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Research article

Artificial neural network based PERSIANN data sets in evaluation of hydrologic utility of precipitation estimations in a tropical watershed of Sri Lanka

Miyuru B Gunathilake[1,2], Thamashi Senerath[1] and Upaka Rathnayake[1,*]

[1] Department of Civil Engineering, Faculty of Engineering, Sri Lanka Institute of Information Technology (SLIIT), Malabe, Sri Lanka
[2] Central Engineering Services (Pvt) Limited, Bauddhaloka Mawatha, Colombo 7, Sri Lanka

* **Correspondence:** Email: upaka.r@sliit.lk; Tel: 94719883318.

Abstract: The developments of satellite technologies and remote sensing (RS) have provided a way forward with potential for tremendous progress in estimating precipitation in many regions of the world. These products are especially useful in developing countries and regions, where ground-based rain gauge (RG) networks are either sparse or do not exist. In the present study the hydrologic utility of three satellite-based precipitation products (SbPPs) namely, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), PERSIANN-Cloud Classification System (PERSIANN-CCS) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Dynamic Infrared Rain Rate near real-time (PDIR-NOW) were examined by using them to drive the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) hydrologic model for the Seethawaka watershed, a sub-basin of the Kelani River Basin of Sri Lanka. The hydrologic utility of SbPPs was examined by comparing the outputs of this modelling exercise against observed discharge records at the Deraniyagala streamflow gauging station during two extreme rainfall events from 2016 and 2017. The observed discharges were simulated considerably better by the model when RG data was used to drive it than when these SbPPs. The results demonstrated that PERSIANN family of precipitation products are not capable of producing peak discharges and timing of peaks essential for near-real time flood-forecasting applications in the Seethawaka watershed. The difference in performance is quantified using the Nash-Sutcliffe Efficiency, which was >0.80 for the model when driven by RGs, and <0.08 when driven by the SbPPs. Amongst the SbPPs, PERSIANN performed best. The outcomes of this study will provide useful insights and recommendations for future research expected to be carried out in the Seethawaka watershed using SbPPs. The results of this study calls for the refinement of retrieval algorithms in rainfall estimation techniques of PERSIANN family of rainfall products for the tropical region.

Keywords: discharge; PERSIANN; rainfall; seethawaka watershed

1. Introduction

Precipitation is a key element of the hydrologic cycle [1]. More importantly, precipitation in the Asian region is a key steering factor for many socio-economic activities. Accurate precipitation estimates are indispensable for many professionals, including meteorologists, hydrologists, agriculturists, ecologists, and river basin managers. Generally, precipitation information is derived from ground-based rain gauges (RGs), satellites, meteorological radars and reanalysis products. The RGs are considered the most reliable source of precipitation measurements since they provide ground truths. However, RGs are unable to capture variations in the spatial and temporal characteristics of rainfall [2], when dense rain gauge networks are not present. This is the case for most developing countries [3]. Meteorological radars are not viable for developing countries due to their high installment and maintenance costs. Hence, satellite-based precipitation products (SbPPs) are a valuable means of estimating precipitation in these regions [3,4]. Another major advantage of SbPPs is that they provide rainfall data with high temporal resolution. With the advancement of satellite technology and remote sensing (RS) techniques, SbPPs are now available with spatial and temporal resolutions as small as 0.10^o and 30 minutes, respectively. Some widely used SbPPs are Climate Prediction Center Morphing Method (CMORPH) [5], Precipitation Estimation from Remotely-Sensed Information using Artificial Neural Networks (PERSIANN), Cloud Classification System (PERSIANN-CCS), PERSIANN-Climate Data Record (PERSIANN-CDR) [6], Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) [7], Multi-Source Weighted-Ensemble Precipitation (MWSEP) [8], and Climate Hazards Group InfraRed Precipitation (CHIRPS) [9]. In addition to these global products, SbPPs which only cover certain regions of the globe are also available. These include Rainfall Estimate (RFE) and Tropical Applications of Meteorology using SATellite covering the African continent (TARCAT v2. TAMSAT v.2 and v.3) (TAMSAT) African Climatology Project (APC) v.2 [10] and Combined Scheme Approach (CoSch) [11] covering the South American continents. Since the accuracy of SbPPs depends on location, season, specific product, watershed size, and hydro-climatic region [4,12] prior to their application in water resources, they need to be evaluated by comparing with available RG data through simulating a hydrologic model.

Hydrologists often need to decide which the best satellite rainfall product is for specific applications from the many available. In doing this, they need to consider the level of estimation error in each satellite rainfall product and its implications for the hydrological predictions they are concerned with [13].

Previous studies, including Alazzy et al. [14] and Bui et al. [15] have assessed the hydrologic utility of SbPPs in different regions of the world. Moreover, several researchers including Nashwan et al. [16], Salehie et al. [17] and Zhang et al. [18] have assessed the accuracy of remotely-sensed precipitation products over different regions of the world by comparing them with rain gauge data. In general, the results of these studies demonstrate that the efficiency of the simulation capacity of extreme rainfall events by remotely-sensed precipitation products and global gridded precipitation products are region specific.

Yoshimoto and Amarnath [19] examined the effectiveness of SbPPs over the Mundeni-Aru River Basin in the eastern Province of Sri Lanka in the context of hydrologic modeling and flood inundation. This study assessed the utility of three SbPPs including TRMM, PERSIANN, GSMap through the Rainfall-Runoff Inundation (RRI) Model. Although the hydrologic performances of these analyzed SbPPs were comparable, the GSMap outperformed others. Noteworthy, all SbPPs under-estimated observed rainfall volumes. Gunathilake et al. [20] previously examined the hydrologic utility of SbPPs for the Seethawaka River at daily time resolution. The results of this study showed that PERSIANN, PERSIANN-CCS, PERSIANN-CDR under-estimated observed streamflow when used to drive the HEC-HMS hydrologic model. However, to date, these are the only two studies, which focused on assessing the hydrologic utility of SbPPs in Sri Lanka. According to the understanding of the authors' of this paper, the present study is the first study, which assesses the utility of PDIR-NOW for driving hydrologic models. The HEC-HMS hydrological model developed by the United States Army Corps of Engineers has been used extensively in Sri Lanka for different applications including streamflow modeling [21,22], simulation of Low Impact Development Measures [23], prediction of streamflow in ungauged catchments [24], simulating bunds in ancient tanks [25], assessing streamflow alterations [26] etc.

Due to the availability of 1 hour or higher temporal resolution of precipitation data records, only three SbPPs were assessed through running the HEC-HMS hydrologic model for the Seethawaka watershed. Hence, for this study PERSIANN, PERSIANN-CCS, PDIR-NOW were analyzed. The extreme flood event streamflow simulation accuracy of SbPPs was assessed using the hydrologic model for two extreme rainfall events that happened in May 2016 and May 2017 in the Seethawaka Region. The outcomes of this research will shed light on the Seethawaka watershed that will be locally useful to inform future research using SbPPs. They will also provide insights of use for future studies using SbPPS in other parts of Sri Lanka, and regions with similar climatic conditions across the world.

2. Study area and data used

2.1. Seethawaka catchment

The present study was carried out for the Seethawaka watershed (drainage area: 223 km^2), a sub-catchment of the Kelani River Basin (2300 km^2), which is shown in Figure 1. The Seethawaka watershed is located in the Kegalle administrative district of the Sabaragamuwa Region, Sri Lanka. The Seethawaka River lies between latitudes of 6°50' and 7°00' N and longitudes of 80°17' and 80°30' E [27]. The mean temperature is around 27 ℃ throughout the year in this region [28]. The annual rainfall pattern is divided into four major seasons. They are, the 1st inter-monsoon from March to April, the Southwest monsoon from May to September, the 2nd inter-monsoon from October to November and the Northeast monsoon from December to February. Among these seasons the Southwest monsoon gives the highest amount of rainfall [29]. Higher annual rainfalls can be expected in the upper parts of the Seethawaka watershed and can be high as 4000 to 5000 mm [30].

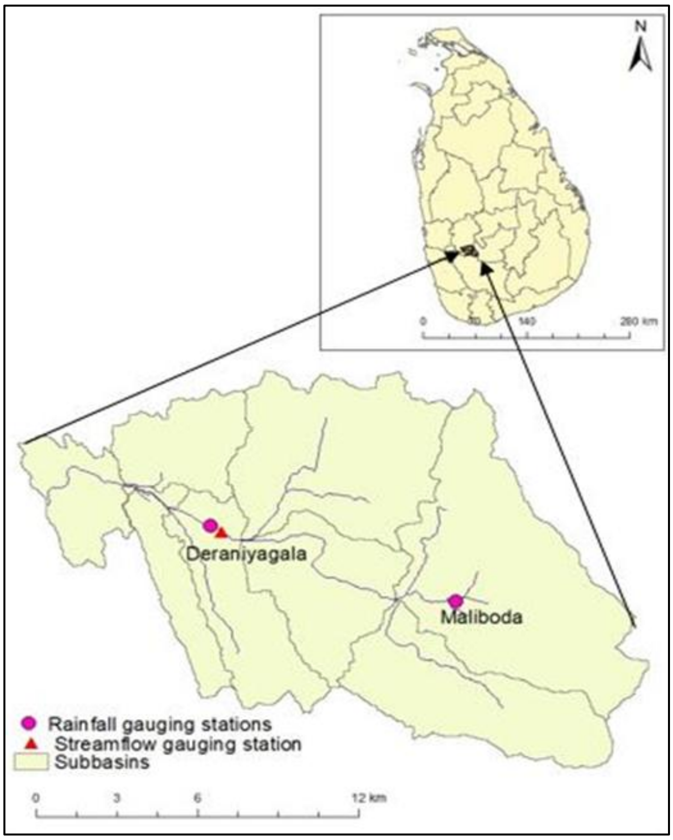
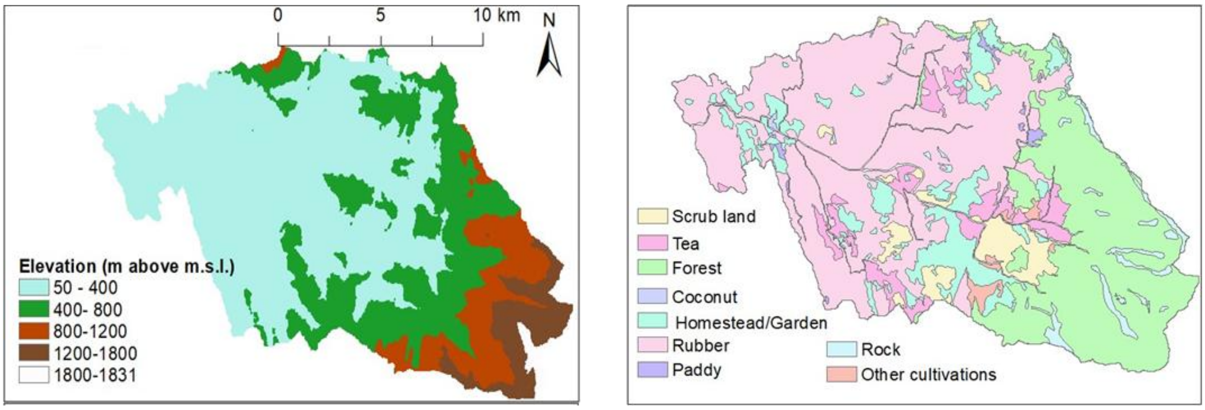


Figure 1. The location of the Seethawaka watershed within Sri Lanka, and the positions of rainfall and streamflow gauging stations within the watershed.



(a) Digital elevation model (b) Land use

Figure 2. Topography and land use of the Seethawaka watershed.

The main land cover types in the Seethawaka watershed are rubber plantations and forests. The upper catchment area is mainly covered by forests with the lower catchment dominated by rubber plantations (refer Figure 2b). The altitude of the Seethawaka watershed ranges from 0 to 1831 m above mean sea level, as shown in the digital elevation model in Figure 2a. The main types of soils found in the study area are clayey soils of moderate infiltration rates [31].

2.2. Ground measured rain gauge data

Only two rainfall gauge stations, Deraniyagala and Maliboda were located inside the Seethawaka watershed. Rain gauge data recorded daily at Maliboda and hourly at Deraniyagala for 14–18 May 2016 (five days) and 25–28 May 2017 (four days) were obtained from the Meteorological Department of Sri Lanka. These periods covered the two extreme rainfall events under consideration. Hourly rainfall data is only available from a few rain gauge stations in Sri Lanka, including Deraniyagala, but not Maliboda. Therefore, the hourly pattern of rainfall at Deraniyagala was combined with the daily rainfall amounts at Maliboda to derive hourly rainfall at Maliboda.

2.3. Satellite-based precipitation products (SbPPs)

The three types of SbPPs used for the analysis in this study are PERSIANN, PERSIANN-CCS, PDIR-NOW. The PERSIANN, PERSIANN-CCS and PDIR-NOW precipitation products are available in hourly, every 3 hours, every 6 hours and daily time resolutions. This PERSIANN family of products have been developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (UCI). These PERSIANN data are available at a spatial resolution of $0.25° \times 0.25°$ (approximately 25 km × 25 km) whereas PERSIANN-CCS and PDIR-NOW are available at $0.04° \times 0.04°$ scale (approximately 4 km × 4 km). The PERSIANN-CCS precipitation records are available from 2003 to present, while the PERSIANN and PDIR-NOW data sets are available from 2000. PERSIANN precipitation rainfall data sets cover regions from 60 N to 60 S. PDIR-NOW has a low time latency compared to PERSIANN-CCS. This has enabled the PDIR-NOW to be used near real time forecasting of floods. Rainfall estimation in PERSIANN is explained in detail at https://chrsdata.eng.uci.edu/.

3. Methodology

Precipitation products were extracted from SbPPs to match the ground measured rainfall data. Therefore, there are four rainfall sets for the catchment: observed rainfall, PERSIANN, PERSIANN-CCS and PDIR-NOW. These rainfall data were separately treated as the inputs of the hydrological model.

The previously developed HEC-HMS hydrologic model by Gunathilake et al. [27] for the Seethawaka watershed was used to assess the hydrologic utility of SbPPs in this study. Hence for precipitation losses, direct runoff, baseflow and routing were calculated using SCS_CN, Clark UH, non-linear Boussinesq, and lag and Muskingum methods, respectively. Thereafter, the HEC-HMS was driven using the meteorological forcing of SbPPs. The four sets of rainfall data were separately fed to the hydrological model to simulate the catchment discharge. The same calibrated parameters for the simulation, which were used under the measured rainfall, were kept for the other 3 PERSIANN family of precipitation data records.

The hydrological model was calibrated for the discharge data in May 2016 and validated for discharge data in May 2017. In addition, the hydrologic model performance was examined by using statistical indicators including Nash-Sutcliffe Efficiency (NSE) and Coefficient of Correlation (R2) for comparing observed and simulated discharge rates as recommended by Moriasi et al. [32]. Mathematical expressions for these two performance evaluators can be seen in Equations 1 and 2.

$$Correlation\,Coefficient\ = \mathrm{R}^2 = \left[\frac{\sum_{i=1}^{n}(O_i - O_{mean}) \times (S_i - S_{mean})}{\sqrt{\sum_{i=1}^{n}(O_i - O_{mean})^2 \times \sum_{i=1}^{n}(S_i - S_{mean})^2}}\right]^2 \tag{1}$$

$$NSE = 1 - \left[\frac{\sum_{i-1}^{N}(o_i - s_i)^2}{\sum_{i-1}^{N}(o - \bar{o})^2}\right] \tag{2}$$

where o_i are the observed streamflows, s_i are the simulated streamflows, $\bar{o}$ and $\bar{s}$ are their means, N is the number of data values. Both R2 and NSE have maximum values of 1, which indicates perfect correlation or efficiency. The closer the value of each is to 1, the better the performance of the hydrological model. For more detailed information on the development of the HEC-HMS hydrologic model the readers are referred to Gunathilake et al. [27].

4. Results and discussion

4.1. Comparison of discharge predicted by different precipitation products

Figure 3 presents the comparison of streamflow discharges obtained from HEC-HMS model against observed streamflows from 14th-18th May 2016 (the calibration period). These streamflows were obtained at the Deraniyagala gauging station.

Figure 3 shows that the accuracy of the rainfall data used to drive the hydrologic simulation clearly impacts its ability to predict streamflow accurately. The HEC HMS model based on measured rainfall predicts the flow peaks and temporal variation of flow to acceptable levels. However, the HEC HMS models based on satellite precipitation products have simulated streamflows, that have little similarity to the measured streamflow at Deraniyagala gauging station.

Figure 4 shows the hydrographs obtained from the HEC-HMS model during the validation period (May 2017) for RGs, PERSIANN, PERSIANN-CCS and PDIR-NOW. Observations in the validation period are similar to those from the calibration period. There is a very good match between the observed streamflows and the streamflow simulated using observed rainfall. The simulated streamflows based on three precipitation products (PERSIANN, PERSIANN-CCS and PDIR-NOW) underestimate the real flows.

Table 1 summarizes the performance indicators for both the calibration and validation periods. The observations from Figures 3 and 4 are supported by the data in Table 1. The *NSE* and R^2 values for both calibration and validation are high (close to 1) for the comparison of simulated streamflow to observed streamflows. However, the *NSE* and R^2 values for other simulated streamflows have much lower values.

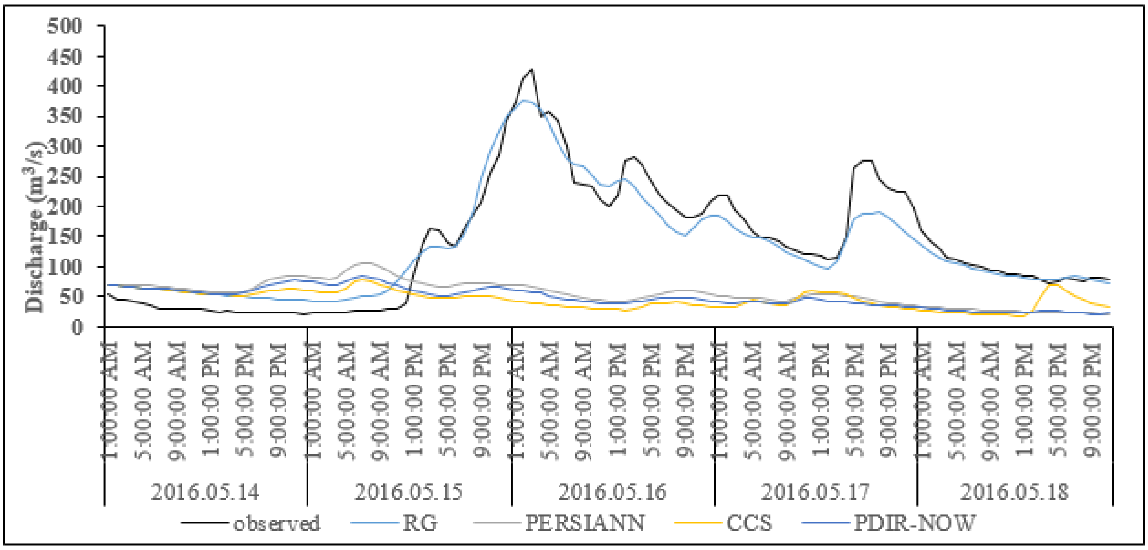


Figure 3. Observed hydrograph at the Deraniyagala gauging station compared to those predicted by the HEC-HMS model driven by different rainfall inputs during the calibration period, 14–18 May 2016.

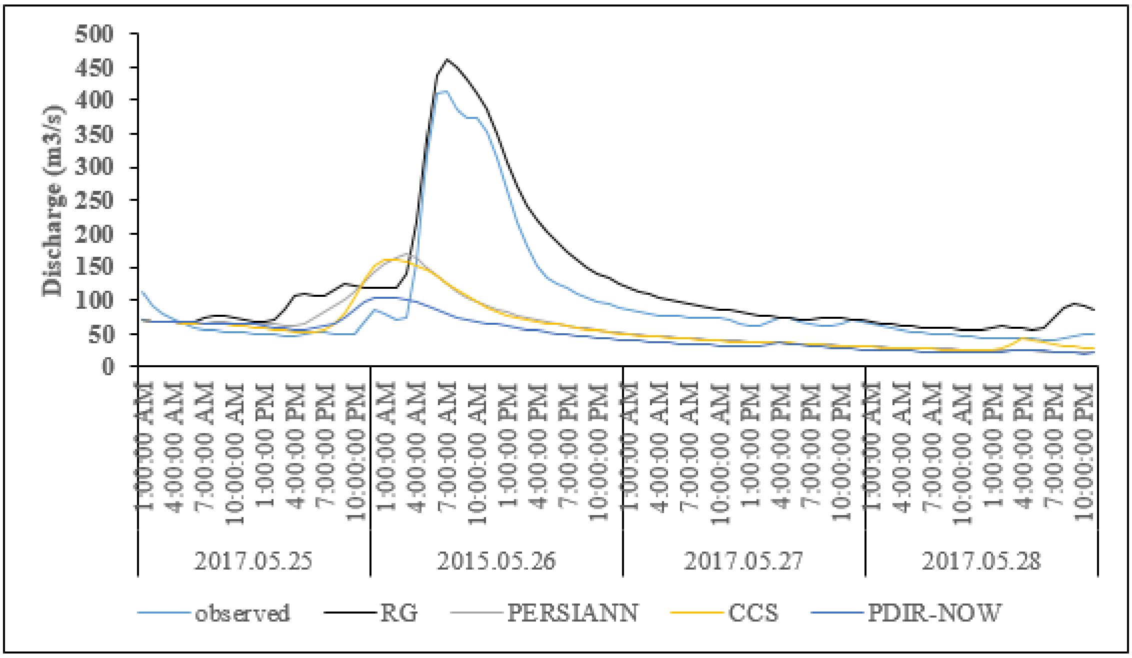
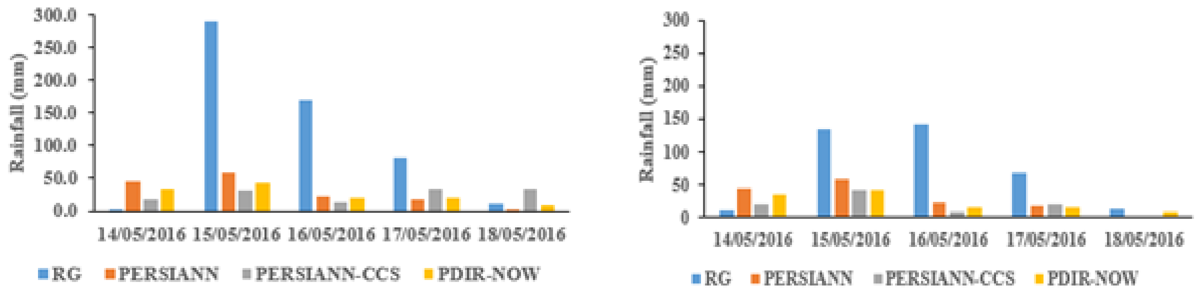


Figure 4. Observed hydrograph at the Deraniyagala gauging station compared to those predicted by the HEC-HMS model driven by different rainfall inputs during the validation period, 25–28 May 2017.

Table 1. Statistical indicators of model performance (Nash-Sutcliffe Efficiency, NSE; Pearson's correlation coefficient, R2) for the calibration and validation periods.

Rainfall product	Calibration		Validation	
	NSE	R^2	NSE	R^2
RG (measured)	0.92	0.93	0.81	0.95
PERSIANN	−0.78	0.04	0.08	0.27
PERSIANN-CCS	−0.98	0.28	0.08	0.30
PDIR-NOW	−0.88	0.06	−0.15	0.08

Therefore, it is evident from visual inspection of hydrographs and the calculated statistical indicators (Table 1), that none of the SbPPs were able to reproduce observed streamflow to a satisfactory level of accuracy. More importantly, none of these SbPPs were able to capture peak flows and timing of peaks, which is essential for near-real time flood forecasting. This deficiency can be mainly attributed to the significant under-estimation of rainfall by the satellite-based products compared to RGs (refer Figures 5 and 6).

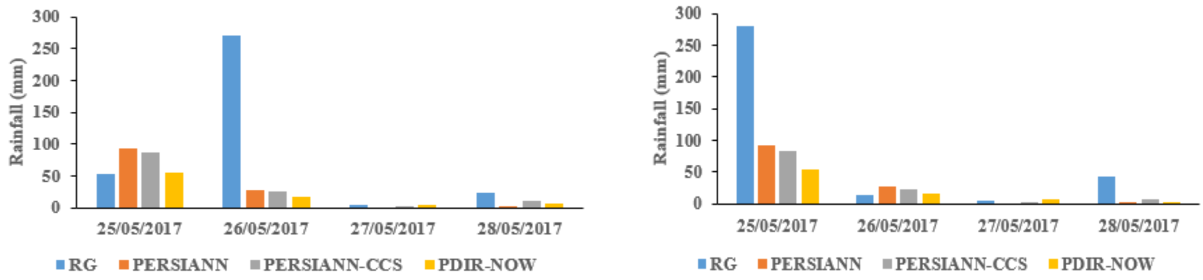


(a) For Deraniyagala

(b) For Maliboda

Figure 5. Comparison of predicted daily rainfall from the satellite-based precipitation products with that measured by RGs for the calibration period.

It can be clearly seen that both Deraniyagala and Maliboda show higher rainfalls on the 15th and 16th May 2016, which the satellite-based products do not reflect. The same pattern can be seen for the validation period in Figure 6. Therefore, satellite-based precipitation products are not good alternatives to RG rainfall measurements for driving hydrological simulations using the HEC-HMS model in this context.



(a) For Deraniyagala (b) For Maliboda

Figure 6. Comparison of predicted daily rainfall from the satellite-based precipitation products with that measured by RGs for the validation period.

Previous studies (e.g. Behrangi et al. [33]) reported that inaccuracy in detecting rainfall is the major issue that requires skill in simulating streamflow using a hydrologic model. However, the hydrologic model performances obtained during the validation period using SbPPs show significant improvements over those for the calibration time period as indicated by their positive NSE values. In a previous study carried out in the Seethawaka watershed by Gunathilake et al. [27], which aimed at assessing the hydrologic utility of the PERSIANN family of precipitation products in the context of continuous simulations, these SbPPs were unable to capture daily streamflow. Hence, the results obtained for event-based hydrologic simulations through this study can be seen as an improvement in comparison. Yoshimoto and Amarnath, [19] demonstrated that PERSIANN under-estimated RG measured rainfall in a study similar to the one presented here. In addition, Gunathilake et al. [34] showed that the HEC-HMS model driven by PERSIANN and PERSIANN-CCS under-estimated streamflow, when compared RGs simulated streamflow in the Upper Nan River Basin of Thailand. Bitew et al. [13] demonstrated that Infrared (IR) based rainfall estimation methods (the algorithm adopted for estimating precipitation in PERSIANN) did not perform well when compared to SbPPs which adopt microwave-based techniques over mountainous regions in Ethiopia. More information on the performance of the PERSIANN family of products over mountainous regions may be found in Hong et al. [36]; Bitew and Gebremichael [35], and Gao and Liu [37] for more information on the performance of PERSIAN family of products over mountainous regions. Nguyen et al. [38] used PERSIANN-CCS to simulate a 2008 flood in Iowa in the USA, which was happened in 2008 in the United States of America. This study demonstrated that PERSIANN-CCS performed better than the radar rainfall data in predicting the hydrograph shape. However, PERSIANN-CCS has been found to over-estimate observed rainfall in the USA [39]. In addition, Sun et al. [40] demonstrated that PERSIANN-CDR also over-estimated observed rainfall in China. In general, it is clear that the PERSIANN family of products under-estimates observed rainfall in tropical region, while it overestimates observed rainfall over the humid climatic conditions.

5. Conclusions

This study examined the hydrologic utility of three SbPPs in the Seethawaka River Basin of Sri Lanka. The same set of calibrated parameters simulated by RGs was used to drive the HEC-HMS model with PERSIANN family precipitation data records. It was clearly seen that the HEC-HMS models simulated using PERSIANN, PERSIANN-CCS and PDIR-NOW were unable to capture the streamflow patterns of the Seethawaka River during the two extreme rainfall events considered. Hence, it is clear that PERSIANN, PERSIANN-CCS and PDIR-NOW are unable to be used in near real time monitoring of flood-forecasting applications of the Seethawaka watershed and, by extension in similar watersheds in tropical regions in general. More importantly, the results of this study clearly manifested that the accuracy of rainfall is a major governing factor in determining the accuracy of streamflow simulations. The results of this study recommend that the algorithm developers refine the retrieval algorithms of the PERSIANN family of precipitation products for tropical regions such as Sri Lanka. Furthermore, the accuracy of these precipitation products can be checked using different hydrological models for the same catchment.

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Conflict of interest

The authors declare no conflict of interest.

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