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Hydrological Simulation Using TRMM and CHIRPS Precipitation Estimates in the Lower Lancang-Mekong River Basin

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Abstract: Satellite-based products with high spatial and temporal resolution provide useful precipitation information for data-sparse or ungauged large-scale watersheds. In the Lower Lancang-Mekong River Basin, rainfall stations are sparse and unevenly distributed, and the transboundary characteristic makes the collection of precipitation data more difficult, which has restricted hydrological processes simulation. In this study, daily precipitation data from four datasets (gauge observations, inverse distance weighted (IDW) data, Tropical Rainfall Measuring Mission (TRMM) estimates, and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) estimates), were applied to drive the Soil and Water Assessment Tool (SWAT) model, and then their capability for hydrological simulation in the Lower Lancang-Mekong River Basin were examined. TRMM and CHIRPS data showed good performances on precipitation estimation in the Lower Lancang-Mekong River Basin, with the better performance for TRMM product. The Nash-Sutcliffe efficiency (*NSE*) values of gauge, IDW, TRMM, and CHIRPS simulations during the calibration period were 0.87, 0.86, 0.95, and 0.93 for monthly flow, respectively, and those for daily flow were 0.75, 0.77, 0.86, and 0.84, respectively. TRMM and CHIRPS data were superior to rain gauge and IDW data for driving the hydrological model, and TRMM data produced the best simulation performance. Satellite-based precipitation estimates could be suitable data sources when simulating hydrological processes for large data-poor or ungauged watersheds, especially in international river basins for which precipitation observations are difficult to collect. CHIRPS data provide long precipitation time series from 1981 to near present and thus could be used as an alternative precipitation input for hydrological simulation, especially for the period without TRMM data. For satellite-based precipitation products, the differences in the occurrence frequencies and amounts of precipitation with different intensities would affect simulation results of water balance components, which should be comprehensively considered in water resources estimation and planning.

Keywords: hydrological simulation; satellite-based precipitation estimates; spatial distribution of precipitation; international river; the Lower Lancang-Mekong River Basin

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1 Introduction

Precipitation is one of the primary controlling factors in the hydrological cycle and thus the reliability of hydrological simulations strongly depends on accurate representation of spatially distributed precipitation (Gao et al., 2017; Worqlul et al., 2017). However, some of the currently available rain gauge networks are inadequate

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to support reliable hydrological modeling, largely owing to their sparse spatial coverage, short length of records, and high proportion of missing data (Rozante et al., 2010; Trejo et al., 2016). When simulating hydrological processes in large river basins or watersheds with complicated terrain, the sparse and heterogeneous spatial distribution of rain gauges often cause weak simulation results (Cho et al., 2009).

In the last decade, satellite precipitation products with high temporal and spatial resolution over widespread regions have been applied in hydrological analysis and simulations, which have provided new information to support water resources management globally (Serrat-Capdevila et al., 2014; Jiang et al., 2016). Satellite-based precipitation products could effectively extend precipitation estimates to regions in which conventional measuring stations are scarce, unevenly distributed, or erratic, making them especially valuable for hydrological simulation in large watersheds in developing countries or remote locations (Li et al., 2012; Trejo et al., 2016; Katiraie-Boroujerdy et al., 2017). Moreover, the choice of the best precipitation data for hydrological model is basin-specific (Tuo et al., 2016), and it has been increasingly recognized that the selection of precipitation input is more important than the hydrological model (Tobin and Bennett, 2013).

The Lancang-Mekong River is the eighth largest river by discharge in the world (Sabo et al., 2017), and also the most important international river in Southeast Asia (Wang et al., 2016). Originating from the Tibetan Plateau, the Lancang-Mekong River runs through China, Myanmar, Thailand, Lao PDR, Cambodia, and Vietnam, and finally enters the South China Sea. The river has a length of 4880 km, and the catchment area of the Lancang-Mekong River Basin is about 806×10^3 km^2. In the Lower Lancang-Mekong River Basin, spatial distribution of precipitation is complex and highly heterogeneous, while rainfall stations are sparse and unevenly distributed (Wang et al., 2016), and frequently have high proportion of gaps in the observations. Moreover, the transboundary characteristic of the Lancang-Mekong River Basin increases the difficulty and complexity of the collection and analysis of precipitation data.

Satellite precipitation products with high spatial and temporal resolution may help to overcome these shortcomings, potentially increasing the accuracy of hydrological modeling in the Lower Lancang-Mekong River Basin. More detailed understanding on the strengths and weaknesses of satellite-based precipitation products for hydrological modeling would be useful for water resources utilization and planning.

The objectives of this study were to evaluate the accuracy of the satellite-based precipitation data, and to study their applicability for hydrological modeling in the Lower Lancang-Mekong River Basin. Tropical Rainfall Measuring Mission (TRMM) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) data were compared with gauge-based precipitation data. Hydrological processes simulation were then conducted using the Soil and Water Assessment Tool (SWAT) model driven by rain gauge observations, inverse distance weighted (IDW) data, TRMM and CHIRPS estimates, and calibration and validation results at monthly and daily scales were compared to investigate the impacts of different precipitation input data on the hydrological modeling in the Lower Lancang-Mekong River Basin.

2 Materials and Methods

2.1 Study area

The mean annual flow of the Mekong River is approximately 475×10^9 m^3. About 16% of the flow comes from China and 2% from Myanmar. Most of the remainder comes from Lao PDR, and the major left bank tributaries, particularly the tributaries below Nongkhai (Mekong River Commission, 2005). The Upper Lancang-Mekong Basin is located from China to Myanmar, and the Lower Lancang-Mekong Basin is located from Lao PDR to the Mekong Delta. The hydrological boundary between them is generally taken to Chiang Saen station on the mainstream. The Upper Lancang-Mekong Basin is narrow and topographically steep, while the Lower Lancang-Mekong Basin is wide with large tributary river systems.

In recent years, hydropower development has altered the flow regimes in the Lancang-Mekong River, particularly after the completion of Xiaowan Dam in 2010 and Nuozhadu Dam in 2014 in the Upper Lancang-Mekong River Basin (Fan et al., 2015; Li et al., 2017; Räsänen et al., 2017). To avoid the influences of hydropower station operation on hydrological modeling, we mainly simulated hydrological processes in the Lower Lancang-Mekong River Basin. Chiang Saen station was taken as the inlet of the study area, and Stung Treng station with long term flow observations was taken as the outlet (Fig. 1). The study area has an area of 446 × 10^3 km^2, accounting for about 55% of the Lancang-Mekong River Basin.

The Lower Lancang-Mekong River Basin is affected by the rainy southwest monsoon and the dry northeast monsoon. The southwest monsoon from the Indian Ocean brings precipitation lasted from mid-May to mid-October, which account for around 85%–90% of annual precipitation. The northeast monsoon causes dry weather from mid-October to April (Zhou et al., 2008). Despite having relatively high annual precipitation, the Lower Lancang-Mekong River Basin is vulnerable to increasing droughts (Thilakarathne and Sridhar, 2017). Furthermore, the Lower Lancang-Mekong River Basin has a total population of approximately 70 million, and water resources in the basin contribute greatly to the economy as well as to local livelihoods and food security (Son et al., 2012). The demand for water resources in this region is increasing under rapid population and economic growth (Johnston and Kummu, 2012).

2.2 Data sources

2.2.1 Rain gauge data

Rain gauge data from 311 rainfall stations in the Lower Lancang-Mekong River Basin were obtained from the MRC historical observation dataset. However, a large amount of the gauge data did not encompass full

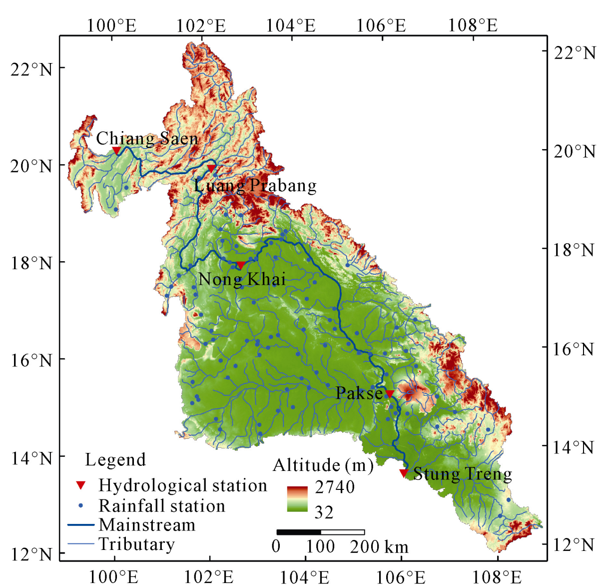

Fig. 1 Topography and the locations of rainfall and hydrological stations in the Lower Lancang-Mekong River Basin

time series or were low in quality, and therefore could not meet the requirements of evaluation and simulation. In consideration of the time series of gauge and TRMM data, we chose the period from 1998 to 2005 to evaluate satellite-based precipitation estimates and calibrate hydrological model. In the study area, the entire time series from 1998 to 2005 were available for only 97 rainfall stations, the locations of which are shown in Fig. 1. When using the data of rain gauge as the input of SWAT model, all available precipitation data are usually applied directly. However, for each subbasin, SWAT model only uses the data of the rainfall station closest to the centroid, disregarding other stations (Galván et al., 2014). The simulation directly using gauge data as input will be referred to as gauge-simulation.

2.2.2 IDW-based precipitation data

Besides observed precipitation at rainfall stations, IDW-based precipitation data were also applied as the input, to examine whether spatial interpolation could obtain more accurate precipitation data for hydrological modeling in the Lower Lancang-Mekong River Basin. IDW assumes that the value of a point is more influenced by closer points than by those further away, and correspondingly estimates precipitation at unknown points by the weighted average of the observed value at neighboring rainfall stations (Ly et al., 2011). In this study, average IDW daily precipitation for each subbasin was calculated and applied as the input at the centroid of the subbasin, and the corresponding simulation will hereafter be referred to as IDW-simulation.

2.2.3 TRMM data

TRMM 3B42V7 algorithm combines multiple independent precipitation estimates from TRMM Microwave Image (TMI), Advanced Microwave Scanning Radiometer for Earth Observing Systems (AMSR-E), Special Sensor Microwave Imager (SSMI), Special Sensor Microwave Imager/Sounder (SSMIS), Advanced Microwave Sounding Unit (AMSU), Microwave Humidity Sounder (MHS), and microwave-adjusted merged geo-infrared (IR). TRMM 3B42V7 precipitation estimates are at 3-hourly temporal resolution and 0.25° × 0.25° spatial resolution. The daily accumulated TRMM 3B42 data were calculated and used as the SWAT input. For each subbasin, daily precipitation was calculated by averaging all TRMM grids within the subbasin boundary and then used as the input of SWAT model, and accordingly the simulation will be referred to as TRMM-simulation.

2.2.4 CHIRPS data

CHIRPS, developed by the U.S. Geological Survey Earth Resources Observation and Science Center and Santa Barbara Climate Hazards Group at the University of California, is a relatively new precipitation product based on multiple data sources (Trejo et al., 2016). This database encompasses three kinds of information, including global climatologies, satellite estimates and *in-situ* observations. Specifically, CHIRPS incorporates monthly precipitation climatology (Climate Hazards Group Precipitation Climatology, CHPClim), quasi-global geostationary thermal infrared satellite observations, TRMM product, atmospheric model precipitation fields from the National Oceanic and Atmospheric Administration (NOAA) Climate Forecast System (CFS), and observed precipitation (Katsanos et al., 2016). The advantage of CHIRPS estimates is the high spatial resolution of 0.05° × 0.05°, which is expected to capture more representative precipitation characteristics (Tuo et al., 2016). Moreover, CHIRPS data provide precipitation time series from 1981 to near present, allowing it to be used for long-term hydrological analysis and simulation. The mean daily CHIRPS data were calculated for each subbasin and applied as the input of SWAT model, and the corresponding simulation will be referred to as CHIRPS-simulation.

2.2.5 Other meteorological data

Besides precipitation data, other meteorological data are required to drive SWAT model, including air temperature, relative humidity, solar radiation, and wind speed. In this study, these meteorological data were obtained from the Climate Forecast System Reanalysis (CFSR) provided by National Centers for Environmental Prediction (NCEP), which was executed as a global, high resolution, coupled atmosphere-ocean-land surface-sea ice system to provide meteorological estimates.

2.2.6 Geographical data

The geographical data used in this study, including digital elevation model (DEM), soil type and attribute data, and land use and land cover, were all from global public data sets. Shuttle Radar Topography Mission (SRTM) provides high-resolution digital topographic database, and SRTM30 data, a 30 arc-second resolution global topography grid, was applied to identify topographical characteristics. Soil type and attribute data were obtained from Harmonized World Soil Database (HWSD), which consists of a 30 arc-second raster image and an attribute database. In addition, land use and land cover data were obtained from Global Land Cover 2000 (GLC 2000), providing a harmonized land cover database over the whole globe for 2000.

2.2.7 Flow data

Flow data were collected from five hydrological stations on the main stream, including Chiang Saen, Luang Prabang, Nong Khai, Pakse and Stung Treng station (Fig. 1). The catchment area and mean annual flow are given in Table 1. At Chiang Saen station, the inlet of the study area, the catchment area is 189 × 10^3 km^2, with an annual flow of about 85.1 × 10^9 m^3. At Stung Treng station, the outlet of the study area, the catchment area is 635 × 10^3 km^2, and the annual runoff volume is about 413.1 × 10^9 m^3. The runoff of the study area accounts for about 69% of that in the whole Lancang-Mekong River Basin.

2.3 Hydrological model

In this study, SWAT, a continuous, semi-distributed, and process-based model, was used to simulate hydrological processes. When applying SWAT model, a watershed is partitioned into a number of subbasins, which are further subdivided into multiple hydrologic response units (HRUs) by topography, soil characteristics, land use, and management schemes (Arnold et al., 1998; Neitsch et al., 2011; Liu et al., 2014; Abbaspour et al., 2015). SWAT has been proven to be an effective tool for hydrological simulation and applied extensively and intensively around the world (Arnold et al., 2015; Tuo et al., 2016; Jin et al., 2018), which was accepted by Mekong River Commission (MRC) member countries for water resources planning in the Lower Lancang-Mekong River Basin and applied in the MRC Decision Support Framework (Johnston et al., 2012).

Table 1 Catchment area and mean annual flow (1960–2004) at selected hydrological stations (Mekong River Commission, 2005)

Hydrological station	Catchment area (10^3 km^2)	Mean annual flow (m^3/s)
Chiang Saen	189	2700
Luang Prabang	268	3900
Nong Khai	302	4500
Pakse	545	9700
Stung Treng	635	13100

2.4 Evaluation statistics

2.4.1 Evaluation of satellite-based precipitation estimates

Two approaches have been widely used to evaluate satellite-based precipitation estimates. The first estimates spatial precipitation from gauge-based data by spatial interpolation methods, and then carrying out pixel-to-pixel comparisons with satellite-based data. In the second approach, the corresponding grid in the satellite-based precipitation products is found for each gauge location, and then precipitation values are extracted to generate the satellite-gauge data pairs for evaluation (Shrestha et al., 2017). In this study, there were only 97 rainfall stations with satisfactory data, which would affect the accuracy of spatial precipitation interpolation, and the second approach was applied to evaluate TRMM and CHIRPS estimates.

Four evaluation statistics were utilized to evaluate the accuracy of the satellite-based precipitation products, including Pearson correlation coefficient (*r*), relative bias (*BIAS*), mean error (*ME*), and mean absolute error (*MAE*) (Duan et al., 2016).

2.4.2 Evaluation of hydrological model performance

The accuracy of hydrological model performance was evaluated by coefficient of determination (R^2) and three statistics recommended by Moriasi et al. (2007), including Nash-Sutcliffe efficiency (*NSE*), percent bias (*PBIAS*), and root mean square error (*RMSE*)-observations standard deviation ratio (*RSR*).

The model performances for monthly time step were classified according to the work of Moriasi et al. (2007) as follows: unsatisfactory performance ($NSE \leq 0.50$, $|PBIAS| \geq 25$, $RSR > 0.70$), satisfactory performance ($0.50 < NSE \leq 0.65$, $15 \leq |PBIAS| < 25$, $0.60 < RSR \leq 0.70$), good performance ($0.65 < NSE \leq 0.75$, $10 \leq |PBIAS| < 15$, $0.50 < RSR \leq 0.60$), very good performance ($0.75 < NSE \leq 1.00$, $|PBIAS| < 10$, $0.00 \leq RSR \leq 0.50$).

3 Results

3.1 Evaluation of satellite precipitation data

3.1.1 Performance measures based on evaluation statistics

The gridded precipitation products (TRMM and CHIRPS) were compared with gauge observation data at monthly scale, and evaluation of satellite precipitation was conducted on the overlapping period (1998–2005). The scatterplot of monthly precipitation from gauge observations against those from TRMM and CHIRPS estimates (Fig. 2) indicates good agreements between satellite-based precipitation estimates and gauge observations, and slight underestimations for TRMM and CHIRPS data on the monthly precipitation.

The evaluation statistics for monthly precipitation are presented in Table 2. TRMM and CHIRPS estimates had high correlation coefficients with gauge observation of 0.862 and 0.820, respectively. The *BIAS* and *ME* of TRMM and CHIRPS estimates were all relatively low, and the *MAE* were both close to 60 mm. These results indicated that TRMM and CHIRPS estimates coincided well with *in-situ* observation in the study area. The *ME* results indicated that the average underestimation for TRMM estimates was about –2.4 mm/mon, while CHIRPS estimates underestimated by about –11.3 mm/mon, showing the underestimation for TRMM estimates was smaller than that of CHIRPS estimates. On the whole, TRMM estimates had higher *r* and lower *BIAS*, *ME*, and *MAE*, illustrating that TRMM estimates could better represent precipitation distribution than CHIRPS estimates.

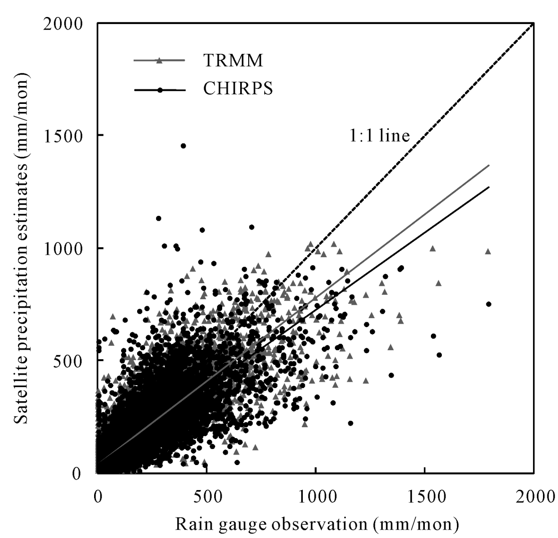

Fig. 2 Scatterplot of monthly precipitation from gauge observations against Tropical Rainfall Measuring Mission (TRMM) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) estimates for 1998–2005

Table 2 Evaluation statistics of Tropical Rainfall Measuring Mission (TRMM) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) estimates at monthly scale for 1998–2005

Statistical metrics	TRMM	CHIRPS
r	0.862	0.820
BIAS	–0.016	–0.072
ME (mm)	–2.4	–11.3
MAE (mm)	56.2	63.2

Notes: Pearson correlation coefficient (*r*), relative bias (*BIAS*), mean error (*ME*), and mean absolute error (*MAE*)

The mean *ME* in each month for TRMM and CHIRPS estimates were further compared (Fig. 3). For TRMM estimates, the mean *ME* ranged from –9.5 to 5.8 mm, indicating slight error for monthly precipitation. During the rainy season, TRMM data mostly underestimated monthly precipitation. In contrast, the mean *ME* for CHIRPS estimates were between –40.0 and 1.4 mm. Except for December, underestimation of precipitation occurred in each month, and the mean *ME* in April, June, and August were –25.2, –40.0, and –22.2 mm, respectively. In the Lower Lancang-Mekong River Basin, both TRMM and CHIRPS estimates tend to underestimate monthly precipitation in the rainy season, and the underestimation of CHIRPS data was much greater than that of TRMM data.

3.1.2 Spatial distribution of precipitation based on various precipitation estimates

At 97 rainfall stations, annual precipitation was between 841.5 and 4698.5 mm (Fig. 4a). Among them, annual precipitation at 64 stations were between 1000.0 and 2000.0 mm, while 23 stations had annual precipitation between 2000.0 and 3000.0 mm. For TRMM estimates, annual precipitation in the study area ranged from 1149.8

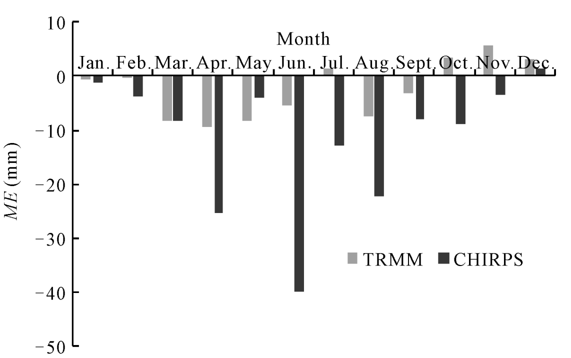

Fig. 3 Mean error (*ME*) of monthly precipitation for TRMM and CHIRPS estimates

to 3587.0 mm (Fig. 4b), while annual precipitation of CHIRPS estimates were between 992.1 mm and 3695.4 mm (Fig. 4c). The spatial distribution of annual precipitation estimated from TRMM data were similar to that from CHIRPS data. As the southwest monsoon crosses the low mountains in Thailand and Cambodia, rain falls onto the south-western parts of the Lower Lancang-Mekong River Basin, and annual precipitation in the right bank were mostly less than 2000 mm. More precipitation occurs when the moisture crosses the Annamese Mountains (Tatsumi and Yamashiki, 2015), and annual precipitation in the left bank were mostly higher than 1500 mm.

3.1.3 Intensity distribution of daily precipitation

For both the occurrence frequencies and the proportions of daily precipitation with different intensities, there were considerable differences among gauge observations, TRMM, and CHIRPS estimates (Fig. 5). The occurrence frequencies of rainstorm (daily precipitation ≥ 50 mm) for gauge observations (2.3%) and TRMM estimates (1.6%) were higher than those for CHIRPS estimates (0.7%). Though the occurrence frequency is relatively low, rainstorm plays an important role in the total precipitation in the Lower Lancang-Mekong River Basin. The rainstorm amounts for gauge observation and TRMM estimates accounted for 32.5% and 22.9% of the total precipitation, respectively, which were both much larger than that for CHIRPS estimates (9.6%). In contrast, for gauge and TRMM data, the occurrence frequencies of moderate precipitation (10 ≤ daily precipitation < 25 mm) were 7.6% and 9.4%, and moderate precipitation took 23.9% and 29.8% of their corresponding total amounts, respectively. Whereas moderate precipitation appeared more frequently for CHIRPS estimates (13.1%), which accounted for 43.3% of the total amounts. Both TRMM and CHIRPS data tend to underestimate rainstorm in the Lower Lancang-Mekong River Basin, which should be noticed when using these data.

3.2 Hydrological modeling results

3.2.1 Model calibration and validation

In this study, SWAT models were set up for the Lower Lancang-Mekong River Basin with 297 subbasins, and the models with four precipitation datasets inputs (gauge, IDW, TRMM, and CHIRPS data) were calibrated for the streamflow at Luang Prabang, Nong Khai, Pakse, and Stung Treng station. Input data from 1998 to

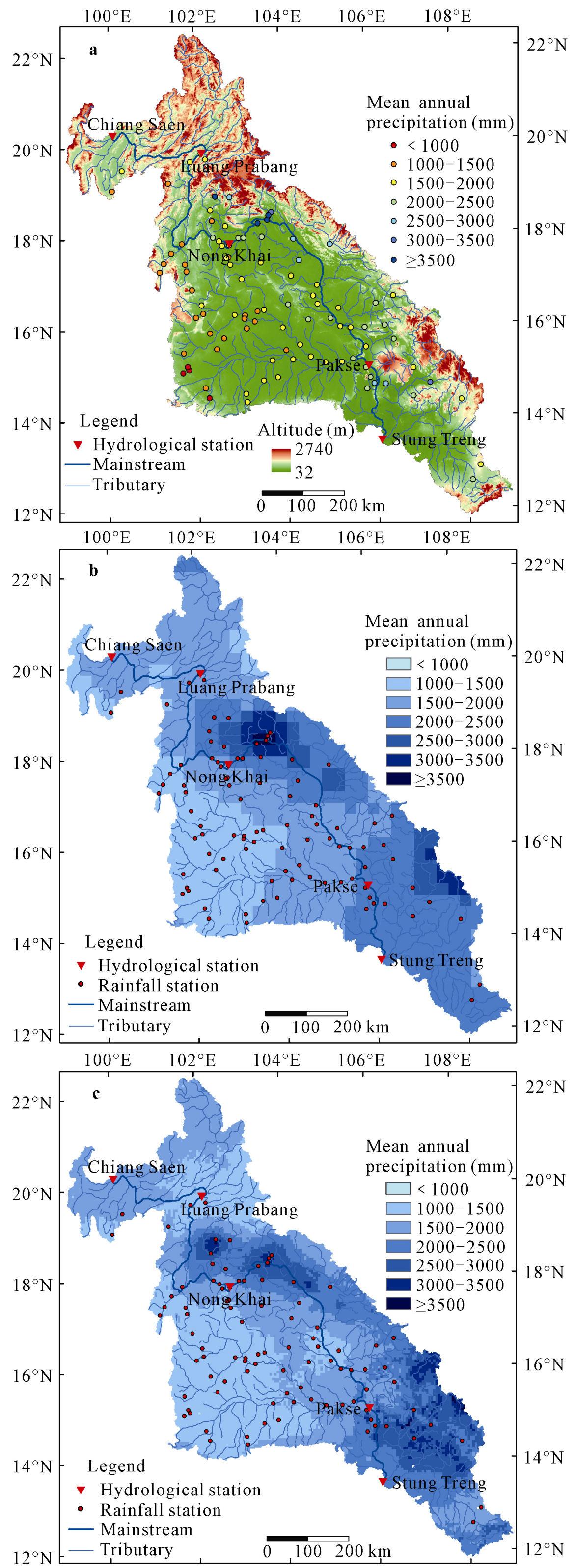

Fig. 4 Spatial distribution of annual precipitation in the study area based on gauge observations (a), TRMM estimates (b), and CHIRPS estimates (c)

2005 were used to calibrate the SWAT model, and the data from 2006 to 2012 were applied for validation. As the entire time series during 2006 to 2012 were unavailable for some gauge stations, gauge and IDW data were not used for validating the model. In addition, TRMM data began at 1998, while CHIRPS data commenced at 1981. Validation results of CHIRPS-simulation from 2006 to 2012 were compared with those of TRMM-simulation, and CHIRPS data from 1981 to 1997 were also used for validation to further analyze their feasibility for hydrological simulation.

Automatic calibration were performed making use of the Sequential Uncertainty Fitting version 2 (SUFI-2) in the SWAT Calibration and Uncertainty Programs (SWAT-CUP). The results indicated that for the SWAT models driven by gauge, IDW, TRMM, and CHIRPS data, some similar parameter values could achieve performance close to each best respectively. Hence, consistent physically reasonable parameters were quantified for the models driven by different precipitation inputs, to eliminate the influences of parameter values on water balance components comparison.

3.2.2 Evaluation of model performances

The hydrographs of observed and simulated monthly flow at Stung Treng station by gauge-simulation (Fig. 6a), IDW-simulation (Fig. 6b), TRMM-simulation (Fig. 6c), and CHIRPS-simulation (Fig. 6d) during the calibration period are presented. Streamflow generation increased in May, which was caused by a rapid increase in the precipitation. From May to October, the southwest monsoon from the Indian Ocean brought precipitation and produce abundant streamflow. From November to April, dry weather influenced by the northeast monsoon caused low river flow. For the flow in flood season, especially the maximum monthly flow, underestimation usually occurred in TRMM-simulation and CHIRPS-simulation at Stung Treng station, and the underestimation of CHIRPS-simulation were higher than that of TRMM-simulation.

The performances of the gauge-simulation, IDW-simulation, TRMM-simulation, and CHIRPS-simulation were compared further using evaluation statistics at monthly (Table 3) and daily (Table 4) scales. According to the performance classification recommended by Moriasi et al. (2007), at monthly scale, the models with different precipitation inputs all achieved very good performances for *NSE* and *RSR* during calibration and validation periods, and mostly very good, good, or satisfactory performances for *PBIAS*.

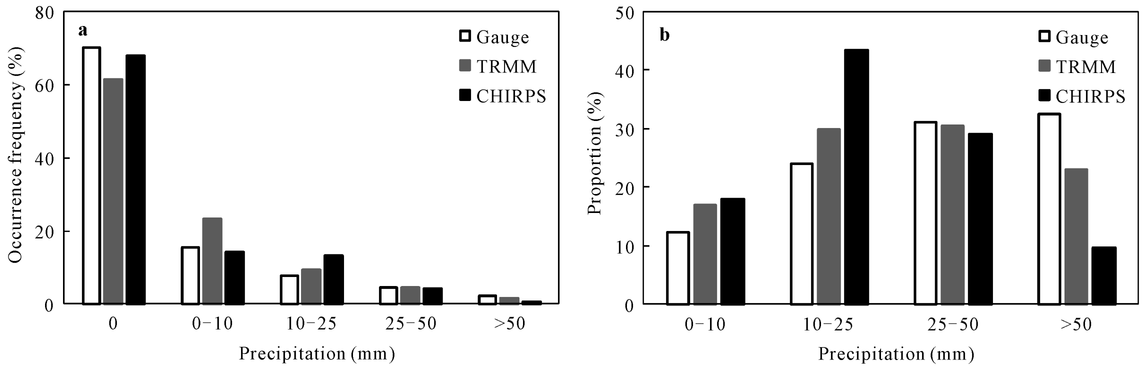

Fig. 5 Occurrence frequencies (a) and proportions (b) of daily precipitation with different intensities for gauge observations, TRMM and CHIRPS estimates (1998–2005)

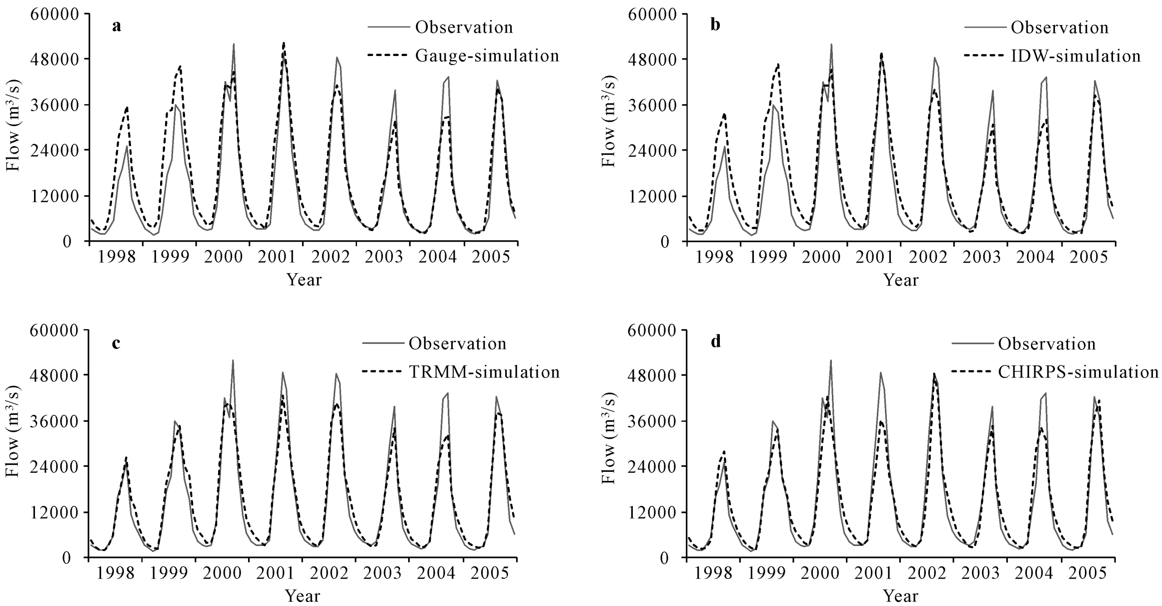

Fig. 6 Calibration results of the gauge-simulation (a), inverse distance weighted (IDW)-simulation (b), TRMM-simulation (c), and CHIRPS-simulation (d) at Stung Treng station

Table 3 Monthly evaluation statistics of gauge-simulation, IDW-simulation, TRMM-simulation, and CHIRPS-simulation

Precipitation data	Hydrological station	Calibration period (1998–2005)				Validation period (2006–2012)			
		R^2	*NSE*	*PBIAS*	*RSR*	R^2	*NSE*	*PBIAS*	*RSR*
Gauge	Luang Prabang	0.94	0.92	–13.2	0.29	–	–	–	–
	Nong Khai	0.90	0.89	–9.4	0.34	–	–	–	–
	Pakse	0.87	0.81	–20.7	0.44	–	–	–	–
	Stung Treng	0.89	0.86	–15.3	0.37	–	–	–	–
IDW	Luang Prabang	0.95	0.90	–19.1	0.32	–	–	–	–
	Nong Khai	0.91	0.87	–14.9	0.35	–	–	–	–
	Pakse	0.87	0.82	–20.4	0.43	–	–	–	–
	Stung Treng	0.89	0.86	–14.9	0.37	–	–	–	–
TRMM	Luang Prabang	0.98	0.97	–10.2	0.18	0.97	0.86	–22.3	0.37
	Nong Khai	0.97	0.96	–7.6	0.20	0.94	0.90	–14.1	0.31
	Pakse	0.97	0.96	–6.4	0.20	0.96	0.95	–5.8	0.22
	Stung Treng	0.95	0.93	–3.5	0.26	0.95	0.93	–12.5	0.27
CHIRPS	Luang Prabang	0.97	0.96	–9.5	0.21	0.96	0.90	–16.9	0.31
	Nong Khai	0.96	0.95	–7.2	0.22	0.93	0.90	–12.8	0.31
	Pakse	0.94	0.92	2.8	0.28	0.95	0.94	–6.5	0.24
	Stung Treng	0.92	0.91	–0.5	0.30	0.93	0.82	–26.9	0.43

Notes: Coefficient of determination (R^2), Nash-Sutcliffe efficiency (*NSE*), percent bias (*PBIAS*), and root mean square error (*RMSE*)-observations standard deviation ratio (*RSR*). Inverse distance weighted (IDW)

Table 4 Daily evaluation statistics of gauge-simulation, IDW-simulation, TRMM-simulation, and CHIRPS-simulation

Precipitation data	Hydrological station	Calibration period (1998–2005)				Validation period (2006–2012)			
		R^2	*NSE*	*PBIAS*	*RSR*	R^2	*NSE*	*PBIAS*	*RSR*
Gauge	Luang Prabang	0.85	0.82	–13.1	0.43	–	–	–	–
	Nong Khai	0.78	0.74	–9.3	0.51	–	–	–	–
	Pakse	0.77	0.68	–20.7	0.56	–	–	–	–
	Stung Treng	0.78	0.75	–15.2	0.50	–	–	–	–
IDW	Luang Prabang	0.89	0.84	–18.9	0.40	–	–	–	–
	Nong Khai	0.82	0.77	–14.8	0.48	–	–	–	–
	Pakse	0.78	0.71	–20.3	0.54	–	–	–	–
	Stung Treng	0.79	0.76	–14.8	0.49	–	–	–	–
TRMM	Luang Prabang	0.92	0.91	–10.1	0.30	0.90	0.79	–22.2	0.46
	Nong Khai	0.88	0.87	–7.6	0.37	0.83	0.78	–14.0	0.46
	Pakse	0.86	0.86	–6.3	0.38	0.85	0.83	–5.7	0.41
	Stung Treng	0.81	0.81	–3.4	0.43	0.84	0.80	–12.4	0.44
CHIRPS	Luang Prabang	0.91	0.90	–8.8	0.31	0.89	0.82	–16.7	0.42
	Nong Khai	0.87	0.86	–6.5	0.38	0.82	0.78	–12.7	0.47
	Pakse	0.84	0.83	4.2	0.41	0.82	0.80	–6.4	0.44
	Stung Treng	0.78	0.78	0.8	0.47	0.80	0.64	–26.7	0.60

Note: Meanings of all abbreviations are shown in Table 3

During the calibration period, the mean monthly and daily *NSE* values of gauge-simulation were 0.87 and 0.75, respectively, which were close to those of IDW-simulation (0.86 and 0.77). For TRMM-simulation, the mean monthly and daily *NSE* values were 0.95 and 0.86, respectively, and these values for CHIRPS-simulation were 0.93 and 0.84, respectively. Moreover, the R^2, *PBIAS*, and *RSR* of TRMM-simulation and CHIRPS-simulation were also much better than those of gauge-simulation and IDW-simulation. Whether at monthly or daily scale, gauge-simulation and IDW-simulation showed similar simulation performances, and TRMM-simulation and CHIRPS-simulation produced improved results. During the validation period, TRMM-simulation also achieved better performance than CHIRPS- simulation. It was clear that TRMM and CHIRPS data were superior for hydrological modeling at both monthly and daily scales, and TRMM data performed better than CHIRPS data in the Lower Lancang-Mekong River Basin.

Besides the period of 2006–2012, CHIRPS data for 1981–1997 were also utilized to further validate SWAT model. At monthly and daily scales, CHIRPS-simulation showed consistent good performances in flow simulation during 1981–1997 (Table 5), and the mean monthly and daily *NSE* values were 0.93 and 0.81, respectively. During the period without TRMM data, CHIRPS estimates could provide useful precipitation information in the Lower Lancang-Mekong River Basin.

Table 5 Evaluation statistics of the simulation with CHIRPS data during 1981–1997

Hydrological station	Monthly scale				Daily scale			
	R^2	*NSE*	*PBIAS*	*RSR*	R^2	*NSE*	*PBIAS*	*RSR*
Luang Prabang	0.97	0.94	–11.8	0.25	0.91	0.88	–11.7	0.35
Nong Khai	0.94	0.93	–9.7	0.27	0.84	0.82	–9.6	0.42
Pakse	0.93	0.93	–3.8	0.27	0.80	0.80	–3.6	0.45
Stung Treng	0.92	0.91	–7.6	0.30	0.77	0.76	–7.5	0.49

Note: Meanings of all abbreviations are shown in Table 3

3.2.3 Water balance components analysis

Besides flow hydrographs and evaluation statistics, water balance components were also analyzed to further examine the effects of precipitation inputs on hydrological simulation. According to the above simulation results from 1998 to 2005, comparisons of water balance components are presented in Table 6.

The water balance components for gauge-simulation, TRMM-simulation, and CHIRPS-simulation showed remarkable differences, especially for the surface runoff. For gauge-simulation, the mean annual surface runoff was 467.8 mm, which was much greater than that of TRMM-simulation and CHIRPS-simulation. However, the mean annual groundwater of CHIRPS-simulation (476.8 mm) was higher than that of the gauge-simulation and TRMM-simulation. Precipitation inputs would affect not only model performance, but also simulated water balance components.

4 Discussion

4.1 Performances of TRMM and CHIRPS estimates

The evaluation results showed that in the Lower Lancang-Mekong River Basin, the monthly precipitation estimates for both TRMM and CHIRPS products correlated well with gauge observations, and TRMM estimates performed better than CHIRPS estimates. Both TRMM and CHIRPS data tended to underestimate monthly precipitation, and CHIRPS data mostly underestimated monthly precipitation much more than TRMM data, especially in the rainy season.

There were some differences in precipitation intensity distribution for different precipitation data. The occurrence frequency and precipitation amount of rainstorms for gauge observations were much greater than those for TRMM and CHIRPS estimates. The rainfall stations had recorded a large number of rainstorms. However, some of these rainstorms had not been represented by TRMM and CHIRPS data. Previous studies have showed that TRMM estimates tend to underestimate high rates of precipitation. In the process of producing TRMM V7 data, when removing bias at the monthly scale, some negative effects may be introduced on daily precipitation, which would affect the accuracies of the estimations on the high rates of precipitation (Yong et al., 2015; Wang et al., 2017).

TRMM and CHIRPS products could effectively represent the spatial distribution of precipitation, and observation data are more accurate for high rates of point precipitation. Both gauge observation and satellite-based precipitation data have respective advantages and disadvantages, which should be considered comprehensively in the processes of hydrological analysis and simulation.

4.2 Feasibility of TRMM and CHIRPS data in hydrological simulation

The variability of the orography in the Lower Lancang-Mekong River Basin leads to the heterogeneity in precipitation distribution, and the representation of precipitation pattern is critical for accurate hydrological simulation. However, most available rainfall stations in the study area are located along the riverside, and high-attitude areas are generally data-scarce regions. In addition, precipitation data in some rainfall stations could not meet the requirements of hydrological analysis and simulation because of their short length and unsatisfactory data quality. Furthermore, the Lancang-Mekong River passes through several countries, making the collection of observed precipitation data more difficult. Spatial precipitation distribution from rain gauges could not be represented accurately because of heterogeneous orographic effects and sparsely distributed rainfall stations. Spatial precipitation interpolations also have limitations affected by data scarcity and unsatisfied quality, and most interpolation methods tend to underestimate spatial variability (Haberlandt, 2007).

The sparsity and uneven distribution of gauges make observed rain data less representative and worsen hydrological simulation performance in the Lower Lancang-Mekong River Basin. Satellite-based precipitation

Table 6 Comparison of the water balance components among hydrological simulations driven by gauge, TRMM, and CHIRPS data

Precipitation data	Precipitation (mm/yr)	Surface runoff (mm/yr)	Groundwater (mm/yr)	Evapotranspiration (mm/yr)
Gauge	1933.1	467.8	445.5	927.8
TRMM	1874.2	356.3	441.3	976.5
CHIRPS	1837.9	288.8	476.8	969.7

estimates provide opportunity to improve hydrological modeling, and the SWAT model driven by TRMM and CHIRPS data performed much better than that by gauge and IDW data in the study area. TRMM and CHIRPS products, with high spatial and temporal resolution, could help to overcome the shortcoming of sparsely and unevenly distributed rainfall stations, and provide more accurate precipitation information for hydrological simulation compared to gauge data in the Lower Lancang-Mekong River Basin. Furthermore, in international river basins, transboundary data sharing is a challenge (Thu and Wehn, 2016), and precipitation data collection and quality assurance are usually cumbersome. Alternatively, the near-real-time availability makes satellite-based data more suitable for hydrological simulation and water resources management.

CHIRPS precipitation estimates has a 0.05° × 0.05° spatial resolution, which is much finer than TRMM data (0.25° × 0.25°). However, in the Lower Lancang-Mekong River Basin, CHIRPS estimates mostly underestimated monthly precipitation to a greater extent than TRMM estimates, making TRMM data superior to CHIRPS data in hydrological simulation. According to the World Meteorological Organization, at least 30 years of historical meteorological data are required for climate studies (Mushore et al., 2016). Although TRMM data performed better than CHIRPS data in representing the spatial distribution of precipitation and driving the SWAT model in the Lower Lancang-Mekong River Basin, the relatively short length of TRMM data partly limits its application in hydrological analysis and simulation (AghaKouchak and Nakhjiri, 2012). CHIRPS estimates were also shown to have good agreement with observed precipitation and satisfactory capability in flow simulation, indicating that CHIRPS data undoubtedly a good choice of alternative precipitation input for hydrological modeling in the Lower Lancang-Mekong River Basin, especially during the period lacking TRMM data.

4.3 Effects of precipitation input on simulation results of water balance components

Though the SWAT models driven by TRMM and CHIRPS data achieved good performances on hydrological simulations in the Lower Lancang-Mekong River Basin, there were also some shortcoming, such as the underestimation of the flow in flood season, especially the maximum monthly flow, should be discussed. In the study area, rainstorms played an important role in the total precipitation, and TRMM and CHIRPS data tend to underestimate rainstorms. Rainstorms generate considerable surface runoff, which contribute largely to the flow in flood season. The underestimation on rainstorms would directly result in lower simulated surface runoff, leading to the flow in flood season of TRMM-simulation and CHIRPS-simulation less than the observed values.

The error in the occurrence frequencies and amounts of daily precipitation with different intensities would affect simulation results of surface runoff, groundwater, and evapotranspiration, and different precipitation data could lead to different amounts and proportions of simulated water balance components. Satellite precipitation error may propagate to runoff simulation, and the transformation process is nonlinear. Hydrological models could tolerate a relatively small error in precipitation, but the error with high magnitudes may be amplified (Mei et al., 2016). In order to apply satellite-based precipitation data more appropriately for hydrological simulation, it is need to improve retrieval algorithms and error-correction schemes in future works (Nikolopoulos et al., 2013).

5 Conclusions

In this study, we investigated the feasibility of four different precipitation inputs, including gauge observations, IDW data, TRMM estimates, and CHIRPS estimates, on hydrological simulation in the Lower Lancang-Mekong River Basin. The application of TRMM and CHIRPS data were found to improve hydrological model performances at monthly and daily scales. The model using TRMM data showed more accurate simulations during the calibration and validation periods, whereas CHIRPS data could provide longer precipitation time series for hydrological simulation. Thus, TRMM and CHIRPS products are both favorable choices for the hydrological modeling in the Lower Lancang-Mekong River Basin. In addition, the differences in intensity distribution for different precipitation inputs could result in varying simulated water balance components, and the underestimation on rainstorm for TRMM and CHIRPS data may affect the simulated results of surface runoff.

Precipitation controls the water balance, and the representation of spatial and temporal distribution of precipitation is critical for accurate hydrological simulation. However, rain gauge stations are sometimes sparse and inadequate to capture the spatial distribution characteristics of precipitation. For large data-poor or ungauged watersheds, there are usually several satellite-based precipitation datasets available besides gauge observations, which are potential to be suitable data sources for hydrological simulation, and comparing the performance of hydrological models driven by different precipitation data is important. In the processes of hydrological simulation, the implications of satellite-based precipitation data should be taken into account comprehensively, and further study need to avoid their disadvantages effectively.

References

Abbaspour K C, Rouholahnejad E, Vaghefi S et al., 2015. A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology*, 524: 733–752. doi: 10.1016/j.jhydrol.2015.03.027

AghaKouchak A, Nakhjiri N, 2012. A near real-time satellite-based global drought climate data record. *Environmental Research Letters*, 7: 044037. doi: 10.1088/1748-9326/7/4/ 044037

Arnold J G, Srinivasan R, Muttiah R S et al., 1998. Large area hydrologic modeling and assessment part Ⅰ: model development. *Journal of the American Water Resources Association*, 34(1): 73–89.

Arnold J G, Youssef M A, Yen H et al., 2015. Hydrological processes and model representation: impact of soft data on calibration. *Transactions of the American Society of Agricultural and Biological Engineers*, 58(6): 1637–1660. doi: 10. 13031/trans.58.10726

Cho J, Bosch D, Lowrance R et al., 2009. Effect of spatial distribution of rainfall on temporal and spatial uncertainty of SWAT output. *Transactions of the American Society of Agricultural and Biological Engineers*, 52(5): 1545–1555. doi: 10.13031/2013.29143

Duan Z, Liu J, Tuo Y et al., 2016. Evaluation of eight high spatial resolution gridded precipitation products in Adige Basin (Italy) at multiple temporal and spatial scales. *Science of the Total Environment*, 573: 1536–1553. doi: 10.1016/j.scitotenv. 2016. 08.213

Fan H, He D, Wang H, 2015. Environmental consequences of damming the mainstream Lancang-Mekong River: a review. *Earth-Science Reviews*, 146: 77–91. doi: 10.1016/j.earscirev. 2015.03.007

Galván L, Olías M, Izquierdo T et al., 2014. Rainfall estimation in SWAT: an alternative method to simulate orographic precipitation. *Journal of Hydrology*, 509: 257–265. doi: 10.1016/j. jhydrol.2013.11.044

Gao J, Sheshukov A Y, Yen H et al., 2017. Impacts of alternative climate information on hydrologic processes with SWAT: a comparison of NCDC, PRISM and NEXRAD datasets. *Catena*, 156: 353–364. doi: 10.1016/j.catena.2017.04.010

Haberlandt U, 2007. Geostatistical interpolation of hourly precipitation from rain gauges and radar for a large-scale extreme rainfall event. *Journal of Hydrology*, 332: 144–157. doi: 10. 1016/j.jhydrol.2006.06.028

Jiang Shanhu, Ren Liliang, Yong Bin et al., 2016. Evaluation of latest TMPA and CMORPH precipitation products with independent rain gauge observation networks over high-latitude and low-latitude basins in China. *Chinese Geographical Science*, 26(4): 439–455. doi: 10.1007/s11769- 016-0818-x

Jin Xin, He Chansheng, Zhang Lanhui et al., 2018. A modified groundwater module in SWAT for improved streamflow simulation in a large, arid endorheic river watershed in Northwest China. *Chinese Geographical Science*, 28(1): 47–60. doi: 10.1007/s11769-018-0931-0

Johnston R, Kummu M, 2012. Water resource models in the Mekong Basin: a review. *Water Resources Management*, 26(2): 429–455. doi: 10.1007/s11269-011-9925-8

Katiraie-Boroujerdy P S, Asanjan A A, Hsu K et al., 2017. Intercomparison of PERSIANN-CDR and TRMM-3B42V7 precipitation estimates at monthly and daily time scales. *Atmospheric Research*, 193: 36–49. doi: 10.1016/j.atmosres. 2017.04.005

Katsanos D, Retalis A, Michaelides S, 2016. Validation of a high-resolution precipitation database (CHIRPS) over Cyprus for a 30-year period. *Atmospheric Research*, 169: 459–464. doi: 10.1016/j.atmosres.2015.05.015

Li D, Long D, Zhao J et al., 2017. Observed changes in flow regimes in the Mekong River basin. *Journal of Hydrology*, 551: 217–232. doi: 10.1016/j.jhydrol.2017.05.061

Li X, Zhang Q, Xu C, 2012. Suitability of the TRMM satellite rainfalls in driving a distributed hydrological model for water balance computations in Xinjiang catchment, Poyang lake basin. *Journal of Hydrology*, 426–427: 28–38. doi: 10.1016/j. jhydrol.2012.01.013

Liu Miao, Li Chunlin, Hu Yuanman et al., 2014. Combining CLUE-S and SWAT models to forecast land use change and non-point source pollution impact at a watershed scale in Liaoning province, China. *Chinese Geographical Science*, 24(5): 540–550. doi: 10.1007/s11769-014-0661-x

Ly S, Charles C, Degré A, 2011. Geostatistical interpolation of daily rainfall at catchment scale: the use of several variogram models in the Ourthe and Ambleve catchments, Belgium. *Hydrology and Earth System Sciences*, 15: 2259–2274. doi: 10.5194/hess-15-2259-2011

Mei Y, Nikolopoulos E I, Anagnostou E N et al., 2016. Evaluating satellite precipitation error propagation in runoff simulations of mountainous basins. *Journal of Hydrometeorology*, 17: 1407–1423. doi: 10.1175/JHM-D-15-0081.1

Mekong River Commission, 2005. *Overview of the Hydrology of* *the Mekong Basin*. Vientiane: Mekong River Commission.

Moriasi D N, Arnold J G, Van Liew M W et al., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the American Society of Agricultural and Biological Engineers*, 50(3): 885–900. doi: 10.13031/2013.23153

Mushore T D, Manatsa D, Pedzisai E et al., 2016. Investigating the implications of meteorological indicators of seasonal rainfall performance on maize yield in a rain-fed agricultural system: case study of Mt. Darwin District in Zimbabwe. *Theoretical and Applied Climatology*, 129(3): 1–7. doi: 10.1007/s00704-016-1838-2

Neitsch S L, Arnold J G, Kiniry J R et al., 2011. *Soil and Water Assessment Tool*: *Theoretical Documentation* (*Version* 2009). Texas: Grassland, Soil and Water Research Laboratory, Agricultural Research Service, Blackland Research Center, Texas Agricultural Experiment Station.

Nikolopoulos E I, Anagnostou E N, Borga M, 2013. Using high-resolution satellite rainfall products to simulate a major flash flood event in northern Italy. *Journal of Hydrometeorology*, 14: 171–185. doi: 10.1175/JHM-D-12-09.1

Räsänen T A, Someth P, Lauri H et al., 2017. Observed river discharge changes due to hydropower operations in the Upper Mekong Basin. *Journal of Hydrology*, 545: 28–41. doi: 10.1016/j.jhydrol.2016.12.023

Rozante J R, Moreira D S, de Goncalves L G G et al., 2010. Combining TRMM and surface observations of precipitation: technique and validation over South America. *Weather and Forecast*, 25: 885–894. doi: 10.1175/2010WAF2222325.1

Sabo J L, Ruhi A, Holtgrieve G W et al., 2017. Designing river flows to improve food security futures in the Lower Mekong Basin. *Science*, 358: eaao1053. doi: 10.1126/science.aao1053

Serrat-Capdevila A, Valdes J B, Stakhiv E Z, 2014. Water management applications for satellite precipitation products: Synthesis and recommendations. *Journal of the American Water Resources Association*, 50(2): 509–525. doi: 10.1111/ jawr.12140

Shrestha N K, Qamer F M, Pedreros D et al., 2017. Evaluating the accuracy of Climate Hazard Group (CHG) satellite rainfall estimates for precipitation based drought monitoring in Koshi basin, Nepal. *Journal of Hydrology*: *Regional Studies*, 13: 138–151. doi: 10.1016/j.ejrh.2017.08.004

Son N T, Chen C F, Chen C R et al., 2012. Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation*, 18: 417–427. doi: 10.1016/j.jag.2012.03.014

Tatsumi K, Yamashiki Y, 2015. Effect of irrigation water withdrawals on water and energy balance in the Mekong River Basin using an improved VIC land surface model with fewer calibration parameters. *Agricultural Water Management*, 159: 92–106. doi: 10.1016/j.agwat.2015.05.011

Thilakarathne M, Sridhar V, 2017. Characterization of future drought conditions in the Lower Mekong River Basin. *Weather and Climate Extremes*, 17: 47–58. doi: 10.1016/j.wace.2017.07.004

Thu H N, Wehn U, 2016. Data sharing in international transboundary contexts: the Vietnamese perspective on data sharing in the Lower Mekong Basin. *Journal of Hydrology*, 536: 351–364. doi: 10.1016/j.jhydrol.2016.02.035

Tobin K J, Bennett M E, 2013. Temporal analysis of Soil and Water Assessment Tool (SWAT) performance based on remotely sensed precipitation products. *Hydrological Processes*, 27: 505–514. doi: 10.1002/hyp.9252

Trejo F J P, Barbosa H A, Peñaloza-Murillo M A et al., 2016. Intercomparison of improved satellite rainfall estimation with CHIRPS gridded product and rain gauge data over Venezuela. *Atmósfera*, 29(4): 323–342. doi: 10.20937/ATM.2016.29.04.04

Tuo Y, Duan Z, Disse M et al., 2016. Evaluation of precipitation input for SWAT modeling in Alpine catchment: a case study in the Adige river basin (Italy). *Science of the Total Environment*, 573: 66–82. doi: 10.1016/j.scitotenv.2016.08.034

Wang W, Lu H, Yang D et al., 2016. Modeling hydrologic processes in the Mekong River Basin using a distributed model driven by satellite precipitation and rain gauge observations. *PLoS ONE*, 11(3): e0152229. doi:10.1371/journal.pone. 0152229

Wang W, Lu H, Zhao T et al., 2017. Evaluation and comparison of daily rainfall from latest GPM and TRMM products over the Mekong River Basin. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 99: 1–10. doi: 10.1109/JSTARS.2017.2672786

Worqlul A W, Yen H, Collick A S et al., 2017. Evaluation of CFSR, TMPA 3B42 and ground-based rainfall data as input for hydrological models, in data-scarce regions: The upper Blue Nile Basin, Ethiopia. *Catena*, 152: 242–251. doi: 10.1016/j.catena.2017.01.019

Yong B, Liu D, Gourley J J et al., 2015. Global view of real-time TRMM multisatellite precipitation analysis: implications for its successor global precipitation measurement mission. *Bulletin of the American Meteorological Society*, 96: 283–296. doi: 10.1175/BAMS-D-14-00017.1

Zhou M C, Ishidaira H, Takeuchi K, 2008. Comparative study of potential evapotranspiration and interception evaporation by land cover over Mekong basin. *Hydrological Processes*, 22: 1290–1309. doi: 10.1002/hyp.6939