Uncertainty and Bias in Satellite-Based Precipitation Estimates over Indian Subcontinental Basins: Implications for Real-Time Streamflow Simulation and Flood Prediction*

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ABSTRACT

Real-time streamflow monitoring is essential over the Indian subcontinental river basins, as a large population is affected by floods. Moreover, streamflow monitoring helps in managing water resources in the agriculture-dominated region. In this study, the authors systematically investigated the bias and uncertainty in satellite-based precipitation products [Climate Prediction Center morphing technique (CMORPH); Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN); PERSIANN Climate Data Record (PERSIANN-CDR); and Tropical Rainfall Measuring Mission (TRMM), version 7, real-time (3B42RTV7) and gauge-adjusted (3B42V7) products] over the Indian subcontinental river basins for the period of 2000–13. Moreover, the authors evaluated the influence of bias in the satellite precipitation on real-time streamflow monitoring and flood assessment over the Mahanadi river basin. Results showed that CMORPH and PERSIANN underestimated daily mean precipitation over the majority of the subcontinental river basins. On the other hand, TRMM-3B42RTV7 overestimated daily mean precipitation over most of the river basins in the subcontinent. While gauge-adjusted products of PERSIANN (PERSIANN-CDR) and TRMM (TRMM-3B42V7) performed better than their real-time products, large biases remain in their performance to capture extreme precipitation (both frequency and magnitudes) over the subcontinental basins. Among the real-time precipitation products, TRMM-3B42RTV7 performed better than CMORPH and PERSIANN over the majority of the Indian subcontinental basins. Daily streamflow simulations using the Variable Infiltration Capacity model (VIC) for the Mahanadi river basin showed a better performance by the TRMM-3B42RTV7 product than the other real-time datasets. Moreover, daily streamflow simulations over the Mahanadi river basin showed that bias in real-time precipitation products affects the initial condition and precipitation forcing, which in turn affects flood peak timing and magnitudes.

1. Introduction

Extreme precipitation and flood events pose a tremendous hazard to human society and infrastructure. For instance, more than 419 people and 16 000 cattle died as a result of heavy rainfall (944 mm in a day) in Mumbai (India) in 2005. In June 2013, a cloudburst in Uttarakhand (India) caused devastating flash floods and landslides, which resulted in the deaths of 6000 people (*Times of India*, accessed on 30 June 2013). Recently in 2014, an extreme precipitation event in Jammu and

Kashmir caused flooding and resulted in enormous loss of property. Moreover, other than flash flooding, which happens in urban areas and fast-responding mountainous catchments (Schmitz and Cullmann 2008), extreme precipitation events may cause disproportionate damage to agriculture (Rosenzweig et al. 2002). According to a 2006 World Bank report, a 0.38-million-ha area was affected by flood in the Brahmaputra basin, leading to an average annual damage cost of 7171.7 million Indian rupees during the period of 1999–2005.

Satellite-based precipitation can provide useful information on near-real-time streamflow monitoring and damage assessment caused by floods. Furthermore, streamflow and flood monitoring can help in decision-making to mitigate losses. Real-time streamflow monitoring requires real-time, gauge-based observed precipitation data, which may not be available at required spatial and temporal resolutions. Remote sensing can offer an alternative source of precipitation information for streamflow simulation and flood protection (Zhang

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et al. 2002; Hong et al. 2007a; Khan et al. 2011). However, differences in datasets may lead to uncertain estimates of flood magnitudes and therefore warrant a careful scrutiny before their application in hydrologic modeling (Asante et al. 2007; Tian et al. 2007; Shrestha et al. 2008).

Satellite-based precipitation products have been widely evaluated for hydrologic applications. For instance, Yang and Luo (2014) used the Tropical Rainfall Measuring Mission (TRMM) real-time product (3B42RT) for the region of northwestern China and found that it accurately detects rainfall occurrences on a daily scale consistent with rain gauge observations. Huang et al. (2013) showed that TRMM-3B42RT captured rainfall spatially and temporally against rain gauge measurements for Beijing. However, Yong et al. (2010, 2012) reported an unrealistic overestimation by TRMM-3B42RT over the high-latitude Laohahe basin, China. Similarly, Curtis et al. (2007) showed that TRMM-3B42RT precipitation amounts were higher than radar and gauge-based rainfall estimates in eastern North Carolina, United States. Among the other satellite products, Sapiano and Arkin (2009) showed that the Climate Prediction Center morphing technique (CMORPH) has the highest correlation with 3-hourly gauge data (up to 0.7) over the United States and the Pacific Ocean when compared with TRMM Multisatellite Precipitation Analysis (TMPA) and Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) datasets. On the other hand, CMORPH underestimated precipitation over the arid region of northwestern China (Yang and Luo 2014). Moreover, the PERSIANN data have been evaluated in the continental United States and in western Mexico (Hong et al. 2007b; Gourley et al. 2010). Recently, Miao et al. (2015) evaluated PERSIANN Climate Data Record (CDR) data for the extreme events in China and reported that the dataset captures spatial and temporal variability in daily extreme precipitation events reasonably well.

Satellite-based observations have been proven essential for streamflow and flood monitoring in various parts of the globe (Hong et al. 2007b; Shrestha et al. 2008; Li et al. 2009; Villarini et al. 2009; Su et al. 2011; Huang et al. 2014). However, bias in precipitation products leads to inaccurate initial conditions and precipitation forcing, which affect accuracy of streamflow and flood monitoring. Gupta et al. (2002) used PERSIANN to predict flash floods over the United States and concluded that the satellite data may help in identifying features, but they lack adequate lead time that is required for forecasting flash floods from large convective thunderstorm systems (Sapiano and Arkin 2009). Asante et al. (2007) developed a flood monitoring system in the Limpopo basin, South Africa, using the TRMM dataset to improve an early flood warning

system. Fotopoulos et al. (2010) used the gauge-adjusted and real-time TRMM products (3B42 and 3B42RT, respectively) for flood forecasting in the Evros catchment in southeastern Europe. Recently, Wu et al. (2014) developed a Global Flood Monitoring System (GFMS) using TRMM-3B43RT, version 6 (TRMM-3B42RTV7), and concluded that flood magnitudes were affected by presence of a reservoir, rainfall estimation, and resolution of the routing model.

In this study, we evaluate the five mainstream satellite precipitation products for their utility in real-time streamflow and flood monitoring over the Indian subcontinental river basins. We address the following scientific questions:

- 1) How well do satellite precipitation products perform for daily and monthly mean precipitation over the Indian subcontinental river basins? What are the differences in the performance of satellite products for mean and extreme precipitation in the region?
- 2) To what extent do gauge-adjusted products perform better than their real-time datasets in the region?
- 3) To what extent does the initial condition influence the streamflow/peak due to bias in the three satellite real-time products?

2. Methods and data

a. Study region

Our assessment and validation were first performed over the 18 Indian subcontinental river basins: Brahmani, Brahmaputra, Cauvery, Ganga, Godavari, India east coast, India northeast coast, India south coast, India west coast, Indus, Krishna, Mahanadi, Mahi, Narmada, Pennar, Sabarmati, Tapti, and Subarnarekha (Fig. 1, Table S1 in the supplemental material). The mean and extreme precipitation information from the five satellite products were evaluated against the observed data for all the selected subcontinental basins. Moreover, we provided a detailed hydrologic evaluation for streamflow simulations derived from the Variable Infiltration Capacity model (VIC) at the selected gauge stations over the Mahanadi river basin, which is located in eastern India. The Mahanadi river flows through the states of Chhattisgarh and Odisha and drains an area of 125 663 km². The basin has been predominantly facing flood risks even after the construction of the Hirakud Dam (Mohapatra and Singh 2003; Gosain et al. 2006; Asokan and Dutta 2008). We selected six streamflow gauge stations (Fig. 1) that are located upstream of the Hirakud reservoir to evaluate streamflow simulations from the different precipitation products. The observed daily streamflow data for the selected gauge stations in

FIG. 1. Location of the Indian subcontinental basins and variability in topography (m MLS; shaded region) in the study region. The figure in the box shows the location of the gauge stations over the Mahanadi river basin and the streamflow routing network. The gauge stations over the Mahanadi river basin were selected upstream of the Hirakud Dam.

the Mahanadi river basin were obtained from the Central Water Commission. Most of the selected gauge stations are those least affected by water management structure; therefore, these can be used for the performance assessment of streamflow derived from the satellite precipitation.

b. The VIC

To derive streamflow from the selected satellite precipitation products, we used the VIC over the Mahanadi river basin. The VIC (version 4.1.2; Liang et al. 1994, 1996; Cherkauer et al. 2003; Cherkauer and Lettenmaier 1999; <http://vic.readthedocs.org/en/vic.4.2.c/>) simulates water and energy fluxes at each grid cell and represents subgrid variability of elevation, soil, and vegetation (Gao et al. 2010). We used vegetation parameters that were extracted from the Advanced Very High Resolution Radiometer (AVHRR) global land-cover information that is available at 1-km spatial resolution (Hansen et al. 2000; Sheffield and Wood 2007). Vegetation parameters were developed for each 0.25° grid cell, while the vegetation library was obtained from the Land Surface Hydrology Group's website (www.hydro.washington.edu) at the University of Washington. We obtained Harmonized World Soil Database (HWSD), version 1.2, soil data, and soil parameters were developed for the VIC. The VIC has been widely used for hydrologic applications at various spatial and temporal

scales (Nijssen et al. 2001; Mishra et al. 2010; Raje et al. 2014; Shrestha et al. 2014; Mishra et al. 2014). We applied the VIC (in water balance mode) at 0.25° spatial resolution, which is consistent with the resolution of precipitation products from the satellite datasets. Precipitation and daily maximum and minimum temperature forcing to derive the VIC were obtained from the India Meteorological Department (IMD). Gridded temperature data were obtained from the IMD, which are based on 395 stations across India. We obtained gridded daily precipitation data from the IMD for the period of 2000–13 at 0.25° spatial resolution. IMD has more than 6329 rainfall observation stations, and station density is highest over the peninsular region and lower in the northern plains (Rajeevan et al. 2006; Pai et al. 2014). Goswami et al. (2006) used IMD data to study the trend of extreme rain events over India for the period of 1951–2000 and concluded that magnitude and frequency of extreme rain events were increased and frequency of moderate rain events was decreased in monsoon seasons. Moreover, Ali et al. (2014) used IMD precipitation data to evaluate trends and variability in extreme precipitation in major urban areas in India. More information on the observed precipitation data from IMD can be obtained from Pai et al. (2014). We obtained daily wind speed data from the NCEP–NCAR reanalyses, which were regridded to 0.25° spatial resolution using the method described in Maurer et al. (2002).

Streamflow routing was performed using a stand-alone routing model (Lohmann et al. 1996), which uses daily surface runoff and base flow simulated by the VIC to route daily flow at a desired location over the basin. The routing model is based on the unit hydrograph method and works on a simple cell-to-cell concept (Lohmann et al. 1996). As the routing model requires flow direction and accumulation files, the routing network for the Indian subcontinental basins was prepared at 0.25° using the Shuttle Radar Topography Mission (SRTM) elevation data. Detailed information on the routing network at different spatial resolution is available in Wu et al. (2012). Please refer to Lohmann et al. (1996) for more details on the routing model used in this study. We used the routing model to evaluate the performance of the satellite precipitation products by providing the appropriate spinup time prior to the simulated streamflow events. However, as described in Wu et al. (2014), the existing routing model may not be suitable for real-time streamflow and flood monitoring because of time lag in the runoff generation in upstream and downstream areas in real time. In the future, approaches such as those based on the physically based hierarchical dominant river tracing-based runoff-routing (DRTR; Wu et al. 2014) can be evaluated over the Indian subcontinental basins.

c. Satellite precipitation datasets

We evaluated satellite products against the observed gridded precipitation data from the IMD for the period of 2000–13, which is an overlapping period for all the datasets. Among the satellite precipitation products, we obtained daily precipitation data at 0.25° resolution from CMORPH (Joyce et al. 2004); PERSIANN (Sorooshian et al. 2000); PERSIANN-CDR (Ashouri et al. 2015); TRMM 3B42, version 7 (3B42V7); and TRMM 3B42RT, version 7 (3B42RTV7) (Huffman et al. 2007). TRMM is a joint U.S.–Japan satellite mission, which is designed for monitoring tropical and subtropical rainfall (Huffman et al. 2007). The TRMM Multisatellite Precipitation Analysis (TMPA), generally known as 3B42, is a gauge-adjusted combination of the two interim products: the passive microwave (PM) and the PM-calibrated infrared (IR; Huffman et al. 2007; Sapiano and Arkin 2009). TRMM-3B42RT (2015) data continuing from January 1998 over 50°S – 50°N and all longitudes can be downloaded from the NASA website (<http://disc.sci.gsfc.nasa.gov/SSW/>; Huffman et al. 2014). The CMORPH data produce precipitation using both microwave (MW) and IR sensors (Joyce et al. 2004). The gridded data are available at a spacing of 25 km ($\sim 0.25^\circ$) at daily resolution from 1998 to present (ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/RAW). The PERSIANN dataset uses a neural network technique

for generating rainfall estimates from IR data (Hsu et al. 1997). It was developed to estimate rainfall from the Geostationary Operational Environmental Satellite IR sounder (GOES-IR) at a spatial resolution of $0.25^\circ \times 0.25^\circ$ at a half-hourly scale, and the accuracy was improved by adjusting the network parameters with the help of instantaneous rain-rate estimates from the TRMM Microwave Imager (TMI), product 2A12 (Sorooshian et al. 2000). The data are available from March 2000 to present (<http://chrs.web.uci.edu/persiann/data.html>). PERSIANN-CDR is a new retrospective satellite-based dataset that is available at daily and 0.25° resolutions for the period from 1983 to near present (Ashouri et al. 2015). The dataset aims to provide quality-controlled, long-term, high-resolution, global precipitation data that can be used for trend analysis of daily precipitation and extreme events and to study the impacts of climate variability and climate change. The data were developed using the PERSIANN product, which was adjusted using the Global Precipitation Climatology Product (GPCP).

d. Analysis approach

We evaluated precipitation data from the satellite product against the observed IMD precipitation for the 18 subcontinental river basins. The analysis for the Indus, Ganges, and Brahmaputra basins was limited to the Indian region because of unavailability of the IMD precipitation outside India. The precipitation products were evaluated for mean daily/monthly precipitation and extreme precipitation for all the basins. Moreover, daily and monthly streamflow at the selected gauge stations was evaluated over the Mahanadi river basin (Fig. 1). To evaluate extreme precipitation from the satellite products, we compared frequency of extreme precipitation events, which was estimated using the 90th percentile for the monsoon season (June–September) of rainy days (precipitation greater than 1 mm) as described in Mishra and Lettenmaier (2011) from the IMD data. We also estimated the total precipitation contributed by the extreme events (above 90th percentile) in the monsoon season to understand bias in the satellite products. The performance of the satellite products was evaluated using statistical measures such as correlation, bias, coefficient of determination, Nash–Sutcliffe efficiency (NSE), false alarm ratio (FAR), and probability of detection (POD; Table S2 in the supplemental material).

3. Results and discussion

a. Evaluation of satellite products for mean precipitation

We evaluated daily mean precipitation from the satellite products for the monsoon season (June–September)

FIG. 2. (a) Mean daily rainfall (mm day^{-1}) for the monsoon (June–September) from the IMD and (b)–(f) bias in mean daily rainfall (mm day^{-1}) in the CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7 datasets for the period of 2000–13.

for the period of 2000–13 (Fig. 2). Daily mean precipitation from the satellite products was compared against the IMD dataset (Fig. 2a). Daily mean precipitation for the monsoon season showed higher values in the Western Ghats and northeastern regions and lower values in peninsular India and the semiarid western parts of India (Fig. 2a). CMORPH showed negative bias in the majority of subcontinental river basins in the monsoon season (Fig. 2b), with higher values in the Western Ghats and northeastern regions. Similar to CMORPH, PERSIANN data showed a negative bias (underestimation) in the majority of the Indian subcontinental river basins; however, the bias was lower than that in the CMORPH data (Fig. 2c). The PERSIANN-CDR data depicted a much better performance for daily precipitation during the monsoon season; however, the negative bias in the Western Ghats region was similar to the CMORPH and PERSIANN datasets. We noticed that TRMM-3B42RTV7 performed better than the other real-time satellite

precipitation products (CMORPH and PERSIANN) over the Indian subcontinental river basins. However, TRMM-3B42RTV7 showed a positive bias (overestimation) in daily rainfall during the monsoon season over the basins in central India as well as in the Brahmaputra basin (Fig. 2e). The negative bias in daily precipitation in the Western Ghats region was improved in the TRMM-3B42V7 product (Fig. 2f). Median biases in daily mean precipitation in the Western Ghats region were -16 , -17 , -12 , -8 , and -4 mm day^{-1} in CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7, respectively. Our results showed that all of the satellite products underestimate daily precipitation in the Western Ghats region (Table 1), which might be associated with the microwave precipitation estimations, which over the coastal regions is a mixture of the radiometrically cold ocean and radiometrically warm land surface, as described in McCollum and Ferraro (2005). On the

TABLE 1. Daily mean precipitation from the IMD and bias in the satellite products in the subcontinental river basins for the period of 2000–13.

Basin	Mean daily precipitation from IMD (mm day ⁻¹)	Bias (mm day ⁻¹)				
		CMORPH	PERSIANN	PERSIANN-CDR	TRMM-3B42RTV7	TRMM-3B42V7
Brahmaputra	11.6	-5.1	-5.6	-0.5	3.8	1.8
Brahmani	9.5	-2.1	1.1	1.3	0.6	0.5
Cauvery	3.0	-0.4	1.3	3.3	1.9	0.8
Ganga	6.8	-1.6	-0.7	1.2	1.6	0.8
Godavari	7.7	-1.5	-0.8	0.9	2.1	0.6
India east coast	3.2	1.0	3.1	1.8	1.6	1.0
India northeast coast	7.0	0.4	3.5	2.9	2.3	1.9
India south coast	3.0	-0.5	0.7	1.1	1.4	0.8
India west coast	20.6	-16.0	-17.0	-11.8	-8.5	-4.0
Indus	2.5	-0.6	-0.8	-0.2	0.8	-0.6
Krishna	4.4	-1.4	-0.9	2.1	1.6	0.8
Mahanadi	9.5	-2.2	0.1	0.8	0.9	0.7
Mahi	7.0	-2.1	-2.4	-0.1	1.9	0.0
Narmada	8.2	-2.3	-2.3	0.0	2.0	0.8
Pennar	3.1	0.0	1.8	1.8	0.9	0.5
Sabarmati	4.5	-1.4	-0.8	0.0	0.9	0.0
Tapti	6.0	-1.6	-1.8	1.7	2.7	1.1
Subarnarekha	8.9	-2.1	1.5	1.6	0.8	0.3

other hand, in the Brahmaputra basin, CMORPH (bias = -5.1 mm day^{-1}), PERSIANN (-5.6 mm day^{-1}), and PERSIANN-CDR (-0.5 mm day^{-1}) underestimated daily precipitation, while TRMM-3B42RTV7 (3.8 mm day^{-1}) and TRMM-3B42V7 (1.8 mm day^{-1}) overestimated (Table 1). The performance across the subcontinental basins for daily mean precipitation indicated that TRMM-3B42V7 and PERSIANN-CDR performed better than their real-time products. Moreover, among the real-time products, the performance varied over the subcontinental river basins as reported in Shen et al. (2010). For instance, Shen et al. (2010) found that the performance of the satellite products varies in different regions and precipitation regimes in China; however, satellites provide better precipitation estimates over the warm and wet regions. Our results showed that TRMM-3B42RT overestimated daily mean precipitation in many areas, which could be adjusted using the gauge-based precipitation data as reported in Shen et al. (2010). Additionally, Yong et al. (2015) reported that use of the historical gauge data and the smooth-fill scheme in the monthly climatological calibration algorithm (CCA; Yong et al. 2012) of TRMM-3B42RTV7 can result in upward estimates of precipitation. Furthermore, Yong et al. (2015) argued that CCA may improve the results at the global scale; however, it can also lead to misrepresentation of local varying rainstorm characteristics.

Figure 3 shows the comparison of performance measures (correlation coefficient, FAR, and POD; see Table S2 in the supplemental material for more details) of daily rainfall for the entire year during the period

of 2000–13. Weaker correlations between daily precipitation from the IMD and satellite products can be noticed in the northern parts of the Indus basin, southern peninsula, and Brahmaputra basin (Figs. 3a–e, see Table S3 in the supplemental material). For the majority of the river basins, CMORPH and PERSIANN showed weaker correlations than that of the PERSIANN-CDR and TRMM products, which is consistent with the results obtained for the bias in mean daily precipitation. Most of the satellite products showed a low FAR in the core monsoon region, while high FAR values were obtained in the peninsular, northern, and western regions (Fig. 3). However, we did not notice significant differences for FAR in the real-time and gauge-adjusted products (see Table S4 in the supplemental material). Consistent with the other performance metrics, CMORPH and PERSIANN showed lower POD for the majority of the subcontinental river basins (Figs. 3k–o). Interestingly, PERSIANN-CDR outperformed the other datasets with the best estimates of POD for most of the basins (see Table S5 in the supplemental material), which may be associated with its ability to simulate the frequency of rainy days. As reported in Ashouri et al. (2015), PERSIANN-CDR is adjusted by the gauge as well as the GPCP dataset, which can result in better performance to capture the timing of rainfall over the subcontinental river basin. Moreover, the improved performance of PERSIANN-CDR for POD may be associated with better estimates of infrared-based precipitation (Tian et al. 2009).

Figures 4 and 5 show the performance of the satellite products for the Indian subcontinental river

FIG. 3. (a)–(e) Correlation in daily rainfall from the IMD and the selected datasets for the monsoon season for the period of 2000–13, (f)–(j) FAR, and (k)–(o) POD in the selected datasets (CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7).

FIG. 4. Comparison of basin-averaged mean monthly precipitation from the satellite (y axis) and observed (IMD; x axis) data for the period of 2000–13 for 9 of the 18 basins.

basins against the observed monthly precipitation for the period of 2000–13. The performance estimated using coefficient of determination R^2 and root-mean-square error (RMSE) showed that CMORPH and PERSIANN underestimated monthly precipitation totals in the majority of the selected river basins. Moreover, TRMM-3B42RTV7 performed better than CMORPH and PERSIANN in most of the subcontinental river basins. The performance of PERSIANN-CDR and TRMM-3B42V7 was better than their real-time products because of gauge

adjustments, which is consistent with the findings of Shen et al. (2010).

b. Evaluation of satellite products for extreme precipitation

We evaluated the satellite products for extreme precipitation during the monsoon season for the selected subcontinental river basins. Figure 6 shows the bias in frequency of extreme precipitation in the satellite products for the period of 2000–13. Frequency of extreme precipitation was selected using the 90th percentile

FIG. 5. As in Fig. 4, but for the other nine basins.

threshold from the IMD dataset as described in the approach section. We used the same (90th percentile of the observed precipitation) threshold to estimate the number of extreme precipitation events during the monsoon season in the satellite products. A higher frequency of extreme precipitation events can be noticed in the Western Ghats, in the Brahmaputra basin, and in the core monsoon region of central India in the observed dataset (Fig. 6a). CMORPH underestimated the frequency of extreme precipitation events in the majority of the selected river basins (Fig. 6b, Table S6 in the supplemental material), and the underestimation was more

prominent in the upper Indus, west coast, central India, and Brahmaputra basin. PERSIANN and PERSIANN-CDR showed both positive and negative biases in the frequency of extreme precipitation events (Figs. 6c,d). For instance, negative bias (underestimation) can be noticed in northern India, the Western Ghats, central India, and the Brahmaputra basin, while positive bias is largely located in the Gangetic Plain and east coast regions in the PERSIANN dataset. The positive bias in the east coast in the PERSIANN dataset was improved in PERSIANN-CDR. However, overestimation in the frequency of extreme events can be noticed in the leeward

FIG. 6. (a) Frequency of extreme rainfall events [above the 90th percentile for the rainy days (rainfall >1 mm) from the IMD datasets] during the monsoon season in the IMD dataset; (b)–(f) bias in frequency of extreme rainfall events during the monsoon season in the CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7 datasets. Frequency of the extreme rainfall events in all datasets was estimated using the 90th percentile threshold of rainy days for the monsoon season during the period of 2000–13 from the IMD dataset.

side of the Western Ghats region, which may be due to the differences in the orographic rainfall in the PERSIANN and PERSIANN-CDR datasets. Unlike the CMORPH and PERSIANN datasets, the TRMM products largely overestimated the frequency of extreme rainfall events across the basins, except the northern and Western Ghats regions. Considering all the subcontinental river basins, it can be observed that PERSIANN-CDR and TRMM-3B42V7 performed better than their real-time products (see Table S6 in the supplemental material).

Consistent with our results, overestimation in extreme daily precipitation in the TRMM data in China and India was found by Zhao and Yatagai (2014) and Shah and Mishra (2014). Shah and Mishra (2015) reported that TRMM-3B42RTV7 showed an overestimation in

extreme precipitation and an underestimation in the number of rainy days. Tian et al. (2007) found that the satellite precipitation products detect a large number of high-intensity rain events, which causes a shift in precipitation patterns. Moreover, part of the overestimation of the frequency of extreme events in the TRMM products can be due to IR retrieval between brightness temperature and rain rates in the level-2 product (Yong et al. 2015). The IR retrieval of precipitation is based on the statistical relationship between cloud-top brightness temperature and precipitation rate, and uncertainty in extreme precipitation may arise because of uncertainty associated with the height, thickness, and cloud type (AghaKouchak et al. 2011). However, Huang et al. (2014) reported that TRMM may not perform well for heavy rain events because of

FIG. 7. (a) Mean monsoon season precipitation (mm) contributed by the extreme (above the 90th percentile) rainfall events during the period of 2000–13; (b)–(f) bias in mean monsoon season precipitation from the extreme rainfall events from CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7.

limitations associated with the coarse resolution. The performance of TRMM-3B42V7 was better for the frequency of extreme precipitation events, as this is adjusted by the gauge data. Interestingly, the performance of the TRMM-3B42V7 product showed relatively less improvement in the topographically complex regions, which can be associated with the gauge density in these regions.

Figure 7 shows mean monsoon season precipitation contributed by the extreme events (above 90th percentile of rainy days >1 mm) from the IMD dataset and bias in the satellite precipitation products during the period of 2000–13. Similar to the spatial pattern observed in the frequency of extreme precipitation events, higher contribution in precipitation totals can be noticed in the core monsoon region, in the Western Ghats, and in the northeastern regions (Fig. 7a). Bias pattern in the precipitation due to extreme events is similar to that obtained for the frequency of extreme precipitation events.

For instance, CMORPH largely underestimated precipitation totals in the majority of subcontinental basins while PERSIANN and PERSIANN-CDR showed both positive and negative bias. On the other hand, the TRMM products (3B42RTV7 and 3B42V7) showed a large positive bias in extreme precipitation totals during the monsoon season. The bias in the PERSIANN-CDR and 3B42V7 products was improved in comparison to their real-time versions. The bias was improved substantially in the west coast region in the TRMM-3B42V7 product (Table S7 in the supplemental material), which may be due to adjustment with the gauge data.

c. Evaluation of satellite data for precipitation and streamflow for the Mahanadi river basin

We evaluated the performance of the satellite datasets against the observed data for the Mahanadi river basin for the period of 2000–13. The Mahanadi river basin was

selected because it is one of the most flood-affected basins in the Indian subcontinent. Moreover, we evaluated the role of antecedent conditions and precipitation forcing on streamflow at the selected gauge stations over the Mahanadi river basin (Fig. 1).

1) SEASONAL CYCLE OF DAILY PRECIPITATION

Figure 8 shows a comparison of basin-averaged daily mean precipitation and its seasonal cycle from the IMD and the selected satellite datasets for the Mahanadi river basin for the period of 2000–13. We noticed a relatively lower R^2 between observed and satellite precipitation for the Mahanadi river basin during the period of 2000–13. A weaker performance was observed for the CMORPH and PERSIANN datasets with R^2 of 0.32 and 0.27, respectively (Figs. 8a,b). Moreover, we found that the CMORPH data overestimated precipitation in the premonsoon (March–May) season and underestimated daily precipitation during the monsoon season (June–September; Fig. 8f). These inconsistencies in daily precipitation can result in a large bias in the simulated streamflow at different locations of the basin. Similar to the CMORPH data, an overestimation in the daily mean precipitation during the premonsoon season was noted in the PERSIANN dataset (Fig. 8g). However, the PERSIANN data captured the magnitude and variability of the monsoon season rainfall better than that of the CMORPH data, which is reflected in the lower RMSE value. For the Mahanadi river basin, TRMM-3B42RTV7 performed better than the other two real-time satellite precipitation products (Figs. 8d,i). However, positive RMSE for daily mean precipitation from the 3B42RTV7 data is consistent with its nature to overestimate precipitation over the Indian subcontinent. Compared to the CMORPH and PERSIANN datasets, relatively lower bias was found in the TRMM-3B42RTV7 dataset for the Mahanadi river basin during the premonsoon season. Consistent with the results reported in the above sections, PERSIANN-CDR and TRMM-3B42V7 performed better than their real-time products because of gauge adjustments. We noted that TRMM-3B42V7 and PERSIANN-CDR provide similar performance for daily mean precipitation over the Mahanadi river basin, but with opposite biases.

2) THE VIC CALIBRATION AND EVALUATION

Since our aim was to evaluate the performance of satellite data for simulated streamflow at the selected gauge stations in the Mahanadi river basin (Fig. 1), we calibrated and evaluated the VIC for monthly and daily streamflow against the observed data (Fig. 9, Table S8 in the supplemental material). The six soil parameters were calibrated to improve the performance of the

model to simulate the flow at the selected locations. More details about the calibration parameters of the VIC can be obtained in Mishra and Cherkauer (2010). The VIC performed well during the calibration period (1980–90) to simulate monthly streamflow at the six selected gauge stations. It should be noted that these gauge stations are located in the upstream of major reservoirs and are therefore less affected by the anthropogenic influence. However, there might be a minimal influence of irrigation practices in the pre- and postmonsoon seasons, which is not accounted in the study because of nonavailability of observed datasets. During the calibration period, the NSE and correlation coefficient were higher than 0.7 and 0.9, respectively, at all the gauge stations (Figs. 9a–f). Similar performance can be noted for the evaluation period to simulate monthly streamflow for the period of 2001–10. Performance for the daily calibration and evaluation periods can also be considered satisfactory ($NSE > 0.4$ and correlation coefficient > 0.6) at the selected gauge station given the high year-to-year variability in daily streamflow over the basin (Table S8 in the supplemental material). Based on the VIC's performance to simulate daily and monthly streamflow at the selected gauge stations, the model setup can provide reasonable information on the differences in streamflow simulated using the observed and satellite precipitation datasets.

3) EVALUATION OF SATELLITE PRECIPITATION FOR DAILY STREAMFLOW SIMULATIONS OVER THE MAHANADI RIVER BASIN

Figure 10 and Figure S1 (in the supplemental material) depict the performance of satellite products in simulating daily streamflow over the Mahanadi basin for the year 2010. For instance, the CMORPH data performed better at the Basantpur gauge station than at Kesinga (Table 2). Similar results showing spatial variability in the performance can be seen for the other satellite products as well. The spatial variation in performance in the satellite products can be associated with the differences in bias in the satellite precipitation over the basin, which affects both initial conditions and precipitation forcing. For instance, the bias in initial conditions due to differences in precipitation forcing in different parts of the basin in the selected satellite products may also result in disparities in the performance. Our results highlight that TRMM-3B42RTV7 performed better than CMORPH and PERSIANN at four out of six stations over the Mahanadi river basin (Fig. 10, Figure S1 in the supplemental material, Table 2). Moreover, PERSIANN-CDR and TRMM-3B42V7 performed better than their real-time products to simulate streamflow over the Mahanadi river basin (Table 2).

FIG. 8. (a)–(e) Comparison of daily rainfall from the selected datasets for the period of 2000–13 and (f)–(j) comparison of the season cycle in the IMD rainfall and in the selected precipitation products for the Mahanadi basin.

Results are consistent for monthly streamflow simulations, as TRMM-3B42RTV7 performed better than the other two products in most of the gauge stations. These results highlight that the performance may vary

spatially and temporally for streamflow simulations using satellite precipitation (Shen et al. 2010), which may be associated with the random bias in satellite precipitation products as found in Shah and Mishra (2015).

FIG. 9. (a)–(f) Calibration and (g)–(j) evaluation of monthly streamflow at the selected gauge stations over the Mahanadi river basin.

Moreover, the variation in performance at different locations in the basin can be related to the biases in initial conditions as well as the precipitation forcing. For instance, a low-intensity precipitation before an extreme event can provide wetter initial conditions that can further introduce the bias in streamflow simulations from the satellite products.

4) ROLE OF INITIAL CONDITIONS AND PRECIPITATION FORCING IN STREAMFLOW SIMULATIONS

We evaluated the influence of bias in the precipitation datasets on streamflow monitoring and uncertainty in flood magnitudes over the Mahanadi river basin. We performed the two experiments over the Mahanadi river basin at the Basantpur gauge station (Fig. 1). First, we evaluated the role of initial conditions on simulated streamflow by using the initial conditions obtained from the satellite and observed precipitation datasets and keeping precipitation from the observed data for all simulations. Second, we considered the role of precipitation forcing keeping the initial conditions the same as those obtained from the observed data, and precipitation forcing was used from the satellite datasets. This was done to understand the relative importance of bias in initial conditions and in precipitation forcing from the satellite datasets. In each case, the run with the observed initial conditions and observed forcing (from the IMD data) was considered as the reference run. At the Basantpur gauge station, we compared simulated flow during the period of 11–30 September 2011 to evaluate the role of initial condition and bias (Fig. 11). As the time of concentration of Mahanadi river basin is about two days, we used the initial state of 9 September 2011 to simulate flow during 11–30 September 2011. Consistent with the results described in the above sections, we noticed that streamflow simulations with different initial conditions and observed forcing showed a large bias in daily streamflow simulations during the period of 11–30 September 2011 (Fig. 11a), which highlights that the accumulated precipitation prior to a flood event can affect the flood magnitudes. Mean bias for 11–30 September was -1600 , -3368 , 387 , 1311 , and $1601 \text{ m}^3 \text{ s}^{-1}$ for CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7, respectively. Daily flow simulations depicted that initial states from CMORPH and PERSIANN with the observed forcing resulted in underestimation in daily streamflow, which is related to negative bias in daily mean precipitation in these datasets. On the other hand, TRMM-3B42RTV7, TRMM-3B42V7, and PERSIANN-CDR overestimated daily streamflow, which highlights that these datasets simulate wetter antecedent conditions

than other satellite datasets. Uncertainty (estimated using standard deviation) in daily simulated flow was higher than $1500 \text{ m}^3 \text{ s}^{-1}$ during the first 7 days of simulations (Fig. 11b), which solely resulted from the bias in the initial conditions obtained from the selected precipitation products. During flooding, peak flow and runoff volume are governed by initial wetness and rainfall resolution (Sturdevant-Rees et al. 2001; Yatheendradas et al. 2008; Nikolopoulos et al. 2011; Kumar et al. 2014), which is consistent with our results.

In the second experiment, we evaluated the role of bias in precipitation forcing on daily streamflow monitoring at the Basantpur gauge station of the Mahanadi river basin (Figs. 11c,d). For this, we considered the observed initial condition obtained from the IMD precipitation and ran the daily streamflow simulations using the VIC with the precipitation from the satellite products. Once again the run with the observed forcing and initial condition was considered as the reference run. Mean bias in daily streamflow from CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7 was -338 , -711 , 452 , 498 , and $520 \text{ m}^3 \text{ s}^{-1}$, respectively. Similar to the results described above, CMORPH and PERSIANN underestimated observed daily streamflow, while TRMM (3B42RTV7 and 3B42V7) and PERSIANN-CDR overestimated the daily streamflow at the Basantpur gauge stations (Fig. 11c). However, we noticed that uncertainty and bias in daily streamflow during the first 7 days of simulations is far lower than what was obtained with different initial conditions and the observed forcing. These results highlight that accurate antecedent conditions are vital to reduce the bias in daily streamflow monitoring. Moreover, accurate initial conditions with bias-adjusted satellite precipitation may lead to a better streamflow monitoring system than can be effectively used as a flood warning system (Wu et al. 2014). However, we may notice that the source of bias in the initial conditions and precipitation forcing remains the satellite precipitation estimates. Improved bias in the satellite precipitation will result in better initial state and precipitation forcing, which in turn can provide more accurate flood estimates.

5) REAL-TIME STREAMFLOW MONITORING USING THE SATELLITE PRECIPITATION DATA

Since our results showed that TRMM-3B42RTV7 performs better than the other two real-time precipitation products in the majority of the subcontinental river basins (Table 1), we evaluated the utility of TRMM-3B42RTV7 for daily streamflow monitoring at the Basantpur gauge station of the Mahanadi river basin for the monsoon season of 2011 (Fig. 12). We evaluated two combinations: initial conditions from the observed

FIG. 10. Comparison of daily simulated flow at the selected gauge stations over the Mahanadi river basin using the IMD data and the selected precipitation products (CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7) for the year 2010.

TABLE 2. Daily and monthly NSE (correlation coefficient) for streamflow obtained using the satellite precipitation products against the streamflow obtained using the observed data (IMD).

Gauge station	CMORPH	PERSIANN	PERSIANN-CDR	TRMM-3B42RTV7	TRMM-3B42V7
Daily					
Basantpur	0.67 (0.87)	0.60 (0.84)	0.80 (0.90)	0.46 (0.90)	0.76 (0.92)
Kantamal	0.66 (0.87)	0.72 (0.86)	0.69 (0.84)	0.75 (0.88)	0.79 (0.89)
Kesinga	0.54 (0.84)	0.71 (0.84)	0.60 (0.80)	0.74 (0.86)	0.71 (0.85)
Kurubhata	0.48 (0.80)	0.53 (0.74)	0.68 (0.83)	0.67 (0.83)	0.72 (0.86)
Simga	0.58 (0.79)	0.37 (0.77)	0.64 (0.83)	0.10 (0.84)	0.58 (0.86)
Sundargarh	0.58 (0.82)	0.53 (0.77)	0.75 (0.87)	0.68 (0.87)	0.71 (0.89)
Monthly					
Basantpur	0.72 (0.94)	0.75 (0.91)	0.91 (0.96)	0.57 (0.95)	0.85 (0.96)
Kantamal	0.72 (0.94)	0.82 (0.92)	0.82 (0.92)	0.89 (0.96)	0.90 (0.95)
Kesinga	0.59 (0.92)	0.83 (0.92)	0.74 (0.89)	0.87 (0.94)	0.81 (0.91)
Kurubhata	0.54 (0.91)	0.67 (0.82)	0.81 (0.91)	0.81 (0.90)	0.85 (0.93)
Simga	0.66 (0.87)	0.57 (0.87)	0.80 (0.93)	0.23 (0.91)	0.72 (0.93)
Sundargarh	0.65 (0.90)	0.68 (0.85)	0.89 (0.94)	0.82 (0.94)	0.86 (0.96)

data and precipitation forcing from TRMM-3B42RTV7, and both initial condition and precipitation forcing from the TRMM-3B42RTV7 data. The reference run was considered with observed initial conditions and observed forcing (IMD–IMD). The simulations were run for each month of the monsoon season (June–September), and the initial conditions of 2 days prior of the start date of simulations were provided. From the results, we found that daily streamflow simulations with IMD–TRMM-RT and TRMM-RT–TRMM-RT overestimated streamflow in June–August (Figs. 12a–c, e–f). However, for September, IMD–TRMM-RT underestimated the 90th percentile of daily streamflow (Figs. 12d,h), which can be attributed to the random bias in the TRMM-3B42RTV7 datasets. We also noted that simulations with IMD–TRMM-RT and TRMM-RT–TRMM-RT resulted in earlier peaks in daily flow, which can be associated with the wet bias in forcing and initial conditions. A higher bias in the TRMM-RT–TRMM-RT run highlights that the wet bias in both initial conditions and precipitation may result in large errors in daily streamflow and flood estimates. Once again, our results demonstrate that for real-time streamflow monitoring, the bias-adjusted real-time forcing and accurate initial conditions can provide the best estimates of daily streamflow and flood magnitudes.

4. Conclusions

CMORPH and PERSIANN showed negative bias in daily mean precipitation in the majority of the Indian subcontinental river basins. Negative bias in the CMORPH and PERSIANN datasets was particularly high in the west coast and Brahmaputra basin. On the other hand, TRMM-3B42RTV7 overestimated daily mean rainfall for the period of 2000–13 in the majority

of the subcontinental basins, except in the west coast basin. The gauge-adjusted satellite precipitation products (PERSIANN-CDR and TRMM-3B42V7) showed a better performance for daily mean rainfall over the majority of basins. The bias in daily rainfall in the satellite datasets can be due to their spatial and temporal resolutions, storm characteristics of the individual events, and algorithms to merge precipitation data from the different sensors (Zeweldi and Gebremichael 2009; Yong et al. 2015).

A large bias was observed in the frequency of extreme precipitation events (above 90th percentile) in the selected satellite products. CMORPH underestimated frequency of extreme precipitation in the majority of the basins, while PERSIANN showed both under- and overestimations. TRMM-3B42RTV7 showed overestimation in the frequency of the extreme precipitation across the selected river basins, except the west coast and part of the Brahmaputra basin. Despite improvements, the gauge-adjusted products (TRMM-3B42V7 and PERSIANN-CDR) showed a high positive and negative bias, respectively, in extreme precipitation frequency over the subcontinental river basins. Compared to daily mean precipitation, satellite products showed larger biases in frequency of extreme precipitation. Moreover, total precipitation contributed by the extreme events was underestimated by CMORPH, PERSIANN, and PERSIANN-CDR while overestimated by TRMM-3B42RTV7 and TRMM-3B42V7.

TRMM-3B42V7 performed better than its real-time product (3B42RTV7) for daily mean precipitation in all 18 subcontinental basins (Table 1). On the other hand, PERSIANN-CDR showed reduced daily mean bias in precipitation in only 9 out of 18 basins (Table 1). However, for correlation, POD, and frequency of extreme

FIG. 11. (a) Daily streamflow with the IMD forcing and initial conditions from the selected precipitation products, (b) std dev in simulated daily streamflow with the same forcing and different initial conditions, (c) daily streamflow with IMD initial condition but with precipitation from the IMD and selected products (CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7), and (d) std dev in simulated daily streamflow with IMD initial condition and precipitation from the selected products at the Basantpur gauge station over the Mahanadi river basin. Numbers in (a) and (c) indicate daily mean bias ($\text{m}^3 \text{s}^{-1}$) in streamflow against the reference run.

precipitation events, PERSIANN-CDR showed a much better performance than its real-time product (see tables in the supplemental material for details). A detailed analysis of daily precipitation for the Mahanadi river basin showed R^2 of 0.32, 0.27, 0.43, 0.40, and 0.42 against the observed data for CMORPH, PERSIANN, PERSIANN-CDR, TRMM-3B42RTV7, and TRMM-3B42V7, respectively, during the period of 2000–13. The seasonal cycle of the daily mean precipitation for the period of 2000–13 showed that CMORPH has a large bias in both premonsoon and monsoon seasons, while PERSIANN overestimated daily precipitation in the premonsoon season. PERSIANN-CDR and TRMM-3B42V7 provided better estimates of daily precipitation and streamflow (Table 2) over the Mahanadi river basin. Among the real-time satellite products, TRMM-3B42RTV7 provided better estimates of daily streamflow at four out of the six gauge stations over the Mahanadi river basin.

Bias in the satellite precipitation affected the antecedent conditions, which resulted in dry and wet bias in

daily streamflow simulations. Our results indicated that for streamflow monitoring, biases in initial conditions led to a larger uncertainty in flow magnitude than the bias in precipitation forcing with the observed initial conditions. Our results highlighted that accurate initial conditions and forcing are desirable for better streamflow and information on flood magnitudes. For instance, initial conditions obtained using the three real-time precipitation products (CMORPH, PERSIANN, and TRMM-3B42RTV7) resulted in -1600 , -3387 , and $1311 \text{ m}^3 \text{s}^{-1}$ mean bias in daily streamflow at the Basantpur gauge station. On the other hand, with the observed initial state, the mean bias in daily streamflow was significantly reduced. Therefore, for real-time streamflow, more accurate initial conditions can be obtained using the data assimilation or implementing the gauge-corrected satellite precipitation data for hydrologic modeling. Ward et al. (2011) argued that despite the advancement and progress due to satellite precipitation measurement, there are limitations and uncertainty in the application of these products for hydrologic

FIG. 12. (a)–(d) Influence of initial condition and precipitation on streamflow simulation during the monsoon season of 2011; (e)–(h) comparison of 90th percentile of simulated streamflow using IMD initial condition and IMD forcing (IMD–IMD), IMD initial condition and forcing from TRMM-RT (IMD–TRMM-RT), and TRMM-RT initial condition and forcing (TRMM-RT–TRMM-RT) at the Basantpur gauge station in the Mahanadi river basin.

modeling. Our results showed that for daily streamflow and flood monitoring over the Indian subcontinental basins, satellite precipitation data will need to be further corrected, as suggested by Tian et al. (2010). Moreover, results for the Mahanadi river basin showed the relative importance of the initial conditions and precipitation for streamflow simulations and flood monitoring, which provide insights for the other subcontinental basins. However, further analysis is required to evaluate the impacts of uncertainty in precipitation products on flood monitoring over the other basins.

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