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## 24 Abstract:

25 On the Tibetan Plateau, the limited ground-based rainfall information owing to a harsh  
26 environment has brought great challenges to hydrological studies. Satellite-based rainfall products,  
27 which allow a better coverage than both radar network and rain gauges on the Tibetan Plateau, can  
28 be suitable observation alternatives for investigating the hydrological processes and climate  
29 change. In this study, a newly developed daily satellite-based precipitation product, termed  
30 Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks–  
31 Climate Data Record (PERSIANN-CDR), is used as input of a hydrologic model to simulate  
32 streamflow in the upper Yellow and Yangtze River Basin on the Tibetan Plateau. The results show  
33 that the simulated streamflow using PERSIANN-CDR precipitation is closer to observation than  
34 that using limited gauge-based precipitation interpolation in the upper Yangtze River Basin. The  
35 simulated streamflow using gauge-based precipitation are higher than the streamflow observation  
36 during the wet season. In the upper Yellow River Basin, PERSIANN-CDR precipitation and  
37 gauge-based precipitation have similar good performance in simulating streamflow. The  
38 evaluation of streamflow simulation capability in this study partly indicates that PERSIANN-CDR  
39 rainfall product has good potentials to be a reliable dataset and an alternative information source  
40 besides the sparse gauge network for conducting long term hydrological and climate studies on the  
41 Tibetan Plateau.

42 Key Words: PERSIANN-CDR daily rainfall product; Streamflow simulation; Tibetan Plateau

## 43 1. Introduction

44 Precipitation is one of the essential meteorological inputs of hydrologic model and the key  
45 driving force for hydrologic cycle. Errors in precipitation estimation can bring significant  
46 uncertainties in streamflow simulation and prediction (Sorooshian et al., 2011). Three methods are



generally used to measure precipitation: traditional gauge observations, meteorological radar observations and satellite observations (Ashouri et al., 2015). In many remote regions and mountainous area, rain gauges and meteorological radar networks are either sparse or non-existent. Thus, satellite-based precipitation is of great importance in such regions. For instance, there is a great potential of using satellite-based precipitation estimate on the Tibetan Plateau known as the “roof of the world” with an average elevation of over 4000m (Yao et al., 2012). Owing to a harsh environment, the existing meteorological stations managed by the Chinese Meteorological Administration only form an extremely sparse network, which create great challenges for water resources management and operation. For example, on average, there is only 0.3 and 1 station per grid of  $1^{\circ} \times 1^{\circ}$  in the upper Yangtze and upper Yellow river basins, respectively. Moreover, the spatial distribution of the meteorological stations is highly uneven and most stations are located around the river channel with relatively low elevation [Figure 1]. Therefore, streamflow simulation using the limited gauge-based rainfall information might not be reliable due to the input uncertainties with such a poor spatial resolution. Satellite-based rainfall products have the advantage of good spatial coverage, which could allow an accurate streamflow simulation on the Tibetan Plateau.

According to Kidd and Levizzani (2011), during the last decade satellite-based precipitation estimates have reached a good level of maturity. Currently, there are many satellite rainfall products are available and have been extensively used globally (e.g., Sorooshian et al., 2000; Huffman et al., 2001; Adler et al., 2003; Xie et al., 2003; Joyce et al., 2004; Turk and Miller, 2005). Recently, a new satellite-based precipitation product is released by National Climatic Data Center (NCDC), which is termed Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR) (Ashouri et al., 2015).



70 PERSIANN-CDR is a multi-satellite, high-resolution and post-time rainfall product that provides  
71 daily precipitation estimates at  $0.25^\circ$  spatial resolution from 1 January 1983 to the present.  
72 According to Ashouri et al., (2015), PERSIANN-CDR rainfall product uses the archive of Gridded  
73 Satellite (GridSat-B1) Infrared Radiation (IR) data (Knapp, 2008) as the input to the Artificial  
74 Neural Network algorithm. The retrieval algorithm uses IR satellite data from global  
75 geosynchronous satellites as the primary source of precipitation information. To meet the  
76 calibration requirement of PERSIANN, the model is pre-trained using the National Centers for  
77 Environmental Prediction (NCEP) stage IV hourly precipitation data. Then, the parameters of the  
78 model are kept fixed and the model is run for the full historical record of GridSat-B1 IR data. To  
79 reduce the biases in the estimated precipitation, while preserving the temporal and spatial patterns  
80 in high resolution, the resulting estimates are then adjusted using the Global Precipitation  
81 Climatology Project (GPCP) monthly  $2.5^\circ$  precipitation products. The performance of  
82 PERSIANN-CDR rainfall product has been tested and reported in different regions (Ashouri et al.  
83 2015; Casse et al. 2015; Miao et al., 2015). Ashouri et al. (2015) found that PERSIANN-CDR  
84 precipitation is performing reasonably well when compared with radar and ground-based  
85 observations in the 1986 Sydney flood event of Australia and the 2005 Hurricane Katrina of United  
86 States. Miao et al. (2015) shows that PERSIANN-CDR rainfall product is able to capture the  
87 spatial and temporal characteristics of extreme precipitation events at daily scale in the eastern  
88 China monsoon region when compared with ground-based precipitation dataset. Casse et al. (2015)  
89 employed PERSIANN-CDR to simulate the flood events in Niamey River and compared with  
90 multiple datasets. It was found out by Casse et al. (2015) that the simulated streamflow with  
91 PERSIANN-CDR has high correlation as compared to streamflow observation. Miao et al. (2015)  
92 also pointed out that the correlation between the PERSIANN-CDR precipitation and ground-based



93 precipitation is not strong on the Tibetan Plateau and speculated that the sparse ground-based  
94 gauge stations may result in uncertainties of the use of ground-based precipitation estimates as  
95 reference on the Tibetan Plateau. Building on Miao et al. (2015), in this study, PERSIANN-CDR  
96 is further applied to a conceptual hydrological model to simulate streamflow of two river basins  
97 on the Tibetan Plateau. The simulated streamflow with PERSIANN-CDR is compared with that  
98 forced by limited gauge information, as well as the streamflow observations at the outlets of these  
99 two basins.

100 Many studies have been carried out to evaluate the suitability of a number of satellite-based  
101 precipitation estimate products in forcing hydrologic models and simulating streamflow for  
102 various regions around the world (e.g., Yilmaz et al., 2005; Artan et al., 2007; Su et al., 2011; Bitew  
103 et al., 2012; Yong et al., 2012). However, there are few evaluation works focusing on hydrological  
104 modeling driven by satellite rainfall products on the Tibetan Plateau. Among limited number of  
105 studies, Tong et al. (2014) evaluated the streamflow simulation capability of four satellite products  
106 (TRMM-3B42-V7, TRMM-3B42RT-V7, PERSIANN and CMORPH) using the Variable  
107 Infiltration Capacity (VIC) hydrologic model in two sub-basins over the Tibetan Plateau and  
108 concluded that the TRMM-3B42-V7 and CMORPH datasets have relative better performance than  
109 others. One of the limitations is that the data of many satellite precipitation products, such as  
110 TRMM-3B42RT-V7 and CMORPH only starts from 2000 to the present, which is rather short. In  
111 this study, there is no such limitation because PERSIANN-CDR daily rainfall product includes  
112 more than 33 years of data and the length of data grows every year. In Tong et al. (2014), the rain-  
113 gauge is set to be reference to compare different satellite-based rainfall products. However, given  
114 the facts that (1) density of rain-gauges on Tibetan Plateau is rather low as compared to other  
115 regions in China, (2) distribution of gauges are uneven according to the investigation from Miao



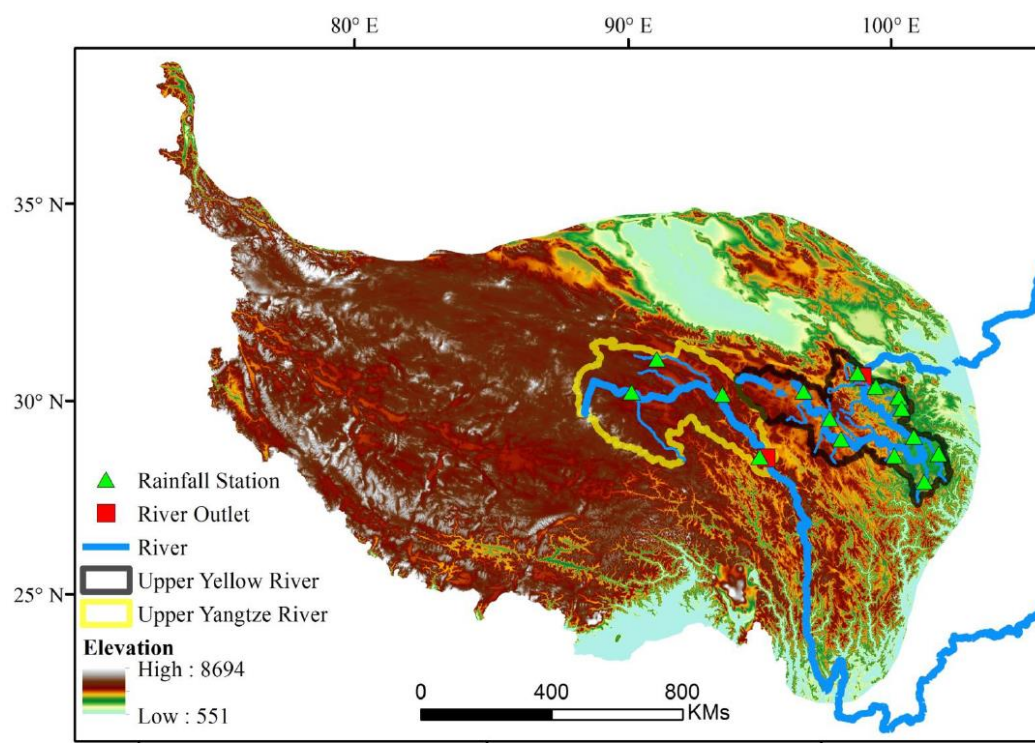
et al, (2015), and (3) rain-gauges are located in low elevation river channels (Figure 1), authors have the similar concern as Miao et al, (2015) that the use of sparse rain-gauge network as reference to compare satellite products is questionable. Therefore, in this study, both PERSIANN-CDR daily rainfall product and ground-based rainfall information are used as the inputs of a hydrologic model for streamflow simulation on two major river basins, the upper Yangtze River Basin and the upper Yellow River Basin, on the Tibetan Plateau. Then, the simulation results are compared with observed streamflow, which is believed to be a more reliable reference than the limited rainfall observation to judge the qualities of satellite rainfall products on the Tibetan Plateau. The uncertainty sources are also discussed with regard to the parameterization of hydrological model and the length of data used for calibration.

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## 2. Study region, data and hydrological modeling

### 2.1 Study region and data

Two river basins on the northern Tibetan Plateau, namely, the upper Yangtze River (UYZR) and upper Yellow River (UYLR) basins are selected, which have a long daily streamflow record from 1983 to 2012. As shown with red squares in Figure 1, two hydrological stations, Tangnaihai and Zhimenda, are the outlet stations of the UYZR and UYLR, which have total drainage areas of 121,972 and 137,704 km<sup>2</sup>, respectively. Elevation in the region varies from 3450 to 6621 m. According to Yao et al. (2012), the climate system of the two selected regions have distinct summer Indian monsoon and East Asian monsoon characteristics during summer. Figure 1 shows the distribution of meteorological and hydrological stations in the two basins. The green triangles show the locations of rain-gauges, which are rather unevenly distributed and sparse as compared to the gauge distribution of in other regions of China (Miao et al., 2015).



139  
 140 Figure 1. The selected river basins (the upper Yellow River and Yangtze River Basin) on the  
 141 Tibetan Plateau and location of rainfall stations and river outlets.  
 142  
 143 The observed daily streamflow data from 1983 to 2012 at the outlets of the two basins is provided  
 144 by the Ministry of Water Resources of China. The runoff is calculated by dividing streamflow by  
 145 corresponding basin area. The daily gauge meteorological data in the two basins from 1983 to  
 146 2012 is obtained from the China Meteorological Administration (<http://cdc.cma.gov.cn>). There are  
 147 4 and 11 meteorological stations in the UYZR and UYLR respectively, which means that on  
 148 average there is only 0.3 and 1 station per grid of  $1^{\circ} \times 1^{\circ}$  in the two basins, respectively. The  
 149 PERSIANN-CDR rainfall dataset is available at the NOAA NCDC website  
 150 (<ftp://data.ncdc.noaa.gov/cdr/persiann/files/>), as well as the Center for Hydrometeorology and



Remote Sensing (CHRS) at the University of California, Irvine. In order to compare PERSIANN-CDR with gauge observation, the gauge precipitation is interpolated into  $0.25^\circ \times 0.25^\circ$  grids with the inverse distance weighting interpolation method, which has been demonstrated as being efficient in precipitation interpolation applications (e.g., Nalder and Wein, 1998; Garcia et al., 2008; Ly et al., 2011). The daily gauge-based precipitation and PERSIANN-CDR precipitation for basin average are compared by the cumulative distribution functions (CDFs) of daily precipitation value (e.g., Sheffield et al., 2014; Zhang and Tang, 2015), wherein the two-parameter Gamma distribution function (Thom, 1958) is used to fit the data.

## 2.2 Hydrological modeling

The hydrologic model used in this study is the Hydro-Informatic Modeling System (HIMS) rainfall-runoff model (Liu et al., 2006, 2008, 2010a, 2010b), which is one of the operational hydrological models in practice by the Tibet Government in China. The HIMS model is a grid-based hydrologic model, which is able to simulate the dominant hydrological processes such as actual evapotranspiration, infiltration, runoff, groundwater recharge and channel routing. In HIMS model, a catchment is divided into grids, and grids are linked throughout the stream network based on topological relationships of channel network and properties of soil, vegetation and land use. In each grid, actual evaporation is calculated by a formulation between soil water content and potential evapotranspiration. Potential evapotranspiration  $ET_0$  (Hargreaves and Samani, 1985) and actual evaporation  $ET_a$  are described as follows:

$$ET_0 = 0.00023 \cdot RA \cdot (T + 17.8) \cdot (T_{\max} - T_{\min})^{0.50} \quad (1)$$

$$ET_a(t) = ET_0(t) \cdot \left(1 - \left(1 - \frac{SMS_t}{SMSC}\right)^c\right) \quad (2)$$

where  $RA$  is extraterrestrial radiation ( $\text{MJ m}^{-2} \text{d}^{-1}$ );  $T$ ,  $T_{\max}$  and  $T_{\min}$  are daily average, maximum and minimum temperatures, respectively ( $^\circ\text{C}$ );  $L$  is latent heat of vaporization ( $\text{MJ kg}^{-1}$ );  $SMS$  and





174  $SMSC$  are soil moisture storage and the maximum soil storage capacity (mm), respectively; and  $C$   
 175 is the evapotranspiration coefficient in need of calibration.

176 Infiltration is modeled using an empirical relationship, which has been confirmed through  
 177 analysis of data measured in a number of experimental watersheds and various physical geographic  
 178 factors in China (Liu et al., 2006):

$$179 \quad f_t = R \cdot P_t^r \quad (3)$$

180 where  $f_t$  is infiltration (mm) and  $P_t$  is precipitation (mm).  $R$  and  $r$  are parameters. Surface runoff  
 181  $RS_t$  (mm) is calculated by:

$$182 \quad RS_t = P_t - f_t = P_t - R \cdot P_t^r \quad (4)$$

183 According to the saturation excess mechanism and spatial variability of watershed  
 184 characteristics, interflow and groundwater recharge are estimated as linear functions of soil  
 185 wetness (soil moisture amount divided by soil moisture capacity). Baseflow is simulated based on  
 186 the linear reservoir assumption, in which the relationship between groundwater storage and  
 187 outflow is linear. Interflow  $RI$  (mm), groundwater recharge  $REC$  (mm), baseflow  $RG$  (mm), and  
 188 total runoff  $TR$  (mm) are determined by:

$$189 \quad RI_t = L_a \times (SMS_t / SMSC) \times f_t \quad (5)$$

$$190 \quad REC_t = R_c \times (SMS_t / SMSC) \times (f_t - RI_t) \quad (6)$$

$$191 \quad RG_t = K_b \times (GW_t + REC_t) \quad (7)$$

$$192 \quad TR_t = RS_t + RI_t + RG_t \quad (8)$$

193 where  $L_a$ ,  $R_c$  and  $K_b$  are efficiencies for interflow, groundwater recharge and baseflow, respectively;  
 194  $SMSC$  is the maximum value of soil moisture storage capacity (mm);  $SMS$  is actual soil moisture  
 195 storage (mm); and  $GW$  is groundwater storage (mm).  $L_a$ ,  $R_c$ ,  $K_b$  and  $SMSC$  are parameters in need



196 of calibration. The degree-day snowmelt algorithm (Hock, 2003) assuming an empirical  
 197 relationship between air temperature and snowmelt rate is used to simulate snowmelt runoff. The  
 198 air temperature within each grid is adjusted by a commonly used temperature lapse rate  
 199 ( $0.65^{\circ}\text{C}/100\text{m}$ ). The degree-day factor of snowmelt is set to  $4.1 \text{ mm}^{\circ}\text{C}^{-1} \text{ day}^{-1}$  in the two basins  
 200 based on the investigation of Zhang et al. (2006). Surface runoff and baseflow for each grid are  
 201 routed to the basin outlet through a channel network. The Muskingum method (Franchini and  
 202 Lamberti, 1994) is used for flow channel routing. The detail descriptions of HIMS model refer to  
 203 Liu et al. (2008) and Jiang et al. (2015).

204 The HIMS model is set up at  $0.25^{\circ} \times 0.25^{\circ}$  spatial resolution grids in the two river basins.  
 205 There are nine parameters requiring calibration in the HIMS model (Table 1). The Shuffle Complex  
 206 Evolution method (SCE-UA) is used for calibrating the model parameters (Duan et al., 1992). The  
 207 optimization objective is to maximize the Nash-Sutcliffe efficiency (*NSE*) (Nash and Sutcliffe,  
 208 1970) between the simulated and measured daily streamflow. There are two stopping criteria for  
 209 calibrating the parameters. The first one is the evolution of all simplexes have converged to a  
 210 limited parameter space, which is the default convergence criterion of SCE-UA. Another stopping  
 211 criterion is the maximum number of function evaluation set by users is met. In our study, the  
 212 settings for SCE-UA are: maximum number of function evaluation equals to  $5 \times 10^8$ ; numbers of  
 213 complexes equals to 2; and the percentage change allowed to define convergence is set to  $1 \times 10^{-6}$ .  
 214 The calibration period is from 1983 to 1997 and the verification period is from 1998 to 2012. The  
 215 performance of the streamflow simulation is evaluated by comparing simulated and observed  
 216 streamflow through two statistics: *NSE* and relative bias (*Rb*) between simulated and observed  
 217 streamflow:



$$NSE = 1 - \frac{\sum_{i=1}^N (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^N (Q_{obs,i} - \overline{Q_{obs}})^2} \quad (9)$$

$$Rb = \frac{\sum_{i=1}^N (Q_{sim,i} - Q_{obs,i})}{\sum_{i=1}^N Q_{obs,i}} \quad (10)$$

where  $Q_{sim}$  and  $Q_{obs}$  are the simulated and observed streamflow, respectively;  $\overline{Q_{obs}}$  is the mean of the observed streamflow; and  $N$  is the total number of days in the calibration period.

Table 1. Description of HIMS model parameters and allowable ranges.

Parameter	Description	Allowable range
$SMSC$	The maximum soil storage capacity (mm)	50-1000
$R$	The infiltration coefficient	0.1-2
$r$	The infiltration coefficient	0.1-1
$L_a$	The interflow coefficient	0.1-2
$R_C$	The groundwater recharge coefficient	0.01-2
$C$	The evapotranspiration coefficient	0.001-10
$K_b$	The baseflow coefficient	0.001-1
$C_1$	The Muskingum coefficient	0.001-1
$C_2$	The Muskingum coefficient	0.001-1

### 3. Results

#### 3.1 Hydrometrological characteristics of the two basins

Figure 2 and Table 2 show the average monthly amounts of precipitation and runoff in the UYZR and UYLR from 1983 to 2012. These two river basins have distinct dry and wet seasons, which are from Sep. to Feb., and Mar. to Oct., respectively. According to Table 2, precipitation between May and October (wet season) accounts for 92.5% and 90.1% of the annual total precipitation for the UYZR and UYLR, respectively. . Similar to the temporal distribution of



precipitation, runoff during May to October accounts for 87.6% and 78.4% of annual runoff in the two basins, respectively. Given the seasonal concurrence of precipitation and runoff, thus, precipitation in wet season plays a dominant role in annual runoff generation in these two river basins. The runoff coefficients are 0.22 and 0.26 in the UYZR based on gauge-based precipitation and PERSIANN-CDR precipitation, respectively. In the UYLR, the runoff coefficient is 0.29 based on both gauge-based and PERSIANN-CDR precipitation.

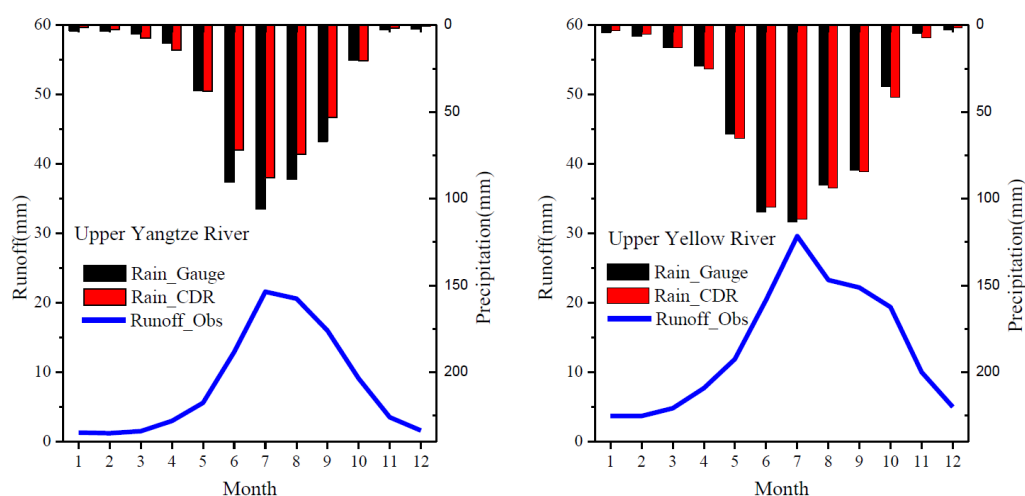


Figure 2. The monthly average runoff observed at the river outlet of the upper Yangtze River and Yellow River Basin, and the precipitation data retrieved from PERSIANN-CDR and ground-based observation.

### 3.2 Comparison between gauge-based precipitation and PERSIANN-CDR precipitation

Figure 3 shows the comparison of CDFs for basin-averaged daily gauge-based precipitation and PERSIANN-CDR precipitation in the UYZR and UYLR from 1983 to 2012. At a given probability, daily precipitation of PERSIANN-CDR product is generally smaller than gauge-based precipitation in the UYZR. In the UYLR, the CDFs of PERSIANN-CDR precipitation and gauge-



based precipitation show overall better agreement than that in the UYZR. Table 2 shows the average monthly amounts of gauge-based precipitation and PERSIANN-CDR precipitation. Gauge-based precipitation is larger than PERSIANN-CDR precipitation in wet season (Jun., Jul., Aug. and Sep.) in the UYZR, while gauge-based precipitation and PERSIANN-CDR precipitation have similar values in the UYLR. In the UYZR, the average annual precipitation is 436.4 mm from gauge-based data and 374.3 mm from PERSIANN-CDR product, and the former is 16.6% larger than the latter. In the UYLR, average annual amounts of gauge-based precipitation and PERSIANN-CDR precipitation are similar, which are 550.2 and 556.6 mm, respectively (Table 2).

Table 2. Average monthly precipitation and runoff in the upper Yangtze and Yellow River basins

Period	Upper Yangtze River			Upper Yellow River		
	Rain_ Gauge	Rain_ CDR	Runoff_ OBS	Rain_ Gauge	Rain_ CDR	Runoff_ OBS
Jan.	3.3	1.4	1.3	4.4	3.2	3.7
Feb.	3.4	2.5	1.2	6.5	5.2	3.7
Mar.	5.0	7.5	1.5	12.9	13.1	4.8
Apr.	10.2	14.6	3.0	23.7	25.0	7.7
May	37.9	38.2	5.6	62.9	65.3	11.9
Jun.	90.4	72.0	12.9	107.6	104.6	20.4
Jul.	105.8	87.8	21.6	113.5	111.8	29.6
Aug.	88.6	74.5	20.6	92.0	94.0	23.3
Sep.	66.9	53.2	16.0	83.4	84.4	22.2
Oct.	20.2	20.5	9.1	35.3	41.4	19.4
Nov.	2.5	1.7	3.5	5.0	7.3	10.0
Dec.	2.3	0.5	1.6	3.0	1.5	5.0
May to Oct.	409.7	346.1	85.8	494.6	501.4	126.8
Annual	436.4	374.3	98.0	550.2	556.6	161.8
Ratio	93.9	92.5	87.6	89.9	90.1	78.4

*Note: Rain\_Gauge and Rain\_CDR indicate gauge-based precipitation and PERSIANN-CDR precipitation (mm), respectively. Runoff\_OBS indicates observed runoff (mm). Ratio means the percentage of precipitation and streamflow during May to November to annual values.*

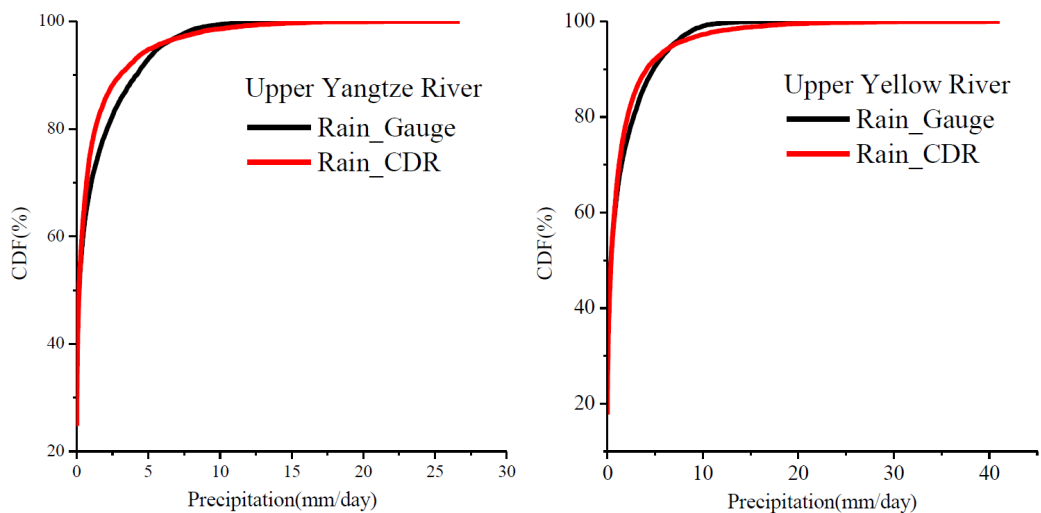


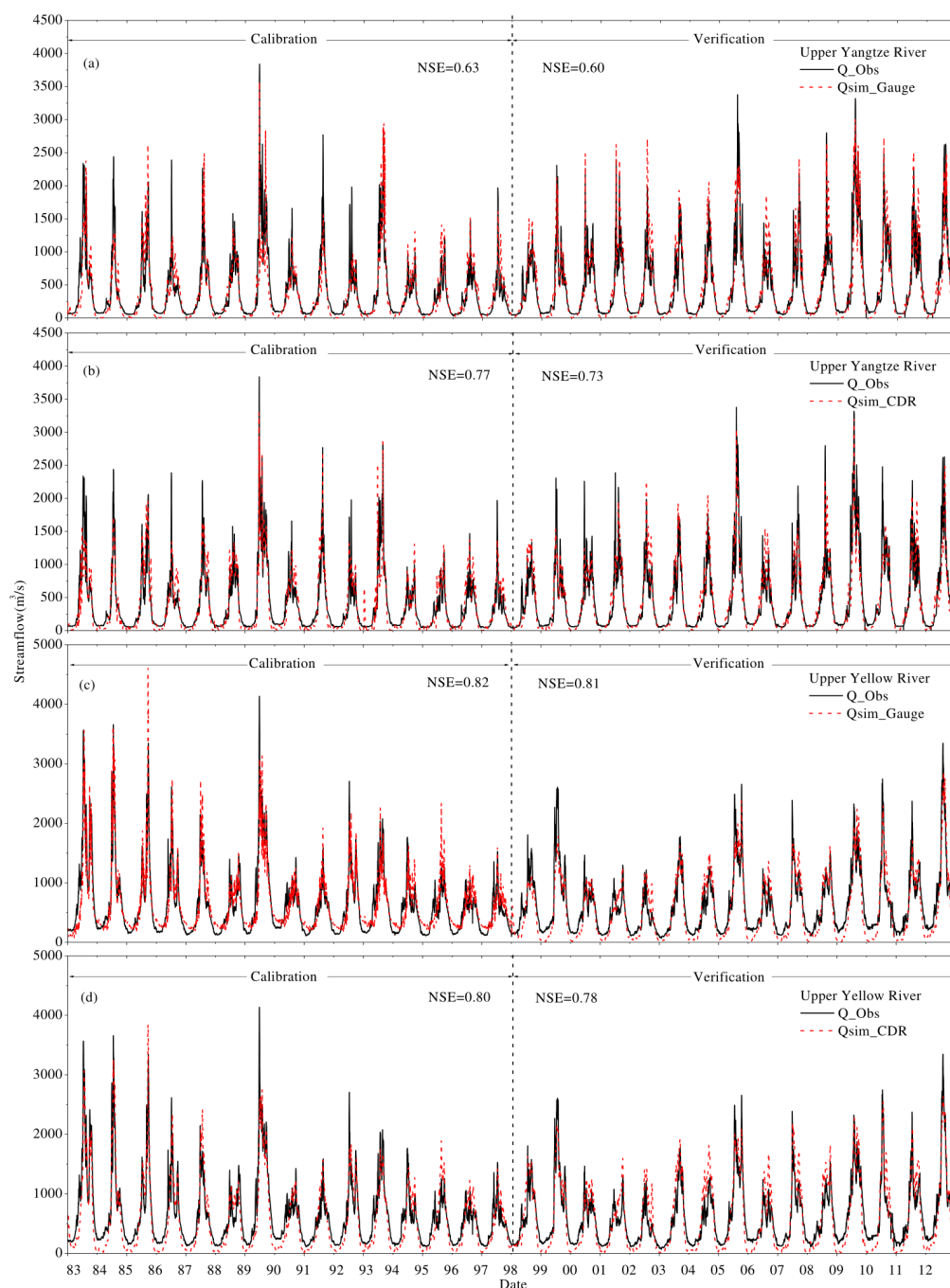
Figure 3. The calculated CDF of rainfall from PERSIANN-CDR and ground-based observation in the upper Yangtze River Basin and upper Yellow River Basin.

### 3.3 Streamflow Simulation in the two basins

Due to the fact that sparse gauge-network and its interpolation cannot perfectly describe the spatial and temporal rainfall characteristics at river basin scale, the alternative is to evaluate streamflow simulated instead of over-confidently using sparse gauge-network as reference. In this section, the streamflow simulated by both gauge-based precipitation and PERSIANN-CDR precipitation are derived from HIMS model, and compared with observed streamflow at the outlet in the UYZR and UYLR. The HIMS model is separately calibrated by maximizing the *NSE* between observed streamflow and simulated streamflow driven by gauge-based precipitation and PERSIANN-CDR precipitation from 1983 to 1997. Table 3 shows the calibrated parameter values of the HIMS model for the two basins. Figure 4 shows daily observed streamflow and simulated streamflow driven by gauge-based precipitation and PERSIANN-CDR precipitation for the two



basins from 1983 to 2012. In the UYLR (Figure 4 (a) and (b)), the *NSE* values between daily observed streamflow and simulated streamflow are 0.82 and 0.80 in the calibration period driven by gauge-based precipitation and PERSIANN-CDR precipitation, respectively. In the verification period, the *NSE* values are 0.81 and 0.78 for the two types of data, respectively. The high *NSE* value in both calibration and verification periods suggest that gauge-based precipitation and PERSIANN-CDR precipitation have similar performances as the drivers of streamflow simulation in the UYLR. In the UYZR (Figure 4 (c) and (d)), the *NSE* values are 0.63 and 0.77 in the calibration period driven by gauge-based precipitation and PERSIANN-CDR precipitation respectively, while they are 0.60 and 0.73 in the verification period, respectively. In both calibration and verification period, the *NSE* values from PERSIANN-CDR precipitation are greater than that from gauge-based precipitation, which indicates that using PERSIANN-CDR precipitation as input to HIMS model is able to generate more accurate streamflow than using the interpolated precipitation from a sparse gauge-network in the UYZR.



291

292 Figure 4. The comparison between the simulated daily streamflow (red) with PERSIANN-CDR





and ground-based precipitation and the observed data (black) at the outlets of the upper Yangtze River Basin (a and b) and upper Yellow River Basin (c and d).

Table 3. Calibrated parameter values in the HIMS model for the upper Yangtze and Yellow River basins.

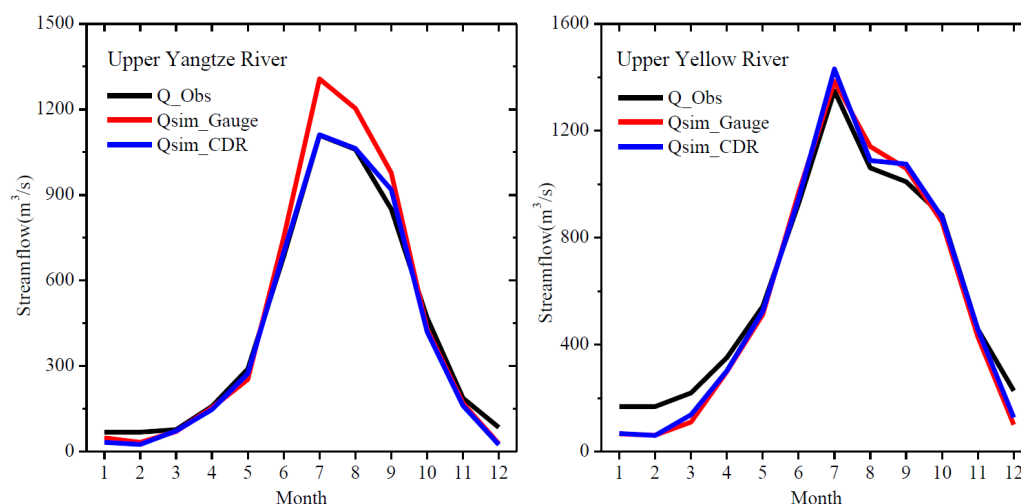
Basin	input	$SMSC$	$R$	$r$	$L_a$	$R_c$	$C$	$K_b$	$C_1$	$C_2$
Yangtze	Gauge_based	302.46	1.47	0.78	0.74	0.05	0.67	0.15	0.18	0.81
	PERSIANN-CDR	343.80	1.71	0.89	0.87	0.07	0.56	0.18	0.17	0.82
Yellow	Gauge_based	334.82	2.08	0.77	1.00	0.03	0.44	0.14	0.14	0.86
	PERSIANN-CDR	342.08	2.01	0.73	0.98	0.05	0.45	0.14	0.12	0.88

Figure 5 and Table 4 compare the simulated and observed average monthly streamflow for the two basins. In the UYZR, the relative bias between observed streamflow and simulated streamflow driven by gauge-based precipitation is 10.3% in wet season, which suggests a considerable overestimate of streamflow. Comparably, the relative bias between observed streamflow and simulated streamflow driven by PERSIANN-CDR precipitation is 0.5% in wet season. As compared with the wet season streamflow simulation results with gauge-based precipitation, the simulated streamflow driven by PERSIANN-CDR precipitation is closer to the observed streamflow. In dry season, streamflow simulations driven by gauge-based precipitation and PERSIANN-CDR precipitation both underestimate streamflow with relative bias of -22.1 and -28.0% in the UYZR, respectively. In the UYLR, both the two precipitation products slightly overestimate the streamflow in wet season with relative bias of 2.6 and 2.9%, respectively. Similar to the results in the UYZR, streamflow simulations driven by gauge-based precipitation and PERSIANN-CDR precipitation have similar good performances in wet season in the UYLR.



313 However, both the two precipitation products tend to produce smaller streamflow in dry season  
314 with relative bias of -33.1% and -27.6%, respectively. One of the reasons that both PERSIANN-  
315 CDR and gauge-based precipitation generate smaller streamflow in dry season is the lack of  
316 complex method or proper algorithm in the HIMS model to handle frozen soil. In dry season, when  
317 the amounts of precipitation and streamflow are small, streamflow melted from frozen soil can  
318 account for a significant proportion of total streamflow. In other words, the frozen soil melt could  
319 significantly influence the streamflow simulation results. The relative high bias of observed  
320 streamflow and simulated streamflow from both gauge-based and satellite-based precipitation  
321 could be due to the lack of proper modeling component in the HIMS hydrologic model that  
322 quantifies the frozen soil melting effects in dry season. However, the bias between simulated and  
323 observed streamflow is much smaller in wet season, when precipitation and streamflow are  
324 relatively large and streamflow melted from frozen soil accounts for a limited proportion in total  
325 streamflow.

326 In summary, the streamflow simulated by PERSIANN-CDR precipitation has a good  
327 agreement with the observed streamflow in the UYZR and UYLR. The good agreement between  
328 observed streamflow and PERSIANN-CDR simulated streamflow reveals a strong streamflow  
329 simulation capability of PERSIAN-CDR product, which also gives community certain confidence  
330 in using PERSIANN-CDR product to study hydrological cycle and climate change on the Tibetan  
331 Plateau.



332

333 Figure 5. The comparison between the observed streamflow (black) and the simulated streamflow  
 334 using PERSIANN-CDR (blue) and ground-based precipitation data (red) in the upper Yangtze  
 335 River Basin and upper Yellow River Basin.

336 Table 4. The performances of streamflow simulations driven by gauge-based precipitation  
 337 and PERSIANN-CDR precipitation in the two basins

Period	Upper Yangtze River					Upper Yellow River				
	Q_obs	Qsim_gauge	Qsim_CDR	Rb_gauge	Rb_CDR	Q_obs	Qsim_gauge	Qsim_CDR	Rb_gauge	Rb_CDR
Jan.	68.1	48.4	32.8	-28.9	-51.8	168.9	65.7	68.0	-61.1	-59.8
Feb.	68.3	32.7	24.9	-52.1	-63.5	168.3	61.6	60.5	-63.4	-64.1
Mar.	76.9	70.2	72.4	-8.7	-5.8	219.7	110.5	138.0	-49.7	-37.2
Apr.	158.6	153.2	147.5	-3.4	-7.0	352.0	299.0	302.5	-15.1	-14.0
May	289.2	253.5	273.4	-12.3	-5.5	543.6	512.9	524.9	-5.7	-3.4
Jun.	683.9	750.5	698.4	9.7	2.1	928.5	968.6	946.6	4.3	1.9
Jul.	1108.9	1306.9	1111.4	17.9	0.2	1350.1	1386.6	1431.3	2.7	6.0
Aug.	1059.7	1204.0	1063.2	13.6	0.3	1061.1	1141.4	1088.5	7.6	2.6
Sep.	850.7	977.4	918.9	14.9	8.0	1009.6	1059.7	1075.7	5.0	6.5
Oct.	469.4	428.1	420.1	-8.8	-10.5	883.7	859.1	876.5	-2.8	-0.8
Nov.	187.6	169.0	161.1	-9.9	-14.1	457.3	429.1	456.6	-6.2	-0.2
Dec.	84.5	28.2	24.5	-66.7	-71.0	227.0	100.7	127.5	-55.7	-43.9
May-Oct.	743.4	819.6	746.9	10.3	0.5	962.7	987.7	990.4	2.6	2.9
Nov.-Apr.	107.2	83.6	77.2	-22.1	-28.0	265.6	177.6	192.3	-33.1	-27.6
Annual	427.9	454.6	414.8	6.2	-3.1	617.0	586.0	594.6	-5.0	-3.6



338 *Note:  $Q_{obs}$  indicates observed runoff (mm).  $Qsim_{gauge}$  and  $Qsim_{CDR}$  indicate*  
 339 *streamflow simulations (mm) driven by the gauge-based precipitation and PERSIANN-CDR*  
 340 *precipitation, respectively.  $Rb_{gauge}$  and  $Rb_{CDR}$  indicate relative bias between observed*  
 341 *streamflow and simulated streamflow driven by the gauge-based precipitation and*  
 342 *PERSIANN-CDR precipitation, respectively.*

343

## 344 **4. Discussions**

### 345 **4.1 Parameter uncertainties of hydrological modeling**

346 In this study, model parameters are separately calibrated in terms of highest *NSE* between  
 347 observed streamflow and simulated streamflow driven by gauge-based precipitation and  
 348 PERSIANN-CDR precipitation. Therefore, these parameter values are highly dependent on the  
 349 precipitation inputs. When the precipitation input changes, the parameter values may change  
 350 accordingly in order to match the streamflow. Table 3 shows the values of calibrated parameters  
 351 separately driven by gauge-based precipitation and PERSIANN-CDR precipitation in the two  
 352 basins. Parameter sensitivity study of the HIMS model indicates that the HIMS model is most  
 353 sensitive to parameters of the maximum soil storage capacity (*SMSC*) and the infiltration  
 354 coefficients (*R* and *r*) (Jiang et al., 2015). In the UYLR, the parameters calibrated by the inputs of  
 355 gauge-based precipitation and PERSIANN-CDR precipitation generally have similar values.  
 356 However, in the UYZR, *SMSC*, *R* and *r* values calibrated from gauge-based precipitation are  
 357 302.46, 1.47 and 0.78 respectively, while *SMSC*, *R* and *r* values calibrated from PERSIANN-CDR  
 358 precipitation are 343.80, 1.71 and 0.89 respectively. By separately calibrating the parameters in  
 359 HIMS model, gauge-based precipitation and PERSIANN-CDR result in different optimal  
 360 parameter values. . Thus, the streamflow simulation bias using gauge-based precipitation and  
 361 PERSIANN-CDR are the joint results of parameter differences and model input bias.  
 362 Correspondingly, soil moisture and evapotranspiration estimation could be different using various



precipitation forcings and calibrated parameters. However, the main purpose of this study is evaluating the streamflow simulation capability of satellite-based precipitation and gauge-based precipitation as inputs to a hydrologic model over the Tibetan Plateau. Therefore, in spite of the influence of cancellation between parameter differences and precipitation bias on streamflow simulation, it does not harm the conclusion that PERSIANN-CDR precipitation is able to produce a reasonably good streamflow in the two river basins on the Tibetan Plateau.

In previous study, Tong et al. (2014) evaluated the streamflow simulation capabilities of four satellite-based precipitation products (TRMM-3B42-V7, TRMM-3B42RT-V7, PERSIANN and CMORPH) using the VIC hydrologic model in the UYZR and UYLR from 2006 to 2012. Different from the PERSIANN product that Tong et al. (2014) used, PERSIANN-CDR is a different product that provides over 33 years of daily and high resolution precipitation with GPCP monthly information incorporated. In addition, the parameters in the VIC hydrologic model are calibrated by the input of interpolated gauge-based precipitation. The calibrated parameter values are then kept fixed when the VIC model are rerun by inputs of satellite-based precipitation datasets to evaluate the streamflow simulation capabilities of satellite-based precipitation datasets. Rerunning the hydrologic model with the fixed parameters calibrated by gauge-based precipitation partly indicates that the authors consider the sparse gauge observations a more reliable dataset than satellite-based precipitation datasets. However, this is a questionable assumption. As we mentioned in the introduction, not only because the location of rain-gauges is conditioned (relatively low elevations), but also the sparse distribution of rainfall stations over the Tibetan Plateau could bring large errors and uncertainties in regional rainfall measurement. We rather cautiously believe that gauge-based precipitation could not be reliable, especially in the UYZR where there is only one station per 34426 km<sup>2</sup> (nearly 1°×3° spatial resolution). Therefore, separately calibrating



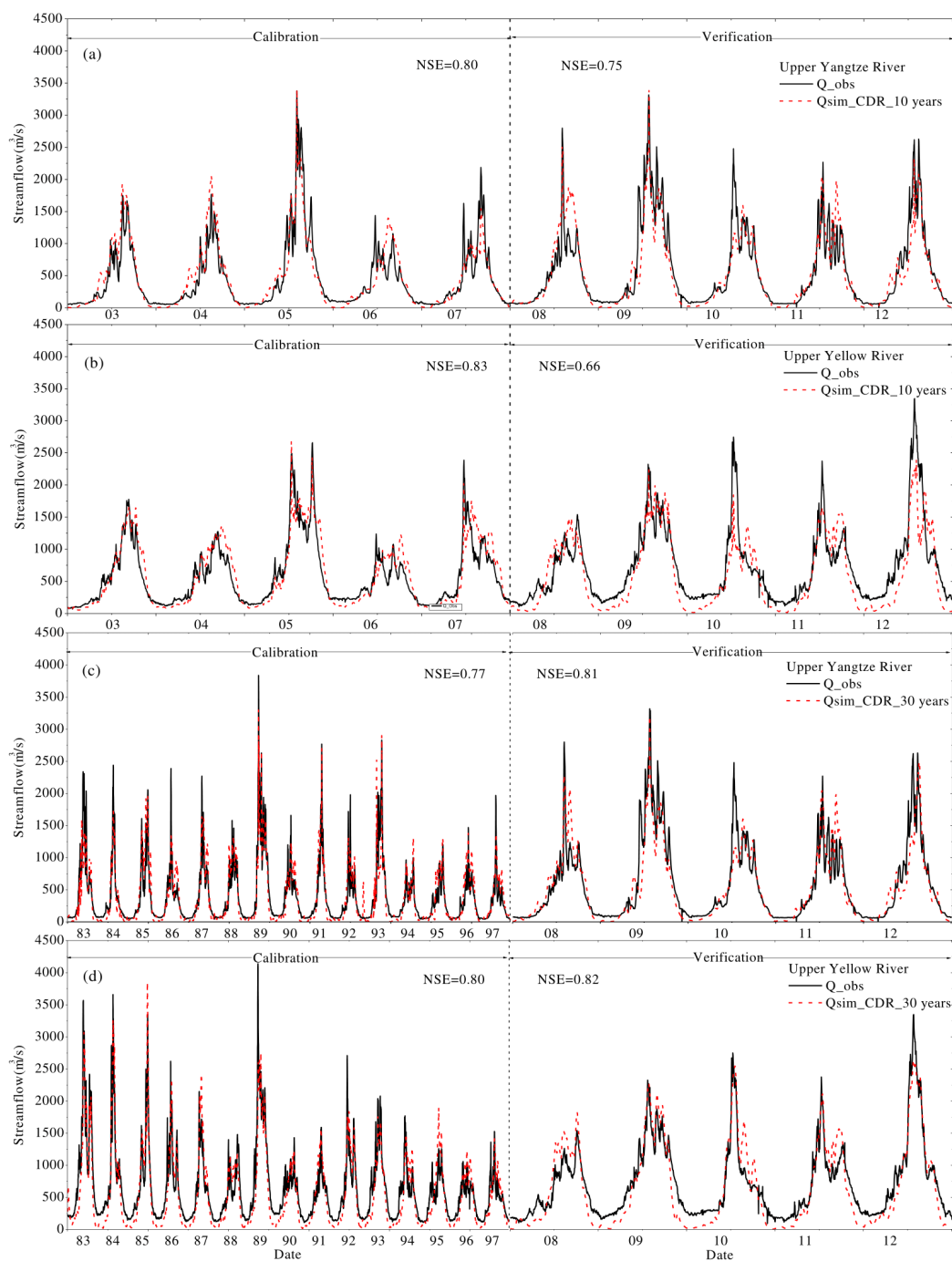
hydrologic model by the inputs of different precipitation datasets instead of using identical parameters will contribute to fairer comparisons when evaluating streamflow simulation capabilities of different precipitation datasets, though other hydrological variables such as soil moisture and evapotranspiration could be incorrectly estimated by different precipitation inputs and calibrated parameters.

#### 4.2 The influences of precipitation record length on streamflow simulation capability

Besides of the uncertainties due to hydrological model calibration, another factor that influences the accuracy of streamflow simulation is the length of precipitation records used for calibration. As mentioned before, one of the advantages of PERSIANN-CDR product is the provision of more than 33 years of continuous sequences of precipitation data, which can allow more extensive streamflow simulation in the Tibetan Plateau. In this study, comparison experiments (Figure 6) were designed to test the influences of precipitation record length on the accuracy of streamflow simulation. In the experiments, we investigate the accuracy of streamflow simulation during 2008 to 2012 with two different calibration scenarios. In the first scenario, the calibration period is from 2003 to 2007 for both the UYZR (Figure 6a) and the UYLR (Figure 6b). In the second scenario (Figure 6c and 6d), 15 years of data from 1983 to 1997 is used for calibration, which is longer than that in the first scenario. As it is shown in Figure 6 (a and b), in the first scenario the *NSE* values between daily observed and simulated streamflow are 0.75 and 0.66 during the verification period (from 2008 to 2012) for the UYZR and UYLR, respectively. Comparatively, in the second scenario the *NSE* values during the verification period (from 2008 to 2012) are 0.81 and 0.82 for the two basins, respectively. The *NSE* values in the second scenario are consistently higher than that in the first scenario in the two basins. For the UYLR in the second scenario (Figure 6d), the *NSE* value during the verification period is significantly greater than that



409 in the first scenario. Figure 6(b) also shows that the HIMS hydrological model significantly  
410 underestimates the flow peaks during the summer of 2010 and 2012 when calibrated by 5 years of  
411 data from 2003 to 2007. The disagreement between the observed and simulated flow peaks is partly  
412 because the magnitudes of flood events during the calibration period are all smaller than that during  
413 the verification period and the HIMS hydrological model cannot be well trained during the  
414 calibration period. Therefore, when using a short length precipitation data as input for a  
415 hydrological model, the accuracy of streamflow simulation could be limited, especially when  
416 precipitation data used for calibration cannot cover the flood and drought conditions of a basin.  
417 However, when the HIMS hydrological model is calibrated by the longer dataset from 1983 to  
418 1997 as it is shown in Figures 6c and d, there is a greater potential that the characteristics of  
419 extreme events can be captured by the hydrological model than only using 5 years of data from  
420 2003 to 2007. Given the availability of long-term precipitation records (over 33 years) provided  
421 by PERSIANN-CDR product, the extreme events in the historical period could be well captured  
422 by a hydrological model. Therefore, using such a product with long-term records, the confidence  
423 of simulating streamflow over the Tibetan Plateau will correspondingly increase.



424

425 Figure 6. The simulated daily streamflow (red) forced by PERSIANN-CDR rainfall product in





different scenarios and the observed daily streamflow (black) at the outlets of the upper Yangtze River Basin and upper Yellow River Basin. (a) and (b) is the scenario that the period 2003 to 2007 is used for calibration and 2008 to 2012 for verification. (c) and (d) is the scenario that the period 1983 to 1997 is used for calibration and 2008 to 2012 for verification

430

## 5. Summary

As it is compared to radar-based precipitation measurement and gauge networks, the main advantage of satellite-based precipitation estimate is the broader coverage at global scale. This allows a comprehensive understanding of the driving force of hydrologic cycle, especially for the gauge sparse area. To verify the accuracy of satellite-based precipitation estimate products, the comparison with ground observation is necessary. However, in gauge sparse area, a direct comparison on precipitation temporal and spatial variation will be arguable due to the limited gauge information. This study provides an alternative way to evaluate satellite-based precipitation products by forcing both rainfall estimates from satellite and limited gauge network into hydrological model. Given the confidence in streamflow measurements, which are more reliable and well monitored than the limited ground-based rainfall measurements, the comparison of simulated streamflow enables an indirect way to evaluate satellite-based precipitation products.

In this study, PERSIANN-CDR precipitation and gauge-based precipitation have good agreements in the UYLR, while the two datasets have different values in the UYZR. Streamflow simulation capabilities of PERSIANN-CDR precipitation and gauge-based precipitation are evaluated as the inputs of the HIMS hydrologic model in the two basins. Both the two datasets have similar good performances in the UYLR, while PERSIANN-CDR precipitation has slightly better performance than gauge-based precipitation in the UYZR. Gauge-based precipitation tends



449 to produce larger streamflow in wet season in the UYZR. This indicates that in the UYZR, a sparse  
 450 gauge network are not a completely reliable reference for water resources management and  
 451 operation due to the fact that the locations of the limited gauge stations cannot be representative  
 452 for measuring the precipitation patterns at the river basin scale.

453 Lack of rainfall gauge stations has brought great challenge to hydrological and climate studies  
 454 over the Tibetan Plateau (e.g., Yao et al., 2012; Zhang et al., 2013). Based on the demonstration in  
 455 this study that PERSIANN-CDR is able to produce reasonably good streamflow in the UYZR and  
 456 UYLR as compared to observed streamflow, we can speculated that PERSIANN-CDR rainfall  
 457 product has the potential to be a useful dataset and alternative of the sparse gauge network for  
 458 future climate change and hydrological studies on the Tibetan Plateau considering the needs for  
 459 long-term (more than 33 years) and high resolution records.

460

#### 461 **Data Availability**

462 The PERSIANN-CDR data used in this study is available from the NOAA CDR Program  
 463 (<https://www.ncdc.noaa.gov/cdr/atmospheric/precipitation-persiann-cdr>) and gauge data is  
 464 retrieved from China Meteorological Administration database (<http://www.cma.gov.cn/en2014/>  
 465 and <http://data.cma.cn/>). The data is public accessible by user registration from the providing  
 466 agencies.

467

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473

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565

566

# 567 **Figure Caption**

568 Figure 1. The selected river basins (the upper Yellow River and Yangtze River Basin) on the  
 569 Tibetan Plateau and location of rainfall stations and river outlets.

570 Figure 2. The monthly average runoff observed at the river outlet of the upper Yangtze River and  
 571 Yellow River Basin, and the precipitation data retrieved from PERSIANN-CDR and ground-based  
 572 observation.

573 Figure 3. The calculated CDF of rainfall from PERSIANN-CDR and ground-based observation in  
 574 the upper Yangtze River Basin and upper Yellow River Basin.

575 Figure 4. The comparison between the simulated daily streamflow (red) with PERSIANN-CDR  
 576 and ground-based precipitation and the observed data (black) at the outlets of the upper Yangtze  
 577 River Basin (a and b) and upper Yellow River Basin (c and d).

578 Figure 5. The comparison between the observed streamflow (black) and the simulated streamflow  
 579 using PERSIANN-CDR (blue) and ground-based precipitation data (red) in the upper Yangtze  
 580 River Basin and upper Yellow River Basin.

581 Figure 6. The simulated daily streamflow (red) forced by PERSIANN-CDR rainfall product in  
 582 different scenarios and the observed daily streamflow (black) at the outlets of the upper Yangtze  
 583 River Basin and upper Yellow River Basin. (a) and (b) is the scenario that the period 2003 to 2007  
 584 is used for calibration and 2008 to 2012 for verification. (c) and (d) is the scenario that the period  
 585 1983 to 1997 is used for calibration and 2008 to 2012 for verification