Evaluation and Comparison of the GWR Merged Precipitation and Multi-Source Weighted-Ensemble Precipitation based on High-density Gauge Measurement

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Abstract

Accurate estimation of precipitation in both space and time is essential for hydrological research. We compared multi-source weighted ensemble precipitation (MSWEP) with multi-source fused satellite precipitation (CHIRPS) based on high-density rain gauge precipitation observations in the Taihu Lake basin. We proposed a new merge precipitation algorithm GWRMP based on the geographically weighted regression (GWR) method. GWRMP corrects the bias of MSWEP by using high-density rain gauge precipitation to address the common problem of daily precipitation underestimation in MSWEP. The large-scale spatial coverage of the water surface in this region leads to the uneven distribution of rain gauges on the lake. There are differences in the descriptive ability of the three spatial precipitation types, MSWEP, GWRMP, and IDW, for spatial and temporal precipitation information in the Taihu Lake basin. A comparison shows that GWRMP has a significant advantage in obtaining the spatial and temporal variability of precipitation in areas with complex topographic conditions. GWRMP compensates the problem of underestimation of precipitation by MSWEP (10% to 25%), and avoids the risk of the high dependence of IDW on rain gauges, and improves the accuracy of spatial and temporal precipitation in large lake areas with sparse distribution of rain gauges (Pbias limited to 10%). GWRMP improved the estimation for different rainfall intensities in the Taihu Lake basin, especially in the mid-level rainfall and above precipitation frequencies. Compared with IDW and MSWEP, GWRMP is more suitable for intense precipitation monitoring and storm flood frequency study in the basin. Therefore, GWRMP is a better choice for spatial and temporal estimation of precipitation in the Taihu Lake basin. The GWRMP algorithm can be applied to other regions with unevenly spaced high-density rain gauges.

Keywords: Multi-Source Weighted-Ensemble Precipitation, GWR Merged Precipitation, Accuracy Evaluation System, Spatial Inhomogeneity, Taihu Lake Basin.

1. INTRODUCTION

As the principal medium of energy, water exchange, and transport between land and the atmosphere, precipitation is one of the most basic meteorological and hydrological elements that have high spatial variability. The acquisition of high-quality spatial and temporal precipitation data is the basis of global and regional climate change studies and land surface hydrological processes (Behrangi et al., 2011). Taking full advantage of different precipitation acquisition methods and integrating spatial distribution information of precipitation from various sources has become an important development direction in the development of regional or global precipitation data internationally.

Radar precipitation is highly dependent on base information for regional and reanalysis rainfall. Satellite precipitation can cover a large part of the globe with high spatial and temporal resolution. Satellite fusion precipitation products include Global Precipitation Climatology Project (GPCP)(George J. Huffman, Adler, Bolvin, & Gu, 2009; 2001), TMPA from Tropical Rainfall Measuring Mission (TRMM) (George J. Huffman, Adler, Bolvin, & Nelkin, 2010), Integrated Multi-Satellite Retrievals (IMERG) for GPM (George J. Huffman, Bolvin, Nelkin, & Jackson 2015) and CHIRPS data (Climate Hazards Infrared Precipitation with Stations) (Funk et al., 2015). With the advancement of observed precipitation technology, the fused precipitation data sources are no longer limited to multi-satellite fusion, but towards multiple pathways such as radar, satellite, and reanalysis. In 2002, the U.S. Climate Prediction Center Morphing Technique developed a high-resolution CMORPH precipitation product with global coverage(Joyce, Janowiak, Arkin, & Xie, 2004).Beck et al. (2017; 2018) integrated various types of precipitation data such as CPC Unified, GPCC, CMORPH, GSMaP-MVK, TMPA 3B42RT, ERA-Interim, JRA-55, etc., and proposed MSWEP V2.1, a multi-source precipitation fusion data based on a weighted ensemble. MSWEP has the advantages of global coverage and high spatial and temporal resolution (3 hours, 0.1×0.1°) and long time series (1979 present). CHIRPS and MSWEP have both long time series and high spatial and temporal resolution features, which are more suitable for precipitation-related meteorological drought monitoring and storm flood frequency analysis (Abro, Zhu, Ali Khaskheli, Elahi, & Aleem ul Hassan Ramay, 2020; Funk et al., 2015; Liu, Wei, Zhang, Zhang, & LIiu, 2020; Xu et al., 2019; Yang et al., 2020).

Integration of precipitation data from various sources requires both spatiotemporal resolution and application conditions. Therefore, accuracy assessment is essential for region-specific applications. The accuracy assessment results of CHIRPS and MSWEP in different regions of the world show that the fused precipitation data, despite the accuracy validation in many studies, have obvious precipitation underestimation problems and limited capability in estimating heavy precipitation. (Akhilesh, nair, & Indu, 2017; Alijanian, Rakhshandehroo, Mishra, & Dehghani, 2017; Awange, Hu, & Khaki, 2019; Darand & Khandu, 2020; Deng, Jiang, Wang, & lv, 2018). Currently, most studies related to the application of CHIRPS and MSWEP evaluate or validate the accuracy of rainfall estimates and analyze the error characteristics, and then determine the applicability of various fused precipitation data to the study area and content. Precipitation accuracy assessment has generally taken a time-series accuracy assessment method based on rain gauges. This method does not consider the correlation between precipitation events and neighboring spatial units, which can be inadequate in characterizing the spatial structure characteristics of precipitation. We evaluate the accuracy of the fused precipitation data in terms of time series, space, and intensity, which can fully describe its accuracy characteristics. Furthermore, it compares the applicability of data from several sources in the study region.

For regions with a good observation database, surface rainfall is mainly obtained based on dense rainfall observation stations. The accuracy of surface rainfall depends on the density and uniformity of distribution of the observation station network. The distribution of rainfall stations in the Taihu Lake basin is relatively dense, and there is a long time series of surface precipitation observation records. However, there are fewer rainfall stations in the large lakes in the basin. Therefore, the limited rainfall observation information is not enough to accurately reflect the real distribution of precipitation in the large lakes. The multi-source ensemble spatial precipitation data applicable to the Taihu Lake basin were chosen preferably as a source of precipitation information analysis, which could help investigate the space-time evolution patterns of meteorological and hydrological elements in the watershed. CHIRPS and MSWEP have high Spatio-temporal accuracy compared with other fused precipitation data, but there is a problem of precipitation underestimation. We correct the accuracy of multi-source fused precipitation based on the precipitation observed by intensive rain gauges and obtain fused precipitation data with a high spatial resolution and accurate precipitation estimation capability. This data provides more refined precipitation data for hydro-meteorological studies in the whole Taihu Lake basin. The excellent surface observation data in the Taihu Lake basin provides both a foundation for the accuracy of MSWEP precipitation calibration and sufficient measured precipitation comparison information for MSWEP and the accuracy assessment of the corrected fused precipitation.

Since the flood season, rainfall is the main part (more than 60%) of the annual precipitation in the Taihu Lake basin, and the heavy rainfall that has an important impact on the regional socio-economy also occurs mostly during this period. We focused on the fusion estimation of precipitation in the Taihu Lake Basin during the flood season. The specific research ideas are as follows: (1) Collect and organize the precipitation data in the Taihu Lake basin during the flood season (May to September), including daily rainfall station observations from 1979 to 2016, MSWEP raster precipitation data from 1979 to 2016 (0.1°× 0.1°), and CHIRPS raster precipitation data from 1981 to 2016 precipitation information (0.05°× 0.05°). (2) Comparative analysis of CHIRPS and MSWEP daily precipitation accuracy based on rain gauge rainfall, and preferable selection of suitable multi-source fused spatial precipitation information sources. (3) Construct a fused precipitation estimation model based on GWR and generate ground-checked multi-source fused precipitation data (GWRMP). (4) Construct a Spatio-temporal precipitation accuracy assessment system to systematically evaluate the capability of GWRMP in capturing multi-source precipitation information such as temporal, spatial, and precipitation intensity in the Taihu basin.

2. DATA AND METHODS

2.1 Study Area

Taihu Lake Basin is located in the Yangtze River Delta area of China (Figure 1). It is adjacent to the Yangtze River in the north, Qiantang River in the south, and the sea in the east. The total area of the basin is 36,869 km^2, of which the water area is 6134 km^2 and the water surface proportion is 17%. It is a typical plain river network area, located in the subtropical monsoon climate zone with four distinct seasons and abundant rainfall. The average annual precipitation is 1,185 mm, with the bulk of precipitation occurring during the flood season (May to September) at 726 mm, approximately 61% of the annual precipitation. The topography of the basin is complex and includes mountainous, plain, and lake topography, with a dense river network and numerous lakes. The Central Lake area is the third-largest freshwater lake in China, with a water area of nearly 2338 km^2. The complex terrain and climate conditions are characterized by low terrain in the middle of the basin and high in the surrounding areas, thus, flooding is easy to produce and difficult to eliminate. Taihu Lake Basin is one of the most developed areas in China, with a dense population and large- and medium-sized cities. Once a flood disaster occurs, the resulting social and economic losses are serious. According to the distribution of the river system, the Taihu Basin (THB) can be categorized into seven water conservancy zones (Figure 1): district of Huxi (HX), Hangjiahu (HJH), HQ, Wuchengxiyu (WCXY), Yangchengdianmao (YCDM), Pudongpuxi district (PDPX), and Zhexi (ZX). Taking into account the terrain height difference, the Taihu Basin can also be divided into three terrain areas: district of mountainous (ZX), lake (HQ), and plain (HX, WCXY, YCDM, HJH, PDPX). Figure 1(a) shows the geographical location of the Taihu Lake Basin, and Figures 1(b) and 1(c) show the physical geography and socio-economic overview of the Taihu Lake Basin, respectively.

[Insert Figure 1]

2.2 Datasets

2.2.1 Precipitation data of the rainfall station network

The observation data of daily precipitation in Taihu Lake Basin mainly originate from the hydrological yearbook of the basin, and the precipitation data have been reorganized and quality controlled. There is a high-density rainfall gauge network in the study area, and the spatial distribution of gauges is shown in Figure 1(d). The number of available rainfall stations varies from year to year. We used 130 gauges of rain daily observation precipitation data in Taihu Lake Basin from 1979 to 2016 as the calibration benchmark to determine the accuracy of the spatial rainfall data in Taihu Lake Basin. Meanwhile, eight rain gauges in the water conservancy zone are reserved, and the remaining 122 rain gauges are used for inverse distance interpolation to obtain the spatial precipitation IDW (0.1°×0.1°).

2.2.2 Climate Hazards Infrared Precipitation with Stations（CHIRPS）

The long series multi-source satellite fusion precipitation uses the CHIRPS daily precipitation dataset proposed by the USGS/Group on Climate Hazards (GCH) science team that can be used in conjunction with surface models. This data covers most of the global land area (50° S to 50° N) and is characterized by low latency, high resolution (0. 05°), and long records (1981 to present). The data can be downloaded at https://data.chc.ucsb.edu/products/CHIRPS-2.0/. We used the global 0.05° × 0.05° CHIRPS daily precipitation data from 1981 to 2016, and obtained the CHIRPS spatial daily precipitation data of Taihu Lake basin by cropping and other pre-processing.

2.2.3 Multi-Source Weighted-Ensemble Precipitation (MSWEP)

The MSWEP precipitation information was obtained using the latest version 2 data released by the European Union Joint Research Centre (EU/JRC), which covers the global region with a spatial and temporal resolution of 3 h and 0.1° × 0.1°, respectively, and the data can be downloaded at http://www.gloh2o.org/. We used the precipitation data from 1979 to 2016 MSWEP periods and obtained the daily precipitation cumulatively based on the three hours of precipitation within each day. The raw data were stitched by MRT and cropped by ArcGIS to obtain the daily spatial precipitation data of MSWEP in the Taihu Lake basin.

2.3 GWRMP Merged Precipitation Estimation and Accuracy Assessment Method

2.3.1 GWRMP merging precipitation estimation

There are many precipitation fusion methods, but the basic idea is to use spatial precipitation products such as satellites as the initial estimation field of precipitation, calculate the difference between the rainfall observed at the same location station and the initial estimation field, use the empirical function method to calculate the weights of the different points and obtain the error field according to the weight interpolation error, and superimpose the error field and the initial estimation field to obtain the prediction field (Wang, 2019). Brunsdon, Fotheringham, and Charlton (1998) proposed a spatial regression model-geographic weighted regression model based on the spatial variable coefficient regression model using the idea of local smoothness, which applies to the quantitative simulation of non-stationary spatial relationships among variables. Hu, Yang, Wang, Yang, and Liu (2013) proposed a residual-based GWR rainfall fusion scheme, which was later widely used in rainfall fusion analysis calculation(Chao et al., 2018;). The GWRMP model mainly includes the following three steps: (1) obtaining the rainfall deviation between rainfall station precipitation and corresponding spatial precipitation. (2) Interpolating the local characteristics of spatial precipitation as weights and interpolating the geographically weighted regression of rainfall station precipitation deviation to obtain the spatial distribution of rainfall error. (3) Through the inverse operation of the rain gauge rainfall bias estimation method, the obtained spatial errors are superimposed with the spatial precipitation to obtain the geographically weighted regression-based fused precipitation data GWRMP. The specific calculation formula refers to the literature (Li, 2018).

2.3.2 Timing accuracy evaluation index system

We take the daily precipitation data of actual sites as the benchmark to evaluate the accuracy of daily precipitation of IDW, MSWEP, and GWRMP grids. The indicator system includes classification, volume classification, and quantitative indicators. Quantitative accuracy indicators reflected the accuracy of daily precipitation description by fused precipitation data. We used the common relative bias (Pbias), the coefficient of determination (RR)(He et al., 2017), Root Mean Square Error (RMSE), and Kling-Gupta efficiency (KGE)(Pool, Vis, & Seibert, 2018) metrics to assess the consistency of fused daily precipitation with the baseline precipitation in terms of time series distribution. The details of each accuracy index are shown in Equations (1) to (7) in the Appendix.

The classification index mainly reflects the ability of fused precipitation to recognize the occurrence of daily precipitation events. We used the probability of detection (POD) to determine the degree of under-reporting of daily precipitation events by MSWEP, and Heidke's skill score (HSS) to synthesize the ability of fused precipitation to estimate the occurrence of daily precipitation events in the raster of the Taihu Lake basin(Hu et al., 2013). The volumetric classification index is an extension of the classification index, which strengthens the ability to identify precipitation and overcomes the shortcomings of the traditional classification index to a certain extent. The study used the volumetric detection index (VHI) to assess the detection ability to merge precipitation to raster precipitation (AghaKouchak & Mehran, 2013). The specific formulas for each time-series accuracy index are detailed in Equations (8) to (10) in Appendix A.

2.3.3 Sliding space precipitation accuracy evaluation

The sliding window statistical method can quantify the spatial precipitation accuracy. We analyzed the relationship between GWRMP and IDW errors and the density of ground rain gauges. The precipitation accuracy of GWRMP is less affected by the density of rain gauges compared to IDW from a side perspective. The precipitation accuracy of GWRMP may be better than that of conventional interpolated precipitation in areas with uneven distribution of ground observations. Under ideal conditions, the higher the density of rainfall stations in the study area, the higher the spatial precipitation accuracy of IDW, and the smaller the difference between GWRMP and IDW.The above statistical results indicate that IDW has significant errors in spatial precipitation accuracy in the area observed by few rainfall stations, and its spatial precipitation information inversion capability is lower than that of GWRMP, which indirectly proves that GWRMP is better than IDW in describing spatial precipitation information. Figure 2 shows the specific process of sliding window statistical analysis of spatial precipitation accuracy. Considering that the statistical results may be affected by the window size, the study selects 2×2, 3×3, and 4×4 sliding windows. The window unit is moved from left to right and from top to bottom, counting the count gauges (CG) and mean deviation (MD) of the rainfall stations in each window.

[Insert Figure 2]

2.3.4 Systematic evaluation of precipitation accuracy with multi-method combinations

Interpolation methods are common to reflect spatial precipitation information in areas where rain gauges are densely and evenly distributed. The Taihu Lake basin has a large lake area where rain gauges are densely distributed but not uniform. Nevertheless, interpolated precipitation is the principal research method for spatial precipitation studies in the Taihu Lake basin. This study took the spatial precipitation obtained by the commonly used inverse distance interpolation algorithm as a reference, analyzed the differences in the accuracy of IDW, MSWEP, and ground checked GWRMP daily precipitation, and systematically evaluated the reliability of GWRMP daily precipitation. Considering the strong dependence of IDW precipitation on the location of rainfall stations, eight rainfall stations (covering seven water subdivisions in the Taihu Lake basin) are reserved for daily precipitation observation data as a reference for spatial precipitation accuracy calibration. Table 1 shows the spatial location information of the reserved rain gauges. The distribution of rain gauges in the Taihu Lake area is extremely uneven (Figure 1), and two rain gauges were reserved for calibration.

[Insert Table 1]

Advance rain gauge methods are affected by objective conditions such as topography, and the accuracy assessment results may have errors. We also applied the counting precision results of rain gauges within each water subarea to evaluate and compare the precipitation precision in all aspects of time series, space, and intensity. This method has the risk of high accuracy of IDW precipitation due to the dual role of interpolated precipitation IDW and accuracy assessment benchmark by 130 rain gauges. However, the accuracy evaluation results are much more statistically significant when the accuracy evaluation and zonal comparison are carried out based on more rain gauge precipitation samples. By the proposed method, we evaluate the accuracy of 130 rain gauges measured precipitation and its corresponding spatial precipitation MSWEP, GWRMP, and IDW. The results overall show the ability of each spatial precipitation data in capturing Spatio-temporal precipitation information in the Taihu Lake basin.

3. RESULTS AND DISCUSSION

3.1 Long series multi-source fusion precipitation data optimization

Multi-source ensemble precipitation combines the advantages of rainfall from different sources. However, there are large differences in the Spatio-temporal accuracy and time series length of precipitation data. For long-term precipitation change statistics in the Taihu Lake basin, we select the multi-source satellite fused precipitation CHIRPS from 1981 to present and the multi-source ensemble precipitation MSWEP v2.1 data since 1979 from numerous spatial precipitation data. We used 130 rainfall stations with measured daily precipitation in the Taihu Lake basin as the benchmark. Analysis of the precipitation detection accuracy of CHIRPS and MSWEP in terms of time series and rain intensity filtered the daily-scale spatial precipitation data that best characterize the Taihu Lake basin.

Using the high-density and long-series ground rain gauge observations, we took the seven hydraulic subareas in the Taihu Lake basin as the statistical unit. We plotted the scatter plots of sub-region rain gauge precipitation with the corresponding raster rainfall of CHIRPS and MSWEP v2.1, respectively (Figure 3). The results show that the consistency of daily precipitation with rainfall stations is significantly higher for MSWEP than CHIRPS. The correlation coefficients between MSWEP daily precipitation series and ground rain gauges observed precipitation are above 0.75 for all water subdivisions. The correlation coefficients between CHIRPS daily precipitation series and ground daily observed precipitation generally range from 0.61 to 0.63. It is worth noting that there is an underestimation of daily rainfall for the MSWEP phenomenon, a problem of systematic errors in this data, which has been proved in many studies (Akhilesh et al., 2017; Alijanian, Rakhshandehroo, Mishra, & Dehghani, 2019; Deng et al., 2018; Liu et al., 2020). In contrast, despite the underestimation of daily precipitation by MSWEP, the explanatory power of daily-scale precipitation changes on the surface is still higher than that of CHIRPS, which can reflect the trends of rainfall in the Taihu Lake basin.

[Insert Figure 3]

The results of the combined assessment of time series and classification accuracy (Figure 4) show that MSWEP has a higher ability to classify and identify and quantitatively characterize daily precipitation events in the Taihu Lake basin. MSWEP accurately characterizes rainfall information better than CHIRPS. The Pbias of CHIRPS is significantly lower than MSWEP in all water sub-regions except for ZX, probably due to the systematic errors prevalent in this data. MSWEP always underestimates surface precipitation to a certain extent, but CHIRPS does not have similar problems. The quantitative accuracy indicators RMSE, KGE, and RR all show that MSWEP precipitation is strongly synchronized with the baseline rainfall gauge precipitation in terms of time series variation (RMSE<10, KGE>0.6, RR>0.6), while CHIRPS is in low agreement with the measured rainfall (RMSE>10, KGE<0.5, RR<0.5). In particular, the RR of CHIRPS in each subzone is less than 0.2, indicating that CHIRPS cannot simulate the temporal variation of daily precipitation in the Taihu Lake basin. Besides, the MSWEP classification indexes POD > 0.75, HSS generally higher than 0.6, and VHI close to 1 are higher than the corresponding classification indexes of CHIRPS (POD lower than 0.6, HSS no more than 0.5, and VHI less than 0.75). The evaluation shows that MSWEP has strong classification recognition ability and precipitation characterization ability for daily precipitation events in the Taihu Lake basin. In general, the quantitative assessment and classification capability of MSWEP for daily precipitation events in the Taihu Lake basin is higher than that of CHIRPS.

[Insert Figure 4]

According to the precipitation classification standard of the China Meteorological Administration (GB/T 28592-2012, 2012), daily rainfall in the Taihu

Lake basin is classified into six levels: no rain (0 to 0.1 mm), light rain (0.1 to 10 mm), moderate rain (10 to 25 mm), heavy rain (25 to 50 mm), rainstorms (50 to 100 mm), and heavy rainstorms (> 100 mm). We counted the precipitation frequency of CHIRPS and MSWEP spatial precipitation in different precipitation intensity class intervals based on various levels of precipitation events at the actual rainfall stations, respectively (Figure 5).

The combined assessment of the ability of CHIRPS and MSWEP in the frequency of precipitation events of different intensities shows that both CHIRPS and MSWEP have the problem of underestimating the frequency of precipitation. CHIRPS is more accurate than MSWEP in evaluating days without rainfall, and MSWEP is more capable of capturing days with rainfall than CHIRPS. With the increase of precipitation intensity, MSWEP's ability to capture precipitation events decreases, and the frequency of captured precipitation tends to be higher than that of CHIRPS. The results indicate that CHIRPS is not sensitive to all levels of rainfall intensity, and the underestimation phenomenon is not related to rainfall intensity. The underestimation problem of MSWEP becomes more obvious with the increase of precipitation intensity, and there is the phenomenon of underestimating high precipitation. On the whole, CHIRPS can be used for the assessment of rainless days in dry areas and is suitable for drought monitoring, while MSWEP is more suitable for precipitation accuracy assessment in wet areas, but not for extreme precipitation analysis.

[Insert Figure 5]

3.2 GWRMP merged precipitation time series accuracy assessment

We selected MSWEP, which has a higher ability to characterize precipitation in the Taihu Lake basin, as the spatial daily rainfall data for this region. To address the common problem of precipitation underestimation in MSWEP, especially the weak ability to capture heavy rainfall. We used 130 long series of rain gauge data to correct the accuracy of MSWEP daily precipitation. Based on a geographically weighted regression model, we fused rain gauges with MSWEP daily precipitation to obtain fused precipitation data (GWRMP). The GWRMP time series are daily precipitation from May to September 1979 to 2016, and the spatial resolution is consistent with MSWEP at 0.1° × 0.1°.

Figure 6 is a scatter plot of the observed and corresponding location MSWEP, GWRMP, and IDW daily precipitation at the reserved rainfall stations from May to September 1979 to 2016. It shows that the consistency between the calibrated GWRMP daily rainfall and the measured value is the highest, and the correlation coefficient of each station reaches above 0.85. The consistent between MSWEP and measured precipitation is slightly lower, and the correlation coefficient between spatial rainfall and measured precipitation at each calibrated station ranges from 0.75 to 0.8. IDW has a high difference between the measured and estimated values at DTXS, located in the lake area of Taihu. Since the distribution of lake-area rain gauges is relatively sparse, inappropriately using IDW to characterize spatial precipitation.

[Insert Figure 6]

We evaluated the quantitative and classification accuracy metrics for spatial and measured precipitation at the eight sites (Table 2). It shows the strongest to weakest ability to characterize the measured precipitation information in the order of GWRMP (Pbias controlled within 12%), IDW, and MSWEP precipitation without error correction (Pbias between -9% and -22%). The consistent agreement between GWRMP daily rainfall and measured precipitation is the highest, with RR generally higher than 0.7 and RMSE controlled at 5~8 mm. The classification indexes show that GWRMP, IDW, and MSWEP have high synchronicity in precipitation frequency and rainfall characterization ability. The POD is generally higher than 0.85, the HSS is more than 0.6, and the VHI is 0.97~0.99. The above spatial precipitation data have a good classification and identification ability for daily precipitation events in the Taihu Lake basin, which can effectively characterize the precipitation changes during the study period. In summary, GWRMP has a higher classification and quantitative characterization ability for daily precipitation events in the Taihu Lake basin, and its daily precipitation accuracy is better than that of IDW and MSWEP.

[Insert Table 2]

In addition to the spatial precipitation accuracy assessment of the reserved rain gauges, we also develop a systematic accuracy assessment of rain gauge scale precipitation for different hydraulic divisions (methods see chapter 4.1). Figures 7 and 8 show the scatter plots and the time-series precision assessment of daily rainfall relative to the baseline precipitation for MSWEP, GWRMP, and IDW. The agreement between GWRMP, IDW, and the baseline rainfall gauge precipitation is high in all the seven hydraulic divisions in the Taihu basin. Both have strong explanatory power for surface daily precipitation events and rainfall variability. MSWEP data generally underestimate daily precipitation (-10% to -20%) in zonal simulations. IDW has minor overall errors, but daily precipitation errors are slightly higher in mountainous areas of western Zhejiang Province and Taihu Lake area than in other zoning areas due to topography and rain gauge distribution. The GWRMP fused precipitation compensates for the underestimation problem of MSWEP. However, the fusion algorithm uses the interpolation of the errors (more positive values) between the point-scale actual measurements and MSWEP to obtain the surface-scale errors, which may cause regional expanded systematic errors in the surrounding area with the imposed errors. It results in a certain degree of overestimation problem in GWRMP. We found that MSWEP can capture the precipitation events in the basin by accuracy evaluation, but there is a significant underestimation error. MSWEP has the lowest accuracy among the three types of spatial precipitation. The index evaluation results of IDW and MSWEP are similar for each hydraulic subdistrict in the Taihu Lake basin. However, there are differences in the quantitative index evaluation results in the Taihu Lake area, with the Pbias of IDW relative to the measured precipitation ranging from -15% to -20%, which is significantly higher than that of GWRMP (7% to 10%).

[Insert Figure 7]

[Insert Figure 8]

3.3 GWRMP merged precipitation intensity accuracy assessment

We analyzed the IDW, MSWEP, and GWRMP raster precipitation data in the Taihu Lake basin to accurately capture the frequency of different levels of rainfall using the reserved eight rainfall stations for various levels of precipitation events (Figure 9). The results of the analysis within each hydraulic subarea show that the frequency of different levels of rainfall during the flood season is no rain (60% to 65%), light rain (22% to 26%), moderate rain (7% to 9%), heavy rain (3% to 5%), rainstorms (1.4% to 1.7%), and heavy rainstorms (0.1% to 0.4%). The study analyzed the sensitivity of IDW, MSWEP, and GWRMP precipitation intensities using rain gauge observed precipitation as a benchmark. The results show that there are differences in their ability to capture the frequency of actual precipitation intensity. The IDW was subject to significant fluctuations due to the topography of the rain gauge distribution. DTXS, WL (Taihu Lake lake area), SP (mountainous region), and ZDG (higher elevation) were weak in capturing each precipitation intensity event compared to other zonal rain gauges. MSWEP and GWRMP observe a low frequency of rainless days, which were more sensitive to precipitation. With the increase of rainfall intensity, the sensitivity of GWRMP to precipitation events gradually increases, especially for precipitation levels above moderate rainfall. The rainfall intensity detection accuracy of GWRMP is significantly better than that of IDW and

MSWEP.

[Insert Figure 9]

Figure 10 shows the statistical results of the zonal accuracy assessment, and it is consistent with the results of the reserved rain gauge assessment. The probability of rainless weather in each subzone of the Taihu basin is about 60%, and ZX is around 55%. The light rainfall weather is between 20% and 30%. Moderate rainfall ranges from 7% to 9%, with ZX reaching 10%. The rainstorm and heavy rainstorm weather are 1% to 2% and 0.2% to 0.4%, respectively. There a high proportion of rainy days in the Taihu Lake basin during the flood season, with nearly half of the weather being rainy days. There are most rainy days in the flood season due to the topography of ZX. The highest frequency of light rainfall occurred in the Taihu Lake basin. With the increase of precipitation intensity, the probability of occurrence decreases significantly. There are some deviations in the frequency of different levels of precipitation in each subzone of the basin. Compared with other divisions, ZX has the highest precipitation frequency in all different levels. Spatial precipitation data have significant differences in their ability to characterize precipitation intensity in the Taihu Lake basin. The GWRMP and IDW are generally higher than MSWEP for different levels of precipitation intensity, and the detection accuracy becomes higher with increasing precipitation intensity. However, the difference in the frequency distribution of IDW precipitation intensity in each partition is significantly higher than that of GWRMP, indicating that the detection ability of IDW for precipitation intensity is less stable than that of GWRMP.

Combining the results of the two precipitation intensity accuracy assessments, we can see that GWRMP is more suitable for precipitation observation in the Taihu Lake basin. It can be applied to extreme rainstorm monitoring and provide a reference for storm flood analysis.

[Insert Figure 10]

3.4 GWRMP merged precipitation spatial accuracy assessment

Under the condition of high density and uniform distribution of ground rain gauge, the precipitation accuracy obtained by interpolation is relatively reliable. To explore the precipitation accuracy of GWRMP at the spatial scale of the Taihu Lake basin, we have selected IDW as the benchmark reference. The study analyzes the errors of GWRMP and IDW using the sliding window statistical method. We compare the differences of error values under different rain gauge density distributions to indirectly diagnose the accuracy of GWRMP in describing spatial precipitation information in the Taihu Lake basin. We compare the differences of error values under different rain gauge density distributions to indirectly diagnose the accuracy of GWRMP in describing spatial precipitation information in the Taihu Lake basin.

Figure 11 shows the rainfall station density and spatial precipitation deviation for different sliding windows in the Taihu Lake basin during the flood period from 1979 to 2016. The total bias of monthly precipitation for each sliding window is less than 60 mm, and the average value is less than 40 mm during the study period. With the increase of rain gauge density, the average bias between GWRMP and IDW tends to decrease. Because of the influence of IDW on the distribution of surrounding rain gauges, there are some error dispersion points between GWRMP and IDW under the same rain gauge density. The error dispersion points and dispersion values decrease as the density of the rain gauge increases. Comparing the statistical results of different window units, the average error within the 2×2 and 3×3 windows has a significant negative correlation with the rain gauge density. Within the 4×4 window, the larger the statistical rain gauge density is, the average error gradually tends to stabilize as a systematic error that is not affected by the rain gauge density. Specifically, when the window rainfall station density is between 0 and 10, the relative deviation is significantly negatively correlated with the rainfall station density. The spatial rainfall accuracy of GWRMP is better than that of IDW. When the window rainfall station density is greater than 11, the trend of decreasing relative deviation is not significant (the average error is 20 mm). The GWRMP spatial rainfall accuracy is relatively consistent with IDW.

To summarize, the GWRMP fused precipitation can accurately reflect the spatial precipitation information in the Taihu Lake basin with better accuracy than the commonly used IDW rainfall.

[Insert Figure 11]

4 CONCLUSIONS

We selected the long-term sequence of high temporal and spatial accuracy multi-source merged rainfall CHIRPS and MSWEP v2.1. It takes the actual precipitation measured by the rain gauge in the Taihu basin as the benchmark for accuracy assessment. Evaluation of daily precipitation detection accuracy on time series and rain intensity for two types of precipitation data. In this way, the daily spatial precipitation data were select to best characterize the daily scale spatial precipitation data in the Taihu Lake basin. Based on the GWR model, we use the precipitation information from the high-density rain gauge and the screened fused precipitation for calibration and revision. Comprehensive integration of GWRMP merged spatial daily precipitation data in the Taihu Lake basin. We conducted the accuracy evaluation of the spatially integrated precipitation data in the Taihu Lake basin, and the main conclusions are as follows:

(1) Both CHIRPS and MSWEP have the advantages of long time series and high spatial and temporal resolution, while MSWEP has the problem of underestimating precipitation due to systematic errors. However, in terms of daily precipitation characterization ability, the quantitative assessment and classification recognition of

daily precipitation events were significantly better than CHIRPS in the Taihu basin. CHIRPS was more suitable for drought monitoring because of its ability to capture rainless days. MSWEP has high precipitation capture ability, so it was useful for precipitation accuracy assessment in wet areas but was not preferable for extreme precipitation analysis.

(2) GWRMP was based on the MSWEP spatial precipitation distribution, with accuracy calibration by used rainfall station precipitation. It has compensated the problem of underestimation of precipitation by MSWEP.GWRMP provides continuous spatial precipitation distribution information of the watershed with a precipitation accuracy guarantee. Compared with IDW, which relies too much on the distribution of rainfall stations, GWRMP raster precipitation has a strong ability to characterize the spatial information in low-density rainfall station distribution areas.

(3) MSWEP has limited ability to characterize intense precipitation information, especially there was a significant underestimation of the frequency of precipitation of medium rainfall intensity and above. IDW has a weak ability for each precipitation intensity event in low-density areas. GWRMP has improved precipitation accuracy for each precipitation level after fusing ground observed rainfall information, and the precipitation accuracy increases significantly with the increase of precipitation amount. Compared with MSWEP and IDW, GWRMP was more suitable for intense precipitation monitoring and storm flood analysis in the Taihu Lake basin.

ACKNOWLEDGMENTS

The authors express their sincere acknowledgement for Dr. Hylke Beck and his team, the developer of MSWEP data, and wish to thank International Science Editing for their valuable comments on the editing of the manuscript. All authors have contributed substantially to this work, as specified below: conceptualization, J Zhao, L C Wang; methodology, J Zhao and L Yang; software, J Zhao and H Wu; validation, J Zhao, Q Q Yuan; formal analysis, J Zhao; investigation, J Zhao, Q Q Yuan;

resources, L C Wang; data curation, J Zhao; writing—original draft preparation, J Zhao, Q Q Yuan; writing—review and editing, J Zhao, Q Q Yuan, L C Wang, and L Yang; visualization, J Zhao, H Wu; supervision, L C Wang and L Yang; project administration, L C Wang; funding acquisition, L C Wang. This research was funded by the Strategic Priority Research Program of the Chinese Academy of Science (XDA230402), and the Fundamental Research Funds for the Central Universities (020914380082).

DATA AVAILABILITY

The gauged data of daily precipitation mainly originate from the hydrological yearbooks of Taihu Lake Basin, it can be found in the library of Hohai University, China. The MSWEP v2.1 data was provided by the European Union Joint Research Center (EU/JRC) (http://www.gloh2o.org/). The program codes of precipitation accuracy evaluation can be accessed on GitHub (https://github.com/Borealis-wxs/zjRepo/).

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APPENDICES

(1) Calculation formula for the time series quantitative accuracy index is as follows:

$$BR = \frac{\sum_{i=1}^{n}(G - \overline{G})(S - \overline{S})}{\sum_{i=1}^{n}(G - \overline{G})^2 \sum_{i=1}^{n}(S - \overline{S})^2} \times 100 \qquad (1)$$

$$RR = \frac{\left[\sum_{i=1}^{n}(G_i - \overline{G}_i)(S_i - \overline{S}_i)\right]^2}{\sum_{i=1}^{n}(G_i - \overline{G}_i)^2 \sum_{i=1}^{n}(S_i - \overline{S}_i)^2} \qquad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(G_i - S_i)^2}{\mathrm{n}}} \qquad (3)$$

$$KGE = 1\text{-}\sqrt{(\alpha - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \qquad (4)$$

$$\alpha = \sqrt{\frac{\sum_{i=1}^{n}(S_i - \overline{S})^2}{\sum_{i=1}^{n}(G_i - \overline{G})^2}} \qquad (5)$$

$$\beta = \frac{\overline{S}}{\overline{G}} \qquad (6)$$

$$\gamma = \frac{\sum_{i=1}^{n}(G_i - \overline{G})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \overline{G})^2 \sum_{i=1}^{n}(S_i - \overline{S})^2}} \qquad (7)$$

where S_i and G_i are fusion precipitation (MSWEP, GWRMP) and surface reference (rainfall station, IDW) daily precipitation, respectively; $\overline{S}$and $\overline{G}$ are the daily average values of fusion precipitation and surface reference precipitation; n = 5814, the total number of days from May to September, 1979 to 2016.

(2) Calculation formula of time series classification accuracy index is as follows:

$$\mathrm{POD} = \frac{n_{11}}{n_{11}+n_{01}} \tag{8}$$

$$\mathrm{HSS} = \frac{2(n_{11}n_{00} - n_{10}n_{01})}{(n_{11}+n_{01})(n_{01}+n_{00})+(n_{11}+n_{10})(n_{10}+n_{00})} \tag{9}$$

where n_{11} is the frequency of daily precipitation events detected by both the reference precipitation data and the fusion precipitation data; n_{01} is the frequency of daily precipitation events detected by the reference precipitation data in which the fusion precipitation data are not detected; n_{10} is the frequency of events detected by the fusion precipitation data, not detected by the reference precipitation data; and n_{00} is the frequency at which both baseline precipitation data and fusion precipitation data are detected as non-precipitation events.

$$\mathrm{VHI} = \frac{\sum_{i=1}^{n}(S_i|S_i \quad P_i\&G_i \quad P_i)}{\sum_{i=1}^{n}(S_i|S_i \quad P_i\&G_i \quad P_i)+\sum_{i=1}^{n}(G_i|S_i < P_i\&G_i \quad P_i)} \tag{10}$$

where S_i, and G_i represent the daily precipitation of the benchmark data and the daily precipitation of the fusion, respectively, and P_i is the daily precipitation event threshold. This study uses 0.1 mm as the threshold for rain.