



Article Evaluation and Correction of IMERG Late Run Precipitation Product in Rainstorm over the Southern Basin of China

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Abstract: Satellite precipitation products play an essential role in providing effective global or regional precipitation. However, there are still many uncertainties in the performance of satellite precipitation products, especially in extreme precipitation analysis. In this study, a Global Precipitation Measurement (GPM) Integrated Multi-satellite Retrievals for GPM (IMERG) late run (LR) product was used to evaluate the rainstorms in the southern basin of China from 2015 to 2018. Three correction methods, multiple linear regression (MLR), artificial neural network (ANN), and geographically weighted regression (GWR), were used to get correction products to improve the precipitation performance. This study found that IMERG LR's ability to characterize rainstorm events was limited, and there was a significant underestimation. The observation error and detection ability of IMERG LR decrease gradually from the southeast coast to the northwest inland. The error test shows that in the eastern coastal area (zone I and II), the central area (zone III), and the western inland area (zone IV and V), the optimal correction method is MLR, ANN, and GWR, respectively. The performance of three correction products is slightly better compared with the original product IMERG LR. From zone I to V, correlation coefficient (CC) and root mean square error (RMSE) show a decreasing trend. Zone II has the highest relative bias (RB), and the deviation is relatively large. The categorical indices of inland area performed better than coastal area. The correction product's precipitation is slightly lower than the observed value from April to November with a mean error of 8.03%. The correction product's precipitation was slightly higher than the observed values in other months, with an average error of 12.27%. The greater the observed precipitation, the higher the uncertainty of corrected precipitation result. The coefficient of variation showed that zone II had the highest uncertainty, and zone V had the lowest uncertainty. MLR had a high uncertainty with an average of 9.72%. The mean coefficient of variation of ANN and GWR is 7.74% and 7.29%, respectively. This study aims to generate a set of precipitation products with good accuracy through the IMERG LR evaluation and correction to support regional extreme precipitation research.

Keywords: satellite precipitation product; southern basin of China; correction; IMERG; rainstorm; uncertainty

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1. Introduction

Measuring the temporal and spatial distribution of precipitation based on satellite remote sensing is one of the most challenging scientific research goals in recent years [1,2]. Early satellite precipitation relied on visible light, infrared, and active/passive microwave sensors on geostationary and low earth orbit satellites. The Tropical Rainfall Measuring Mission (TRMM), launched in November 1997, carried the world's first space-borne precipitation radar, ushering in a new era of global precipitation monitoring [3]. At present, a series of satellite precipitation products have been released and opened to the public, such as Precipitation Estimation from Remotely Sensed Information using Artificial Neural



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Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations. Networks (PERSIANN) [4], Climate Prediction Center Morphing Technique (CMORPH) [5], Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) [6], TRMM Multi-satellite Precipitation Analysis (TMPA) [7], and Global Precipitation Measurement (GPM) [8]. These products have been widely used in hydrological simulation [9], flood management [10], drought monitoring [11,12], and climate change analysis [13]. Some studies have evaluated the accuracy of satellite precipitation products [14–16]. However, further evaluation of satellite precipitation products is needed to improve the reliability in estimating extreme precipitation.

Satellite-based precipitation estimation has become a vital data resource and has been applied in extreme precipitation events worldwide. Tashima et al. [17] confirmed the effectiveness of Global Satellite Mapping of Precipitation (GSMaP) products in monitoring extreme precipitation in East Asia and Western Pacific. Kiany et al. [18] evaluated TRMM's ability to detect extreme precipitation in southwestern Iran from 1998 to 2016. It showed that precipitation products could capture the temporal and spatial behavior of most extreme precipitation indices. The evaluation of extreme precipitation in Tunisia in 2007–2009 demonstrated that satellite precipitation products need to be combined with other nearreal-time data to make a reliable estimation [19]. Lockhoff et al. [20] asserted that satellite precipitation products could reliably reproduce extreme precipitation characteristics over Europe. However, some studies had found that satellite precipitation products had limited ability to characterize extreme precipitation. Palharini et al. [21] found that precipitation products' ability to retrieve extreme precipitation in tropical South America depends on geographical location and large-scale rainfall conditions. Paska et al. [22] measured extreme precipitation in Malaysia. The correlation between satellite precipitation products and rain gauge data was usually low in heavy precipitation. Precipitation products showed an underestimation in terms of the extreme precipitation index results. Evaluation in the Amazon region of Brazil indicated that satellite precipitation products tended to underestimate the month's highest precipitation [23]. Similarly, the evaluation in the United States suggested that precipitation products are not ideal for detecting extreme precipitation [24]. With the increase of extreme precipitation threshold, the performance of precipitation products tended to deteriorate. Some scholars have also used satellite precipitation products to carry out extreme precipitation evaluation in China. Studies showed that satellite precipitation products still have limited resolution and accuracy in their application to extreme precipitation [25–27]. Precipitation products produced a good estimation of extreme precipitation with 1050 yearly recurrence intervals but exhibited consistent underestimation in these periods [28]. Moreover, there are spatial and seasonal differences in precipitation products' ability to detect extreme precipitation [29].

It is of great significance to improve the accuracy of satellite precipitation products by using appropriate correction methods [30]. The mean error of the precipitation product is closely related to the rainfall intensity of the rain gauge data and can be characterized by polynomial fitting, thus providing useful information for correction [31]. The relationship between precipitation products and ground observations can correct satellite precipitation data, showing the spatial variation of precipitation [32]. Lu et al. [33] showed that the correction product by stepwise regression model had excellent performance in Xinjiang, China. The correction methods have been tested in French Guiana and the Mekong river basin [34,35]. The results proved that the correction method can effectively improve the performance of precipitation products and has the potential to solve the precipitation bias problem. Previous studies focused on the overall evaluation of precipitation products, and relatively few regional correction experiments have restricted the application of precipitation products. The comparative studies on multi-satellite precipitation products showed that Integrated Multi-satellite Retrievals for GPM (IMERG) has good performance in precipitation monitoring [28,36,37]. However, how IMERG performs in extreme precipitation requires further study to evaluate and calibrate error.

This study has two main purposes. One is to evaluate the performance of IMERG under extreme precipitation conditions. The other is to use correction methods to improve

the precipitation product's accuracy. The samples with daily precipitation above 50 mm in the southern basin of China from 2015 to 2018 were selected as rainstorm events to evaluate the performance of the IMERG and reveal its error characteristics. Three correction methods, multiple linear regression (MLR), artificial neural network (ANN), and geographically weighted regression (GWR), were adopted to improve the accuracy of the IMERG product in measuring precipitation during rainstorms. Then, the precipitation results of correction products were analyzed, along with the uncertainty associated with each correction method. This study can refer users to decide whether and how to correct precipitation products to better use them in specific study areas.

2. The Study Area and Datasets

2.1. The Study Area

The geographical location, elevation, and spatial distribution of rainstorm frequency in the study area are shown in Figure 1. The study area is the southern basin of China, including Huaihe river basin, Yangtze river basin, Southeast basin, and Pearl river basin. The study area is located at $90^{\circ}22'-122^{\circ}40'$ E, $18^{\circ}13'-37^{\circ}08'$ N, with a total area of 2.72 million km². The south of the study area is close to a tropical climate, and the north is a temperate climate. The mean annual precipitation in the study area ranges from 400 mm in the western region to 1800 mm in the eastern region. The precipitation mainly concentrated in summer (June to August) and mostly in the form of rainstorms. Moreover, the temporal and spatial distribution of extreme precipitation in the study area is uneven. Rainstorm events in the southeast coast have high frequency, and the frequency gradually decreases toward the inland area (Figure 1c). The regional division of extreme precipitation and its related statistical characteristics based on the satellite precipitation products are worthy of in-depth analysis.



Figure 1. (a) The location of the study area in China, (b) the study area's DEM and basins, (c) the rainstorm frequency distribution in the study area from 2015 to 2018.

2.2. IMERG Precipitation Product

As a new generation of satellite precipitation product, GPM IMERG's core satellite was launched in February 2014 and can provide global rain and snow data at an interval of 0.5 h. GPM IMERG first used a dual-frequency precipitation radar including Ka and Ku bands to provide physical information about cloud precipitation particles (shape, intensity, and convective processes of raindrops). This can depict the spatial distribution of precipitation particles more accurately. GPM IMERG data are verified by precipitation

inversion mechanism based on ground-based observation tests and fusion verification oriented by hydrometeorological application [38].

GPM IMERG has three run products (early, late, and final run products). This study uses a daily IMERG late run (IMERG LR) product (https://gpm.nasa.gov/data/directory). IMERG LR is a quasi real time product with a release delay of 12 h and spatial resolution of 0.1°. Compared with early run (ER) product, IMERG LR has backward propagation, which improves product accuracy. The final run (FR) product reveals the good quality, but the performance level of LR and FR is comparable according to the evaluation values [37,39,40]. Moreover, IMERG LR has a better time response than FR product with 3.5 months release delay.

2.3. Rain Gauge Data

The rain gauge daily data provided by the China Meteorological Administration (http://data.cma.cn/) were used. Rain gauge data have undergone strict quality control, and are reliable and suitable for satellite precipitation products evaluation [41]. The rain gauge data were screened in the following two steps. First is to remove gauges with incomplete observation data; then to select gauges with rainstorm records. Finally, 242 rain gauges were selected for this study. These rain gauges have passed the uniformity test and have high accuracy and reliability [42,43]. The criterion for judging a rainstorm is to set the precipitation threshold (50 mm/day). If the daily precipitation exceeds this value, it will be judged as a rainstorm.

2.4. Normalized Difference Vegetation Index (NDVI)

The NDVI data were used as the input parameter of the correction methods and were obtained from the Atmosphere Archive and Distribution System (https://ladsweb.modaps.eosdis.nasa.gov/search/). The product has a temporal resolution of one month and a spatial resolution of 1 km. The annual NDVI data were obtained by averaging the monthly NDVI data.

3. Methods

3.1. Statistical and Categorical Indices

In this study, the correlation coefficient (CC), root mean square error (RMSE), and relative bias (RB) were used to evaluate the accuracy of precipitation products. CC reflects the linear correlation between IMERG LR and rain gauge data. The higher the value, the higher the correlation between them. RMSE describes the difference between IMERG LR and rain gauge data. The closer the RMSE is to 0, the more accurate the precipitation product is. RB describes precipitation products' systematic error, and its positive or negative value indicates that IMERG LR overestimates or underestimates the rain gauge data. The calculation formula of each statistical index is shown below.

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

RMSE =
$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - G_i)^2}$$
 (2)

$$RB = \frac{\sum_{i=1}^{n} (S_i - G_i)}{\sum_{i=1}^{n} G_i} - 1$$
(3)

where *G* is the rain gauge data, and *S* is the satellite precipitation product. \overline{G} and \overline{S} denote mean value.

The probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) were adopted to reflect the detection ability of precipitation products to the rainstorm. POD represents the detection hit ratio of precipitation products on whether daily precipitation events occur, and the value range is 0–1. The higher the value, the higher the detection hit ratio of precipitation products. FAR reflects the probability of precipitation products misreporting precipitation events, and the value range is 0–1. The lower the value, the lower the degree of vacancy and false ability of precipitation products. CSI comprehensively reflects the ability of precipitation events occur, and the value range is 0–1. The larger the value, the stronger the comprehensive performance of precipitation products.

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

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

$$CSI = \frac{H}{H + M + F}$$
(6)

where H (hit) is the frequency of rainstorm events observed and detected. F (false alarm) is the frequency of rainstorm events not observed but detected; M (miss) is the frequency of rainstorm events observed but not detected.

3.2. Evaluation Regional Division Based on Hot Spot Clustering

The spatial clustering factor was used to identify the statistically significant clustering zones of precipitation evaluation indices. Hot spot clustering analysis can determine the spatial clustering of high or low value features. According to the z score, when z > 2.58, it is regarded as the significant high value spatial clustering (hot spot). When z < -2.58, it is regarded as the significant low value spatial clustering (cold spot). When |z| < 2.58, there is no significant spatial clustering.

The clustering distributions of statistical and categorical indices were obtained, and the number of hot and cold spots at each rain gauge was counted. Rain gauges with the same clustering characteristics were identified as the same type. The spatial region of the same gauge type was obtained by the processing of Tyson polygon. In this way, based on the aggregation of spots, the regional division based on evaluation performance was realized.

3.3. Precipitation Product Correction Methods

Three correction methods were used in this study, including multiple linear regression (MLR), artificial neural network (ANN), and geographically weighted regression (GWR). The correction methods aim to eliminate the precipitation difference (the *y* of Formulas (7)–(9)) between the observed value and the precipitation product.

MLR contains trend and residual term. The difference between rain gauge data and precipitation product was taken as a dependent variable, while longitude, latitude, elevation, and NDVI were taken as multiple independent variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \tag{7}$$

where x_1-x_4 are longitude, latitude, altitude, and NDVI. $\beta_0-\beta_4$ are the corresponding parameters.

ANN is an efficient method that can handle the complicated relationship between different variables and has a powerful nonlinear mapping capability. The ANN used in this study is a three-layer back propagation network structure, including an input layer, a hidden layer, and an output layer. The input layer contains four nodes, which are longitude, latitude, elevation, and NDVI; the output layer is precipitation data; the number of hidden layer nodes is determined as ten by trial and error method.

$$y = \varphi(\sum_{i=1}^{2N+1} \omega_i x_i + b) \tag{8}$$

where *x* is the input layer parameter, ω is the weight of parameter, *b* is the bias, and *N* is the number of input layer nodes.

GWR uses the idea of local regression to explore the spatial relationship between independent and dependent variables. GWR selects test samples based on geographical distance and assigns them different weights. GWR introduces spatial relationship weight into the operation and establishes the regression model by estimating different spatial position parameters.

$$y_{i} = \beta_{i0}(u_{i}, v_{i}) + \sum_{k=1}^{n} \beta_{ik}(u_{i}, v_{i})x_{ik} + \varepsilon_{i}$$
(9)

where (u_i, v_i) is the position of grid i, β_{i0} (u_i, v_i) is the constant estimation value, β_{ik} (u_i, v_i) is the parameter estimation value, which refers to NDVI and elevation. ε_i is the residual estimation value.

To avoid multicollinearity and overfitting of the regression equation, the stepwise regression method was used in MLR construction. No correlation was found between the four parameters and IMERG LR. Before the training network, ANN preprocessed the input and output vectors to normalize them to (-1,1), avoiding slow convergence and long training time caused by inconsistent data units or extensive range. For all sample data, approximately 2/3 were used as training samples and the remaining 1/3 as validation samples.

3.4. Correction Method Verification and Uncertainty Evaluation

The mean squared error (MSE), mean absolute error (MAE), and standard deviation (SD) were used to evaluate the correction methods. MSE is the square of the difference between estimated and real values. The smaller MSE indicates that the correction method has better accuracy. MAE is the average of absolute errors. MAE can reflect the actual level of correction error. SD is the arithmetic square root of the variance. SD can reflect the discrete degree of a data set.

Through the coefficient of variation, the precipitation evaluation uncertainty by correction products was studied. The larger the coefficient, the greater the discrete degree of the correction product, and the higher the uncertainty.

$$C = \frac{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})/n}}{|\bar{x}|} \times 100\%$$
(10)

where x_i is the precipitation value of each correction method, and \overline{x} is the mean value of all correction methods.

4. Results

4.1. IMERG LR Performance Evaluation for Rainstorm

All daily rainstorm events recorded by rain gauges in the southern basin from 2015 to 2018 were obtained, and the scatter points corresponding to IMERG LR were plotted (Figure 2). The fitting results showed that IMERG LR significantly underestimates rainstorms. IMERG LR underestimated 90.72% of the rainstorm events, and only overestimated 9.28% of the rainstorm events. The density center of precipitation scatter point appeared at (56.8, 10.6) mm, and the IMERG LR precipitation was much lower than the rain gauge data. In Figure 2, the proportion of rainstorm events in each month is listed. Heavy rainfall



events were relatively concentrated in summer from June to August, accounting for 58.33% of the total.

Figure 2. Precipitation scatter plot of rain gauge data and Integrated Multi-satellite Retrievals for Global Precipitation Measurement (GPM) (IMERG) late run (LR).

Based on statistical and categorical indices, the performance of IMERG LR for rainstorm was evaluated. In addition, the evaluation results of all rainfall events (>0.1 mm/day) were obtained for comparison (Table 1). IMERG LR had a low correlation with rainstorm (CC was 0.30), RMSE was 7.66 mm, and RB was -0.52 mm. IMERG LR's POD decreased from 0.73 for all rainfall to 0.20 for rainstorm. The FAR of IMERG LR in rainstorms was 0.68, and the CSI was 0.18. On the whole, IMERG LR's evaluation indices for rainstorm are worse than all rainfall.

Table 1. Performance comparison of IMERG LR in rainstorms and all rainfall events.

	Statistical Indices			Categorical Indices			
	CC	RMSE (mm)	RB (mm)	POD	FAR	CSI	
Rainstorm	0.30	7.66	-0.52	0.20	0.68	0.18	
All rainfall	0.42	4.41	-0.05	0.73	0.44	0.45	

The spatial distribution of IMERG LR statistical and categorical indices is shown in Figure 3. CC had poor spatial differentiation (Figure 3a). Some rain gauges in the northern region showed high CC values, and the rainstorm frequency in these regions was relatively low. RMSE decreased gradually from the southeast coast to the northwest inland (Figure 3b). The southeast coast was a subtropical monsoon climate zone, where rainstorms frequently occur, leading to high error results. The spatial distribution of RB shows that the IMERG LR precipitation is generally lower than the observed value in the study area (Figure 3c). CSI performs relatively well in the southeast coastal region (Figure 3d). In the western region, POD is low and FAR is high (Figure 3e,f). The evaluation indices performed slightly better in the eastern region, but IMERG LR's detection ability of rainstorms needs to be further improved.



Figure 3. The spatial distribution of IMERG LR statistical indices ((**a**) CC, (**b**) RMSE, and (**c**) RB) and categorical indices ((**d**) CSI, (**e**) POD, and (**f**) FAR).

4.2. Hot Spot Clustering and Regional Division

According to the evaluation indices, the spatial clustering characteristics of the results were obtained. Among statistical indices, CC had 15 hot spots clustered in the northern region of Yangtze river basin. Cold spots appeared in the western Yangtze river basin and the southeast corner of Huaihe river basin. A total of 80.99% of the gauges had no significant CC clustering. RMSE showed cold clustering in the western and northern regions. There was a hot clustering phenomenon in the south through the transition of non-significant gauges in the central region. RB's clustering mainly occurred in the west (hot spot) and south (cold spot).

The categorical indices clustering characteristics were similar in spatial distribution. POD showed cold spots in the western region and hot spots in the eastern region. FAR clustering distribution was the opposite, and the range of hot spots was small. The southeast coastal area was the CSI hot clustering range, indicating that IMERG LR had the optimal ability to detect rainstorms in this area. Correspondingly, the western inland showed cold spots, and the central and northern regions of the study area were non-significant clustering as shown in Figure 4.



Figure 4. The spatial clustering of statistical indices ((**a**) CC, (**b**) RMSE, and (**c**) RB) and categorical indices ((**d**) CSI, (**e**) POD, and (**f**) FAR).

The spatial clustering phenomenon of the evaluation indices reflects the different performance characteristics of IMERG LR in different zones of the study area. Based on clustering characteristics, the regional division was considered. The evaluation performance of IMERG LR to rainstorm will be improved effectively by exploring a unique precipitation product correction scheme for different zones.

Therefore, the study area was divided into five zones according to the spatial clustering characteristics of evaluation indices. The southeast coastal region contained zone I and II. Zone III was located in the central region. North and west of the study area were Zone IV and V, respectively. The performance of IMERG LR in zone I and II was satisfactory. In these zones, correlations were strong (CC 0.39 and 0.37), and the categorical index CSI showed relatively good performance (0.16 and 0.14) but had high RMSE (both 7.75 mm) and RB (-0.78 and -0.63 mm). From zone III to zone V, the performance of CSI gradually decreased from 0.11 to 0.03, and the correlation was relatively weakened (CC was 0.36, 0.25, and 0.11, respectively), see Figure 5.



Figure 5. Regional division and evaluation indices of each zone.

4.3. Correction Statistics Results in Different Zones

MLR, ANN, and GWR were used to correct the IMERG LR. Here, the three correction methods were used in each zone to improve precipitation product performance and compare the correction differences. The error results of correction methods are summarized in Table 2. The correction errors of MLR in three zones were the smallest, which were zone I, II, and V. ANN performed relatively better in zone III, and GWR performed relatively better in zone IV.

Table 2. Error test of precipitation product correction method (the shadow represents the best performing method of test index in each zone).

Zon	ie	Ι	II	III	IV	V
	MLR	71.85	121.99	101.34	226.53	128.17
MSE (mm)	ANN	88.96	123.11	90.50	248.59	139.70
	GWR	83.68	125.63	103.82	227.06	136.34
MAE (mm)	MLR	6.26	8.47	7.73	11.13	8.91
	ANN	7.68	8.52	7.33	11.67	9.36
	GWR	7.35	8.63	7.92	11.11	9.15
SD (mm)	MLR	8.47	11.04	10.07	15.05	11.32
	ANN	9.43	11.09	9.51	15.77	11.82
	GWR	9.05	11.21	10.15	15.07	11.67

It should be noted that in each zone, the errors of the three correction methods were roughly at the same magnitude. On the whole, MLR correction had the best effect, with mean MSE equal to 129.98 mm, MAE 8.50 mm, and SD 11.19 mm. GWR mean error results were: MSE was 135.31 mm, MAE was 8.83 mm, and SD was 11.43 mm. The ANN mean error results were: MSE was 138.17 mm, MAE was 8.91 mm, and SD was 11.52 mm. The order of correction error in each zone from good to bad was: I > III > II > V > IV.

The precipitation differences between correction products and observation data were calculated, and the difference result of the original product of IMERG LR was added for comparison (Figure 6). It can be seen that in each zone, the precipitation difference of the correction products was significantly improved compared with the original product. The difference range of the original product IMERG LR in all zones was 42.48–55.09 mm. After correction, the mean difference was reduced to -0.42-1.36 mm.



Figure 6. The precipitation difference of original IMERG LR product (Origin) and three correction products (multiple linear regression (MLR), artificial neural network (ANN), and geographically weighted regression (GWR)) compared with observation data.

The mean difference in the original precipitation product from zone I to V increased gradually. After correction, the differences in all zones were reduced to the same range. The difference near the zero value means low correction deviation and good correction effect. The differences of MLR (zone I) and GWR (zone IV) were relatively clustered, similar to the error test results in Table 2.

Sample gauges were selected to verify the error of correction methods (Figure 7). The gauge with the highest rainstorm frequency in each zone was selected. The best method for rain gauge No.59,087 (zone I) and No.58,538 (zone II) was MLR with a difference of 0.37 and 2.26 mm, respectively. The ANN difference of rain gauge No.58,506 (zone III) was the smallest (0.67 mm). The best method for rain gauge No.57,447 (zone IV) and No.59,021 (zone V) was GWR with a difference of 5.11 and 4.45 mm, respectively. From a comprehensive evaluation, MLR, ANN, and GWR is the optimal correction method for the eastern coastal area (zone I and II), central area (zone III), and the western inland area (zone IV and V), respectively.



Figure 7. The precipitation difference comparison of the correction methods for sample gauges in zone I–V (**a**–**e**).

4.4. Spatio-Temporal Comparison of Correction Products

The evaluation indices results of three correction products in each zone were analyzed (Table 3). On the whole, the performance of correction products was improved compared with that of original products. For the statistical indices of the study area, CC was 0.30 before correction and 0.40 after correction. RMSE decreased from 7.66 to

5.43 mm, and RB decreased from -0.52 to -0.07 mm. For categorical indices, the correction products performed well. CSI reached 0.72, POD rose to 0.75, and FAR decreased to 0.13. Compared with Table 1, it can be seen that the statistical indices of correction products in rainstorm events were lower than all rainfall events, but the categorical indices had improved significantly.

	Come alien Mathe	Statistical Indices			Categorical Indices		
	Correction Methods	CC	RMSE	RB	POD	FAR	CSI
Ι	MLR	0.48	5.71	-0.04	0.77	0.16	0.71
	ANN	0.46	5.75	-0.04	0.76	0.15	0.71
	GWR	0.47	5.72	-0.06	0.74	0.16	0.68
II	MLR	0.53	5.78	-0.12	0.63	0.21	0.55
	ANN	0.52	5.80	-0.13	0.62	0.20	0.54
	GWR	0.46	5.79	-0.12	0.62	0.20	0.54
III	MLR	0.42	5.37	-0.02	0.86	0.08	0.83
	ANN	0.48	5.36	-0.02	0.86	0.08	0.83
	GWR	0.43	5.38	-0.03	0.84	0.11	0.80
IV	MLR	0.29	5.49	-0.03	0.80	0.09	0.77
	ANN	0.29	5.50	-0.04	0.80	0.12	0.76
	GWR	0.31	5.50	-0.04	0.83	0.11	0.79
V	MLR	0.16	4.76	0.00	0.84	0.08	0.81
	ANN	0.16	4.78	-0.01	0.83	0.06	0.81
	GWR	0.17	4.74	0.00	0.82	0.07	0.79

Table 3. Evaluation indices results of correction products.

There were some differences in the evaluation indices under different zones. From zone I to V, CC and RMSE showed a decreasing trend. Zone II had the highest RB, and the deviation is relatively large. Compared with the coastal region, the inland region had better performance in categorical indices. The best correction method for each zone was similar to the statistical conclusions through the evaluation indices. The precipitation product performance can be effectively improved by selecting the optimal correction method in different zones.

The absolute precipitation differences between the original product and the correction products based on rain gauge data were compared, and the results are displayed by gauge interpolation (Figure 8). The difference of the original product in zone I and II was relatively low, while zone V was relatively high. The correction product improved the performance of zone V based on the overall reduction of the difference. The difference results were relatively high in the southwest area of zone V due to the lack of gauges. The spatial distribution trend of the absolute difference of correction products was consistent. The north of zone I and the west of zone III were good correction regions.



Figure 8. Spatial distribution of the absolute precipitation difference between the (**a**) original product and three correction products ((**b**) MLR, (**c**) ANN, and (**d**) GWR).

The observation mean value for rainstorms in each month was obtained by rain gauge data, and the differences of precipitation products before and after correction were compared (Figure 9). The difference between the original product and the observed value was large, which showed that the precipitation is significantly underestimated, and the relative error ranged from 14.24% to 68.93%. After correction, the relative error is reduced to 2.50–19.64%. The precipitation of the correction products from April to November was slightly lower than the observed value, with a mean error of 8.03%, which could better characterize the rainstorm events. In other months, the precipitation of the correction products was slightly higher than the observed values.



Figure 9. Difference comparison of monthly precipitation products before and after correction.

5. Discussion

Previous studies have shown that IMERG products' performance in describing precipitation is highly dependent on regional topography [44,45]. The conclusion of this study supports that topographic conditions may affect the precipitation product. Figure 8a showed a large error between the precipitation product and observed data in the western high altitude region. The main reason may be that the snow covered surface and cloud ice mixing meteorological conditions easily lead to signal acquisition difficulty [36]. Compared with the original product, the correction products have a significant improvement in categorical indices. This is because the product's precipitation value can be directly improved through regression and weighting processing to meet the indices' statistical requirements.

The correction method of this study is based on latitude and longitude, DEM, and NDVI data. Satellite precipitation products have regional and seasonal errors [46]. These errors will disturb the correlation between precipitation and environmental factors, leading to uncertainty in precipitation correction [47]. With the increase of observed precipitation, correction products' uncertainty presented an upward trend (Figure 10). The uncertainty bandwidth changed steadily in the range of observed precipitation (50.20, 71.72) mm, increasing from 12.14 to 18.44 mm. With the observed precipitation improvement, the uncertainty error also increased from 20.23 to 68.90 mm.





The coefficient of variation was used to reflect the uncertainty of the correction method in processing precipitation products (Table 4). The mean coefficient in five regions ranged from 3.87% to 12.95%. Zone II had the highest uncertainty, and zone V had the lowest uncertainty. The mean coefficients of ANN and GWR were 7.74% and 7.29%, respectively, showing good correction results. Comparing the correction methods, MLR had a high uncertainty. The coefficient is 5.83–12.88%, with an average of 9.72%. The mean coefficients of ANN and GWR are 7.74% and 7.29%, respectively, and the correction results are stable.

Zone	MLR	ANN	GWR
Ι	12.03%	4.31%	8.80%
Π	12.88%	13.06%	12.92%
III	5.83%	8.52%	7.24%
IV	11.37%	9.30%	5.90%
V	6.51%	3.54%	1.57%

Table 4. The coefficient of variation of the correction methods.

There are still some limitations to this study. The study period of IMERG LR was 2015–2018. In terms of the time span, the 4-year data are relatively less, which will bring errors to the test. In the correction process, only the correlations among precipitation, DEM, and NDVI were considered. The influence of other factors, such as humidity, wind speed, and temperature, were ignored. Other environmental factors affecting precipitation distribution should be considered as much as possible in the follow-up study. The spatial variation of the rainfall field [48] was not considered in this study. The spatial inconsistency of the rain gauge (point) and the IMERG LR (area) may cause potential uncertainty to the

evaluation results. It is of great significance to further quantify and summarize the error characteristics of IMERG products in a rainstorm.

6. Conclusions

This study evaluated IMERG LR precipitation product's performance in the southern basin of China from 2015 to 2018. Furthermore, the regional division was realized based on the hot spot clustering of the evaluation indices. MLR, ANN, and GWR correction methods were used to improve precipitation products' performance and accuracy. The main conclusions are as follows.

- (1) Based on evaluation indices, IMERG LR's performance ability of reproducing a rainstorm is limited and needs to be further improved. IMERG LR underestimates heavy precipitation. The correlation between IMERG LR and rain gauge data is relatively good in the northern region with low rainstorm frequency. The observation error and detection ability gradually decrease from the southeast coast to the northwest inland.
- (2) The statistical indices performance of correction products in rainstorm events is lower than that of all rainfall events, but categorical indices have improved significantly. The precipitation of the correction precipitation product from April to November is slightly lower than the observed value, with an average error of 8.03%. The correction product's precipitation was slightly higher than the observed values in other months, with an average error of 12.27%.
- (3) Through error tests and sample gauges analysis, the optimal correction method in the eastern coastal area (zone I and II), the central area (zone III), and the western inland area (zone IV and V) is MLR, ANN, and GWR, respectively. From zone I to V, CC and RMSE show a decreasing trend. Zone II has the highest RB, and the deviation is relatively large. The categorical indices of the inland region perform better than the coastal region. The correction product improves the performance of rainstorms, and the excellent correction range is in the north of zone I and the west of zone III.
- (4) With the increase of observed precipitation, the correction product's uncertainty shows an upward trend. The coefficient of variation shows that the uncertainty range of all regions is 3.87–12.95%. Zone II has the highest uncertainty, and zone V has the lowest uncertainty. MLR has high uncertainty, with an average of 9.72%. The mean coefficients of ANN and GWR were 7.74% and 7.29%, respectively.

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