Article

Evaluation of Satellite Precipitation Products in Simulating Streamflow in a Humid Tropical Catchment of India Using a Semi-Distributed Hydrological Model

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Received: 30 July 2020; Accepted: 22 August 2020; Published: 26 August 2020

Abstract: Precipitation obtained from rain gauges is an essential input for hydrological modelling. It is often sparse in highly topographically varying terrain, exhibiting a certain amount of uncertainty in hydrological modelling. Hence, satellite rainfall estimates have been used as an alternative or as a supplement to station observations. In this study, an attempt was made to evaluate the Tropical Rainfall Measuring Mission (TRMM) and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), employing a semi-distributed hydrological model, i.e., Soil and Water Assessment Tool (SWAT), for simulating streamflow and validating them against the flows generated by the India Meteorological Department (IMD) rainfall dataset in the Gurupura river catchment of India. Distinct testing scenarios for simulating streamflow were made to check the suitability of these satellite precipitation data. The TRMM was able to better estimate rainfall than CHIRPS after performing categorical and continuous statistical results with respect to IMD rainfall data. While comparing the performance of model simulations, the IMD rainfall-driven streamflow emerged as the best followed by the TRMM, CHIRPS-0.05, and CHIRPS-0.25. The coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), and percent bias (PBIAS) were in the range 0.63 to 0.86, 0.62 to 0.86, and -14.98 to 0.87 , respectively. Further, an attempt was made to examine the spatial distribution of key hydrological signature, i.e., flow duration curve (FDC) in the 30–95 percentile range of non-exceedance probability. It was observed that TRMM underestimated the flow for agricultural water availability corresponding to 30 percent, even though it showed a good performance compared to the other satellite rainfall-driven model outputs.

Keywords: CHIRPS; FDC; hydrological signature; SWAT; TRMM; Western Ghats

1. Introduction

Precipitation is a critical element of the hydrological cycle which is responsible for replenishing freshwater on the planet. It is an essential input for hydrological modelling and also forms the basis of hydrological, agricultural research applications, environment studies, and climate change studies [1,2]. It is seen that areas of high rain gauge density give more reliable precipitation estimates than those of low-density areas [3,4]. However, due to economic constraints and infeasible natural conditions, such as in the Arctic [5] and in the Tibetan Plateau, ground-based observations are usually sparse, especially in several developing countries, where ground-based rainfall observation networks have always been relatively sparse [6–8]. Hence, precipitation data retrieved from satellite sensors act as a

valuable source for several research applications [9,10]. Recently, many satellite rainfall estimates were made available free of cost from different sources with high temporal and spatial resolutions providing global coverage at sub-daily, daily, and monthly time steps [11]. Various rainfall satellite products are available worldwide which could be broadly categorised into satellite only (SM2-RAIN product), satellite-adjusted (PERSIANN CDR, GPCC), reanalysis category (CHIRP, ERA, and MSWEP), and near real-time products (TRMM RT) [12–14]. With the advancement in blending infrared, microwave, and gauge datasets and availability of spatial and global coverages, multi-temporal resolutions have increased the applicability of satellite rainfall datasets over a wide range of applications. However, signal calibration and corrections for beam filling, bright band, and attenuation could be considered as their limitations [15,16]. These satellite data could be validated either by comparing them to station data and ground-based radar estimates or by confirming their predictive ability and effectiveness through a hydrological modelling framework [17].

A comparative analysis of various satellite-derived datasets with gauge datasets is available elsewhere [18–21]. The statistical evaluation displays the inherent data consistency of the satellite precipitation data. In contrast, the hydrological simulation of these data gives insight into the utility of the datasets within the given application. Many investigators addressed the assessment and evaluation of satellite precipitation products' efficiency for statistical and hydrological analysis [13,17,19,22], out of which only a few were conducted over the Indian basins [23,24]. Several investigations [19,25,26] have reported that better statistical analysis for precipitation data has not yielded reliable hydrological analysis. This mandates the testing of all precipitation data using hydrological models for different applications.

Flow duration curve (FDC) performance assessment can help assess the ability of the hydrological model to simulate streamflow [27]. The FDC is perceived as a legitimate descriptor for catchments. The FDC is described by [28] as 'a key runoff variability signature' that could be applied for obtaining the catchment response as daily streamflow magnitude and as a function of the percent of time exceeded [29]. The use of FDC provides more information on the hydrological activity of the modelled basins, as well as their underlying processes [30,31]. The hydrological models have the advantage of simulating continuous runoff but come at the expense of calibrating them with a specific objective function like NSE. Such models are also biased towards high and medium flows and underperform over regression techniques when they come to low flow and dynamic flows [32]. Hence, the present study is focused on characterising the medium and high flows. To the best of the authors' knowledge, spatial representation of these flow duration curves for evaluating the ability of satellite-based precipitation data has not been explored earlier for a poorly gauged catchment. The main objective of this paper is to derive the streamflow from different sets of precipitation data and their spatiotemporal variability. An attempt is made here to examine the spatial distribution of FDC in the range Q5–Q70, i.e., 95–30 percentile range of non-exceedance probability. Since the study catchment experiences high flow from June to November due to the Indian monsoon season (June to September), and low flows over the rest of the year, it is of interest to study streamflow over the range of the 30 to 90 percentile range.

Based on the literature above, there exists a need to examine the effectiveness and reliability of precipitation data for hydrological simulations. Because of the above considerations, the present work is framed with the following objectives: (i) to evaluate the capability of satellite-based precipitation data for simulating the streamflow using a semi-distributed hydrological model (SWAT); (ii) to evaluate the responsiveness of calibrated parameters under different scenarios for simulating the streamflow with gauge-based and satellite precipitation datasets; (iii) to quantify the uncertainty in the parameters for hydrological process simulation; (iv) to represent the key hydrological signatures using the flow simulated from different datasets with optimised parameters for a typical Western Ghat catchment of India. The novelty of this paper lies in utilising the ability of the SWAT model to generate the streamflow for ungauged subcatchments by gauge and satellite precipitation datasets and using them to derive hydrological signatures spatially. The simulation of the flow from different satellite datasets under different calibration scenarios is yet to be explored for the Western Ghat catchments of India. This is the first study to use satellite precipitation products for generating hydrological signatures.

A similar approach using calibration scenarios for developing hydrological signatures in ungauged catchments could be carried out to formulate a hypothesis regarding the effects of sensitive parameters of each dataset to understand the catchment characteristics worldwide. The above investigations would help to identify the most appropriate dataset for hydrological application.

2. Materials and Methods

2.1. Study Area

The Western Ghats (WG) are the mountain ranges along the west coast of India that extend for about 2300 km parallel to the seacoast. They are located at a distance of about 100 to 200 km from the seacoast across the Gujarat, Maharashtra, Karnataka, and Kerala states of India [33]. The Gurupura river is one of the west-flowing rivers originating in the WG of India, at an elevation of 1880 m above mean sea level. The catchment has two river gauging stations at Addoor and Polali, which are maintained by the Central Water Commission, Government of India and the Public Works Department of the Government of Karnataka [34], respectively. For the present investigation, the Addoor gauging station was selected, which drains out an area of about 840 km² (Figure 1). The west coast consists of a coastal plain with agricultural cropland followed by the lateritic plateau dominating the central portion of the river basin and dense forest in the hilly regions of the Western Ghats. The mean annual precipitation over the basin is about 3812 mm, mostly occurring during the southwest monsoon season (June to September). It is characterised by a humid and tropical climate with a temperature range of 20 to 35 °C. It is one of the vital river basins within the WG, which supplies drinking water to the suburban region of Mangalore city and a few industrial units and agricultural activities in the basin.

Figure 1. Location map of the Gurupura river basin.

2.2. Hydrological Model

The Soil and Water Assessment Tool (SWAT) is a physically based semi-distributed model intended to compute and route water, sediments, and contaminants from the individual drainage units (subbasins) to their outlets throughout the river basin [35]. The SWAT model is widely used for simulating biophysical processes, viz., erosion, vegetative growth, water quality, streamflow, and pollutant concentration for quite a long period [36–38]. It segments the river basin into several subbasins leading to Hydrological Response Units (HRUs), defined by various combinations of land use, soil characteristics, topography, and management systems.

The hydrological cycle is determined based on water balance, which is regulated by climate inputs such as daily precipitation and maximum/minimum air temperature. The SWAT simulates the daily, monthly, and annual water fluxes and solutes in river basins using daily input time series. The simulations begin by calculating the amount of water, sediment, and pollutants loading to the main channel from the land of each subbasin; loads are conveyed and routed through the streams and reservoirs within the basin. The Shuttle Radar Topography Mission (SRTM), the Digital Elevation Model (DEM) (Figure 1), the Land use land cover map (LULC) obtained from the supervised classification technique (maximum likelihood algorithm) for the year 2003 (Figure 2), and the soil map were the input to the SWAT model. The spatial/temporal resolution and source of data obtained are listed in Table 1. After providing the land use and soil maps as input, a total of 27 subbasins and 266 Hydrological Response Units (HRU) were generated. The residual climate data such as solar radiation, relative humidity, and wind speed could be supplied or generated by the user-defined weather generator (Table 1).

Figure 2. LULC used for the SWAT model.

Table 1. Data source and description.

Input Data Type	Spatial/Temporal Resolution	Source/Period
SRTM Digital Elevation Model (DEM)	30 m/-	https://earthexplorer.usgs.gov/
Land use map	30 m/-	Landsat imageries (http://earthexplorer.usgs.gov/2003)
Soil map	500 m/-	Food and Agriculture Organization of the United Nation (FAO)/2002
Meteorological data (rainfall and min-max temperature)	0.25°/daily	India Meteorological Department (IMD)/1998–2013
TRMM rainfall data	0.25°/daily	https://disc.gsfc.nasa.gov
CHIRPS rainfall data	0.05° and 0.25°/daily	ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_daily/netcdf/p25
Meteorological data (solar radiation, relative humidity, and wind velocity)	0.25°/daily	https://globalweather.tamu.edu/1998--2013
Observed Hydrological data (streamflow)	Point/Daily	Central Water Commission (https://indiaiwris.gov.in/wris/#/)/2006–2012 at Addoor

2.2.1. Gauge-Based Meteorological Data

Since the study area is poorly gauged, daily precipitation data for the period 1998–2013 were collected from $0.25^\circ \times 0.25^\circ$ grid points from the India Meteorological Department (IMD), Government of India [39]. Similarly, daily maximum and minimum temperature, relative humidity, wind speed, and solar radiation for the same period were obtained from the IMD ($1^\circ \times 1^\circ$) [40] and Climate Forecast System Reanalysis (CFSR, $0.25^\circ \times 0.25^\circ$) for calculating the potential evapotranspiration (PET), which is required for the SWAT model. Even though CFSR data are not up to the mark compared to, for example, ERA, in terms of resolution and near real-time availability, ERA was proved to give poor streamflow simulation for Indian basins in the study by [41]. In addition, studies have proved that CFSR data suit watershed modelling for meeting the challenges of modelling ungauged watersheds and real-time hydrological modelling [42–44]. Hence, in the present study, CFSR data were used for hydrological modelling. The daily discharge data for 2006–2012 at Addoor gauging station were collected from the Central Water Commission (CWC) via the India Water Resources Information System (IWRIS) platform.

2.2.2. TRMM Rainfall Data

The Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) 3B42 version 7 algorithm (the post real-time version) is a gauge-adjusted product, superseding all the previous versions of TRMM launched by the National Aeronautics and Space Administration NASA and the Japanese Aerospace Exploration Agency (JAXA) in order to monitor precipitation in the tropical and subtropical areas of 50°S – 50°N with near-global coverage [45]. Its spatial and temporal resolutions are $0.25^\circ \times 0.25^\circ$ and 3-hourly, respectively, spanning from 1998 to the present. Daily TRMM 3B42 v7 data is obtained by summing 3-hourly precipitation, which is obtained as a combination of microwave, IR and gauge precipitation estimates from multiple independent satellites. The daily rainfall data obtained from <https://disc.gsfc.nasa.gov> for the period 1998–2013 were used as input to drive the SWAT model.

2.2.3. CHIRPS Rainfall Data

The CHIRPS rainfall dataset, Climate Hazards Group InfraRed Precipitation with Station data version 2 (CHIRPS-2.0), is a 30+ year quasi-global rainfall dataset to analyse precipitation at different scales. The CHIRPS was created in collaboration with scientists at the U.S. Geological Survey (USGS)

and Earth Resources Observation and Science (EROS) Center [11] to deliver reliable, up to date, and more complete datasets for several early warning objectives. Spanning 50° S–50° N (and all longitudes), starting from 1981 to present, CHIRPS incorporates $0.05^\circ \times 0.05^\circ$ and $0.25^\circ \times 0.25^\circ$ resolution satellite imagery with in situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. The CHIRPS is a gridded land-only precipitation dataset developed by the synergistic use of satellite infrared cold cloud duration measurements and ground-based rain gauge observations [11]. The daily rainfall data were extracted from ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_daily/netcdf/p25 for 1998–2013 as an input for the rainfall runoff model. The main difference of climate hazard group climatology from other precipitation climatology is that it uses long period satellite rainfall for deriving climatological surfaces, which improves its performance in mountainous terrain [11].

2.3. Statistical Evaluation for the Satellite Precipitation Data

In the present work, categorical and continuous statistics were executed between the satellite precipitation data and the gauge-based products (IMD gridded data) to understand the error characteristics and estimation capabilities of these data. The categorical statistics included Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index/Threat score (CSI/TS) metrics, whereas continuous statistical indices included Correlation Coefficient (r), Root Mean Square Error (RMSE), and Percentage Bias (PBIAS). The categorical statistics are the number of rainfall events detected or missed by the satellite rainfall data with respect to gauge data. The continuous statistics signify efficiency of satellite datasets in estimating the amount of precipitation. The POD refers to the ratio of hits (successful detection of rainfall as reference data) to the actual number of rainfall events recorded according to base datasets (sum of hits and misses), whereas FAR represents the ratio of false alarms (satellite precipitation products detecting the rainfall during non-occurrence of precipitation in the base dataset) to the events that are not diagnosed by reference dataset [19,46].

R represents the degree of significance or the synchronicity of precipitation differences between satellite precipitation products and gauge or gridded data. The RMSE measures the precision of data or the average error magnitude between the gauge and satellite data, while PBIAS shows the likelihood of overestimation and underestimation. Lower bias and RMSE and higher R -value reflect higher accuracy of satellite datasets with respect to reference datasets [47,48]. The POD and CSI/TS values close to one, and FAR values close to zero reflect a satellite precipitation dataset's capacity to detect rainfall events.

2.4. Model Calibration, Validation, and Uncertainty Analysis

The first five years (2001–2005) were used as a warm-up period to alleviate the initial conditions in the model. The model was calibrated against the daily runoff during 2006–2009 and validated for the period 2010–2012 for the Gurupura river. The calibration and validation of the model were performed using Sequential Uncertainty Fitting version 2 (SUFI2) [49] in the SWAT Calibration and Uncertainty Program (SWAT-CUP) tool developed for SWAT as an interface. The SUFI2 program parameter uncertainty accounts for all the sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. Initially, the models were calibrated using the initial ranges of parameters listed in Table 2. According to the new parameters suggested by the program [50] and their physical limitations, the ranges of each parameter are modified after each iteration. The sensitivity analysis before calibration helps to reduce the number of parameters and thereby reduce the computational time. Many iterations were carried out to obtain an optimised parameter value. In each step, previous parameter ranges were updated to a new set of value-based sensitivity matrix calculations. The parameters were then updated in such a way that the new ranges were always smaller than the previous ranges and were centred around the best simulation as per [50]. SUFI-2 methodology can be found elsewhere [51,52].

Table 2. The optimised value of each sensitive parameter for the four scenarios (“v_” and “r_” stand for replacement and a relative change to the initial parameter values, respectively).

Parameter	Description	Lower Limit	Upper Limit	Optimal Value				Process
				S1	S2	S3	S4	
r_CN2	Initial SCS CN II Value	−0.20	0.20	−0.08(2)	0.18(7)	−0.18(1)	−0.12(4)	Runoff
v_GW_DELAY	Groundwater delay (days)	10	350	22.09(9)	309.25(8)	9.56(4)	14.61(3)	Groundwater
v_CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)	0	500	291.50(7)	483.44(5)	422.13(8)	487.19(9)	Channel
v_Alpha_Bnk	Baseflow alpha factor for bank storage [days]	0.5	1	0.79(1)	0.70(6)	0.54(9)	0.89(8)	Channel
r_SOL_AWC	Available water capacity of the soil layer	0	1	0.31(3)	0.79(2)	0.24(2)	0.73(2)	Soil
v_ALPHA_BF	Base flow alpha factor (day)	0	1	0.89(6)	0.42(9)	0.43(7)	0.86(5)	Groundwater
v_GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	5000	4100.8(8)	1391.14(4)	1706.12(6)	3742.63(7)	Groundwater
v_ESCO	Soil evaporation compensation factors	0	1	0.88(4)	0.45(3)	0.41(5)	0.36(6)	Evaporation
v_GW_REVAP	Groundwater “revap” coefficient	0.02	0.2	0.17(5)	0.02(1)	0.11(3)	0.19(1)	Groundwater

Note: Numbers in the parenthesis represent the rank of sensitive parameters.

2.5. Performance Indices for Streamflow Simulation

The ability of a hydrological model to reproduce observed streamflow could be expressed through various output measurement indices. A variety of performance indices usually evaluate the streamflow simulations. These evaluations include statistical performance measurements, e.g., Pearson's correlation coefficient; weighted R^2 ; hydrological performance measurements (e.g., Nash and Sutcliffe Efficiency (NSE)). The performance evaluation of hydrological models is commonly made by comparing the simulated and observed values. The statistical coefficients used for assessing the model performance were the percent bias (PBIAS), coefficient of determination (R^2), and the Nash–Sutcliffe efficiency (NSE). The criteria suggested by [53] were used for evaluating the model performance. The statistical indices were determined as follows:

The percent bias (PBIAS) measures the tendency of the simulation compared to the observed streamflow [33]. The optimal value of the percent bias is zero. A negative value indicates that the model is overestimating, and a positive value indicates that the model is underestimating [54].

$$PBIAS = 100 \times \frac{\sum_{i=1}^n (O_i - P_i)}{\sum_{i=1}^n (O_i)} \quad (1)$$

where O is the observed value, P is the predicted value, n is the number of samples, and $\bar{O}$ and $\bar{P}$ denote the average observed and predicted values, respectively.

The coefficient of determination (R^2) is the proportion of the variation which can be explained by fitting a regression line. It is a crucial output of regression analysis. The coefficient of determination is a number that shows how well the data fit a statistical model. R^2 is the squared value of the correlation coefficient (r). Its value ranges from 0 to 1, higher values indicating lesser error variance.

$$R^2 = \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \quad (2)$$

The Nash–Sutcliffe Efficiency (NSE) is a statistical criteria used to assess the predictive power of hydrological models. It is a normalised statistic that determines the relative magnitude of the residual variance compared to the measured data variance [54].

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (3)$$

2.6. Hydrological Signatures

The FDCs are the tools used for hydrological behaviour interpretation [55]. The FDCs are used to systematically explain the frequency of high flows and low flows in the stream, and to determine the probability of exceedance during the study duration. This provides both analytical and graphical information to understand flow variability in the past and future. The SWAT model was run for all four precipitation datasets, viz., IMD, TRMM, CHIRPS-0.25, and CHIRPS-0.05. Exceedance flow analysis, performed by fitting an empirical equation [56] to the simulated flows at 5%, 10%, 25%, 50%, and 70%, is identified. Q5 is the flow that exceeds 5% of the period of analysis, and Q10 is the flow that exceeds 10% of the period of analysis, and so on. The flows corresponding to 5% and 10% are indicative of the extreme flood events, 50% dependability indicates the median flow, 70% dependable flow corresponds to the water availability for agriculture, and higher dependable flows correspond the water availability for domestic requirements [57]. Since the study catchment experiences very high flow during the monsoon season and negligible flows over the rest of the year, spatial variations of above 30 percentile flow for the catchment are attempted. The simulated outflows obtained from the SWAT model were further analysed to identify spatial heterogeneity at the subbasin scale for the events and availability of

water in the basin. The flow duration curve (FDC), a significant variability signature, is the relationship between the discharge and the percentage of time that the discharge is equalled or exceeded [28].

For simulating streamflow using the SWAT model, four calibration scenarios were considered using gauge and satellite precipitation datasets.

Scenario 1 (S1): (a) the daily IMD rainfall data were first used to drive the model and optimise the parameter values, (b) the daily TRMM, CHIRPS-0.25, and CHIRPS-0.05 rainfall data were subsequently used to run the model with the same optimised parameter values, and (c) the simulated runoffs for the three model runs were compared with IMD rainfall-driven results.

Scenario 2 (S2): the daily TRMM rainfall was used to drive the SWAT model and optimise the parameter values, and then, the IMD, CHIRPS-0.25, and CHIRPS-0.05 rainfall were taken to drive the model.

Scenario 3 (S3): CHIRPS-0.25 rainfall data were used to obtain the parameters, and the IMD, TRMM, and CHIRPS-0.05 rainfall data were used to drive the model.

Scenario 4 (S4): CHIRPS-0.05 was used to run the model and obtained the optimal parameter value, and the other three rainfall datasets viz. IMD, TRMM, and CHIRPS-0.25 were utilised to run the model for comparison.

3. Results and Discussion

3.1. Spatial Distribution of Rainfall Data

Figure 3 represents the isohyetal maps for IMD, TRMM, CHIRPS-0.25, and CHIRPS-0.05 and time series of daily rainfall data. The spatial distribution of annual average rainfall portrays interesting characteristics of rainfall intensity in the windward side of the Western Ghats.

Figure 3. Spatial distribution and time series plot of (a) IMD (b) TRMM (c) CHIRPS-0.25 (d) CHIRPS-0.05 rainfall datasets.

The catchment adjoining the Arabian Sea receives the highest annual rainfall (3700–3920 mm). The midland of the catchment receives an annual average rainfall of 3400–3700 mm. This portion of the catchment is characterised by agricultural and plantations. The upstream portion of the Gurupura basin is dominated by the Western Ghats forest, having higher elevation that receives annual average rainfall ranging from 3200 to 3400 mm. From Figure 3, it can be interpreted that all four datasets exhibit a similar pattern of annual average rainfall over the catchment, with the highest amount of rainfall at downstream followed by midland and minimum rainfall near the Ghats (Mountain Ranges), whereas the TRMM projected less rainfall at high altitudes compared with others. This is because TRMM uses passive microwave sensors of different wavelengths. Since these passive sensors are not capable of detecting the orographic change in the liquid phase over the complex terrain [58], the flow of the catchment in the mountainous area is underestimated. It could be observed that the maximum annual average rainfall does not occur at the high altitude of the Western Ghats, which may be due to the nonlinear temperature dependence of the saturation pressure. Similar findings were observed by [33], which indicated that the peak rainfall in the Western Ghats is 50 km away on the windward side from the crest. From the time series plot of daily rainfall (Figure 3), it can be observed that CHIRPS-0.25 and CHIRPS-0.05 precipitation products detect a higher amount of rainfall during the monsoon season when compared with TRMM precipitation data. TRMM can capture high flow during the monsoon season, whereas the CHIRPS precipitation product was able to detect high flows for the rest of the year with respect to IMD precipitation data.

3.2. Categorical and Continuous Statistical Metrics

In the current study, three categorical statistical metrics (POD, FAR, and CSI/TS) were used to understand the capability of satellite precipitation products to detect rainfall events (Table 3). The TRMM exhibited a higher POD value (0.74) than CHIRPS-0.25 (0.71) and CHIRPS-0.05 (0.58). The TRMM also exhibited a lower FAR value of 0.11 than CHIRPS-0.25 and CHIRPS-0.05 (0.18 and 0.16, respectively). The FAR value near to zero represents the capability of a satellite rainfall product to detect rainfall events accurately. The critical success index, which measures the satellite precipitation products event that was correctly predicted, should have values closer to 1. CHIRPS-0.25 exhibited an excellent value for CSI, which has better rainfall detection capabilities than TRMM.

Table 3. Categorical and continuous statistical values of precipitation datasets.

	TRMM	CHIRPS 0.25	CHIRPS 0.05
POD	0.74	0.71	0.58
FAR	0.11	0.18	0.16
CSI/TS	0.67	0.85	0.52
CC	0.56	0.47	0.47
Bias	0.91	1.02	1.02
RMSE	19.44	22.78	23.74

Continuous statistics such as correlation coefficient (CC), bias, and root mean square error (RMSE) were obtained for the satellite datasets with respect to IMD data. The correlation between TRMM and IMD data was better than the correlation between CHIRPS and IMD data. Among the satellite data, TRMM exhibited lower bias with IMD data, and a similar pattern was observed in the case of RMSE also. From the overall statistical analysis of rainfall, TRMM produced better results than CHIRPS-0.25 followed by CHIRPS 0.05.

3.3. Evaluation of Streamflow Generation

As a large number of parameters are available, sensitive parameters are identified based on the previous literature [59] and are used for calibration and validation of streamflow. The calibration of the SWAT model was carried out by comparing the observed and simulated streamflow on a daily

scale at the outlet of the basin, i.e., Addoor. Around 14 parameters with varying ranges were used for a different set of iterations required for different input product calibrations. The various parameters used in the present study are CN2 (Initial SCS CN II Value), GW_Delay (Groundwater delay (days)), CH_K2 (Effective hydraulic conductivity in main channel alluvium (mm/h)), ALPHA_BNK (Baseflow alpha factor for bank storage (days)), SOL_AWC (Available water capacity of the soil layer), Alpha_BF (Base flow alpha-factor (day)), GWQMN (Threshold depth of water in the shallow aquifer required for return flow to occur (mm)), ESCO (Soil evaporation compensation factors), GW_REVAP (Groundwater “revap” coefficient), CH_N2 (Manning ‘n’ coefficient for the main channel), SOL_K (Saturated hydraulic conductivity of soil), REVAPMN (Depth of water required for revap to occur in the shallow aquifer), SLSUBBSN (Average slope length), and SLSOIL (Slope length for lateral subsurface flow). Out of the above parameters, a global sensitivity analysis was performed using the SUFI-2 algorithm of SWAT-CUP and the nine most sensitive parameters were selected for simulating the flow using the model. The allowable ranges and fitted values for each dataset are represented in Table 2.

The daily simulation of streamflow using the four datasets is represented in Figure 4. It is noticed that the IMD gridded data, which were derived from the observed gauged data, are the best at simulating the observed flow compared with other datasets. At the daily time scale, the TRMM underestimates the low flow, whereas it tries to match with the peak flow. This may be mainly because of orographic precipitation during the monsoon season resulting due to the Western Ghats mountainous region in the study area. The orographic lifting of moist air leads to cloud formation, and even when the cloud top is relatively warm, rainfall will occur. The deep convection of this cloud system is due to latent heat release. The infrared satellite sensors may not detect precipitation from warm clouds and may lose the capture of ice loft, thereby detecting only a portion of rain from deep convection [6,11,34,60]. This process may be the reason for the lower performance of the satellite data-driven model than the IMD data-driven model. Even though the spatial resolution of both CHIRPS datasets (0.25° and 0.05°) is different, it was found that the finer resolution does not make much improvement in the flow simulation.

Figure 4. Daily simulation of streamflow for different precipitation datasets.

3.4. Hydrological Process Simulation

For the assessment of runoff predictions obtained from the IMD and satellite rainfall datasets, a specific analysis was performed, applying the SWAT model with inputs from both datasets over the Gurupura catchment. The SWAT model includes the parameters which need calibration for reasonable simulation of the flow. Nonetheless, due to the correlation between model parameters and the observed data, calibrated values were swayed [19]. The objective function for testing the hydrological processes for four scenarios is the NSE. Each scenario is explained below to eliminate the calibration effects of different datasets that are important [19] but not adequately discussed in the relevant literature:

Scenario 1 (S1) was used to check the capacity of IMD gridded data and to assess the other datasets in the simulation process. In the first phase of S1, the daily IMD rainfall data were used to calibrate the model and to obtain the optimised value for each sensitive parameter. In the second phase of S1,

the daily TRMM, CHIRPS 0.25, and CHIRPS 0.05 rainfall data were used to drive the model with the same optimised parameter values as phase S1. The rationale behind implementing this second phase was to understand the effect of satellite precipitation products on the variations in streamflow simulations under a set of standard calibration sensitive parameters [47]. The last phase of S1 was to compare the simulated runoff of satellite datasets with the IMD rainfall-driven results.

In Scenarios 2, 3, and 4 (S2, S3, S4), the daily TRMM, CHIRPS 0.25, and CHIRPS 0.05 rainfall were used to drive the SWAT model and optimise the parameter values, respectively. The corresponding phases used in the case of S1 were performed. The rationale behind this scenario was that (i) calibrating the model with different satellite precipitation products collected from various sources reveals the impact of the rainfall data source on calibration performance and discharge simulations and (ii) understanding the hydrological usability of these data products, which especially helps in data-scarce and ungauged regions.

Based on the SUFI-2 algorithm of SWAT-CUP, sensitivity analysis was performed before calibration for identifying the most sensitive parameters (Table 2). In general, in subtropical and tropical regions, the SUFI-2 approach is a promising technique in calibration and uncertainty analysis [61] and was adopted for the present study. It may be noted that each parameter exhibited different optimised values for different scenarios. The curve number, which was the most sensitive parameter among all, showed different optimised values for all the datasets. The values of CN2 for S1, S2, S3, and S4 were -0.08 , 0.18 , -0.18 , and -0.12 , respectively. These values corresponded to the relative values of the parameter in the SWAT model.

The shallow aquifer transit parameter GW_DELAY [62] showed a higher value of 309.25 days for TRMM rainfall, whereas IMD and CHIRPS datasets had lower values. As the value was higher, the lag between the entry of water to the shallow aquifer to release increased. Other groundwater parameters, such as ALPHA_BF, which is a direct index for altering the recharge of groundwater response, GWQMN—the measure of capillary rise, and GW_REVAP—the indicator of water removed from the aquifer, corresponded to different optimised values for meeting up with the observed streamflow.

It could be observed that the pairs of IMD and CHIRPS-0.05 and TRMM and CHIRPS-0.25 datasets represented an optimised value closer to each other for groundwater parameters. It may be presumed that the spatial resolution in the CHIRPS datasets and their optimised parameter values were significantly different, which showed a variation in resolution and parameter value.

The parameter ESCO is directly related to the evapotranspiration process [62]. As the value of ESCO decreases, it makes the lower layer to compensate for the water deficit in the upper layer such that the soil evapotranspiration increases. The satellite-based rainfall datasets depicted an opposite trend to IMD, with a lower value of ESCO corresponding to higher soil evapotranspiration. Similar patterns were expressed by the channel parameter CH_K2, which was used for estimating the peak runoff. The sensitive parameter values of SOL_AWC, which influenced the streamflow and base flow with a range of 0–1, are given in Table 2. As the value increased, the ability of soil to hold water also increased, which led to decreased streamflow.

The details of model performance under all the four scenarios are presented in Table 4. In Scenario 1, the model using IMD rainfall generated a strong overall fit for hydrological processes. The NSE, PBIAS, and R^2 for the Gurupura river using IMD data were 0.86, 0.87, 0.86 during calibration and 0.76, -13.5 , 0.81 for the validation period, respectively. This exhibited an excellent performance rating as per [53], indicating that IMD rainfall data led to a robust and reliable testing model for applicability and precision that could be used for validating and comparing the results obtained from TRMM and CHIRPS rainfall (phase one in S1). Nevertheless, the subsequent performances using TRMM and CHIRPS data exhibited relatively lower agreements (see phase two above).

Table 4. Statistical indexes for Gurupura streamflow using different rainfall data.

Scenario	Period of the Model Run	IMD Rainfall Based Model			TRMM Rainfall Based Model			CHIRPS-0.25 Rainfall Based Model			CHIRPS 0.05 Rainfall Based Model		
		NSE	PBIAS	R ²	NSE	PBIAS	R ²	NSE	PBIAS	R ²	NSE	PBIAS	R ²
1	Calibration	0.86	0.87	0.86	0.66	−21.69	0.74	0.61	−7.21	0.61	0.65	−2.32	0.66
	Validation	0.76	−13.50	0.81	0.70	−12.92	0.73	0.57	−7.03	0.57	0.63	0.44	0.64
2	Calibration	0.75	10.71	0.77	0.71	−14.98	0.75	0.55	4.90	0.56	0.54	−1.85	0.58
	Validation	0.72	−5.52	0.73	0.71	−8.18	0.72	0.55	3.98	0.56	0.55	2.40	0.59
3	Calibration	0.73	2.08	0.73	0.63	−27.25	0.74	0.64	−6.20	0.65	0.63	−0.70	0.64
	Validation	0.67	−13.19	0.70	0.67	−19.22	0.73	0.62	−7.41	0.63	0.61	1.66	0.62
4	Calibration	0.75	−0.91	0.75	0.60	−30.8	0.74	0.67	−9.67	0.65	0.66	−13.76	0.69
	Validation	0.70	−16.09	0.65	0.66	−22.60	0.75	0.62	−10.71	0.65	0.65	−11.01	0.67

Note: Values in bold represent the statistical index values obtained when those particular sets of precipitation data were used for calibrating the model.

The NSE, R^2 , and PBIAS were in the range 0.57 to 0.7, 0.57 to 0.74, and -21.69 to 0.44 , respectively, which are in the range of satisfactory and good performance rating as per [53]. The TRMM results showed better agreement compared to CHIRPS-0.05 spatial resolution, which was better than the coarser-resolution product of CHIRPS with 0.25 spatial resolutions.

For scenario 2, the model performance using TRMM also produced a good score, with NSE, PBIAS, and R^2 of 0.71, -14.98 , 0.75 and 0.71, -8.18 , 0.72 during calibration and validation, respectively. The performance of IMD data with the TRMM optimised parameter showed a higher value than the parent model (TRMM model), which is interesting. The CHIRPS data under S2 were also in the acceptable range. In the case of S3 and S4, it was found that, as spatial resolution increased, the performance of the model improved. This indicates that the resolution of datasets also has a vital role in model performance and hydrological processes.

It showed higher performance for the IMD gridded data, irrespective of the parameters of the models which were used for calibrating. While comparing the performance of the model simulations, the IMD rainfall with driven streamflow emerged as the best followed by the TRMM, CHIRPS 0.05, and CHIRPS 0.25. Since the TRMM and CHIRPS rainfall-driven model results were in the acceptable range, they could be utilised for similar catchments for analysing hydrological responses, since these datasets are available free of cost with different spatial and temporal resolutions. This result and the performance of satellite precipitation products are particularly desirable for data-scarce and ungauged river basins. Since the performance of the satellite precipitation data-driven model reduced while using the calibrated parameters of the other datasets, it may be suggested that each dataset should be calibrated and validated separately. Such findings are consistent with the findings of [21,47,63].

It is noteworthy that the parameters of a dataset that provided better results during calibration of the model served similar or higher performance for the other datasets by transferring the same parameters in the model. For example, the IMD rainfall-driven model outperformed both TRMM and CHIRPS models which were forced with calibrated parameters using TRMM and CHIRPS. When TRMM data was used to simulate using the calibrated parameters of the CHIRPS-0.05 model, it yielded better or higher results than when forced with CHIRPS-0.05 parameters. It is, therefore, inferred from these results that the parameters from a dataset that proves efficient when calibrated could be transferred to calibrate the model with other datasets. Nonetheless, it is recommended to apply satellite precipitation product-specific sensitive parameters for calibration, because this often leads to substantially improved hydrological simulations compared to a model calibrated with other sensitive parameters of the satellite dataset or gage dataset [47,64].

3.5. Uncertainty of Model Parameters

The hydrological models reproduced streamflow by adjusting relevant model parameters and converged to different optimal intervals of calibrated parameters [17]. The distribution of the range of the most sensitive parameters for the four rainfall datasets is illustrated in Figure 5. Typically, the most sensitive parameter in the streamflow simulation was curve number CN2 [46]. A different set of rainfall data produced different ranges of parameter values. Among these, the most apparent difference was seen in the TRMM range of values. A wide range of values was obtained using TRMM for each iteration, whereas IMD fell within a very short range. Groundwater parameters such as GW-DELAY, GW-REVP, GWQMN, and ALPHA-BF also portrayed different ranges of values for different datasets. However, it was not possible to find a typical range of values since the models tried to merge with the observed value. The channel parameters, such as CH-K2 and ALPHA-BNK, also exhibited different patterns. In brief, it could be inferred that no consistent pattern exists to correlate the parameter ranges and their uncertainty for the precipitation products used in this study. Additionally, it is not possible to determine which dataset will have higher uncertainty for the parameters. A similar approach of study and results were analysed by [17], and the variability in the estimated parameter was basin-specific.

To generate an accurate and reliable output, SWAT-CUP will adjust volumes of different hydrological components during calibration. Hence, it is essential to select a proper hydrological

model for finding the effectiveness of a particular dataset. Even though all input datasets produced reasonable outputs, the distribution of a single parameter for streamflow differed apparently.

The value of ESCO was very high for the IMD data, which resulted in low soil evapotranspiration when compared with other data estimates. Similarly, the value for SOL_AWC was very low for IMD, which meant that the soil would have less capacity to hold water, increasing the streamflow. These will subsequently affect different management practices such as groundwater and surface water management, conjunctive use of water, etc. Consequently, these uncertainties may be a cause of concern in the right decision-making process for water management practices [65].

Figure 5. Distribution of the sensitive parameter values using four rainfall datasets.

3.6. Distribution of Hydrological Signature over the Catchment

Figure 6 depicts the FDCs for all rainfall-driven models at the outlet of the Gurupura catchment. It is observed that CHIRPS-0.05 follows the same pattern as that of the IMD. The minimum flow required for water supply and irrigation projects corresponds to Q90. The TRMM portrays a shifted pattern for high flows when compared with other datasets, whereas it overlaps with other flow quantiles as it moves towards the low flow.

To perform a reliable flow analysis, dependable flow exceedances of Q5, Q10, Q25, Q50, and Q70 for the Gurupura catchment have been considered for all rainfall datasets. As the IMD gridded data showed better results for the hydrological process, it could be considered as baseline data for testing the capability of satellite datasets for illustrating the FDC spatially. Since the SWAT model was calibrated for a subbasin over which the gauging station was present, it would likely simulate the flow for all subbasins of the entire catchment. Applicability of the SWAT model to generate streamflow for ungauged subcatchments was adopted here for deriving the hydrological signatures spatially. Figure 7 illustrates the spatial variation of the dependable flow for the Gurupura catchment. High flows depicting the extreme flood events are represented by Q5, Q10, and Q25 dependable flow. The satellite datasets were capable of capturing these high flows for the catchment area. The TRMM and CHIRPS indicated extreme events similar to the baseline established by the IMD data, which

indicates that these satellite data are useful for extreme event analysis. It is interesting to note that the ability of TRMM data ceased for low flows when compared with CHIRPS data. Even though the model performance of TRMM data superseded CHIRPS data, it failed to perform spatial dependable flow analysis. Studies have reported that better statistical analysis for the precipitation data has not yielded reliable hydrological analysis [19,25,26].

Figure 6. Daily flow duration curve for the Gurpura river at the Addoor station.

The IMD and CHIRPS-0.25 data depicted the same kind of median flow (Q50) distribution, whereas TRMM underestimated it at the mountainous region of the catchment. For estimating agricultural water availability corresponding to Q70, CHIRPS-0.25 data were good since they exactly corresponded to the IMD flow. The TRMM underestimated Q70 for more than half of the catchment, indicating its weakness for producing this flow. It is to be noted that one cannot judge a dataset as the best merely by just finding the performance indices. Further analysis has to be carried out for finding the capability of data and its uses based on its application of the study [19,26]. For simulating high flows, TRMM and CHIRPS may be used, whereas the TRMM is not suitable for low flow studies. It also may be noted that the increased resolution of CHIRPS data did not improve the spatial representation of flow quantile.

Connecting land use (Figure 2) and distribution of dependable flow, it was found that the TRMM data underestimated the flow for the forested region of the catchment and at the places of high altitude. This is because TRMM uses passive microwave sensors with multiple wavelengths. As these passive sensors are not able to detect the orographic enhancement in the liquid phase over the complex terrain [58], it underestimated flow at the mountainous region of the catchment. This confirms the results reported earlier [66]. Since the catchment is dominated by agricultural land use, the utmost care has to be taken while choosing the type of dataset for simulating Q70, which corresponds to agricultural water availability. The majority of catchments in the coastal region of the Western Ghats is agriculturally dominated. Hence, for analysing water availability for agricultural purposes, it is recommended to choose IMD and CHIRPS-0.25 rainfall data over these regions. This methodology could be applied for similar catchments elsewhere along the west coast of India. In addition, TRMM overestimated the flow at the subbasin scale, which predominantly represents the urban area. The land use land cover also affects satellite-based rainfall data for producing the hydrological signature. Hence, the estimation of dependable flow and LULC will give a significant linkage for the selection of satellite-based precipitation models. It is important to note that one should be concerned not only with satellite-based precipitation but also with the selection of the hydrological model [67].

Even if satellite-based precipitation is not capable of estimating the accurate amount of rainfall, it could simulate accurate streamflow due to better calibration. Conversely, the precipitation dataset which represents accurate rainfall may fail to generate proper streamflow due to poor selection of the hydrological model. The results of this study, thus, would be helpful for users in the selection of appropriate precipitation datasets based on their requirements.

Figure 7. Spatial distribution of the dependable flow of (a) IMD-Q5, (b) TRMM-Q5, (c) CHIRPS 0.25-Q5, (d) CHIRPS 0.05-Q5, (e) IMD-Q10, (f) TRMM-Q10, (g) CHIRPS 0.25-Q10, (h) CHIRPS 0.05-Q10, (i) IMD-Q25, (j) TRMM-Q25, (k) CHIRPS 0.25-Q25, (l) CHIRPS 0.05-Q25, (m) IMD-Q50, (n) TRMM-Q50, (o) CHIRPS 0.25-Q50, (p) CHIRPS 0.05-Q50, (q) IMD-Q70, (r) TRMM-Q70, (s) CHIRPS 0.25-Q70, (t) CHIRPS 0.05-Q70, rainfall datasets for the Gurupura catchment.

4. Conclusions

The present work investigated the capability of four datasets of rainfall viz., IMD rainfall, TRMM, CHIRPS-0.25, and CHIRPS-0.05 in simulating streamflow under different calibration scenarios in a typical medium-sized catchment (Gurupura river) on the west coast of India. From categorical and continuous statistical results, TRMM was able to detect better rainfall than CHIRPS with respect to IMD rainfall data. All rainfall datasets were forced into the SWAT hydrological model and calibrated separately to obtain the optimised parameters. The performance rating was found to be in the following order as IMD, TRMM, CHIRPS-0.05, and CHIRPS-0.25. As the spatial resolution of the CHIRPS dataset increased, the performance of the model to simulate the streamflow also increased. The performance indicators R^2 , NSE, and PBIAS were in the ranges 0.63 to 0.86, 0.62 to 0.86, and -14.98 to 0.87, respectively, which showed that all datasets were in the acceptable range for streamflow generation.

It could be inferred from the hydrological simulations that calibrated sensitive parameters of the gauge or IMD dataset should not be used to calibrate the model with other satellite precipitation products. Instead, each satellite dataset should be calibrated separately. The parameters of a best-calibrated dataset should be transferred to calibrate other datasets. The optimised parameter values for different rainfall datasets were different, with a varied range of parameter value distribution.

Even though the streamflow is adjusted to match the observed streamflow using the calibrated parameters, other water balance components need to be accurate for adopting efficient water management practices.

The potential of the SWAT model to produce streamflow for ungauged subcatchments was evidenced by deriving the spatial hydrological signatures. The TRMM data underestimate the water availability for agriculture purposes corresponding to Q70 dependable flow, whereas the CHIRPS rainfall data are capable of capturing flow quantiles produced by the IMD gridded data. At the high altitude and forest areas, TRMM underestimates rainfall and overestimates for the urban areas. The CHIRPS-0.25 rainfall produces a similar pattern of flow quantiles of IMD than CHIRPS-0.05, which conveys that the improvement in spatial resolution does not cause any significant improvement in the flow quantiles, the key hydrological signature. Hence, it could be concluded that the uncertainties in the model performance and parameters critically depend on the selection of precipitation datasets. Different sets of data exhibit different results which may be a cause of concern while making appropriate decisions related to water management practices. Hence, it is recommended to choose appropriate rainfall data depending on the application. A similar strategy of calibration scenarios and hydrological signatures in ungauged catchments may be used to interpret the effects of each dataset's sensitive parameters to understand catchment characteristics worldwide. The observations above will help determine the most suitable dataset for hydrological application. In addition, the findings in the study are useful for satellite-based rainfall developers to improve their products and provide for users satellite rainfall-related applications.

Author Contributions: Investigation, T.M.S. and S.D.B.; Conceptualisation, T.M.S. and S.D.B.; Methodology, T.M.S.; Writing—Original Draft, T.M.S.; Writing—Review and Editing, S.D.B., A.M., N.A.-A.; Funding acquisition, N.A.-A.; Supervision, A.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors would like to extend their heartfelt gratitude to the Department of Water Resources and Ocean Engineering of National Institute of Technology for providing valuable research data. We are also thankful to all the institutes, organisations, and developers for providing the precipitation datasets.

Conflicts of Interest: The authors declare no conflict of interest.

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