Tracking the error sources of spatiotemporal differences in TRMM accuracy using error decomposition method

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ABSTRACT

Tropical Rainfall Measuring Mission (TRMM) products are widely utilized, but the causes of the differences in their spatiotemporal accuracy require further investigation to improve satellite precipitation estimation. In this study, the spatiotemporal accuracy of TRMM 3B42 V7 data was systematically evaluated using the rain gauge data of the densely gauged Xiangjiang River basin, a humid region in South China. The effects of the precipitation intensity and elevation on different error components derived from the error decomposition method were analysed to reveal the causes of spatiotemporal differences of the data errors. The results showed the following. (1) TRMM performs better in the wet season than in the dry season, and it underestimates precipitation in winter and in high-elevation areas. (2) Precipitation intensity directly influences the occurrence and magnitude of error components. Most of the missed precipitation (precipitation detected only by rain-gauged data) and false precipitation (precipitation detected only by TRMM data) occur in low-intensity precipitation events. Hit events (precipitation detected by both TRMM and rain-gauged data) tend to overestimate low-intensity precipitation and underestimate high-intensity precipitation. Elevation has no direct relation with daily bias, but affects the distribution of occurrence and intensity of precipitation events. (3) Missed precipitation is the main contributing source of error in winter. The negative error increases in high-elevation areas, which is contributed by the larger proportion of high intensity hit precipitation and the missed events. This study is not only beneficial for understanding the effect of topography and climate factors on the accuracy of TRMM precipitation data but also provides a reference for the application and error improvement of satellite precipitation products.

Key words | elevation, error decomposition, precipitation intensity, satellite precipitation estimation, spatiotemporal accuracy

INTRODUCTION

The accurate measurement of precipitation in time and space is important for many applications, including meteorological and climatological forecasting, hydrological simulation, agricultural practice, water resources management, etc. Traditionally, the most widely used precipitation measurement is rain gauge observation, which can capture accurate point measurements. However, gauged data need to be interpolated to achieve the spatial distribution of precipitation in a basin or a region, and their accuracy has been proven to be limited by the sparseness and unevenness of the rain gauge network (Camera et al. 2014; Girons Lopez et al. 2015). In recent years satellite-based precipitation estimations have provided effective ways to obtain global precipitation coverage with high spatiotemporal resolution, which has become a focus of attention (Huffman et al. 2001; Ebert et al. 2007; Katirae-Boroujerdy et al. 2015). As outputs
of one of the most recognized satellite precipitation estimations, the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) products (Huffman et al. 2007) have been widely studied and applied in various fields, including meteorology and climatology, agriculture, hydrology, and disaster management (e.g. Su et al. 2008; Bitew & Gebremichael 2011; Lemons et al. 2012; Armajanos & Fisher 2014; As-syakur et al. 2014).

Although the TRMM satellite re-entered the Earth’s atmosphere in June 2015, the unique scientific data produced by TRMM still play an important role in the research based on satellite precipitation measurement technology. The accuracy evaluation and error analysis of TRMM data not only are helpful for data correction but also give guidance for data application. As a successor to TRMM, the Global Precipitation Mission (GPM) has released only a short period of precipitation data (from 2014 to the present), and its retrieval algorithm is still under improvement. Therefore, to achieve a better transition from the TRMM era to the new GPM era, in-depth analysis of the influencing factors and error sources of TRMM should be conducted to provide valuable references to data producers and algorithm developers for further improvement.

Many studies have been conducted which seek to accurately validate satellite precipitation estimation all over the world by using ground observation. Many of these indicated that the TMPA research products (3B42 V6 and V7) outperform their corresponding real-time counterparts (RTV6 and RTV7) because of data adjustment using the monthly gauged dataset (Liu 2015; Yong et al. 2016). The newer version V7 performs better than the previous V6 because of the improved algorithm and the updated data inputs (Chen et al. 2013a, 2013b; Zulkafli et al. 2014). In addition to the intra-comparison among the different TRMM products, 3B42 V7 data also perform better than other satellite precipitation products (e.g., CMORPH, PERSIANN, etc.) and show relatively greater consistency with gauged data, especially on larger spatiotemporal scales (Mei et al. 2014; Tong et al. 2014). Moreover, TRMM accuracy is found to be related to latitude, topography and climate, which all display obvious spatiotemporal uncertainty (Chen et al. 2013c; Gebregiorgis & Hossain 2013; Cai et al. 2015; Mantas et al. 2015). The overestimation and underestimation of TRMM precipitation data vary from region to region (Milewski et al. 2015; Zhang et al. 2016). Inconsistent performance of TMPA 3B42 data can be found in wet and dry seasons (Chen et al. 2013a, 2013b; Li et al. 2013; Cai et al. 2016). Therefore, some studies attempted to examine the effect of physical factors on TRMM accuracy. Evaluation results of Cai et al. (2016) in Northeast China indicated that the correlation between TMPA V7 product and rain gauge data increases with elevation. However, a study in Morocco by Milewski et al. (2015) found that the correlation between TMPA satellite products and gauge precipitation data decreases with the increase in elevation, and that better performance of TMPA precipitation products is found in regions with larger annual precipitation. This inconsistency in the effect of elevation on satellite precipitation performance requires in-depth investigation.

As for the precipitation intensity, most studies (e.g., Chen et al. 2013c; Tan et al. 2015) found consistently that TRMM 3B42 data could overestimate low precipitation but underestimate high precipitation. Some studies attempted to adjust the bias of satellite precipitation products through bias correction (Roy et al. 2017) and data assimilation (Li & Shao 2010; Nerini et al. 2015). However, these bias adjustments are based on ground precipitation observation and data error characteristics. To systematically analyse the errors embedded in satellite precipitation products, Tian et al. (2009) proposed a methodology to decompose total errors into hit events (precipitation detected by both TRMM and rain-gauged data), false precipitation (detected only by TRMM data) and missed precipitation (detected only by rain-gauged data), and found that the amplitude of individual error components is sometimes larger than the amplitude of the total errors because of the mutual cancellation of the three error components. Yong et al. (2016) adopted this method to quantify the error over diverse climate regimes and found that the error components resulting from diverse retrieval processes exhibit significant regional and seasonal differences. Their study recommended that future efforts should pay attention to the improvement of hit bias in humid regions, the false error in arid regions, and the missed snow events in winter.

Although much effort has been put into the evaluation of the TMPA products, there are still some issues worthy of in-depth exploration. First, the analysis of spatiotemporal differences of TRMM accuracy should be continually examined because they can help to determine the factors affecting
data accuracy. Second, the effect of the influencing factors on the errors must be considered more fully. On the one hand, most previous studies only analysed the relationship between the influencing factors and accuracy assessment indices but rarely considered how these influencing factors affect the errors. It is worth noting that the analysis of error characteristics can directly contribute to the improvement of the satellite-based precipitation retrieval algorithm and bias correction techniques. On the other hand, the error components from diverse sources directly related to the satellite retrieval process were not widely examined. Moreover, the relationship between the influencing factors and the diverse-source error components are rarely investigated. To our knowledge, the use of this relationship in explaining the differences in spatial and seasonal distribution of error components (hereafter referred to as error-spatiotemporal differences) has not been seen in previous literature. Tracking the sources of error-spatiotemporal differences and investigating the dependency of diverse error components on topography and climate can provide a basis for the further improvement of satellite precipitation estimation accuracy. Therefore, comprehensively considering the issues above is necessary for the systematic and scientific evaluation of TRMM. All of these factors have motivated the current study.

Therefore, the objectives of this study are as follows: (1) to systematically evaluate the spatiotemporal accuracy of the TRMM 3B42V7 dataset over a densely gauged basin; and (2) to analyse the relationship between the error components and the influencing factors to explain the causes of the distribution of error components in time and space. The rest of this paper is organized as follows. The study area and data are presented in the next section; then the methodology used in the study is briefly introduced; then, results and discussion are presented; and the paper’s conclusions are set out in the final section.

STUDY AREA AND DATA

Study area

This study was conducted in the Xiangjiang River basin, which is located between longitudes 110°31′E and 114°00′E and latitudes 24°31′N and 29°00′N, in a humid region in South China. The Xiangjiang River is one of the seven main tributaries of the Yangtze River, the longest river in China with a total length of 6,300 km. It originates from Lingui County in the Guangxi Autonomous Region, flows northward through Hunan Province, and finally runs into the Dongting Lake in the middle stream of the Yangtze River. The main stream of the Xiangjiang River is 856 km in length and covers a drainage area of 94,660 km². As shown in Figure 1, the basin is abundant with tributaries and surrounded by mountains to its east, south, and west, with hills upstream and plains downstream. Basin elevation varies from 2,100 m a.s.l. in the southern mountainous region to near sea level at the outlet of Dongting Lake. The basin is influenced by the southeast monsoon during summer and controlled by the Mongolia high-pressure system during winter (Zeng et al. 2016). The mean annual precipitation is about 1,500 mm and is mostly concentrated in the rainy season from April to August. The mean annual temperature is around 17°C, with the average temperature of the coldest month (January) as 4°C.

Data

The precipitation datasets used in this study are the TMPA 3B42V7 data and rain gauge data, which covered the period of 1 January 2006 to 31 December 2014 and a spatial range of 140 grids (0.25° × 0.25°) over the Xiangjiang River basin. The Digital Elevation Model (DEM) data were also collected to represent the topographic relief of the study area. The related introduction and preparation of these data are as follows.

The TMPA 3B42V7 data were obtained from https://disc2.nascom.nasa.gov/data/s4pa/TRMM_L3/TRMM_3B42/. The spatial resolution of the 3B42V7 is 0.25° × 0.25°, and the temporal resolution is 3 hours. Specific descriptions of the dataset are available at http://trmm.gsfc.nasa.gov. The 3B42V7 data were converted from the 3-hour precipitation rate into daily precipitation data in this study (processed 3B42V7 daily precipitation data are hereafter abbreviated as TRMM data).

The ground reference data used in this work are based on the daily precipitation data derived from 281 rain gauges. The rain gauge data from the Hydrological Year
Book were provided and quality controlled by the Hydrology Bureau of Hunan Province, China. Note that the TRMM data represent grid homogenization data and the rain gauge data are point samples. To make the two datasets comparable, rain gauge data need to be pre-processed. The ordinary kriging method (ORK) was considered to be a robust method for daily precipitation interpolation (Ly et al. 2014). Therefore, this study adopted the commonly used ORK method (Krige 1951) to interpolate the rain-gauge data into a 1 km × 1 km grid system covering the study area. Then, the interpolated precipitation data within each 0.25° × 0.25° grid were aggregated into an average value to match the TRMM data. Here, the resultant precipitation data are used as the ground validation data (later called the GV data). The GV data are considered to characterize the actual daily precipitation of this basin because of the high density (three stations per 10^3 km^2 approximately) and uniform distribution of rain gauges in the Xiangjiang River basin (Figure 1).

The ASTER GDEM V2 Digital Elevation Model of the Xiangjiang River basin was downloaded from the Geospatial Data Cloud site, Chinese Academy of Sciences (http://www.gscloud.cn). In this study, the DEM data with a 30 m spatial resolution were resampled into a 0.25° × 0.25° resolution, which represents the average elevation of each TRMM grid.

**METHODS**

The accuracy assessment of the precipitation amount estimation and precipitation event detection is based on a statistical analysis method using continuous statistical indices and categorical statistical indices. The error decomposition method is used to analyse the TRMM data bias.

**Statistical analysis method**

The several continuous statistical indices (Table 1) were introduced to evaluate the accuracy of precipitation amount estimates. The linear correlation coefficient (CC) and the Nash–Sutcliffe efficiency (NSE) denote the degree of consistency between the TRMM data and the GV data. The mean error (ME) and the mean absolute...
error (MAE) represent the magnitude of the deviation of the TRMM data from the GV data. The relative error (RE) and the normalized mean absolute error (NMAE) reflect the degree of relative deviation of the TRMM data to GV data (Chen et al. 2010).

To determine the occurrence of precipitation events, this work used 1 mm/d as the daily precipitation threshold to distinguish rain and no-rain, as in some previous studies (Tian et al. 2009; Moazami et al. 2013). Moreover, the Boolean values (1 for rain, 0 for no-rain) are adopted to represent the precipitation conditions recorded by the TRMM or GV data. Thus, the precipitation events are divided into the following four events (see Table 2 for details): (1) hit events represent the precipitation which is detected by both GV data and TRMM data; (2) false events indicate the precipitation detected only by the TRMM data; (3) missed events refer to the precipitation detected only by the GV data; and (4) no rain events occur when no rain is reported by both datasets. Three categorical statistical indices are used for assessing the accuracy of precipitation events detection in Table 1. These indices are the probability of detection (POD), which reflects the ability of TRMM data in detecting precipitation and the possibility of missing precipitation, the false alarm rate (FAR), which indicates the degree of false alarm, and the Heidke skill score (HSS), which gives a

### Table 1 | Evaluation indices used in this study

<table>
<thead>
<tr>
<th>Indices</th>
<th>Equations</th>
<th>Explanation</th>
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<tbody>
<tr>
<td>CC</td>
<td>$CC = \frac{\sum_{i=1}^{n} (T_i - \overline{T})(G_i - \overline{G})}{\sqrt{\sum_{i=1}^{n} (T_i - \overline{T})^2} \sqrt{\sum_{i=1}^{n} (G_i - \overline{G})^2}}$</td>
<td>Correlation Coefficient</td>
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<tr>
<td>NSE</td>
<td>$NSE = 1 - \frac{n}{\sum_{i=1}^{n} (G_i - \overline{G})^2}$</td>
<td>Nash-Sutcliffe Efficiency Coefficient</td>
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<td>ME</td>
<td>$ME = \frac{1}{n} \sum_{i=1}^{n} (T_i - G_i)$</td>
<td>Mean Error</td>
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<tr>
<td>MAE</td>
<td>$MAE = \frac{1}{n} \sum_{i=1}^{n}</td>
<td>T_i - G_i</td>
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<tr>
<td>RE</td>
<td>$RE = \frac{\frac{1}{n} \sum_{i=1}^{n} (T_i - G_i)}{\overline{G}} \times 100% = \frac{\frac{1}{n} \sum_{i=1}^{n} (T_i - G_i)}{\sum_{i=1}^{n} G_i} \times 100%$</td>
<td>Relative Error</td>
</tr>
<tr>
<td>NMAE</td>
<td>$NMAE = \frac{1}{n} \sum_{i=1}^{n}</td>
<td>T_i - G_i</td>
</tr>
<tr>
<td>POD</td>
<td>$POD = \frac{n_{11}}{n_{11} + n_{01}}$</td>
<td>Probability of Detection</td>
</tr>
<tr>
<td>FAR</td>
<td>$FAR = \frac{n_{10}}{n_{11} + n_{10}}$</td>
<td>False Alarm Ration</td>
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<td>HSS</td>
<td>$HSS = \frac{2(n_{11}n_{00} - n_{10}n_{01})}{(n_{11} + n_{01})(n_{01} + n_{00}) + (n_{11} + n_{10})(n_{10} + n_{00})}$</td>
<td>Heidke Skill Score</td>
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Where $n$ represents the length of precipitation data series; $G_i$ and $T_i$ are the $i^{th}$ values of GV data and TRMM data; $\overline{G}$ and $\overline{T}$ are the mean values of GV data and TRMM data; meanings of $n_{11}$, $n_{01}$, $n_{10}$, $n_{00}$ are annotated in Table 2.
comprehensive description of the ability to capture precipitation events (Wilks 2006; Hyvärinen 2014).

Error decomposition

In this study, an effective method of error decomposition (Tian et al. 2009) is adopted to further explore the composition and the source of satellite precipitation estimation errors. With this method, the total bias (TBIAS), which is calculated as TRMM data minus GV data for all the precipitation events except for no rain events, is divided into three error components, namely, hit bias (HBIAS), missed precipitation (MBIAS), and false precipitation (FBIAS), according to the satellite precipitation retrieval process. The first step is the screening process, which is to identify the raining regions and no-raining regions. If raining regions are not detected, it will lead to missed precipitation, which are negative values causing underestimation of precipitation. Conversely, no-raining regions may be mistaken for raining ones, and this confusion may produce false positive precipitation, which results in precipitation overestimation. Once the raining regions are correctly identified, hit bias (positive or negative value) occurs during the rain rate estimation process based on the relations between the remote sensing signals and the precipitation rate in the second step (Yong et al. 2016). The relationship between the three error components and the total bias can be expressed as follows:

\[ TBIAS = HBIAS + MBIAS + FBIAS \]  

where TBIAS, HBIAS, MBIAS, and FBIAS represent the cumulative values of the total bias, hit bias, missed precipitation and false precipitation on a daily scale in each grid, respectively.

RESULTS AND DISCUSSION

Temporal and spatial distribution of TRMM accuracy

Figure 2 compares the cumulative departure curves of the areal mean precipitation derived from the TRMM data and GV data on daily and monthly scales. As shown in Figure 2,
the dry and wet variation trends depicted by the TRMM data agree well with those observed by the GV data. Both datasets indicate that the humid period of the Xiangjiang River basin is from March to August, and that the dry period is from September to the following February. Figure 3 compares the spatial patterns of the mean annual precipitation of the TRMM and GV data. Both datasets show that the annual precipitation experiences a downward trend from the southeast to the northwest. This is mainly because of the combined effects of the monsoon climate and the undulating terrain. However, it is noticeable that the TRMM data tend to underestimate precipitation in the basin. In general, TRMM data can depict the intra-annual and inter-annual variation of precipitation on basin scale and characterize the spatial patterns of annual precipitation.

Table 3 shows the values of statistical indices which reflect the accuracy of precipitation amount estimation and precipitation event detection at different temporal and spatial scales.

**Table 3** | Values of statistical indices between TRMM and GV data at different spatial and temporal scales (2006–2014)

<table>
<thead>
<tr>
<th>Indices</th>
<th>Unit</th>
<th>Range</th>
<th>Perfect value</th>
<th>Basin scale</th>
<th>Grid scale (min–max)</th>
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<td>Daily</td>
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The index values on basin scale are calculated by averaged areal precipitation, while those on grid scale display the range from the minimum to maximum values of 140 grid cells in Xiangjiang River basin.
spatial scales. The daily areal mean precipitation amount of TRMM data and GV data are 3.86 mm/d and 3.97 mm/d in the basin, and the values of ME and RE are −0.11 mm and −2.9% respectively, indicating that TRMM data slightly underestimate precipitation amount over the entire basin. According to the values of MAE (1.82 mm) and NMAE (45.8%) in Table 3, the absolute bias between TRMM and GV data is still large on a daily scale. In addition, the indices CC and NSE take the values of 0.88 and 0.72 at daily scale and 0.99 and 0.97 at monthly scale, which suggests that TRMM data have a good correlation with GV data, especially at monthly scale. Generally, the indices' values (CC, NSE and NMAE) are closer to the optimal values at a larger spatiotemporal scale. Meanwhile, the wide ranges of the statistical indices values of 140 grids indicate that TRMM accuracy exhibits large variation at different grids. As for the accuracy of precipitation event detection, the values of POD, FAR and SHH show that the ability of TRMM to detect precipitation events is poor and needs to be improved.

To investigate the spatiotemporal distribution difference of TRMM data accuracy, the statistical indices of each month and that of each grid are shown in Figures 4 and 5. The values of CC and NSE in Figure 4(a) illustrate that TRMM data agree better with GV data in the wet season than in the dry season. Figure 5(a) indicates that the higher NSE values appear in regions with larger annual precipitation (Figure 3). Therefore, TRMM data have higher correlation with GV data in periods or regions with more precipitation, which is consistent with the results of Cai et al. (2016) and Milewski et al. (2015). However, their studies show that the inconsistent impact of elevation on correlation between GV and TRMM data is due to the opposite relationship between elevation and annual precipitation. In addition, negative values of RE or ME suggest an underestimation of precipitation, which tends to happen in winter (Figure 4(b)) or in mountainous areas (Figure 5(b)). It can be clearly seen in Figure 4(c) that the values of POD are higher while the values of FAR are lower in the wet season than those in the dry, respectively. However, Figure 5(c) shows that the spatial distribution of POD values is not impacted significantly by elevation or annual precipitation.

According to the results above, the accuracy of the TRMM data is mainly affected by the seasonal factor in terms of time and is related to topography and annual precipitation in terms of space. Moreover, the seasonal pattern and annual total amount of precipitation are related to the magnitude and distribution of precipitation intensity. Therefore, elevation and precipitation intensity were selected as two physical influencing factors to explore the cause of spatiotemporal distribution differences in TRMM accuracy. These two influencing factors are also supported by some previous research (Bharti & Singh 2015; Cai et al. 2016).

**Relationship between the TRMM error components and their influencing factors**

Figure 6 shows the occurrence frequency of three kinds of precipitation estimation events and their accumulative errors as the ratio to total gauge-observed precipitation. It is seen that hit events have the largest occurrence frequency at 51.6%, followed by missed events at 40.0% and false events at 8.4%. This result verifies the dominant role of hit and missed precipitation events in all the precipitation estimation events. MBIAS accounts for the highest percentage (−18.1%) of total gauge-observed precipitation, which is the main source of precipitation underestimation. However, HBIAS and FBIAS contribute to precipitation overestimation at 12.3% and 4.2% of the total gauge-observed precipitation, respectively. TBIAS is small and accounts for only −1.4% of total gauge-observed precipitation because of the mutual compensation of error components.

For each error component, Figure 7 shows the relationship between elevation and grid accumulative error, as well as the relationship between elevation and the occurrence number of error components. From Figure 7(a) it is seen that TBIAS shows a downward trend with increasing elevation, while the three error components perform differently. With the increase of elevation, HBIAS experiences an obvious decreasing trend and MBIAS presents a slight downward trend, while FBIAS displays no significant trend, which indicates that the trend of TBIAS is mainly controlled by HBIAS. In terms of occurrence of events, Figure 7(b) shows that the occurrence of hit and missed events obviously increases with elevation, while no significant tendency can be found for the occurrences of false events and elevation. The slight decrease of MBIAS is
caused by the increasing missed events, and false events are relatively independent of elevation.

The relationship between individual daily hit bias and elevation is further analyzed herein. Figure 8 implies that there is no obvious relationship between elevation and the magnitude of individual daily hit bias under different precipitation intensity intervals with different quantiles. In addition, Figure 9 displays the distribution range and the sign of the daily hit bias from 140 grids with diverse elevation. It can be seen that with the increase of elevation, the positive and negative components of the daily hit bias between the 1% and 99% quantiles of each grid show no obvious change. However, the outliers of the negative components of daily hit bias tend to increase significantly in higher elevation areas (elevation >400 m). Overall, the analysis above suggests that lower cumulative HBIA in higher elevation area is mainly due to the increase of the large negative daily hit bias.

Figure 4 | Box plots of several statistical indices for different months (2006–2014). (a) NSE and CC, (b) RE and ME and (c) POD and FAR. Symbols △ and ○ indicate indices at basin scale, and the box plots indicate indices at grid scale which contain indices of 140 grids in Xiangjiang River basin (Boxes indicate the first (q25) and the third (q75) quartiles, and the black horizontal line indicates the minimum, median and maximum. All the indicators are calculated based on daily precipitation data of TRMM data and GV data for different months (2006–2014).
To investigate the effects of precipitation intensity on TRMM data error components (Table 4), four precipitation intensity levels (light rain, moderate rain, heavy rain, and rainstorm) are defined according to the standards issued by the National Meteorological Administration in China.

Figure 10 presents the occurrence frequency and error contribution ratio of false events and missed events under each intensity level. With the increase of precipitation intensity, the occurrence frequency and contribution ratio of both false events and missed events decrease gradually. Most of the false and missed precipitation events tend to occur at lower precipitation intensity with the light rain class (<10 mm/d) occupying the largest proportion, while higher-intensity precipitation (>25 mm/d) occupies a very small proportion with regard to occurrence frequency and contribution rate. Although these two errors form a canceling effect, the negative missed precipitation still prevails relative to positive false precipitation because the missed events occur much more frequently than the false events (Figure 6).
Figure 11 shows the relationship between precipitation intensity and individual daily hit bias with respect to error magnitude and occurrence number. The daily hit bias exhibits a trend from positive to negative with increasing precipitation intensity (Figure 11(a)). Especially when the precipitation intensity is greater than 100 mm/d, the value of the daily hit bias is mostly negative and tends to present a larger negative value with increasing precipitation intensity. Therefore it can be inferred that the large negative daily hit bias in high-elevation areas originates from the high-intensity precipitation. From Figure 11(b) we can see that the mode of the daily hit bias histogram is close to 0 for light rain. With increasing precipitation intensity the mode of the daily hit bias histogram shifts to negative,
showing that the proportion of negative daily hit bias increases while the proportion of positive daily hit bias decreases. In addition, TRMM data systematically overestimate lower-intensity precipitation as the cumulative HBIAS of light rain and moderate rain accounts for 14.3% and 4.6%, respectively. Simultaneously, the TRMM data tend to underestimate high-intensity precipitation, as the cumulative HBIAS of heavy rain and rainstorm accounts for −0.3% and −3.4%, respectively.

Causal analysis of the spatiotemporal variation of error components

Figure 12 demonstrates the mean monthly cumulative error of each error component and the total bias during the entire study period. HBIAS and MBIAS generally have significant seasonal differences, and FBIAS shows small magnitude and less amplitude variations in different months. HBIAS and MBIAS both display higher amplitude in the dry season than in the wet. Furthermore, MBIAS plays a dominant role in data errors and leads to negative TBIAS during the winter months; this phenomenon is primarily due to the low detection rate of precipitation events in the cold season (Figure 4(c)). However, the monthly cumulative HBIAS is always positive during the year and has a relatively lower value in the wet season than in the dry. Light rain occurs more in each month (Figure 13), thus resulting in a positive HBIAS as TRMM data tend to overestimate precipitation in low-intensity hit events. Strong precipitation has a large contribution rate in the wet season (Figure 13), and it is responsible for the decrease in HBIAS in that period due
to the underestimation of precipitation in high-intensity hit events. Combining the three error components, TBIAS is negative in winter owing to the dominant role of missed precipitation and is close to zero in other months because of the error components cancelling each other.

The spatial distribution of error components and that of the total bias over the study area are demonstrated in Figure 14. Most grids are controlled by the positive HBIAS (see Figure 14(b)), which are mainly because of the overestimation of light rain, which accounts for the largest proportion of the study area (see Figure 15(a)). The variation amplitudes of HBIAS and of MBIAS are larger than those of FBIAS, indicating the dominant roles of the former two error components in affecting the spatial distribution of TBIAS. Furthermore, HBIAS and MBIAS have similar spatial distribution patterns with TBIAS, sharing the characteristic of low values being found in highly elevated regions. To explain this phenomenon, we analyzed the combination of the four precipitation intensity levels of hit events in each grid. With the increase in elevation, the occurrence frequency of the four precipitation intensity events has no significant change, and the contribution rate of rainstorm exhibits an obvious uptrend (Figure 15). Therefore, highly elevated areas have a large proportion of high-intensity precipitation. As a result, the underestimation of high-intensity hit events causes the increase in negative hit
Figure 14 | Spatial distribution of mean annual error components and total bias.

Figure 15 | (a) Occurrence frequency and (b) contribution ratio of hit events under different intensity levels for each grid with different elevation (2006–2014).
bias rising in highly elevated areas. In addition, the number of missed precipitation events increases with elevation (see Figure 7), which also slightly increases the negative components in areas with higher elevation. As indicated by the spatial behavior of error components in the study area, 3B42V7 data tend to underestimate precipitation in highly elevated areas with a greater significant proportion of high-intensity precipitation events and more rainy days.

Based on our findings, efforts to improve accuracy should take into account two aspects: precipitation event detection and precipitation amount estimation. The former influences missed and false precipitation in relation to the screening process, and the latter produces hit bias in relation to the rain rate estimation process. As false precipitation is weakly related to topography and season with a low amplitude, more attention should be paid to the two other error components. Missed precipitation is the dominant error component especially in the cold season, which is severely affected by snow cover and cold air masses. It is recommended that dividing the seasons to correct the errors and considering the occurrence frequency of rain events may be an effective way to bias correction. However, reducing the missed error component by an algorithm remains a challenge, and thus efforts should be focused more on strengthening the precipitation detection instruments. The GPM extends this capability to detect light rain and solid precipitation by improving both active and passive microwave instruments. As for the leading component hit bias, the key point is to correct the underestimation of high-intensity hit precipitation events. Gebregiorgis & Hossain (2013) found that runoff error is strongly correlated with hit bias. Therefore, improving hit bias is important for runoff simulation, particularly in simulating flood peak values. It is noted that elevation does not directly affect the individual daily hit biases, verifying that the improvement of rainfall estimation in mountain areas has achieved remarkable results in the V7 data.

Xia et al. (2015) found that topographical and climatic information is valuable for correcting 3B43V7 products on monthly and annual scales. To further improve accuracy on a daily scale, it is necessary to focus on the negative hit bias of intense rainfall and comprehensively consider the effect of topography and climate on the frequency and intensity distribution of precipitation. This study shows that there is still room for improvement in terms of regional and seasonal bias and that the relevant conclusions are conducive to the future development of a new satellite precipitation dataset.

CONCLUSIONS

In this study, we systematically evaluated the accuracy of the TRMM 3B42 V7 data by comparing them with those of the rain gauge data over the Xiangjiang River basin in the period of 2006–2014. We analyzed the spatiotemporal accuracy disparities of the TRMM data in detail and tracked their origin using the error decomposition method. The effects of precipitation intensity and elevation on diverse sources of error components were investigated to further explain the cause of temporal and spatial variation characteristics of the error components. The conclusions are summarized as follows.

(1) The TRMM data perform better on a large temporal-spatial scale because of the inter-compensation of errors. The ability to detect precipitation events still requires improvement. The accuracy of TRMM shows significant spatiotemporal differences: TRMM data perform better in the humid season than in the dry season, and the underestimation of precipitation amount is obvious in winter and in mountain areas.

(2) Daily bias is more dependent on precipitation intensity than on elevation. Precipitation intensity directly affects the occurrence and the magnitude of error components. Missed and false precipitation events tend to occur in low-precipitation intensity, and hit events tend to overestimate low-intensity precipitation and underestimate high-intensity precipitation. The daily hit bias shifts toward negative with increased precipitation intensity. Elevation has no direct effect on individual daily hit bias, but it affects the cumulative error by affecting precipitation intensity distribution and the rainy days.

(3) Spatiotemporal accuracy differences are controlled by the hit and missed biases. Missed precipitation is the main error source underestimating precipitation in winter, and it is caused by the poor detection of light rain events during this period. The underestimation of
precipitation in highly elevated areas can be explained in two ways. On the one hand, the increasing number of rainy days with many missed events causes an increase in negative error. On the other hand, the greater occurrence numbers and the larger magnitude of high-intensity precipitation result in a larger negative component of hit bias. False precipitation is independent of elevation and precipitation intensity.

The accuracy evaluation of the TRMM data can help product users to understand their performance and predict their application ability in similar humid regions. The analysis of error features and influencing factors is beneficial for improving the accuracy of TRMM data and other satellite precipitation products and hydrologic applications. Tracking the error sources for spatiotemporal accuracy differences guides the direction of improvement. The lessons learned from the TRMM era provide richer reference to the succeeding GPM and other missions. Therefore, improved satellite precipitation estimates are anticipated in the near future.

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