
PERSIANN or GSMaP_NRT. Maintaining the consistent spatial pattern with the original
SPPs in overall, the downscaled ones provided more detailed information due to the
introduction of NDVI and topography information. The MPP, derived from gauge
observation and multiple downscaled SPPs, had higher accuracy and spatial
representativeness in contrast to any one of the downscaled SPPs.

[Figure 8 here]

Figure 9 shows the time series of gauge sites-averaged monthly accumulated
precipitation of gauge observation, original SPPs and MPP for the period 2010-2017. In
general, compared to the four original SPPs, the time series of MPP is much closer to that of
gauge observation, although the violent precipitation was somewhat underestimated in MPP.
From 2010 to 2017, the average daily precipitation of the original TMPA3B42-RT, CMORPH,
PERISIANN, GSMaP_NRT were 4.12 mm, 2.34 mm, 6.67 mm and 2.57 mm, respectively;
and that of gauge observation and MPP were 3.74 mm and 3.33 mm, respectively.

[Figure 9 here]

4.3.2 Performance evaluation

To assess the merging scheme, the continuous indices (CC, ME, rBIAS and KGE) for
the four original SPPs and MPP with reference to gauge observation across the entire period
and different seasons are listed in Table 4. All these indices of MPP got much better scores
than the four original SPPs, indicating that the GWRR-based two-step merging scheme
substantially improved the quality of the daily precipitation maps. The continuous indices of
MPP had best scores in winter, followed by spring, autumn and summer. Considering the
characteristics of the precipitation in these seasons, it can be inferred that the MPP generated
by the GWRR-based two-step merging scheme did not perform perfectly for light
precipitation and violent precipitation events. In addition, the performance difference among
the four original SPPs shown in Table 4 revealed that each SPP had its individual strength and
weakness in various seasons, which was the theoretical basis for the fusion of gauge
observation and multiple SPPs.

Taylor diagrams for daily precipitation from the gauge observation, the four original
SPPs and MPP (Figure 10) were also drawn to visually compare the accuracy. In Taylor
diagram, if the point of SPP is closer to the gauge point, then it is considered as a better
product. Figure 10 confirms that the GWRR-based two-step merging scheme significantly
improved the spatial estimates of daily precipitation.

Figure 11 plots the values of the four categorical indices for five classes of precipitation
intensity, including no rain ([0, 1) mm/d), light rain ([1, 5) mm/d), moderate rain ([5, 20)
mm/d), heavy rain ([20, 40) mm/d) and violent rain (≥40 mm/d). All the products, i.e., the
four original SPPs and MPP, identified the no-rain events well but showed poor performance
in rainy events detection. In addition, all the products overestimated the number of no-rain
events and underestimated the amount of light rain, moderate rain and heavy rain event.
MPP performed the best in terms of the four categorical indices for all the five rain events,
with exception of the FBI for heavy rain event.

Figure 12 shows the KGE values for the daily precipitation of original SPPs and MPP at
42 gauge sites during 2010-2017. KGE values varied so vastly from product to product and
from space to space. Among the four original SPPs, TMPA-3B42RT performed the best, with
KGE values ranging from 0.48 to 0.75 at the 42 gauge sites, followed by GSMaP_NRT and
CMORPH, and then the PERSIANN, with KGE values ranging from -0.57 to 0.44. There
was no consistent space distribution of KGE in relation to the original SPPs, for example, the high KGE values for the original MPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT occurred in the central, southeastern, northeastern and northwestern regions, respectively. Compared with the original SPPs, MPP had much better performance in terms of KGE, with values of 0.79-0.94 at the 42 gauge sites. The lowest KGE values were distributed in the northwestern mountains with the highest elevation, which may be attributed to the poor performance of the four original SPPs.

5. Discussion

The quality of MPP depends on many factors, such as the ability of SPP to capture the precipitation spatial pattern, the merging algorithm and the density of rain gauge network (Chao et al. 2018).

In terms of traditional merging algorithms, gauge observation can be merged with only one SPP, and researchers need to evaluate the performance of various SPPs first to select a well-performed SPP for merging, since no one SPP has proven to be superior to others for all time and regions (Maggioni et al. 2016; Sun et al. 2018). Given that each SPP has its own strengths and weaknesses in the capture of precipitation spatial pattern, Beck et al. (2019) derived a new SPP for merging by combining lots of released SPPs together. The GWRR-based merging algorithm proposed in this paper, in contrast, allows to make use of the strength of each SPP, with no need for a SPP selection or multiple SPPs combination process.

To investigate whether the introduction of multiple SPPs could improve the fusion performance, we also used only one SPP to construct the GWRR model for fusion. These GWRR models for fusion were constructed by replacing the independent variables of Equation (21) and (22), i.e., the four Box-Cox transformed downscaled SPPs, with a single
transformed downscaled TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT, and
termed as GWRR_T, GWRR_C, GWRR_P and GWRR_G, respectively. In order to avoid confusion,
the GWRR model for fusion with multiple Box-Cox transformed downscaled SPPs as
independent variables, which was expressed with Equation (21) and (22) in our two-step
merging scheme, was termed as GWRR_M in this section.

Table 5 shows the evaluation statistics with reference to gauge observation for the fusion
models (i.e., GWRR_T, GWRR_C, GWRR_P, GWRR_G and GWRR_M model) across the entire
period and different seasons during 2010-2017. For the fusion of gauge observation and a
single SPP, GWRR_G model showed the best statistical scores in the entire period, with CC of
0.79, ME of -1.30 mm, rBIAS of -34.9% and KGE of 0.59. By contrast, these four indices in
GWRR_M were 0.86, -0.98 mm, -26.3% and 0.70, respectively. Furthermore, such better
statistical scores of GWRR_M relative to GWRR_T, GWRR_C, GWRR_P and GWRR_G model were
also be found for all the seasons. Figure 13 present the KGE at 42 gauge sites for the
precipitation estimated by various GWRR models over the period of 2010-2017. Among the
GWRR models with a simple SPP as independent variable, GWRR_G model had best KGE
scores, with values ranging from 0.46 to 0.71 at 42 gauge sites, which were inferior than that
for GWRR_M model ranging from 0.55 to 0.82. These comparisons demonstrated that, in the
fusion step, the use of multiple SPPs provided more reliable spatial precipitation estimates
than a single SPP, which is consistent with the results obtained by Golian et al. (2015) and
Ma et al. (2017).

Sparse rain gauge network density would lead to huge uncertainty, as only very few
samples are used for the regression coefficient calculation in GWRR and the semi-variance
calculation in ordinary Kriging (Jongjin et al. 2016). It is a well-known fact that the increase
of network density could reduce error and uncertainty in precipitation interpolation based on ordinary Kriging (Adhikary et al. 2015). With regard to the merging of gauge observation and SPP, increasing the gauge network density also could reduce the uncertainty and help to improve the quality of MPP (Li et al. 2015; Park et al. 2017; Chen et al. 2018). However, once the network density reaches a critical threshold, the quality of MPP will be not affected by the increase of network density (Yang et al. 2017). The optimal network density for obtaining the best-performed MPP may varies with the merging algorithms and need further investigation.

6. Conclusions

This study proposed a two-step scheme, consisting of downscaling and fusion, for merging gauge observation with multiple SPPs to improve the spatial estimates of daily precipitation. Both steps of downscaling and fusion employed geographically weighted ridge regression (GWRR) method, which was established by combining ridge regression with GWR to overcome the potential local collinearity problem associated with GWR. Deriving spatial precipitation estimates from gauge observation and four near real-time SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT), with the support of NDVI and DEM data, the proposed GWRR-based two-step merging scheme was applied to Xijiang Basin of China from 2010 to 2017. The main findings of this study are as follows.

1) Collinearity problem often occurred in the GWR model both for downscaling and for fusion. The perfect collinearity problem, representing extreme cases of collinearity that causes the parameter of GWR to become unsolvable, never troubled GWR model for downscaling (PCR in all the regions was 0) but frequently plagued the GWR model for fusion (spatially averaged PCR reached 37%).

2) The relationship between gauge observation and the four downscaled SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) was spatiotemporally
non-stationary, and thus, GWRR, the linear regression method with time-varying and space-varying regression coefficients, provided a promising method for the fusion.

(3) Kriging-based residual correction benefited the spatial representativeness of the downscaled TMPA-3B42RT (CC increased by 0.01) and both spatial representativeness (CC increased by 0.10) and accuracy (ME and rBIAS decreased by more than half, KGE increased by 0.18) of the MPP; thus, it was helpful for both the GWRR-based downscaling and fusion step.

(4) The merged precipitation product (MPP) generated by the proposed GWRR-based two-step merging scheme had much higher resolution (1 km resolution) and accuracy (KGE of 0.88), compared with the four original SPPs (0.25° and 0.1° resolution; KGE of 0.04-0.64).

(5) In the fusion step, the use of multiple SPPs provided more reliable spatial precipitation estimates than using a single SPP. The KGE of GWRR\textsubscript{M}-estimated precipitation increased by 0.11 compared with that of GWRR\textsubscript{G}-estimated precipitation, which performed best for the fusion of gauge observation and a single SPP, with KGE of 0.59.

In summary, the proposed GWRR-based two-step merging scheme consisting of downscaling and fusion could be successfully implemented to improve the spatial estimates of daily precipitation.

**Acknowledgments**

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### Tables

#### Table 1. Summary of the four near real-time SPPs used in this research

<table>
<thead>
<tr>
<th>Products</th>
<th>Input data</th>
<th>Retrieval algorithm</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
<th>Latency</th>
<th>Period</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMPA-3B42 RT</td>
<td>IR: GOES-IR, Meteosat-IR and MTSat-IR; PMW: TMI, SSM/I, SSMIS, AMSR-E, AMSR2, AMSU-B and MHS</td>
<td>Probability matching</td>
<td>3 hourly</td>
<td>0.25×0.25°</td>
<td>8h</td>
<td>2000-present</td>
<td>(Huffman et al. 2007; Huffman, and Bolvin, 2018)</td>
</tr>
<tr>
<td>CMORPH</td>
<td>IR: GOES-IR, Meteosat-IR and MTSat-IR; PMW: TMI, SSM/I, AMSR-E, and AMSU-B</td>
<td>Morphing technique</td>
<td>3 hourly</td>
<td>0.25×0.25°</td>
<td>18h</td>
<td>2002-present</td>
<td>(Joyce et al. 2004)</td>
</tr>
<tr>
<td>PERSIANN</td>
<td>IR: GOES-IR and Meteosat-IR; PMW: TMI, SSM/I and AMSU-B</td>
<td>Adaptive artificial neural network</td>
<td>3 hourly</td>
<td>0.25×0.25°</td>
<td>2 day</td>
<td>2000-present</td>
<td>(Sorooshian et al. 2000; Nguyen et al. 2019)</td>
</tr>
<tr>
<td>GSMaP NRT</td>
<td>IR: GOES-IR and Meteosat-IR; PMW: TMI, GMI, SSM/I, SSMIS, AMSR, AMSR-E, AMSR2 and AMSU-A/MHS</td>
<td>Kalman filter model</td>
<td>1 hourly</td>
<td>0.1×0.1°</td>
<td>4h</td>
<td>2000-present</td>
<td>(Ushio et al. 2009; GPM Global Rainfall Map Algorithm Development Team 2014)</td>
</tr>
</tbody>
</table>

Microwave Sounding Unit-A on the NOAA-series and MetOp satellites; AMSU-B: Advanced Microwave Sounding Unit-B on the NOAA-series satellites; MHS: Microwave Humidity Sounder (MHS) on later NOAA-series satellites and the European Operational Meteorological satellite.

Table 2. List of the statistical metrics used in the performance evaluation.

<table>
<thead>
<tr>
<th>Statistical Indices</th>
<th>Equation</th>
<th>Comments</th>
<th>Optimum score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coefficient (CC)</td>
<td>$CC = \frac{\sum_{i=1}^{n}(S_i - \overline{S})(O_i - \overline{O})}{\sqrt{\sum_{i=1}^{n}(S_i - \overline{S})^2} \times \sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}}$</td>
<td>$n$, the number of samples; $S_i$, the estimated precipitation; $O_i$, the observed precipitation; $\overline{S}$, the mean of estimated precipitation; $\overline{O}$, the mean of observed precipitation.</td>
<td>1</td>
</tr>
<tr>
<td>Mean error (ME)</td>
<td>$ME = \frac{1}{n} \sum_{i=1}^{n}(S_i - O_i)$</td>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Relative bias (rBIAS)</td>
<td>$rBIAS = \frac{\sum_{i=1}^{n}(S_i - O_i)}{\sum_{i=1}^{n}O_i} \times 100%$</td>
<td>$\sigma_s$, the standard deviations of estimated precipitation; $\sigma_o$, the standard deviations of observed precipitation</td>
<td></td>
</tr>
<tr>
<td>Modified Kling-Gupta efficiency (KGE)</td>
<td>$KGE = 1 - \sqrt{(CC - 1)^2 + \left(\frac{\overline{S}}{\overline{O}}\right)^2 \left(\frac{\sigma_s/\overline{S}}{\sigma_o/\overline{O}} - 1\right)^2}$</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Centered root mean square difference (RMSD)</td>
<td>$RMSD = \sqrt{\frac{1}{n} \sum_{i=1}^{n}[(O_i - \overline{O}) - (S_i - \overline{S})]^2}$</td>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Probability of detection (POD)</td>
<td>$POD = \frac{H}{H + M}$</td>
<td>$H$, the precipitation events reported correctly by gauge and satellite-based products; $F$, the precipitation events detected by satellite products but not recorded by the gauge; $M$, the precipitation events recorded by gauge but not detected by satellite products.</td>
<td>1</td>
</tr>
<tr>
<td>Metric</td>
<td>Formula</td>
<td>Value</td>
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</tr>
<tr>
<td>--------------------------------</td>
<td>----------------------------------------------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>False alarm ratio (FAR)</td>
<td>$\text{FAR} = \frac{F}{H + F}$</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Frequency bias index (FBI)</td>
<td>$\text{FBI} = \frac{H + F}{H + M}$</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Critical success index (CSI)</td>
<td>$\text{CSI} = \frac{H}{H + M + F}$</td>
<td>1</td>
<td></td>
</tr>
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</table>
Table 3. Evaluation statistics for the downscaled satellite precipitation and fused precipitation before and after kriging-based residual correction with reference to gauge observation during 2010-2017.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Downscaling</th>
<th>Fusion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TMPA-3B42RT</td>
<td>CMORPH</td>
</tr>
<tr>
<td>CC</td>
<td>before residual correction</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>after residual correction</td>
<td>0.61</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>before residual correction</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>after residual correction</td>
<td>0.39</td>
</tr>
<tr>
<td>RMSE (mm)</td>
<td>before residual correction</td>
<td>12.26</td>
</tr>
<tr>
<td></td>
<td>after residual correction</td>
<td>12.29</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>before residual correction</td>
<td>10.3</td>
</tr>
<tr>
<td></td>
<td>after residual correction</td>
<td>10.6</td>
</tr>
<tr>
<td>KGE</td>
<td>before residual correction</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>after residual correction</td>
<td>0.54</td>
</tr>
</tbody>
</table>
Table 4. Evaluation statistics for the four original SPPs and the MPP with reference to gauge observation across the entire period and different seasons during 2010-2017.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Entire period</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC</td>
<td>0.67</td>
<td>0.67</td>
<td>1.49</td>
<td>-0.44</td>
<td>0.08</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>0.45</td>
<td>0.67</td>
<td>2.68</td>
<td>-0.44</td>
<td>0.08</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>12.0</td>
<td>18.2</td>
<td>21.3</td>
<td>-14.3</td>
<td>7.0</td>
</tr>
<tr>
<td>KGE</td>
<td>0.64</td>
<td>0.61</td>
<td>0.59</td>
<td>0.64</td>
<td>0.27</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>-0.45</td>
<td>-1.97</td>
<td>-1.97</td>
<td>-1.84</td>
<td>-0.89</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>-12.0</td>
<td>-24.7</td>
<td>-28.1</td>
<td>-60.4</td>
<td>-74.5</td>
</tr>
<tr>
<td>KGE</td>
<td>0.64</td>
<td>0.50</td>
<td>0.43</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>CC</td>
<td>0.67</td>
<td>0.64</td>
<td>0.59</td>
<td>0.63</td>
<td>0.64</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>-0.44</td>
<td>-1.84</td>
<td>-0.36</td>
<td>-0.44</td>
<td>-0.89</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>-12.0</td>
<td>-24.7</td>
<td>-28.1</td>
<td>-60.4</td>
<td>-74.5</td>
</tr>
<tr>
<td>KGE</td>
<td>0.67</td>
<td>0.64</td>
<td>0.59</td>
<td>0.63</td>
<td>0.64</td>
</tr>
<tr>
<td>Indices</td>
<td>TMPA-3B32RT</td>
<td>CMORPH</td>
<td>PERSIANN</td>
<td>GSMaP_NRT</td>
<td>MPP</td>
</tr>
<tr>
<td>CC</td>
<td>0.59</td>
<td>0.54</td>
<td>0.43</td>
<td>0.43</td>
<td>0.54</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>-1.17</td>
<td>-2.92</td>
<td>78.4</td>
<td>-0.3</td>
<td>-4.0</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
</tr>
<tr>
<td>KGE</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
</tr>
<tr>
<td>CC</td>
<td>0.95</td>
<td>0.96</td>
<td>0.99</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td>ME (mm)</td>
<td>-0.41</td>
<td>-0.41</td>
<td>-0.41</td>
<td>-0.41</td>
<td>-0.41</td>
</tr>
<tr>
<td>rBIAS (%)</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
<td>-10.9</td>
</tr>
<tr>
<td>KGE</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
</tr>
</tbody>
</table>
Table 5. Evaluation statistics with reference to gauge observation for various fusion models (i.e., GWRR\textsubscript{T}, GWRR\textsubscript{C}, GWRR\textsubscript{P}, GWRR\textsubscript{G} and GWRR\textsubscript{M} model) across the entire period and different seasons during 2010-2017.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Entire period</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GWRR\textsubscript{T}</td>
<td>GWRR\textsubscript{C}</td>
<td>GWRR\textsubscript{P}</td>
<td>GWRR\textsubscript{G}</td>
<td>GWRR\textsubscript{M}</td>
</tr>
<tr>
<td>CC</td>
<td>0.78</td>
<td>0.78</td>
<td>0.75</td>
<td>0.79</td>
<td>0.86</td>
</tr>
<tr>
<td>ME(mm)</td>
<td>-1.41</td>
<td>-1.43</td>
<td>-1.58</td>
<td>-1.30</td>
<td>-0.98</td>
</tr>
<tr>
<td>rBIAS(%)</td>
<td>-37.7</td>
<td>-38.3</td>
<td>-42.5</td>
<td>-34.9</td>
<td>-26.3</td>
</tr>
<tr>
<td>KGE</td>
<td>0.56</td>
<td>0.55</td>
<td>0.51</td>
<td>0.59</td>
<td>0.70</td>
</tr>
<tr>
<td>CC</td>
<td>0.79</td>
<td>0.81</td>
<td>0.76</td>
<td>0.79</td>
<td>0.87</td>
</tr>
<tr>
<td>ME(mm)</td>
<td>-1.32</td>
<td>-1.28</td>
<td>-1.48</td>
<td>-1.30</td>
<td>-0.91</td>
</tr>
<tr>
<td>rBIAS(%)</td>
<td>-35.6</td>
<td>-34.5</td>
<td>-40.0</td>
<td>-35.1</td>
<td>-24.5</td>
</tr>
<tr>
<td>KGE</td>
<td>0.59</td>
<td>0.60</td>
<td>0.54</td>
<td>0.59</td>
<td>0.72</td>
</tr>
<tr>
<td>CC</td>
<td>0.74</td>
<td>0.74</td>
<td>0.71</td>
<td>0.75</td>
<td>0.84</td>
</tr>
<tr>
<td>ME(mm)</td>
<td>-2.78</td>
<td>-2.86</td>
<td>-3.08</td>
<td>-2.58</td>
<td>-1.94</td>
</tr>
<tr>
<td>rBIAS(%)</td>
<td>-39.6</td>
<td>-40.8</td>
<td>-44.0</td>
<td>-36.9</td>
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<tr>
<td>KGE</td>
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<td>0.51</td>
<td>0.47</td>
<td>0.56</td>
<td>0.68</td>
</tr>
<tr>
<td>CC</td>
<td>0.81</td>
<td>0.79</td>
<td>0.78</td>
<td>0.82</td>
<td>0.88</td>
</tr>
<tr>
<td>ME(mm)</td>
<td>-1.14</td>
<td>-1.21</td>
<td>-1.31</td>
<td>-0.99</td>
<td>-0.78</td>
</tr>
<tr>
<td>rBIAS(%)</td>
<td>-37.3</td>
<td>-39.6</td>
<td>-43.1</td>
<td>-32.5</td>
<td>-27.0</td>
</tr>
<tr>
<td>KGE</td>
<td>0.57</td>
<td>0.55</td>
<td>0.50</td>
<td>0.63</td>
<td>0.72</td>
</tr>
<tr>
<td>CC</td>
<td>0.88</td>
<td>0.90</td>
<td>0.86</td>
<td>0.90</td>
<td>0.93</td>
</tr>
<tr>
<td>ME(mm)</td>
<td>-0.41</td>
<td>-0.38</td>
<td>-0.47</td>
<td>-0.35</td>
<td>-0.31</td>
</tr>
<tr>
<td>rBIAS(%)</td>
<td>-34.3</td>
<td>-32.2</td>
<td>-39.7</td>
<td>-29.5</td>
<td>-26.2</td>
</tr>
<tr>
<td>KGE</td>
<td>0.60</td>
<td>0.62</td>
<td>0.56</td>
<td>0.66</td>
<td>0.69</td>
</tr>
</tbody>
</table>
Figure 1. Location of the study area, distributions of 42 gauge sites and satellite pixels used in this study
Figure 2. Flowchart of the GWRR-based two-step merging scheme proposed in this study. Noting that the subscript $i$ and $d$ refer to the sequence number of location and day, respectively.
Figure 3. Spatial patterns of the collinearity rate (CR) in the GWR model for downscaling developed for (a) TMPA-3B42RT, (b) CMORPH, (c) PERSIANN, and (d) GSMaP_NRT during 2010-2017.
Figure 4. Spatial distributions of the (a) collinearity rate (CR) and (b) perfect collinearity rate (PCR) in the GWR model for fusion at 42 gauge sites during 2010-2017.
Figure 5 Spatial patterns of regression coefficients generated by the GWRR model for fusion on (left) June 21, 2014 and (right) September 30, 2014. Label (1) is the intercept, and labels (2)-(5) are the slopes of the Box-Cox transformed downscaled TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT precipitation. Noting that only the values with light orange are close to zero.
Figure 6. Scatter plots with color density between the original satellite precipitation and the estimated precipitation by the GWRR model for downscaling at monthly and original spatial scale for (a) TMPA-3B42RT, (b) CMORPH, (c) PERSIANN and (d) GSMaP_NRT from 2010-2017.
Figure 7. Scatter plots with color density between rain gauge observation and the estimated precipitation by the GWRR model for fusion from 2010-2017.
Figure 8. Precipitation maps of (a1) the original 3B42RT with 0.25° resolution; (a2) the original CMORPH with 0.25° resolution; (a3) the original PERSIANN with 0.25° resolution; (a4) the original GSMaP_NRT with 0.1° resolution; (b1) the downscaled 3B42RT with 1km resolution; (b2) the downscaled CMORPH with 1km resolution; (b3) the downscaled PERSIANN with 1km resolution; (b4) the downscaled GSMaP_NRT with 1km resolution; (c) the gauge observation; and (d) the merged precipitation product (MPP) with 1km resolution on June 21, 2014.
Figure 9. Time series of areal-average monthly precipitation of gauge observation, original SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) and MPP for the period 2010-2017.
Figure 10. Taylor diagrams for daily precipitation of gauge observation, original SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) and MPP across the entire period and different seasons during 2010 to 2017.
Figure 11. Evaluation statistics for categorical indices at five precipitation intensity classes (in mm/d). From left to right and top to bottom: POD, FAR, FBI and CSI. The black line represents the optimal value of each index.
Figure 12. Modified Kling-Gupta efficiency (KGE) for daily precipitation of original SPPs (i.e., TMPA-3B42RT, CMORPH, PERSIANN and GSMaP_NRT) and MPP based on Equation (23) at 42 gauge sites during 2010-2017.
Figure 13. Modified Kling-Gupta efficiency (KGE) for daily precipitation estimated by (a) GWRR$_T$ model, (b) GWRR$_C$ model, (c) GWRR$_P$ model, (d) GWRR$_G$ model and (e) GWRR$_M$ model at 42 gauge sites during 2010-2017.