Seasonal Error Component Analysis of the GPM IMERG Version 05 Precipitation Estimations Over Sichuan Basin of China

S. Tang, R. Li, J. He, X. Fan, H. Wang, and S. Yao

1College of Meteorological Observation, Chengdu University of Information Technology, Chengdu, China, 2Key Laboratory of Atmospheric Sounding, China Meteorological Administration, Chengdu, China, 3Department of Earth, Environmental, and Atmospheric Sciences, Western Kentucky University, Bowling Green, KY, USA

Abstract An error decomposition method is used to analyze and track seasonal error sources of the Integrated Multi-satellite Retrievals for the Global Precipitation Measurement (IMERG) Version 05 daily precipitation estimations, including Early-, Late-, and Final-run products (IMERG-DE, IMERG-DL, and IMERG-DF, respectively) over the Sichuan Basin of China from January 2016 to December 2018. The method decomposes the total errors into hit bias, missed precipitation, and false precipitation, which can be attributed to the satellite retrieval processes. Results show that in spring, all the estimations had serious overestimation in the northwest of the basin. The major error source is the hit bias of the intensity over 25 mm/day. In summer, the three IMERG estimations overestimated the precipitation in almost the entire Sichuan Basin, especially in the south and southwest. The principal determinants of the error sources are missed and false light precipitation (<25 mm/day), while hit bias and false precipitation are the leading error sources for the moderate precipitation (25–54 mm/day). In autumn, the IMERG-DF’s overestimation mainly comes from hit false moderate precipitation (15–64 mm/day), while the underestimation of the IMERG-DE and DL is mainly determined by missed and false precipitation of the precipitation less than 15 mm/day. In winter, the main contributors to the underestimation of the IMERG-DE and DL estimations are missed and false lighter precipitation (<8 mm/day). However, the total errors of the IMERG-DF are resulting from the three components canceling one another. Additionally, missed precipitation often takes place in the autumn and winter and false precipitation in summer and winter. The IMERG-DL shows better error control of positive hit bias and false precipitation than do the other estimations in summer.

1. Introduction

Human activities and socioeconomic stability in developing countries are strongly influenced by the availability and variability of precipitation (Kidd et al., 2009). Catastrophic natural disasters such as floods, mudslides, and landslides caused by precipitation have seriously affected people’s production and the safety of life and property in the past few decades in China, especially in topographically complex areas such as the Sichuan Basin (Ma & Zhou, 2015; Piao et al., 2010; Sadeghi et al., 2019; Shuhua, 2003). Therefore, accurate estimation of the spatial and temporal distribution characteristics of precipitation is conducive to the early warning and prediction of these natural disasters and provides more effective responding strategies for relevant emergency management (Hou et al., 2014). However, the precipitation estimation errors exist in precipitation retrieval algorithms in addition to the observation and instrumentation errors. At present, the ground rain gauge is considered the most direct and accurate way to observe precipitation. However, it cannot obtain the precipitation distribution information with high spatial resolution due to the sparse and uneven distribution of the observation sites, especially in the mountainous and complex terrain regions, such as western China (Ma et al., 2015; Seo & Krajewski, 2011). Another way of precipitation observation is from radar remote sensing including both ground-based radar and airborne radar. However, it has limitations in marine or mountainous regions because their detection range is greatly affected by site distribution and topographic barriers. Meanwhile, errors in precipitation measurements often result from the radar beam blockage, electromagnetic wave attenuation, and other interfering factors (Li et al., 2017; Mei et al., 2014). A last resort for precipitation detection is the satellite remote sensing. Although the spatial...
resolution of satellite-based precipitation estimations (SPEs) is not very high, satellite detection provides better spatial coverage and near-real-time precipitation data. Therefore, for the mountainous and complex terrain regions and marine and remote regions, the most reliable and stable way to obtain a comprehensive estimation of precipitation is the satellite-based remote sensing, which also provides more continuous monitoring and more stable operation state than other precipitation detection equipment (Hou et al., 2014; Lu et al., 2018; G. Tang et al., 2016).

Currently, two meteorological satellite missions equipped with active precipitation radar have provided very positive impacts on global precipitation estimation. The first one is the Tropical Rainfall Measuring Mission (TRMM), which was launched by the National Aeronautics and Space Administration (NASA) and National Space Development Agency (NASDA) in 1997 (Kummerow et al., 1998). Since then, by combining as many satellite platforms as available, various quasi-global SPEs with high spatiotemporal resolutions have been released publicly, including NASA’s TRMM Multi-satellite Precipitation Analysis (TMPA), NOAA's Climate Prediction Center MORPHing technique (CMORPH) (Joyce et al., 2004), University of California Irvine’s the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and the Global Satellite Mapping of Precipitation (GSMaP) of Japan Aerospace Exploration Agency (JAXA) (Kubota et al., 2007). The application of these SPEs has greatly promoted the advancement of atmospheric science and the early warning and prediction of natural disasters (Bitew et al., 2012; Kirstetter et al., 2013). However, TRMM’s limited detection capability for light precipitation (<0.5 mm/h) and solid precipitation has contributed to errors in precipitation estimation. Then, as TRMM’s successor, the Global Precipitation Measurement (GPM) Mission was jointly developed by NASA and JAXA and launched in 2014. The GPM core observatory satellite carry more advanced meteorological observation instruments such as the dual-frequency precipitation radar and 10–183 GHz microwave imager compared with the single frequency precipitation radar and 10–85.5 GHz microwave imager on TRMM. The application of these advanced instruments has improved the detection accuracy of light and solid precipitations. The U.S. GPM science team provides the Integrated Multi-satelliteE Retrievals for GPM (IMERG products), which include near-real-time (NRT) “Early” (IMERG-E) and “Late” (IMERG-L), and post-real-time (PRT) “Final” (IMERG-F) precipitation estimations. Compared with the TRMM precipitation products, the IMERG estimations have wider spatial coverage and finer spatiotemporal resolutions than that of the TRMM products (60°N to 60°S vs. 50°N to 50°S; 0.1° × 0.5 h vs. 0.25° × 3 h) (Huffman et al., 2015).

At this stage, a number of studies have shown that the performance of the IMERG estimations is better than TMPA in the capturing capability and precipitation estimation accuracy (Kim et al., 2017; Liu, 2016; Lu et al., 2018; G. Tang et al., 2016; Z. Wang et al., 2017; Xu et al., 2019). However, these studies mainly focused on the IMERG-F estimation. Only a few studies have evaluated all three types of the IMERG estimations, and these assessments usually used the continuous and contingency statistical metrics (Jiang et al., 2018; Sungmin et al., 2017; Z. Wang et al., 2017). For example, correlation coefficient, relative bias (RB), root-mean-square error, and probability of detection, false alarm ratio, and critical success index, and so forth have been used to evaluate the precipitation estimations and their deviations on different spatiotemporal scales. In addition, most existing research has mainly focused on evaluating the overall performance of the three IMERG estimations, but seldom carried out more in-depth analysis of the error sources. In order to better analyze and trace the error sources of SPEs, a particularly effective error decomposition scheme was first devised and applied to investigate the errors source of six high-resolution satellite-based precipitation data sets (Tian et al., 2009). Xu et al. (2016) later used the error decomposition method and investigated the error sources of the uncalibrated IMERG estimations over the eastern China during the warm seasons. Ning et al. (2017) comprehensively analyzed the error characteristics of the IMERG and GSMaP over eastern China. Su et al. (2018) systematically analyzed the error sources of the four GPM-based precipitation estimations, that is, the final-run uncalibrated IMERG Version 05, gauge-calibrated IMERG Version 05, IMERG Version 04, and GSMaP Version 07 over mainland China. However, for the precipitation estimations in the complex terrain regions over the southwestern China, little research focused on the error source analysis of all four seasons of SPE precipitations, especially for the NRT and PRT IMERG estimations. In addition, G. Tang et al. (2016) evaluated the IMERG hourly and daily estimations in southwest China, including part of the Sichuan Basin, based on the statistical metric of RB, which describes the error and bias of satellite estimations compared with gauge observations. Their results showed that the RB of the IMERG daily
estimations (23.86%) is higher than that of the IMERG hourly estimations (20.69%). Therefore, the IMERG daily precipitation estimations with greater RB should be selected first as the object of error analysis.

Based on the above analysis, taking the Sichuan Basin as a case of the complex terrain and mountainous area, and on the basis of our previous research (S. Tang et al., 2020), we conducted a more in-depth error components analysis of the three IMERG estimations. In this study, we applied the error decomposition scheme of Tian et al. (2009) to the three IMERG daily precipitation estimations, which include the IMERG-DE, IMERG-DL, and IMERG-DF (where “D” signifies “daily”) over the Sichuan Basin for analyzing the spatiotemporal and intensity distribution of error components during the four seasons from January 2016 to December 2018. Such an error decomposition yields less ambiguous assessment for data producers to infer the origin of the errors and for users to understand the unique and common strengths and weaknesses among these SPEs (Tian et al., 2009).

The remaining sections of the paper are structured as following: The study area, GPM IMERG precipitation estimations, and ground observations used for validation are introduced in section 2. The error decomposition scheme and data preprocessing method are described in section 3. Section 4 presents the results, including spatial characteristics of seasonal mean precipitation and the error components, temporal variations of the error components in different seasons, and intensity distribution of the total errors and their components for the three IMERG daily estimations. Finally, discussions and conclusions are provided in sections 5 and 6, respectively.

2. Study Area and Data Sets

2.1. Study Area

The study area is over the Sichuan Basin in China, which is located to the east of the Qinghai-Tibet Plateau and has a total area of 2.6 × 10^5 km² (103°03’ to 109°15’E and 28°15’ to 32°03’N), covering the central and eastern Sichuan province and most of the Chongqing city. The Sichuan Basin is surrounded by Qinghai-Tibet Plateau, Daba mountain, Huaying mountain, and Yunnan-Guizhou Plateau. The elevations of the surrounding mountains are mostly between 1,000 and 3,000 m above sea level, and the elevations of the basin floors are between 250 and 750 m above sea level. Its terrain contour is approximately in a diamond shape (Figure 1). Therefore, the study area can be divided into two parts: marginal mountains and the basin floor. Numerous studies show that, for the complex topography and geographic locations, heavy rains occur frequently in summer over the Sichuan Basin (Dan et al., 2018; Haoran et al., 2009; Luo et al., 2019). So it is easy to trigger geological disasters such as debris flow and landslide. Besides, close to 70% of the total precipitation occur at night, which is usually called “Bashan Yeyu” (Jiong, 1942), and mostly occur at the edge of the basin (Xue et al., 2012; Zhou et al., 2019).

2.2. GPM IMERG Precipitation Estimations

The IMERG is the Level 3 multisatellite precipitation product of GPM. It combines intermittent precipitation estimates from all passive microwave (PMW) sensors and infrared (IR) observations from geosynchronous satellites (Hou et al., 2014; Huffman et al., 2015). More detailed descriptions about the IMERG products and precipitation retrieval algorithm can be found in Huffman et al. (2015). Three types of precipitation estimations, including the NRT “Early Run” (IMERG-E) and “Late Run” (IMERG-L) estimations, and the PRT “Final Run” (IMERG-F) estimation, are provided by IMERG at different delay times depending on the complexity of their processing and generation strategies. In particular, the generation of IMERG-E estimation, which is released 4 h after real time, is mainly for users who need to preliminarily estimate the probability of flooding or geological disasters in time. The IMERG-L estimation is produced with approximately 12 h latency and mainly provided for weather forecasters, geological monitors, or other users. The climatological gauge calibration is not done for the NRT IMERG estimations in Version 05 due to the unavailability of long record of data needed for building the climatology. On the other hand, the NRT IMERG estimations are calibrated by adopting the Global Precipitation Climatology Project (GPCP) climatological data. As for the IMERG-F estimation, it takes the longest time (delay about 3.5 months) to generate after being calibrated with monthly Global Precipitation Climatology Centre (GPCC) analyses and used in some research that does not involve near-real-time application. For instance, instantaneous PMW precipitation estimates are only propagated forward in time by the morphing scheme of IMERG-E estimation, whereas both forward and
backward morphing schemes are employed in IMERG-L and IMERG-F estimations (Sungmin et al., 2017; S. Tang et al., 2020). Therefore, the IMERG-F estimation is supposed to be better than the two NRT IMERG estimations in describing the features and changes of precipitation structure and has more accurate precipitation information (Huffman et al., 2015). In addition, the IMERG precipitation estimations have a relatively finer spatial and temporal resolutions (0.1° and 0.5 hourly).

In this study, the research period is from January 2016 to December 2018. Moreover, the GPM daily IMERG-E, IMERG-L, and IMERG-F Version 05 data are used for tracing the error sources of seasonal precipitation estimation over the Sichuan Basin. The IMERG daily estimations are produced by accumulating the IMERG half-hourly data over 24 h, and the unit is mm/day. The IMERG products can be downloaded from the Precipitation Measurement Missions (PMM) website (https://disc.gsfc.nasa.gov/datasets/GPM).

2.3. Ground Observation Data Sets
The China Merge Precipitation Analysis (hereafter called CMPA) V1.0 product is used as the benchmark in this study. The CMPA has fine temporal and spatial resolutions (hourly and 0.1° × 0.1°), which is produced
by integrating the observations from more than 30,000 automatic meteorological stations (national and regional stations) in China and the CMORPH satellite precipitation product. The CMPA data sets are provided by the National Meteorology Information Center (NMIC) of the China Meteorological Administration (CMA) and can be downloaded from the website of China Meteorological Data Service Center (http://data.cma.cn). In order to generate the gridded CMPA data and ensure the data set consistency, validity, and reliability, the entire process includes four steps: (1) interpolating the refined values by using a modified climatology-based optimal interpolation (OI) algorithm on gauge data and carrying out the strict quality control including checks for abnormal values and spatiotemporal consistency (Shen, Feng, et al., 2010; Xie et al., 2007); (2) accumulating the CMORPH precipitation estimations with the half-hourly and 8 km spatiotemporal resolutions to an hourly resolution and resampling onto the 0.1° × 0.1° grids (Joyce et al., 2004); (3) correcting the systematic error of hourly CMORPH data by using the probability density function matching method based on the hourly gauge observations (Yu et al., 2013); and (4) merging the error-corrected CMORPH data with gauge-based analysis to generate the gridded merged precipitation products with hourly and 0.1° × 0.1° resolutions. More details on processing methods of the CMPA are described in Shen et al. (2014). The CMPA has been proved to have high accuracy in East Asia (Shen, Xiong, et al., 2010), especially in China, where it performs reasonably well and is able to capture the varying features of precipitation in heavy rain events (Shen & Xiong, 2016). Furthermore, the CMPA has already been used as the preferred reference data in the evaluation of many satellite precipitation products (Su et al., 2018; G. Tang et al., 2017; Z. Wang et al., 2017). In this study, the CMPA daily data are generated by accumulating the hourly data over 24 h, and the unit is mm/day.

3. Error Decomposition and Data Preprocessing

3.1. Error Decomposition

In order to quantitatively analyze and track the sources of the errors in the IMERG precipitation estimations, we adopt an effective error decomposition scheme, which was proposed by Tian et al. (2009) and has been used to evaluate the satellite precipitation estimations. According to this scheme, the total precipitation errors (hereafter referred to as TE) will be decomposed into three independent components, including the biases of hit precipitation (HB), missed precipitation (MP), and false precipitation (FP). First, a small precipitation threshold should be chosen, which is usually used to determine whether a precipitation event has occurred. In this paper, considering the detection resolution of rain gauges is 0.1 mm/h, we chose 2.4 mm/day as the threshold for daily precipitation events. Then, “hit” represents the precipitation events were detected by both IMERG and CMPA observations simultaneously, “missed” (or MP) represents the precipitation events that were only observed by CMPA but not detected by IMERG, and “false” (or FP) indicates the precipitation events that were only detected by IMERG but not observed by CMPA.

For a gridded precipitation field \( R(\vec{x}, t) \), we can derive a binary precipitation event mask \( P(\vec{x}, t) \),

\[
P(\vec{x}, t) = \begin{cases} 1 & \text{if } R(\vec{x}, t) \geq 2.4 \\ 0 & \text{if } R(\vec{x}, t) < 2.4 \end{cases}
\]

(1)

For the CMPA filed \( R_g(\vec{x}, t) \) and the satellite precipitation field \( R_s(\vec{x}, t) \), which are CMPA and IMERG daily precipitation estimations, respectively, their precipitation event masks are \( P_g(\vec{x}, t) \) and \( P_s(\vec{x}, t) \), respectively. Therefore, the hit mask \( P_{gs}(\vec{x}, t) \), missed mask \( P_{gs}(\vec{x}, t) \), and false mask \( P_{gs}(\vec{x}, t) \) can be defined as follows:

\[
\begin{align*}
P_{gs}(\vec{x}, t) &= P_g(\vec{x}, t) \times P_s(\vec{x}, t) \\
P_{gs}(\vec{x}, t) &= P_g(\vec{x}, t) \times P_s(\vec{x}, t) \\
P_{gs}(\vec{x}, t) &= P_g(\vec{x}, t) \times P_s(\vec{x}, t)
\end{align*}
\]

(2)

where \( P_g(\vec{x}, t) \) and \( P_s(\vec{x}, t) \) are the Boolean complement of the binary masks \( P_g(\vec{x}, t) \) and \( P_s(\vec{x}, t) \), respectively. Thus, the total errors, bias of hit precipitation, missed precipitation, and false precipitation are defined as follows (Tian et al., 2009):
\[
\begin{align*}
TE &= R_s(\vec{x}, t) - R_g(\vec{x}, t) \\
HB &= TE \times P_{gs}(\vec{x}, t) \\
MP &= -R_g(\vec{x}, t) \times P_{gs}(\vec{x}, t) \\
FP &= R_s(\vec{x}, t) \times P_{gs}(\vec{x}, t)
\end{align*}
\] (3)

Because three error components are independent to each other, it can be shown that

\[
TE = HB + MP + FP
\] (4)

In practice, the total errors and bias of hit precipitation could be either positive or negative values, which indicate that the precipitation is underestimated or overestimated, respectively. The missed precipitation is always negative, and false precipitation is always positive, which means that they could cancel each other. Tian et al. (2009) noted that the relationship of the three error components and total errors described in Equation 4 implies that any error components could have larger amplitudes than the total errors, and the smaller total errors do not necessarily mean that the satellite precipitation estimations have better estimation performance. Therefore, relying on the total errors alone cannot capture the source of error and is not enough to accurately evaluate the performance of the IMERG precipitation estimations. In view of this, separating the TE into three independent error components (HB, MP, and FP) is important not only for user to better understand the error but also for algorithm developer to trace the sources of errors and improve the quality of IMERG estimates.

3.2. Data Preprocessing

During data preprocessing, the independence of the CMPA data and the IMERG estimations should be analyzed first. The NRT IMERG estimations and the CMPA are obviously independent because there is no intersection between them. However, it is noteworthy that the IMERG-F is calibrated using GPCC monthly precipitation data from four International Exchange Stations (IES) over the Sichuan Basin (H. Wang et al., 2020), which accounts for only 0.1% of the 4,107 stations used in the CMPA. Therefore, we can reasonably consider the IMERG-F also being independent of the CMPA data. Second, in order to make a fair analysis of the errors of the IMERG daily precipitation estimations and minimize the impact of missing data on the results, we need to preprocess the IMERG and gridded rain gauge data to ensure their consistency and accuracy. The data preprocessing includes the following steps: (1) check the continuity of the three IMERG daily precipitation estimates and the CMPA data and eliminate the abnormal data that does not meet the climatic threshold inspection, station extreme value inspection, and spatiotemporal consistency inspection (Ren et al., 2010; Shen, Xiong, et al., 2010) and then set the abnormal and missing data to the null value; (2) find the locations in spatial and temporal sequences where the CMPA (IMERG) appear as null values and set the corresponding value of IMERG (CMPA) to the null as well; (3) make sure the same physical time is being used for the CMPA data and the IMERG estimations; and (4) combine the data for the corresponding season during January 2016 to December 2018 and generate the data for three springs (March, April, and May 2016–2018), summers (June, July, and August 2016–2018), and autumns (September, October, and November 2016–2018) and two winters (December 2016 and January and February 2017; December 2017 and January and February 2018).

4. Results

4.1. Spatial Analysis of Seasonal Mean Precipitation

To analyze the precipitation capture capability of the IMERG daily estimations between January 2016 and December 2018, the spatial distributions of seasonal mean daily precipitation derived from CMPA and all the IMERG daily estimations over the Sichuan Basin are illustrated in Figure 2. Obviously, the spatial patterns of CMPA in four seasons show that in spring, the precipitation intensity gradually decreases from the east and southeast to the northwest and southwest, and the highest precipitation area is concentrated in the east. However, the spatial distribution of summer precipitation is opposite to that of spring precipitation. For autumn and winter precipitation, the mean precipitation intensity of the whole region is relatively low. Moreover, the heavy precipitation mainly occurs in summer for most areas of the Sichuan Basin except for some eastern areas, where the heavy precipitation often takes place in spring. In addition, taking the
CMPA’s spatial distribution as a reference, the spatial distribution differences of the three IMERG daily estimations in four seasons are analyzed. For spring precipitation, all the three IMERG daily estimations can accurately capture the main characteristics of the spatial distribution in the northern, western, and southern regions of the Sichuan Basin. But they show obvious differences in the northeast and east, where the IMERG‐DF overestimates precipitation most significantly, while the IMERG‐DE captures more details of the true spatial distribution characteristics of precipitation. For summer, all the IMERG daily estimations show large overestimation in the entire basin, especially in the western edge of the basin where topographic precipitation often occurs. Therefore, the three IMERG daily estimations over the Sichuan Basin should be used with caution in summer. For autumn, the IMERG‐DE can accurately represent the true spatial distribution of precipitation over the Sichuan Basin, while the IMERG‐DF still overestimates the precipitation in the eastern region. For winter, although the differences of the precipitation capture ability between the three IMERG estimations are small, we can still find that the IMERG‐DF performs better among those estimations.

In general, for spring, summer, and autumn precipitations, the IMERG‐DE can more accurately reflect the true spatial distribution characteristics. For winter, the IMERG‐DF performs better than the NRT IMERG estimations, which suggests that the calibration using GPCC monthly observations intensifies the overestimation of the IMERG‐DF in the first three seasons and makes it to lose the spatial distribution characteristics of true precipitation (Z. Ma et al., 2020). However, the calibration improves the estimation accuracy of precipitation in winter. These conclusions can provide a basis for the study on the spatial distribution characteristics of precipitation over the Sichuan Basin.

4.2. Spatial Analysis of Seasonal Error Components

The spatial distributions of the total errors and their components, which are each accumulated in the corresponding season during the entire study period, are displayed in Figures 3–6.
Figure 3. The accumulated errors (columns) of three IMERG estimations (rows) for the three springs 2016–2018 over the Sichuan Basin: columns from left to right are (a, e, and i) total errors (TE), (b, f, and j) hit bias (HB), (c, g, and k) missed precipitation (MP), and (d, h, and l) false precipitation (FP), respectively; rows from top down are IMERG-DE, IMERG-DL, and IMERG-DF, respectively. The error components are related by $TE = HB + MP + FP$, all in mm.

Figure 3 displays that for spring, all three IMERG daily estimations show considerable similarities in their spatial distribution of the total errors and three components. The most obvious common feature is the significant overestimation over the northwest part of the Sichuan Basin (black circles). The overestimation over these areas is attributed primarily to false precipitation, followed by the positive hit bias. The false precipitation is largely focused on the northwest and south. On the other hand, many important differences exist between the three IMERG daily estimations. For false precipitation, the IMERG-DL shows a smaller bias than other IMERG estimations, especially over the central and eastern regions (black rectangles). This
shows the benefit of the added backward morphing and the bias adjustment using climatological gauge data schemes in reducing the bias of false precipitation for IMERG-DL. However, for hit bias and false precipitation, the IMERG-DF shows larger overestimation, which indicates that the revision of GPCC monthly observation intensifies the overestimation of hit precipitation and false precipitation, and expands the overestimation area, especially in the eastern and southeastern regions.

As shown in Figure 4, for summer, each product shows different spatial distribution characteristics from the corresponding products in other seasons. However, the similarity of the error features between the three IMERG daily estimations remains and is still noteworthy. Large-scale overestimation in the total bias almost occupies the entire Sichuan Basin, and substantial overestimation of the two NRT IMERG daily estimations...
takes place over the south and southeast and, to a lesser extent, the west, while the IMERG-DF shows severe overestimation in the southwest, west, and northwest. These overestimated regions are also reflected in the spatial distribution of the hit bias and false precipitation. In addition, the precipitation accumulation amplitude of missed precipitation is much less than that of false precipitation. By analyzing the spatial distribution difference of error components, it is found that the IMERG-DL shows better precipitation estimation performance in hit precipitation compared with the other two products, suggesting that the backward morphing scheme and bias adjustment with using climatological gauge data can effectively suppress the hit bias component but cannot significantly improve missed and false precipitation. Moreover, compared with the NRT IMERG daily estimations, the larger hit bias and false precipitation of the IMERG-DF are mainly concentrated in the edge of the southwest region (black circles), which indicates that the calibration of GPCC monthly observation causes a considerable overestimation of the topographic precipitation in the southwestern margin of the Sichuan Basin.

For autumn (Figure 5), the IMERG-DF shows significantly different spatial distribution of the total errors from the two NRT IMERG daily estimations. Specifically, the NRT IMERG daily estimations overestimate the precipitation over the northwest and the east but underestimate in other regions, while the IMERG-DF overestimates the precipitation in almost the entire Sichuan Basin. Additionally, all three IMERG daily estimations show severe overestimation in the northwest (black ellipses). After analyzing the distribution characteristics of the three error components, it is found that the cumulative amplitude of missed precipitation for the IMERG-DF is generally much less than that of false precipitation (red ellipses) and hit bias of almost the entire region is positive, which eventually leads to the overestimation in the entire region. However, for the NRT IMERG daily estimations, their cumulative missed precipitations have magnitudes that are greater than those of false precipitations in the southern and central regions of the basin, and the hit bias is also negative, which leads to underestimate the total precipitation in this region. According to Figure 2, the autumn precipitation over the Sichuan Basin is mainly moderate and light precipitation. As for the large cumulative missed precipitation, it may be related to the limited detection capability of the remote sensors for light precipitation.

Figure 6 presents that for winter, the spatial distributions of the total errors and components are very similar in all three IMERG daily estimations. Specifically, the distribution characteristics of the positive total precipitation bias are similar to that of false precipitation (black ellipses), while the spatial pattern of the negative total precipitation bias is similar to that of missed precipitation (black rectangles), and the accumulation of missed precipitation generally has a greater magnitude than that of hit precipitation. This presumably reflects IMERG’s insufficient ability to measure snowfall in winter or precipitation over snow/ice-covered land surfaces with PMW, or it is often related to low levels of precipitation capturing capability (Yu et al., 2013). In addition, the IMERG-DF, with smaller hit bias and false precipitation, performs better than the NRT IMERG daily estimations in estimating precipitation.

4.3. Temporal Analysis of Seasonal Error Components

In order to analyze the error characteristics of the IMERG DE, DL, and DF estimations during four seasons over the Sichuan Basin, we also study the error components as functions of seasons from January 2016 through December 2018 and draw the variation diagram of hit bias, missed precipitation, false precipitation, and total errors in four seasons. These error indicators, including three springs, summers, and autumns and two winters, show a relatively consistent trend of change in the corresponding season, so we only present in Figure 7 the results of the four seasons during March 2016 to February 2017. It is noteworthy that, to avoid losing details, the moving average or any smoothing are not applied to each time series, which is different from other studies such as Tian et al. (2009) and Su et al. (2018).

For spring precipitation, the three IMERG daily estimations have the similar variations in the corresponding error components, in which missed precipitation occurs in a limited time period with a small intensity. The probability of false precipitation is slightly higher than that of missed precipitation, but its contribution to the total errors is also limited. The amplitudes of hit bias and total errors are highly consistent, which means that the total errors are almost entirely determined by hit bias. It is noteworthy that compared with the NRT IMERG daily estimations, the IMERG-DF has significantly larger positive hit bias and smaller amplitudes of the negative hit bias in the corresponding times (e.g., times marked with the baby blue rectangles), which means that the hit bias of the IMERG-DF calibrated by the GPCC monthly gauge observation gets an
extra positive shift. This might be related to the set range of ratio values ([0.2, 3.0]) between the monthly satellite-gauge and the monthly accumulation of half-hourly multisatellite-only fields during the generation of the final IMERG estimations (Z. Ma et al., 2020). In particular, the cap of 3.0 might be too large for the precipitation over the Sichuan Basin.

As for summer precipitation, the three IMERG daily estimations have consistent variations in all error components. The total errors are primarily dominated by hit precipitation, as the missed precipitation and false precipitation are considerably small. Although both being small, the amplitudes of false precipitation are obviously higher than that of missed precipitation. Similar with the spring precipitation, all IMERG daily estimations in summer show large overestimations for hit precipitation. By comparison, the IMERG-DL presents a little better performance (with lower average intensity of false precipitation and positive hit bias) than the IMERG-DE and IMERG-DF, but the IMERG-DF performs slightly better than the NRT IMERG daily estimations on the underestimation of hit precipitation.

Figure 7. Time series of the error components (MP, FP, and HB) and total error TE for the three IMERG daily estimations (i.e., IMERG-DE, DL, and DF in left, middle, and right columns, respectively) in spring, summer, autumn, and winter (rows from top-down, respectively) of March 2016 to February 2017.
In terms of autumn precipitation, the frequency and amplitudes of missed precipitation are significantly higher than that of spring and summer precipitation, while false precipitation has a low probability of occurrence in most of the time, and its precipitation estimation error is lower than that of missed precipitation. This is also reflected in the consistent variations and amplitudes of hit bias and total error in the overestimation of precipitation. For the underestimated precipitation, the absolute values of total errors are sometimes less than that of hit bias value (baby blue circles), which means that the total errors of underestimation are mainly composed of hit bias and missed precipitation. Compared with the IMERG-DE and DL, the IMERG-DF, with the larger amplitude of the total errors and hit bias, overestimates precipitation more significantly, while presenting a slightly smaller precipitation underestimation and better error control ability for missed precipitation.

Regarding winter precipitation, large amplitudes (>0.5 mm/day) of missed precipitation (negative) and false precipitation (positive) rarely occur at the same time, implying that they do not cancel each other and result in much smaller total errors than the hit bias. Moreover, the bias of hit precipitation shows a small amplitude (<0.5 mm/day) during most of the time, which might be related to less precipitation in winter and leads to a small contribution to the total errors. Overall, the overestimation mainly comes from false precipitation, while the underestimation mainly comes from missed precipitation. Several factors may explain this phenomenon: In winter, solid precipitation or composite phase (solid and liquid) precipitation events may affect the detection capability of the microwave and infrared sensors of GPM and, consequently, lead to a severe underestimation of the hit precipitation (baby blue ellipses) or more missed precipitation events (Sharifi et al., 2016). The large size of fog or cloud droplets increased by the higher concentrations of aerosols in winter may intercept the ability of precipitation estimation by the IMERG, which may increase the false precipitation events (baby blue triangles) (Dipu et al., 2013). As for the error performance of the three IMERG daily estimations, the IMERG-DF presents a more severe overestimation and less severe underestimation of precipitation than the NRT IMERG daily estimations.

### 4.4. Intensity-Based Distribution of Error Components

To look further into the nature of the characteristics of error components and total errors in four seasons, we computed the accumulated total precipitation, hit precipitation, missed precipitation, and false precipitation as functions of various daily precipitation intensities. These accumulated precipitations are shown as distributions over daily precipitation intensities in Figures 8–11, respectively. Each accumulation distribution is computed over all the grid points with valid values over the Sichuan Basin for the three springs, summers, and autumns and two winters.

Figure 8 shows that for spring, the distribution of total precipitation over intensity is very similar to those of the three components, that is, hit, missed, and false precipitation; however, the overall amplitudes of the components are smaller than that of total precipitation. Meanwhile, the amplitudes of missed precipitation under the same intensity are slightly smaller than that of false precipitation. The IMERG-DF overestimates the precipitation at almost all intensities, while the NRT IMERG daily estimations overestimate the precipitation with intensity less than 11 mm/day (to the left of the vertical dashed line). This is mainly due to the fact that within this precipitation intensity range, although the cumulative precipitation of missed and false precipitation is relatively large, most of the time underestimation and overestimation can cancel one another, resulting in their limited contribution to the total cumulative precipitation. Therefore, the total errors are mainly from hit bias and the offset of missed and false precipitation. However, for the moderate to heavy precipitation (>25 mm/day) (baby blue rectangle), the cumulative precipitation of missed and false precipitation is very small, and the errors of the total cumulative precipitation are almost entirely due to the bias of hit precipitation.

Figure 9 clearly shows that for summer precipitation, all three IMERG daily estimations overestimate the total precipitation in the intensity spectrum. More specifically, considerable overestimation of precipitation, of which the maximum cumulative deviation exceeds 2.5 × 10^4 mm, is mainly concentrated in the light precipitation (<25 mm/day) (to the left of the vertical dashed line at 25 mm/day intensity). In addition, the underestimation caused by missed precipitation is far less than the overestimation caused by false precipitation, and false precipitation is mainly concentrated in the range of intensity less than 25 mm/day. Meanwhile, in this intensity range, the maximum cumulative deviation of hit precipitation between the three IMERG daily estimations and CMPA data is less than 0.5 × 10^4 mm (baby blue circle). Therefore,
Figure 8. Intensity-based distribution of the accumulated total, hit, missed, and false precipitations for the IMERG-DE, DL, and DF estimations. The results are computed from the three springs in the study period.

Figure 9. As in Figure 8. The results are computed from the three summers.
Figure 10. As in Figure 8. The results are computed from the three autumns.

Figure 11. As in Figure 8. The results are computed from the two winters.
for light precipitation, the major error sources of the overestimation are missed and false precipitation. For the moderate precipitation (25–54 mm/day), the total errors are mainly from hit and false precipitation, and for heavy precipitation (>54 mm/day), the total errors are only determined by hit precipitation. Figure 10 shows that in autumn, for the total precipitation and hit precipitation, the relatively large overestimation of the IMERG-DF is concentrated in the intensity range of 15–64 mm/day. However, the IMERG-DE and IMERG-DL can accurately estimate the precipitation in this intensity range. For light precipitation of less than 15 mm/day intensity, the cumulative missed precipitation of the IMERG-DF is generally lower than that of the NRT IMERG daily estimations. Conversely, the IMERG-DF has the largest cumulative false precipitation in this range. Therefore, the total errors of the IMERG-DF overestimation mainly come from hit and false precipitation of moderate precipitation (15–64 mm/day), while the underestimation of the NRT IMERG daily estimations is the result of the combined effect of missed and false precipitation of light precipitation (<15 mm/day).

Figure 11 displays that in winter, for the total precipitation, the overestimation of the IMERG-DF is concentrated in the intensity range of 8–16 mm/day. For light precipitation with intensity less than 8 mm/day, all the IMERG daily estimations show underestimation. By comparing the cumulative amplitudes of hit, missed, and false precipitations, it is found that for the intensity less than 8 mm/day, the overall amplitudes of hit precipitation are significantly smaller than that of missed and false precipitation. Meanwhile, the amplitudes of missed precipitation are larger than that of false precipitation. However, for the precipitation in the intensity range of 8–16 mm/day, the amplitudes of missed and false precipitation for all the IMERG daily estimations are similar. Therefore, the underestimation of the NRT IMERG daily estimations is mainly determined by missed and false precipitation of light precipitation (<8 mm/day), while the total errors of the IMERG-DF along the entire intensity spectrum are mainly from the three components canceling one another.

5. Discussion

We adopted the error decomposition scheme from an earlier research (Tian et al., 2009), in which the total errors are decomposed into three independent components: hit bias, missed precipitation, and false precipitation corresponding to the satellite-based retrieval processes. This method can identify the contributions to the total errors of the precipitation estimations from the three components not only in spatial and temporal error analysis but also in the analysis of error variation with precipitation intensity and has more effective error tracking capability than the conventional deviation analysis (Su et al., 2017; G. Tang et al., 2017; Yuan et al., 2017).

The results of this study show that the error components of the three IMERG estimations present notable differences throughout the four seasons. These error components can show better correspondence to the retrieval steps than more conventional approaches and provide evidence for data producers to infer the sources of errors (Tian et al., 2009). For example, missed precipitation or false precipitation may be introduced in detecting raining or no-raining of PMW and IR. Besides, hit bias may exist for establishing the relationship between remote observation and surface rain rates and calibrating the IMERG products using the microwave and the surface gauge observations.

In the first three seasons from spring to autumn, the IMERG-DF presents more significant overestimation than the NRT IMERG estimations. This phenomenon is consistent with our previous research on the evaluation of the three IMERG hourly estimations over the Sichuan Basin, where the RB of the IMERG-HF (“H” signifies “hourly”) product exhibits a significant overestimation in the first three seasons (21.49% in spring, 22.49% in summer, and 17.77% in autumn) than the IMERG-HE and IMERG-HL products but only a slight overestimation (3.87%) in winter (S. Tang et al., 2020). In addition to our researches, G. Tang et al. (2016) also evaluated the IMERG-DF over the southwestern part of China by using the ground gauge observations. Their results indicated that the IMERG-DF showed great overestimation with the RB up to 23.86%. Ma et al. (2020) found that the IMERG-F calibrated by using the monthly GPCC observations significantly overestimates the precipitation in the tropical rain range along Indonesia and the southern Himalayas with complex terrain.
Several factors may explain this phenomenon. Shen, Feng, et al. (2010), Su et al. (2018), and Prakash et al. (2019) indicated that an increase in weather station density is very important to improve the quality of the precipitation analysis. However, only four IES are provided by GPCC over the Sichuan Basin, meaning that relatively sparse stations further limit the performance of the calibration algorithm (H. Wang et al., 2020). Besides, the IES’s observations in and around the basin may vary considerably due to their large elevation differences. Therefore, the interpolation scheme of GPCC depending on these IES may bring a large deviation to the observed values within the basin. And then the set range of ratio values ([0.2, 3.0]) between the monthly satellite gauge and the monthly accumulation of half-hourly multisatellite-only fields during the generation of the final IMERG estimations may be inappropriate. The cap of 3.0 may lead to severe precipitation overestimation. By contrast, the Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE, 0.25° daily) has been demonstrated to replicate ground truth observations very well (Duncan & Biggs, 2012). Z. Ma et al. (2020) compared the monthly Asian mean precipitation estimates of both APHRODITE and GPCC from 1951 to 2015 and found that the GPCC overestimates the precipitation by more than 30% compared with APHRODITE.

For the moderate and strong precipitation (>25 mm/day) in the first three seasons, the overestimations of all the IMERG daily estimations are mainly from hit bias and false precipitation, which are probably caused by the undersampling of short-lived thunderstorms and degrading of IR-PMW detection capability (Tian et al., 2009). Besides, the scale of convective precipitation may be smaller than the resolution of GPM, which may also result in large hit bias (Sharifi et al., 2016). For the winter season, missed precipitation and false precipitation are the dominant error sources for the underestimation and overestimation of all the IMERG daily estimations, respectively. The most likely reasons are that the remote sensors of GPM cannot capture snowfall or have very limited capability to measure rainfall over snow/ice-covered land surfaces, which will lead to the occurrence of missed precipitation events. Additionally, thick fog often occurs over the Sichuan Basin, especially on the edges of the basin. So the sizes of fog or cloud droplets that were increased by higher concentrations of aerosols may intercept the capability of precipitation estimation by the IMERG estimations, which leads to false precipitation (Dipu et al., 2013). On the other hand, the techniques for merging multiple remote sensing data could also be a source of errors. For example, the improved morphing algorithm of CMORPH improves the probability of precipitation detection, leading to over-detection of precipitation events, possibly introducing more false precipitation events, which then results in overestimation of precipitation (Ma et al., 2020; Tian et al., 2009).

In summary, the results of the error component analysis can provide evidence, advice, and feedback, not only for the GPM IMERG producers to identify sources of error in their products but also for the meteorology-related researchers to choose the right data when studying seasonal precipitation over the basin and for other comparable regions. However, we want to point out that this error decomposition scheme cannot directly attribute or connect the error components to any specific sensors or processing stages. This is because the generation of the IMERG estimations is a several-step process including merging and blending of multisource data (e.g., dual-frequency precipitation radar, PMW imager, multiple partner PMW instruments, and IR), and error messages caused by a single sensor may be overwhelmed or offset in data processing. Additionally, in the future in-depth tracking and analysis of precipitation estimation errors, the retrieval algorithms of IMERG Level 2 products (e.g., the dual-frequency radar's reflectivity factor and rainfall drop size distributions) should be assessed by comparing with the observation of ground-based weather radar and raindrop spectrometer. These investigations may provide the underlying insights of how the uncertainty propagates to the IMERG Level 3 precipitation products (Su et al., 2018).

6. Conclusions

In this study, we comprehensively analyzed the error characteristics of the GPM IMERG daily precipitation estimations over the Sichuan Basin during the four seasons from January 2016 to December 2018 (please see supporting information Figures S3–S11). The main conclusions are summarized as following:

1. For the three seasons of spring, summer, and autumn, the IMERG-DE can more accurately capture the characteristics of spatial distribution of average precipitation than other IMERG estimations. However, in winter, the IMERG-DF shows better capturing capability. It is worth noting that in summer, all three products significantly overestimate the topographic precipitation that often occurs on the southwest edge
of the Sichuan Basin. Hence, the application of the IMERG daily estimations should be used with caution when studying precipitation in this area.

2. The significant overestimation of the three IMERG daily estimations for spring and autumn precipitation over the northwest of the Sichuan Basin can be traced back to significant false precipitation and noticeable positive bias of hit precipitation, while the overestimation of winter precipitation is almost all from false precipitation. As for summer precipitation, the significant overestimation of the NRT and PRT IMERG daily estimations is mainly concentrated in the south and southwest, respectively. Much of the significant overestimation over these regions is the comprehensive impact of positive hit bias and false precipitation, although missed precipitation may counteract some of this impact. Additionally, the IMERG-DL shows better performance in estimating hit precipitation, while the IMERG-DF exhibits severer hit bias and larger false precipitation than the NRT estimations for topographic precipitation, which often occurs in the southwest margin of the Sichuan Basin.

3. Hit bias is the most important contributor to the total errors of the precipitation in the first three seasons. However, for winter, the major error sources of the IMERG estimations are missed and false precipitation. Missed precipitation often takes place in autumn and winter and false precipitation in summer and winter. From the perspective of the intensity-based distribution, missed and false precipitation are the main error sources for summer light precipitation (<25 mm/day), while the hit bias and false precipitation are the leading error sources for the moderate precipitation (25–54 mm/day). For summer heavy precipitation (>54 mm/day), the overestimation of all three IMERG daily estimations is only determined by hit bias. For autumn precipitation, the underestimation of the NRT IMERG estimations mainly comes from missed and false light precipitation (<15 mm/day), and hit bias and false moderate precipitation (15–64 mm/day) are the main contributors to the overestimation of the IMERG-DF. In winter, the major error sources of the NRT IMERG estimations are missed and false precipitation for lighter precipitation (<8 mm/day), while the total errors of the IMERG-DF are jointly contributed by the three components canceling one another.

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