Evaluation of reanalysis and satellite-based precipitation datasets in driving hydrological models in a humid region of Southern China

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Evaluation of reanalysis and satellite-based precipitation datasets in driving hydrological models in a humid region of Southern China

Hongliang Xu · Chong-Yu Xu · Nils Roar Sælthun · Bin Zhou · Youpeng Xu

Abstract This paper compares the original and bias corrected global gridded precipitation datasets, tropical rainfall measuring mission (TRMM) and water and global change forcing data (WFD) with gauged precipitation and evaluates the usefulness of gridded precipitation datasets for hydrological simulations using the distributed soil and water assessment tool (SWAT) and lumped Xinanjiang model in Xiangjiang River basin, Southern China. The results show that the differences in areal mean rainfalls of original TRMM and WFD datasets and gauged dataset are in acceptable limits of less than 10%, while larger differences exist in maximal 5-day rainfalls, dry spells and Fréchet distance. The bias correction methods are able to significantly improve the biases in the mean values of TRMM and WFD datasets. The nonlinear bias correction method gives good results in correcting the standard deviations of TRMM/WFD data. The hydrological modelling results show that the WFD datasets perform relatively better than TRMM datasets even though the results are poor as compared with using gauged rainfall as input in daily step hydrological models. At monthly time step, both TRMM and WFD data produce acceptable model simulation results in terms of Nash–Sutcliffe efficiency ($E_{ns} > 0.7$ for original TRMM/WFD data and $E_{ns} > 0.8$ for linearly corrected TRMM/WFD data) and relative error ($|R_e| < 10\%$).

Keywords Tropical rainfall measuring mission (TRMM) · Water and global change forcing data (WFD) · Xinanjiang model · Soil and water assessment tool (SWAT)

1 Introduction

Information about precipitation rates, amounts and distribution is indispensable for a wide range of applications including agronomy, hydrology, meteorology and climatology (Scheel et al. 2011). The spatial and temporal distribution of precipitation greatly influences land surface hydrological fluxes and states (Gottschalck et al. 2005). The precise measurement of precipitation at fine space and time resolution has been shown to improve our ability in simulating land surface hydrological processes and states (Faurès et al. 1995; Nykanen et al. 2001). Rain gauges provide rainfall measurements at individual points, but there is still a challenge in using gauged data to estimate rainfall at basin level with appropriate spatial and temporal scales (Sawunyama and Hughes 2008).

With technological advancements, high resolution global topographical and hydrological data are currently
available. There are many global rainfall databases (e.g., the Global Precipitation Climatology Project (GPCP), the Global Precipitation Climatology Centre (GPCC), the Climatic Research Unit (CRU) precipitation database, the Climate Prediction Centre of NOAA (National Oceanic and Atmospheric Administration) Merged Analysis of Precipitation (CMAP), etc.), radar observations, and numerical weather precipitation models. However, their usefulness in driving hydrological models at basin scale is yet to be evaluated (Cheema and Bastiaanssen 2012; Parmesan et al. 2013; Adjei et al. 2014).

Much effort has been made in the correction of satellite products by using gauged rainfall (Kang and Merwade 2014). The mismatch between the rainfall estimates from satellite sensors and the gauges unavoidably leads to distrust in both datasets (Ciach et al. 2000; Grimes et al. 1999; Omotosho and Oluwafemi 2009; Nair et al. 2009). Some studies have compared the differences between the various precipitation datasets and rain gauge data as well as their impact on hydrological modeling (e.g., Abdella and Alfredsen 2010; Pan et al. 2010; Cheema and Bastiaanssen 2012; Fekete et al. 2004; Zhang et al. 2012; Li et al. 2013). They have shown that global precipitation products can be used as a source of information but need calibration and validation due to the indirect nature of the radiation measurements. Comparing with gauged data, although these global precipitation datasets generally agree in their long-term temporal trends and large scale spatial pattern, remarkable differences at small time scale and at smaller spatial scale (basin, grid, etc.) can be observed (Adler et al. 2001; Costa and Foley 1998; Oki et al. 1999; Castro et al. 2014). Fekete et al. (2004) compared six monthly precipitation datasets to assess their uncertainties and associated impacts on the terrestrial water balance. The study demonstrated a need to improve precipitation estimates in arid and semi-arid areas, where slight changes in rainfall could result in significant changes in the runoff simulation due to the nonlinearity of the runoff-generation processes. Biemans et al. (2009) compared seven global gridded precipitation datasets at river basin scale in terms of annual mean and seasonal precipitation, which revealed that the representation of seasonality is similar for all the datasets but noted large uncertainties in the mean annual precipitation, especially in mountainous, arctic and small basins. Li et al. (2013) compared two global gridded precipitation datasets (Tropical rainfall measuring mission (TRMM) 3B42 (TRMM dataset contains a number of sub-datasets and 3B42 denotes one globally daily precipitation sub-dataset) and WATCH (WATer and global CHange) forcing data (WFD) and evaluated their performance in hydrological simulations of the WASMOD-D model over 22 basins in Southern Africa. The study showed that the two datasets had similar spatial variation patterns in the mean annual rainfall and temporal trends, while WFD data slightly outperformed the TRMM 3B42 data in the hydrological simulations over Southern Africa. Li et al. (2012) studied the difference of TRMM 3B42 rainfall with gauged precipitation data at different time scales and evaluated the usefulness of the TRMM 3B42 rainfall for hydrological processes simulation and water balance analysis using a distributed water flow model for lake catchment (WAT-LAC) in Xinjiang catchment in China. The study suggested that the TRMM 3B42 rainfall data were unsuitable for daily streamflow simulations but better performance can be achieved in monthly streamflow simulations. Rasmussen et al. (2013) investigated the range of the TRMM rainfall biases in storms over South America and indicated that the TRMM rainfall data significantly underestimate the storms with deep convective cores, while the bias is unrelated to their echo top height. Müller and Thompson (2013) adjusted the bias of the distributions of daily rainfall observed by the TRMM satellite through stochastic modeling in Nepal with a sparse gauge network and complex topography, and the results indicated that the bias adjusted satellite data through stochastic modeling outperformed the directly interpolated gauged rainfall. The study of Castro et al. (2014) showed that the tropical rainfall measuring mission multi-satellite precipitation analysis (TMPA) products for the rainfall are able to capture the mean spatial pattern for flat areas on a monthly basis; however, satellite estimates tend to miss precipitation that is enhanced by flow lifting over the mountains. Although some studies comparing global gridded precipitation datasets and their performance in driving hydrological models have been carried out, an integrated approach that (1) compares the differences of original and bias corrected gridded precipitation datasets with gauged precipitation data in terms of basic statistics, seasonal patterns as well as the spatial distributions, and (2) examines the performances of the original and bias corrected gridded precipitation datasets in driving both distributed and lumped hydrological models at different time and spatial resolutions has not been seen in the literature, which motivated the current study.

This paper is therefore designed to: (1) compare and evaluate the temporal characteristic and the spatial distribution of the original and bias corrected TRMM 3B42 and WFD datasets with gauged precipitation data in a humid climate basin in southern China, and (2) evaluate the performance of the original and bias corrected TRMM 3B42 and WFD data and gauged precipitation in driving a distributed hydrological model (SWAT) and a lumped hydrological model (Xinanjiang model) in the simulation of daily and monthly streamflows in the catchment. This study contributes to the enhancement of understanding the difference between the TRMM/WFD and gauged rainfall and improves the knowledge regarding the utility of the
raw and bias corrected TRMM 3B42 and WFD rainfall datasets in driving lumped and distributed hydrological models in varying time steps. The study significantly contributes to hydrology as there is a clear need for evaluating the skills and usefulness of new global precipitation datasets with different spatial and temporal resolutions as an alternative data source for hydrological studies especially in data scarce regions.

2 Study area and data

2.1 Study area

The Xiangjiang River basin (Fig. 1) is located between 24°30'-29°30'N and 110°30'-114°E in the central-south China with a total area of 94,660 km² and a total river length of 856 km. The basin is surrounded by mountains in its headwaters with plains in the downstream. The basin's rolling terrain accelerates the rainfall convergence and the variation of runoff. It is heavily influenced by monsoon climate, which brings heavy rainfall from the south in summer. The mean annual precipitation reaches approximately 1,600 mm, of which 68 % occurs in the main rainy season from April to September. The mean annual depth of runoff of Xiangjiang River basin is 910 mm. The mean annual temperature is about 17 °C, the annual mean relative humidity is about 75 % in summer and about 80 % in winter, and the mean annual potential evapotranspiration is about 1,000 mm. There are clear differences in runoff among different seasons with 50 % of the flooding events occurring in June and July.

2.2 Data

Three precipitation datasets were used in this study: (1) TRMM 3B42 dataset, which is a number of climate rainfall products produced from the passive microwave (TMI) and precipitation radar (PR) sensors on board the tropical rainfall measuring mission (TRMM) satellite launched in November of 1997. The TRMM project aims to provide small-scale variability of precipitation by frequent and closely spaced datasets. TRMM uses a combination of microwave and infrared sensors to improve accuracy, coverage and resolution of its precipitation estimates; however, the ability of TRMM to specify moderate and light precipitation over short time intervals is poor (Huffman et al. 2007; Li et al. 2013). The TRMM 3B42 dataset, covering from 1st January 1997 to 31st December 2008 in time and 50°S–50°N in space, is one of the TRMM rainfall datasets used in the study.
products which uses the TMI 2A12 rain estimates to adjust high temporal resolution (3-hourly or higher) IR rain rates over daily gridded 0.25 × 0.25° latitude/longitude boxes. It has been used to drive distributed hydrological models in large river basins as well as in flood modelling (Huffman et al. 2007, 2010) (in the following text, TRMM 3B42 is abbreviated as TRMM). (2) WFD dataset was developed by the WATCH project (Weedon et al. 2011) as input for large-scale land-surface and hydrological models. WFD dataset is named as reanalysis data in the literature which is weather observation data assimilated into global grids by a numerical atmospheric model. The WFD dataset, from 1st January 1958 to 31st December 2001, consists of meteorological variables needed to run hydrological models, including 2 m air temperature, dew point temperature and wind speed, 10 m air pressure and specific humidity, downward long wave and shortwave radiation, rainfall and snowfall rates (Uppala et al. 2005; Li et al. 2012). (3) The gauged precipitation dataset which consists of 181 rain gauges (Fig. 1) from 1st January 1963 to 31st December 2005 was provided by the Hydrology and Water Resources Bureau of Hunan Province, China.

The meteorological data including daily maximum and minimum air temperature, precipitation, wind speed, solar radiation, average daily humidity and runoff used in this study have been quality controlled by the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn).

The spatial data for the watershed (i.e., elevation, land use map, and soils distribution map) were prepared as inputs to the SWAT Model. The DEM with 90 m resolution was downloaded from SRTM (The Shuttle Radar Topography Mission; http://www2.jpl.nasa.gov/srtm/). The 1 km resolution soil dataset with respect to texture, depth and drainage attributes was supplied by the SinoTropia Project (Watershed EUTROphication management in China through system oriented process modeling of Pressures, Impacts and Abatement actions). The land use images which consist of five classes (forest, agriculture, grass, urban, and water) were interpreted from the Landsat satellite images (downed from http://www.landsat.org/) by using ENVI Image Analysis Software.

3 Methodology

3.1 Statistical analysis methods

In order to evaluate and compare the consistency and differences between the TRMM/WFD and gauged rainfall datasets, several basic statistical indices (i.e. annual areal mean rainfall, annual areal rainfall in wet/dry season, relative error \( R_E \)), Standard deviation (STDE), maximum 5-day rainfall amount, maximum dry spell length, Nash–Sutcliff model efficiency coefficient \( E_n \) and Root mean squared error (RMSE) are assessed in the study. Meanwhile, the discrete Fréchet distance (Fréchet 1906; Alt and Godau 1995) which takes into account the location and ordering of the points along the curves are used to measure the closeness of two time series (TRMM/WFD and gauged rainfall series) if stretching and compression in time is allowed, but temporal succession is to be preserved. Unlike similarity measures (e.g. RMSE) which average over a set of similarity values, and dynamic time warping which minimizes the sum of distances along the curves (data series) (Driemel and Har-Peled 2013), the Fréchet distance captures similarity under small non-affine distortions and for some of its variants also spatiotemporal similarity (Maheshwari et al. 2011).

Statistical methods used in this paper to evaluate the TRMM/WFD and gauged rainfall datasets include: (1) Kolmogorov–Smirnov (K–S) test for checking whether the three datasets have the same distribution pattern; (2) student’s \( t \) test and (3) \( F \) test for checking the equality of mean value and variance between the three datasets, respectively. A 5 % significance level was used for the tests (1)–(3). Meanwhile, the areal mean precipitation used in the analysis is computed by using Thiessen Polygons algorithm (Zquiza 1998) and the spatial patterns of the three datasets are interpolated on the catchment using Ordinary Kriging method (Cressie 1988).

3.2 Bias correction methods

Due to the fact that satellite data and reanalysis data have biases and random errors which are caused by various factors like sampling frequency, nonuniform field-of-view of the sensors, and uncertainties in the rainfall retrieval algorithms, many algorithms have been developed for bias correction (e.g. Yang et al. 1999; Li et al. 2010; Piani et al. 2010; Dosio and Paruolo 2011; Kang and Merwade 2014). In this paper, two widely used bias correction algorithms were adopted to correct the biases of TRMM and WFD precipitation data.

3.2.1 Linear bias correction method

The linear bias correction method (Teutschbein and Seibert 2012) is simple and widely used, in which TRMM/WFD daily precipitation amounts, \( P \), are transformed into \( P^* \) such as \( P^* = aP \), using a scaling parameter, \( a = \overline{P_0}/\overline{P} \), where \( \overline{P_0} \) and \( \overline{P} \) are monthly mean gauged and TRMM/ WFD precipitation respectively. The monthly scaling factor is applied to each uncorrected daily TRMM/WFD data of that month to generate the corrected daily time series.
3.2.2 Nonlinear bias correction method

Leander and Buishand (2007) developed a nonlinear bias correction algorithm to correct the precipitation \( P \) in the following form:

\[
P^* = aP^b
\]

(1)

where \( P^* \) and \( P \) are the corrected and the original TRMM/WFD precipitation data, respectively. The parameters \( a \) and \( b \) are obtained for each grid point of the considered domain on a monthly basis by using daily data iteratively with a root finding algorithm (Brent 1973):

\[
b(x, i); CV(P^b(x,i)) = CV(P_{obs})
\]

(2)

\[
a(x, i); a(x, i)P^b(x,i) = P_{obs}
\]

(3)

where \( x \) is the grid point to be corrected, \( i \) represents the month, the overbar alludes to the monthly average, and \( CV() \) is the coefficient of variation of the variables simulated at \( x \) in \( i \) by the TRMM/WFD \( (P) \) and of the observed variables \( (P_{obs}) \).  

3.3 Hydrological models

Xinanjiang Model is by far the most widely used hydrological model in China (Zhao et al. 1995) which was developed in 1973 and the English version was first published in 1980 (Zhao et al. 1980). Its main feature is the concept that runoff is not produced until the soil moisture content of the aeration zone reaches field capacity, and thereafter runoff equals the rainfall excess without further loss. The inputs to the model are daily areal precipitation, the measured daily pan evaporation and observed discharge for calibration. The outputs are the modelled outlet discharge from the whole basin, the estimated actual evapotranspiration from the whole basin, which is the sum of the evapotranspiration from the upper soil layer, the lower soil layer, and the deepest layer (Zhao 1992). Xinanjiang model has been applied successfully since it was published over very large areas including all of the agricultural, pastoral and forested lands of China except the loess. The model is mainly used for hydrological forecasting (Yao et al. 2009), and the use of the model has also spread to other fields of application such as water resources estimation, design flood and field drainage, water project programming, hydrological impact of climate change and water quality accounting, etc. (Hu et al. 2005; Ren et al. 2006; Liu et al. 2009; Yao et al. 2009; Bao et al. 2011; Zhang et al. 2012).

The US National Weather Service River Forecast System has also reported its good performance in the arid Bird Creek watershed in the United States (Singh 1995).

The SWAT (Soil and Water Assessment Tool) Model is a distributed-parameter model designed to predict the effects of land management practices on the hydrology, sediment, and contaminant transport in agricultural watersheds under varying soils, land use, and management conditions (Arnold et al. 1998). SWAT is based on the concept of Hydrologic Response Units (HRUs), which are portions of a subbasin that possess unique land use, management, and soil attributes. The runoff from each HRU is calculated separately based on weather, soil properties, topography, and vegetation and land management and then summed to determine the total loading from the subbasin. The SWAT Model is based on the water balance equation (Neitsch et al. 2002):

\[
SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})
\]

(4)

where \( SW_t \) is the final soil water content, \( SW_0 \) is the initial soil water content on day \( i \), \( t \) is the time (days), \( R_{day} \) is the amount of precipitation on day \( i \), \( Q_{surf} \) is the amount of surface runoff on day \( i \), \( E_a \) is the amount of evapotranspiration on day \( i \), \( W_{seep} \) is the amount of water entering the vadose zone from the soil profile on day \( i \), and \( Q_{gw} \) is the amount of return flow on day \( i \).  

4 Results and discussion

The results of the study are presented in the following order: (i) Comparison of original TRMM and WED data with gauged precipitation data, (ii) comparison of bias corrected TRMM and WED data with gauged precipitation data, (iii) evaluation of daily and monthly model simulation results using original TRMM and WED data and gauged precipitation data as inputs, and (iv) evaluation of model simulation results using bias corrected TRMM and WED data and gauged precipitation data as inputs.

4.1 Comparison of TRMM, WFD and gauged precipitation datasets

Precipitation is the immediate source of water for the land surface hydrological budget, and its uncertainty will strongly impact the model calibration results (Li et al. 2012). The comparison between the Gauged, TRMM and WFD precipitation datasets was conducted in four steps: First, several statistical indices of the original TRMM and WFD (named as TRMMO and WFD0 from now on) datasets and gauged precipitation data in the common period of 1997–2001 were analyzed; second, the intensity distribution and relative contribution of each rainfall class to the total amount of rainfall are evaluated; third, seasonal variation and correlations between TRMMO, WFD0 and gauged rainfalls are quantified, and finally, spatial patterns of TRMMO, WFD0 and gauged rainfalls were compared.
4.1.1 Basic statistical indices of original TRMM, WFD and gauged rainfalls

The results of basic statistical indices are shown in Table 1. As an important and useful index to reflect the accuracy of rainfall amount, the annual areal mean gauged rainfall calculated by Thiessen polygon interpolation method is 1,605.8 mm/year, and for TRMM O and WFD O data the values are 1,543.6 and 1,535 mm/year, respectively. The average monthly rainfalls are 177.3, 175.8 and 171.6 mm/month for gauged, TRMM O and WFD O data respectively in wet season, while the values are 90.3, 81.5 and 84.2 mm/month respectively in the dry season. The $R_E$ of annual areal mean rainfall shows that both TRMM O and WFD O datasets recorded slightly less rainfall than gauged data in the region. A comparison of STDE computed from the three datasets showed that the difference of STDE between WFD O and gauged rainfall is smaller than the difference between TRMM O and gauged rainfall. The differences in the extreme rainfall which is reflected by the maximum 5-day rainfall (Dankers and Hiederer 2008) show that TRMM O dataset recorded 65 % more rainfall than gauged data in storms while the WFD O data only recorded 4 % more rainfall than gauged data. Considering the maximum dry spell days, both TRMM O and WFD O datasets suggest more non-rainy days compared with the gauged data. The $E_{ns}$ (taking the gauged data as “Observed data” and TRMM O/WFD O data as “Simulated data”) and between gauged data and TRMM O data (denoted as $E_{nsT-G}$) and between gauged data and WFD O data (denoted as $E_{nsW-G}$) showed that the values of $E_{nsW-G}$ are higher than the values of $E_{nsT-G}$, and both are lower than 0.5 during the period 1997–2001. The values of RMSE also show that the WFD O dataset is better than TRMM O data in the region. However, the Fréchet distances computed between TRMM O/WFD O and gauged monthly areal mean rainfall are 35.3 and 80.5 respectively, which means that the TRMM O rainfall is more similar with the gauged rainfall than that of the WFD O rainfall in monthly level in terms of the Fréchet distance measure. This inconsistency of result as compared with other statistical indices mentioned above is probably due to the Fréchet distance easily leads to irrelevant results if the temporal interdependence of values is of importance, which is true in the case of rainfall graphs and hydrographs (Chouakria-Douzal and Nagabhushan 2006; Ehret and Zehe 2011).

In summary, the above comparisons showed that in the study region the WFD O data agreed better with the gauged data than the TRMM O data in most of the statistical indexes. Similar conclusions are also found in the literature. Li et al. (2013) showed that WED data provide better results than TRMM data in driven a large scale hydrological model in Southern Africa. In another study carried...
out by Li et al. (2014), it is shown that WED data agreed better with observed precipitation data than TRMM data in India.

4.1.2 Intensity distribution of different rainfall classes of original TRMM, WFD data and gauged rainfalls

Figure 2 shows the intensity distributions of the TRMM₀, WFD₀ and gauged daily precipitation in different classes and their contributions to the total rainfall from 1997 to 2001. It is seen that non-rainy days have the largest occurrence for the WFD₀ data, occurring 34% of the total days, but for the TRMM₀ and gauged data, the largest class is 0 < rainfall < 3 mm, occurring more than half of the total days. The second largest class for the WFD₀, TRMM₀ and Gauged data are 0 < rainfall < 3 mm, non-rainy days and 3 < rainfall < 10 mm respectively, occurring about 20–30% of the total days. It is obviously seen that both TRMM₀ and WFD₀ data observed much more non-rainy days than gauged data, which is partly because of the poor ability of recording trace rainfall for the TRMM satellite and the data assimilation algorithm, observation system and observation data applied in producing reanalysis WFD dataset (Ebisuzaki and Kistler 2000; Bengtsson et al. 2004; Wu et al. 2005; Bengtsson et al. 2007). The statistics for TRMM₀ rainfall are however different from WFD₀ and gauged rainfall, with the dominant rainfall classes contributing to the total rainfall of TRMM₀ data being 10 < rainfall < 25 mm and 25 < rainfall < 50 mm, both accounting for about 30% of the total rainfall, while the 10 < rainfall < 25 mm is the dominant class contributing more than 40% of total rainfall for the WFD₀ and gauged data. The sum of the first two classes, i.e. non-rainy and small rain (0 < rainfall < 3 mm) classes, gives a similar high percentage (approximately 65%) of total days for all the three datasets, but the contributions to the total

![Figure 2](image-url)
rainfall amount are all below 10% in the low rain class. The occurrences of the middle class rainfall (3 < rainfall < 50 mm) decrease progressively class by class for the three datasets, but with different contribution rates to the total rainfall. The highest rainfall class (>50 mm) occurs below 0.5% of the total days and contributes 6.2, 2.1 and 3% of the total rainfall for TRMMₒ, WFDO and gauged data respectively. The TRMM satellite obviously records more precipitation in high rainfall class than the rain gauges which is mainly because the heavy rainfall in the study area is dominated by the frontal rains and connective rains, and inside these heavy frontal rains and connective rains, rain rate is distributed heterogeneously in vertical and horizontal directions. Therefore, the complex distribution of rain in the clouds produces large error in rainfall volume detected by the Precipitation Radar on TRMM satellite (Zipser and Lutz 1994). It is important to note that the high rainfall ranges play a vital role in contributing to the total rainfall amount. This kind of information is essential because heavy rains cause the geographical slides and flash floods and hence threaten the economies and human life (Varikoden et al. 2010; Li et al. 2012).

4.1.3 Seasonal variation and correlations between TRMMₒ, WFDO and gauged rainfalls

Figure 3 shows a quantitative comparison of the spatial average of the mean monthly precipitation over Xiangjiang River basin from TRMMₒ, WFDO and gauged data during 1997–2001. The figure graphically demonstrates that WFDO data agree better with the gauged data than TRMMₒ data do in 9 months except March, May and July. It is seen that the monthly rainfall values of TRMMₒ data are lower than gauged rainfall in winter (December–February) and autumn (September–November), but in spring (March–May) and summer (June–August), the comparison of TRMMₒ and gauged rainfall varies irregularly. On the other hand, the monthly rainfall values of WFDO data are always lower than Gauged rainfall except in August.

Correlation of the three datasets is shown through the scatter plots of monthly areal mean precipitation from TRMMₒ, WFDO and gauged data (1997–2001) in Fig. 4. It is seen that there are good linear relationships between the WFDO data and gauged data, with the highest determination coefficient ($R^2$) of 0.96. The $R^2$ value for the correlation between TRMMₒ data and gauged data is 0.93. From the comparison of the two scatter plots and the $R^2$ values, slope and intercept of the regression lines, it is seen that the WFDO data reproduced the observed amount of monthly rainfall slightly better than the TRMMₒ data in the study region.

4.1.4 Spatial patterns of TRMMₒ, WFDO and gauged rainfalls

Figure 5 shows the spatial distribution of relative error of precipitation (Fig. 5a–f) and $E_{rel}$ computed between gauged
Fig. 5 The spatial distribution of Relative error of precipitation and $E_{\text{ens}}$ between gauged and TRMM$_{0}$/WFDO$_{0}$ datasets (computed in the common period of 1997–2001): Relative error of precipitation between gauged and TRMM$_{0}$ datasets in a annual mean, b mean monthly rainfall in wet season, c mean monthly rainfall in dry season; Relative Error of precipitation between gauged and WFDO$_{0}$ datasets in d annual mean, e mean monthly rainfall in wet season, f mean monthly rainfall in dry season; g is the $E_{\text{ens}}$ computed by gauged and TRMM$_{0}$ datasets and h is the $E_{\text{ens}}$ computed by gauged and WFDO$_{0}$ datasets.
and TRMM\textsubscript{O}/WFD\textsubscript{O} datasets (Fig. 5g, h) interpolated by using Ordinary Kriging method in the common period of 1997–2001. It is seen that the TRMM\textsubscript{O} data underestimate the annual rainfall in the whole basin while the $R_E$ is larger in western and southern parts of the basin than it is in central-north part of the basin (Fig. 5a). In wet season, the distribution of $R_E$ varies regularly from TRMM\textsubscript{O} data overestimating the rainfall in the north/west to underestimating the rainfall in the south/east (Fig. 5b). In dry season, the TRMM\textsubscript{O} data underestimate the rainfall in the whole basin and $R_E$ values increase gradually from north to south (Fig. 5c). The distribution of $R_E$ computed by WFD\textsubscript{O} data and gauged rainfall shows similar spatial variation pattern in annual mean rainfall (Fig. 5d) and mean monthly rainfall in wet season (Fig. 5e), and WFD\textsubscript{O} data vary from overestimating rainfall in the north to underestimating in the south gradually, while Fig. 5f shows that the WFD\textsubscript{O} data overall underestimate the mean monthly rainfall in dry season except a slight overestimation in the northern part of the basin. Figure 5g, h shows that the WFD\textsubscript{O} data match the gauged rainfall much better than the TRMM\textsubscript{O} data do. The WFD\textsubscript{O} data match the gauged rainfall best in the northwest of the basin with $E_{\text{NTW-G}}$ value reaching 0.4, and with the worst estimates in the north. The TRMM\textsubscript{O} data match the gauged rainfall poorly in the western and northern parts of the basin with the $E_{\text{NTF-G}}$ values below zero and the highest value of $E_{\text{NTG-G}}$ in eastern part of the basin is still lower than 0.3.

The consistency test of the TRMM\textsubscript{O} and WFD\textsubscript{O} datasets in terms of their distribution patterns (K–S test), long-term mean values ($t$ test) and variances ($F$ test) is performed for the areal average values and for each grid cells at the significance level of 0.05. As for the areal average values, the $t$ test shows the differences in mean annual and seasonal values of TRMM\textsubscript{O} and WFD\textsubscript{O} data with gauged data are insignificant at 5% significant level. The differences in their spatial distribution patterns and the variances are significant at 5% significant level. The results of consistency test for individual grid cells are summarised in Table 2, which shows that: (1) The Null Hypotheses that TRMM\textsubscript{O} and gauged data belong to the same distribution and have same variance are not rejected in only four grids; whereas the Null Hypotheses that WFD\textsubscript{O} and gauged data belong to the same distribution and have same variance is therefore rejected in all grids. And (2) the student’s $t$ test shows two thirds of the grids (24 grids) of TRMM\textsubscript{O} rainfall and one third of the grids (11 grids) of WFD\textsubscript{O} rainfall in the basin have the same mean values as gauged rainfall.

### Table 2: The results of hypothesis test among TRMM, WFD and Gauged precipitation in Xiangjiang River Basin

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Number of grids</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRMM\textsubscript{O} versus Gauged (1997–2005)</td>
<td>WFD\textsubscript{O} versus Gauged (1963–2001)</td>
</tr>
<tr>
<td>Total grid number = 36</td>
<td></td>
</tr>
<tr>
<td>Kolmogorov–Smirnov test: The same distribution</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Not the same distribution</td>
</tr>
<tr>
<td>Student’s $t$ Test</td>
<td></td>
</tr>
<tr>
<td>The same mean</td>
<td>24</td>
</tr>
<tr>
<td>Not the same mean</td>
<td>12</td>
</tr>
<tr>
<td>$F$ Test</td>
<td></td>
</tr>
<tr>
<td>The same variance</td>
<td>4</td>
</tr>
<tr>
<td>Not the same variance</td>
<td>32</td>
</tr>
</tbody>
</table>

**4.1.5 Comparison of bias corrected TRMM and WFD datasets with gauged data**

The areal mean precipitation is one of the decisive factors for the lumped hydrological models due to lumped models consider a watershed as a single unit for computations, and model inputs and watershed parameters are averaged over this unit. However, the spatial distribution of precipitation amounts is vital for the distributed hydrological models. Figure 6 shows the comparison of bias corrected TRMM/WFD precipitation data using the linear and nonlinear correction methods (in the following part of the paper, the linear corrected TRMM/WFD data are abbreviated as TRMM\textsubscript{LC}/WFD\textsubscript{LC} and nonlinear corrected TRMM/WFD data are abbreviated as TRMM\textsubscript{NL}/WFD\textsubscript{NL}) with gauged rainfall for the individual grid as well as for the areal average. It is seen that: (1) The biases existed in the uncorrected annual mean rainfall of TRMM/WFD data disappeared after using linear/nonlinear bias correction algorithms both in grid and areal mean rainfall level. (2) In case of the original and bias corrected TRMM datasets, it is seen that the values of STDE (which were computed by the TRMM\textsubscript{O} in each grid and the areal mean TRMM\textsubscript{O}) are larger than the values of STDE of gauged rainfall in most grids and in areal mean level in the catchment. The values of $E_{\text{nm}}$ calculated between TRMM\textsubscript{O} and gauged rainfall in each grid are all smaller than 0.4 while the $E_{\text{nm}}$ calculated between areal mean TRMM\textsubscript{O} and areal mean gauged rainfall is 0.52. It is evidently seen in Fig. 6a that the nonlinear bias correction method removes the bias of the STDE both in grid and areal mean rainfall level, and the
values of $E_{ns}$ computed between TRMM_{NL}C and gauged rainfall improved in both grid and areal mean level. However, the linear bias correction method neither remove the bias of the STDE nor improve the values of $E_{ns}$ computed between TRMM_{LC} and gauged rainfall in both grid and areal mean rainfall level obviously. (3) In case of the original and bias corrected WFD datasets, it is seen that the values of STDE (which were computed by the WFD in each grid and the areal mean WFD) are smaller than the values of STDE of gauged rainfall in most grids and in areal mean level in the catchment. It is seen in Fig. 6b that the non-linear bias correction method removes the bias of the STDE in grid level, but the STDE computed by the areal mean WFD_{NL}C is 15 % larger than the STDE computed by the areal mean gauged rainfall. However, comparing with the gauged rainfall, the linear bias correction method removes the bias of the STDE which was computed by the areal mean WFD_{LC} but does not remove the bias of the STDE in grid level. Comparing the values of $E_{ns}$ computed between WFD_{O}WFD_{LC}WFD_{NL}C and gauged rainfall in each grid, it is seen that the linear bias correction method improves the $E_{ns}$ values slightly at grid level while the non-linear bias correction method does not improve the $E_{ns}$ values in most of the grids. Meanwhile, the worst $E_{ns}$ values which were calculated by the areal mean WFD_{LC}/WFD_{NL}C and areal mean gauged rainfall are observed in Fig. 6b. The worsening of $E_{ns}$ values in grid level of WFD_{NL}C is mainly because the non-linear bias correction algorithm can correct the water balance (relative error) well, but cannot correct the zero values in WFD precipitation when the gauged precipitation is not zero, since only the non-zero records are adjusted to achieve the solution of objective function in the correction period which could lead to considerable variation of nonzero rainfall values.

4.2 Evaluation of streamflow simulation using TRMM, WFD and gauged precipitation as inputs

The common period of the TRMM, WFD and gauged precipitation datasets 1997–2001 was taken for model calibration. In order to make best use of the available data which cover different record periods, the validation period for gauged and TRMM data was 2002–2005 and the period 1993–1996 was taken for validation of WFD data. The period 1st January 1997–31st May 1997 was taken as warming-up period during calibration. In the SWAT model, the catchment was delineated into 55 sub-basins and 555 HRUs (Hydrological Response Units) depending on elevation, soil types and land-use types. In model calibration, the Nash–Sutcliffe efficiency coefficient was taken as objective function, the Genetic Algorithm and SUFI2 (Sequential Uncertainty Fitting version 2) Algorithm provided by SWAT CUP were used for calibrating the Xinanjiang Model and SWAT Model respectively. All the 15 parameters of Xinanjiang Model and the 12 most sensitive parameters of SWAT Model (ranked by CN2, SOL_AWC, GWQMN, ESCO, GW_DELAY, ALPHA_BF, SOL BD, SOL K, REVAPMN, SLSUBBSN, SURLAG and GW_REVAP) were selected for calibrating the models (Table 3). The same initial values and range of parameters were applied in calibrating the different data based models.

4.2.1 Evaluation of the daily step simulated streamflow

The evaluation of model simulation results at daily time step is performed on two aspects in this study and results are presented in the following three paragraphs in this section, i.e., statistical quality measures of $E_{ns}$ and $R_{E}$ and graphical comparison of observed and model simulated daily discharges.

Table 4 shows the $E_{ns}$ values and Relative Error ($R_{E}$) for the Xinanjiang and SWAT Models’ simulation results. In case of $E_{ns}$ values, it is seen that: (1) The gauged precipitation data based hydrological models performed best while the performances of the TRMM_{O} and WFD_{O} precipitation based models were far from being satisfactory at daily time step. (2) The $E_{ns}$ values using the linearly corrected TRMM and WFD data as input improved from 0.62
and 0.79 to 0.65 and 0.81 in the Xinanjiang Model as compared to the $E_{nt}$ values using uncorrected data. The $E_{nt}$ values improved from 0.56 and 0.71 to 0.63 and 0.73 in SWAT Model respectively. However, the $E_{nt}$ values using nonlinear correction method show slightly worse results in case of WFDNLC data in both models. Specifically, the $E_{nt}$ values using the non-linearly corrected TRMM and WFD data as input changed from 0.62 and 0.79 to 0.64 and 0.66 in SWAT Model respectively as compared to the $E_{nt}$ values using uncorrected data.

Table 3  The calibrated parameters of Xinanjiang model and SWAT model

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Parameter range</th>
<th>Name</th>
<th>Description</th>
<th>Parameter range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Um</td>
<td>Averaged soil moisture storage capacity of the upper layer (mm)</td>
<td>10–60</td>
<td>ALPHA_BF</td>
<td>Base flow recession factor (days)</td>
<td>0–1</td>
</tr>
<tr>
<td>Lm</td>
<td>Averaged soil moisture storage capacity of the lower layer (mm)</td>
<td>50–160</td>
<td>GW_DELAY</td>
<td>Ground water delay (days)</td>
<td>0–15</td>
</tr>
<tr>
<td>Dm</td>
<td>Averaged soil moisture storage capacity of the deep layer (mm)</td>
<td>100–180</td>
<td>GW_REVAP</td>
<td>Ground water revaporation coefficient</td>
<td>0–0.5</td>
</tr>
<tr>
<td>B</td>
<td>Exponential parameter with a single parabolic curve, which represents the non-uniformity of the spatial distribution of the soil moisture storage capacity over the catchment</td>
<td>0.3–0.7</td>
<td>GWQMN</td>
<td>Threshold depth for ground water flow to occur (mm)</td>
<td>0–10</td>
</tr>
<tr>
<td>Im</td>
<td>Percentage of impervious and saturated areas in the catchment</td>
<td>0–0.1</td>
<td>SLSUBBSN</td>
<td>Average slope length (m)</td>
<td>0–100</td>
</tr>
<tr>
<td>K</td>
<td>Ratio of potential evapotranspiration to pan evaporation</td>
<td>0.1–1.2</td>
<td>SOL_BD</td>
<td>Moist bulk density (g/cm$^3$)</td>
<td>0–25</td>
</tr>
<tr>
<td>C</td>
<td>Coefficient of the deep layer that depends on the proportion of the basin area covered by vegetation with deep roots</td>
<td>0.1–0.3</td>
<td>SOL_K</td>
<td>Saturated hydraulic conductivity (mm/hour)</td>
<td>0–10</td>
</tr>
<tr>
<td>Sm</td>
<td>Areal mean free water capacity of the surface soil layer, which represents the maximum possible deficit of free water storage (mm)</td>
<td>30–60</td>
<td>REVAPMN</td>
<td>Threshold depth for revaporation to occur (mm)</td>
<td>0–100</td>
</tr>
<tr>
<td>Ex</td>
<td>Exponent of the free water capacity curve influencing the development of the saturated area</td>
<td>1–2</td>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
<td>0–1</td>
</tr>
<tr>
<td>Kg</td>
<td>Outflow coefficients of the free water storage to groundwater relationships</td>
<td>0.9–0.99</td>
<td>SOL_AWC</td>
<td>Available water capacity (m/m)</td>
<td>0–1</td>
</tr>
<tr>
<td>Ki</td>
<td>Outflow coefficients of the free water storage to interflow relationships</td>
<td>0.8–0.9</td>
<td>CN2</td>
<td>Curve number</td>
<td>–25–30</td>
</tr>
<tr>
<td>Cg</td>
<td>Recession constants of the groundwater storage</td>
<td>0.3–0.7</td>
<td>SURLAG</td>
<td>Surface runoff lag coefficient (days)</td>
<td>0–20</td>
</tr>
<tr>
<td>Ci</td>
<td>Recession constants of the lower interflow storage</td>
<td>0.3–0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ke</td>
<td>Parameter of the Muskingum method</td>
<td>0.1–4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Xe</td>
<td>Parameter of the Muskingum method</td>
<td>0.1–4</td>
<td></td>
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</table>

and 0.79 to 0.65 and 0.81 in the Xinanjiang Model as compared to the $E_{nt}$ values using uncorrected data. The $E_{nt}$ values improved from 0.56 and 0.71 to 0.63 and 0.73 in SWAT Model respectively. However, the $E_{nt}$ values using nonlinear correction method show slightly worse results in case of WFDNLC data in both models. Specifically, the $E_{nt}$ values using the non-linearly corrected TRMM and WFD data as input changed from 0.62 and 0.79 to 0.64 and 0.66 in SWAT Model respectively as compared to the $E_{nt}$ values using uncorrected data. (3) Similar conclusions can be drawn for the validation period. Both linear and nonlinear correction methods improved the simulation results in the validation period for both models in the case of TRMM data, while in the case of WFD data linear correction method improved model simulation results but opposite results were obtained for the nonlinear correction method. And (4) in summary, WFD data, both original and bias corrected, suggest better results than TRMM data in the calibration period at daily time step for both models; nonlinear correction method performs better model simulation results than linear correction method for both models in the case of TRMM data; as for WFD data, linear correction method provides better model simulation results than the nonlinear correction method for both models.

In case of Relative Error values, it is seen from Table 4 that (1) comparing simulations with uncorrected data the values of $R_E$ produced by TRMM$_{LC}$ reduced in both models, and the values of $R_E$ produced by WFD$_{LC}$ reduced in Xinanjiang model and increased in SWAT model in the calibration period. In the validation period, the values of $R_E$ increased/decreased in the case of TRMM$_{LC}$/WFD$_{LC}$ for Xinanjiang model, while opposite is true for SWAT model. (2) The $R_E$ values produced by TRMM$_{NL}$ increased/decreased in the case of Xinanjiang/SWAT models in both calibration and validation periods, while opposite is true in case of using WFD$_{NL}$ data. Above comparison reveals that, combining both quality measures of $E_{nt}$ and $R_E$, the
WFD data is relatively better suited for the daily step hydrological simulation than the TRMM data in this study basin.

For illustrative purpose, Fig. 7 shows the comparison of the observed and simulated daily stream flow hydrographs of year 2000 in the calibration period in Xiangtan gauge which are produced by the original and bias corrected TRMM and WFD rainfall datasets in Xinanjiang Model and SWAT Model respectively. It is seen that: (1) The WFD daily rainfall based Xinanjiang Model matches the observed discharge well, followed by the WFD daily rainfall based Xinanjiang Model. Compared with the WFD data based hydrological models, TRMM data perform poorly in simulations. The simulated hydrographs show a tendency for the models to misestimate the extreme peak flows. This can be attributed to the low precision of original and mean monthly bias corrected TRMM and WFD rainfall data in matching the maximum rainfalls. And (2)

<table>
<thead>
<tr>
<th></th>
<th>Calibration period</th>
<th>Validation period</th>
<th>Calibration period</th>
<th>Validation period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$E_{ns}$</td>
<td>Relative error</td>
<td>$E_{ns}$</td>
<td>Relative error</td>
</tr>
<tr>
<td>Xinanjiang model</td>
<td>0.96</td>
<td>−1.8 %</td>
<td>0.94</td>
<td>−3.9 %</td>
</tr>
<tr>
<td></td>
<td>0.62</td>
<td>−5.9 %</td>
<td>0.85</td>
<td>5.1 %</td>
</tr>
<tr>
<td></td>
<td>0.65</td>
<td>−3.6 %</td>
<td>0.72</td>
<td>16.5 %</td>
</tr>
<tr>
<td></td>
<td>0.67</td>
<td>−9.6 %</td>
<td>0.78</td>
<td>16.6 %</td>
</tr>
<tr>
<td></td>
<td>0.79</td>
<td>1.8 %</td>
<td>0.75</td>
<td>−3.3 %</td>
</tr>
<tr>
<td></td>
<td>0.81</td>
<td>0.8 %</td>
<td>0.74</td>
<td>−2.4 %</td>
</tr>
<tr>
<td></td>
<td>0.76</td>
<td>1 %</td>
<td>0.71</td>
<td>2.1 %</td>
</tr>
<tr>
<td>SWAT model</td>
<td>0.9</td>
<td>1.3 %</td>
<td>0.9</td>
<td>−0.7 %</td>
</tr>
<tr>
<td></td>
<td>0.56</td>
<td>7.5 %</td>
<td>0.63</td>
<td>20.4 %</td>
</tr>
<tr>
<td></td>
<td>0.63</td>
<td>5.2 %</td>
<td>0.64</td>
<td>16 %</td>
</tr>
<tr>
<td></td>
<td>0.64</td>
<td>−6.3 %</td>
<td>0.72</td>
<td>11.6 %</td>
</tr>
<tr>
<td></td>
<td>0.71</td>
<td>−1.2 %</td>
<td>0.73</td>
<td>−1 %</td>
</tr>
<tr>
<td></td>
<td>0.73</td>
<td>−1.7 %</td>
<td>0.66</td>
<td>1.9 %</td>
</tr>
<tr>
<td></td>
<td>0.66</td>
<td>11 %</td>
<td>0.62</td>
<td>−11.5 %</td>
</tr>
</tbody>
</table>
the corrected and uncorrected TRMM/WFD data (except WFD$_{NL}$ based SWAT Model) all show lower discharge than observed discharge in dry season while they show higher values than observed discharge in the wet season in both hydrological models.

### 4.2.2 Evaluation of the monthly step simulated streamflow

To demonstrate the suitability of the TRMM and WFD datasets in monthly step hydrological simulation, Table 5 shows the precision of the original and bias corrected TRMM and WFD precipitation data based models for monthly streamflow simulation. It is seen that the gauged data based models still gave the best model performances, and the $E_{ns}$ values are 0.98, 0.98, 0.95 and 0.94 for the calibration and validation periods of the Xinanjiang and SWAT models respectively. The relative errors are all smaller than 3%. As for the results of TRMM and WFD datasets, the following results are obtained: (1) the largest $R_E$ value is reduced from 9.6% for the case of uncorrected TRMM data to 4.4% for linearly corrected TRMM data. The $R_E$ values for all other bias corrected cases are smaller than 3%. (2) The $E_{ns}$ values of WFD$_{LC}$ based Xinanjiang Model are the highest, achieving 0.94 and 0.95 in calibration period and validation period respectively. (3) The non-linearly corrected datasets generally perform worse results than linearly corrected datasets with an exception of TRMM data for Xinanjiang model. And (4) it can be concluded that both

<table>
<thead>
<tr>
<th></th>
<th>Gauged</th>
<th>TRMM</th>
<th>WFD</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Uncorrected</td>
<td>Linear corrected</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Xinanjiang model</td>
<td>$E_{ns}$</td>
<td>Calibration period</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Validation period</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Relative error</td>
<td>$-2.8%$</td>
</tr>
<tr>
<td>SWAT model</td>
<td>$E_{ns}$</td>
<td>Calibration period</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Validation period</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Relative error</td>
<td>$-1.9%$</td>
</tr>
</tbody>
</table>

| Fig. 8 | Comparison of the relative error of mean monthly runoff simulation driven by original and bias corrected TRMM and WFD rainfall data in a TRMM datasets based Xinanjiang model, b TRMM datasets based SWAT model, c WFD datasets based Xinanjiang model and d WFD datasets based SWAT model |
TRMM and WFD rainfall data can be used as model input for monthly flow simulation in the study region and again WFD data perform better than TRMM data.

The seasonal biases of the simulated discharges using observed precipitation and original and bias corrected TRMM/WFD datasets are compared for both Xinanjiang and SWAT models (Fig. 8). It can be seen from the figure that: (1) In case of original and bias corrected TRMM data based Xinanjiang Model (Fig. 8a), the TRMM_{NL∕C} data produce the best simulation results in general (all \( |R_E| < 10\%\) except in April). The TRMM_{NL∕C} based model misestimated the flow obviously (\( |R_E| > 10\%\)) in most of the months except January, May, June and September. (2) In case of original and bias corrected TRMM data based SWAT Model (Fig. 8b), compared with the TRMM_{O} based model, TRMM_{NL∕C} data considerably improve the flow simulation in February, August, September, October and November. Meanwhile, the TRMM_{NL∕C} data considerably improve the flow simulation in January, April, August, October, November and December. (3) In case of original and bias corrected WFD data based Xinanjiang Model (Fig. 8c), the WFD_{LC}∕WFD_{NL∕C} data obviously produce larger error than the WFD_{O} data in flow simulation in January-April and November and the WFD_{NL∕C} data also considerably overestimate the flow in the model in September. However, in June–September (raining season), the WFD_{LC} based model estimates the flow very well (\( |R_E| < 5\%\)). (4) In case of original and bias corrected WFD data based SWAT Model (Fig. 8d), the WFD_{O} based SWAT model underestimates the streamflow obviously except in May and July. The WFD_{LC} based model considerably improves the flow simulation compared with the WFD_{O} data based model in most months (except May, July and November). Meanwhile, the \( R_E \) values of flow produced by the WFD_{NL∕LC} based model improve in January, June, August–October and December obviously compared with the \( R_E \) calculated by the WFD_{O} data based model, but considerably worsen \( R_E \) values can also be observed in March, may, July and November.

In summary, above results reveal that the linearly corrected WFD rainfall data give the best prospect for monthly step streamflow simulation in both models. However, the nonlinearly corrected TRMM dataset has the potential to be a suitable data source for the data-poor or ungauged basins due to its real-time updating, particularly for the large-scale or meso-scale basins in remote locations.

5 Conclusions

This paper compared the differences between TRMM and WFD rainfall datasets with gauged rainfall data at daily and monthly time steps and evaluated the accuracy of bias corrected TRMM and WFD rainfall for discharge simulation using lumped Xinanjiang Model and distributed SWAT Model in Xiangjiang River Basin, south China.

The following conclusions can be drawn from the results of this study:

1. The differences of the mean annual and seasonal areal precipitation calculated from the gauged precipitation and the two original global datasets (TRMM_{O} and WFD_{O}) are in general very good. The differences of the mean annual and seasonal areal precipitation calculated from the gauged precipitation and the two original global datasets (TRMM_{O} and WFD_{O}) are in general within the acceptable value of less than 10\%, and the linear correlation between the monthly gauged precipitation and TRMM_{O} and WFD_{O} data as reflected by the interception, slope and \( R^2 \) are in general very good. However, the spatial differences as reflected by the results of K–S test and \( F \) test on each grid for distribution pattern and variance are found to be significant between the gauged and the two global datasets (TRMM_{O} and WFD_{O}) in most grids, while the student’s \( t \) test shows two thirds (one third) of the grids of TRMM_{O} (WFD_{O}) rainfall in the basin have the same mean values as gauged rainfall. The differences in maximum dry spell are significant between the two global datasets and the gauged rainfall, while the difference in maximum 5-day rainfall is significant between TRMM_{O} and gauged values.

2. The bias correction methods are able to remove the biases existed in the mean values of TRMM_{O} and WFD_{O} datasets. The nonlinear bias correction method gives good results in correcting the standard deviation values in TRMM/WFD data at grid level. The \( E_{\text{as}} \) values of TRMM data improved after nonlinear bias correction in most of the grids as well as in the areal mean rainfall. The linear bias correction method gives good results in correcting the standard deviation of areal mean WFD data. But the \( E_{\text{as}} \) values of WFD data do not improve in both grid and areal mean level after linear or nonlinear bias correction.

3. The comparison of model simulation results using gauged precipitation and the two original global datasets (TRMM_{O} and WFD_{O}) as inputs to the two hydrological models reveals that at daily time step both TRMM_{O} and WFD_{O} produce much worse results than using observed precipitation data in terms of Nash–Sutcliffe efficiency \( E_{\text{ns}} \) and relative error, \( R_E \). Both linearly and nonlinearly bias corrected TRMM and WFD data do not significantly improve the model simulation results at daily time step.

4. At monthly time step the modelling study shows that both TRMM and WFD data produce acceptable
model simulation results in terms of both Nash–Sutcliffe efficiency ($E_{ns} > 0.7$ for original and nonlinear corrected TRMM/WFD data, $E_{ns} > 0.8$ for linear corrected TRMM/WFD data) and relative error (all $|R^2| < 10\%$). Linear correction method produces better simulation results than nonlinear correction method and the best results were found from Xinanjiang Model using linearly corrected WFD data without considering gauged data based models.

(5) In general, it can be said that the reanalysis WFD data matches the gauged precipitation better and produce slightly better model simulation results in the region than the TRMM data, and the lumped Xinanjiang model performs better than the distributed SWAT model at both monthly and daily time steps.

However, it should be noted that:

(1) Several shortcomings still exist in using global datasets in hydrological simulations, as TRMM and WFD overestimate or underestimate the rainfall in different years and areas, and have a generic failure to detect the small and extreme rainfall which limit the precision of discharge simulation at daily time steps and in hydrological applications including drought and flood forecasting. These shortcomings in TRMM and WFD datasets indicate that further efforts of evaluating the satellite-based and reanalysis datasets need to be continued in more areas with different scales and climatic conditions and using hydrological models with different spatial–temporal resolutions.

(2) The spatial autocorrelation is not considered due to a dense network of rain gauge stations is available in this study to remedy the bias of TRMM and WFD datasets grid by grid. However, when the reanalysis/satellite based datasets are used in the basins without such densely distributed rain gauges to interpolate grid rainfall, the Biased Sentinel Hospitals-Based Area Disease Estimation (B-SHADE) model which takes into account prior knowledge of geographic spatial autocorrelation and non-homogeneity of target domains, remedies the biased sample, and maximizes an objective function for best linear unbiased estimation (BLUE) of the regional mean (total) quantity (Wang et al. 2011) can be adopted as an alternative choice to correct the bias. Unlike the bias correction methods applied in the study that simply considers the statistical relationship between data series, the B-SHADE model considers coexistence of homogeneity and heterogeneity of the variant in land surface (Wang et al. 2009, 2010).

Meanwhile, the B-SHADE model uses correlation between stations and selecting several observation stations of greatest correlation that can better reflect the reality (Xu et al. 2013).

(3) Furthermore, the newly released WATCH-Forcing-Data-ERA-Interim (http://www.eu-watch.org/data_availability), a dataset produced post-WATCH using WFD methodology applied to ERA-Interim data, extends the meteorological forcing dataset into early twenty first century (1979–2012) and provides an alternative dataset for ungauged or sparsely gauged basins for hydrological analysis and modeling. The usefulness of this dataset will be evaluated in the on-going research.

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