A COMPARISON OF SIMULATED RUNOFF BASED ON GROUND RAIN GAUGES AND PERSIANN-CDR SATELLITE PRECIPITATION RECORDS USING SWAT MODEL

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ABSTRACT:

Easy access to valid climatic data has always played a fundamental role in progressing hydrological studies. That is why numerous satellite-based precipitation products (SPPs) have been generated in the contemporary era. Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR) is considered one of the most popular climatic databases which started to produce daily rainfall data with $0.25^\circ \times 0.25^\circ$ temporal and spatial resolutions in 1983. The aim of this research is to evaluate how well PERSIANN-CDR has performed in a rainfall-runoff modeling application over the period of 1994 to 2015. In this regard, using Soil & Water Assessment Tool (SWAT), two rainfall-runoff models based on Ground-based Rain Gauge stations (GRGs) and PERSIANN-CDR precipitation records were developed for the Chelgerd sub-basin, which is the main branch of the Zayandeh-Roud Basin in central Iran, in order to analyze how accurate the simulated runoff by PERSIANN-CDR database is. Comparing the developed SWAT model calibration results using the satellite database precipitation (NS = 0.78, P-Factor = 0.52, and R-Factor = 0.41) to calibration results of the developed model based on GRGs (NS = 0.81, P-Factor = 0.54, and R-Factor = 0.42) showed that although PERSIANN-CDR precipitation magnitudes were typically less than GRGs records, accuracy indicators of simulated runoffs to Ghale-Shahrokh were almost the same.

1. INTRODUCTION

The hydrologic cycle depends critically on precipitation. Accurate precipitation data are essential for decision-making and planning for many technical experts, including meteorologists, hydrologists, ecologists, agriculturists, disaster management personnel, and energy planners (Chaudhary et al., 2021; Emami and Zarei, 2021; Kamali and Asghari, 2022). Due to the fact that precipitation is considered a high small-scale variability in place and time, it is one of the most challenging meteorological variables to detect. Ground-based Rain Gauge stations (GRGs) have traditionally been used to access in situ precipitation data (Messmer and Simmonds, 2021). Rain gauge and meteorological radar networks, however, are insufficient to capture the geographical and temporal variability of precipitation systems (Borga et al., 2022). Considering the radar-derived data limitations, such as coverage area restrictions, expensive infrastructures, and inadequate accuracy under complicated atmospheric circumstances, hydrological models perform inadequately (Lammers et al., 2021).

To overcome these challenges, at the moment, more detailed precipitation records at a greater measurement frequency are offered by visible and thermal infrared sensors on geostationary Earth-orbiting satellites, as well as passive microwave sensors on low-Earth-orbiting satellites. Several satellite-based precipitation products with global high-resolution (up to 0.25), such as those derived from the MORPHing technique (CMORPH), Naval Research Laboratory developed blended-satellite precipitation technique (NRL-blend), Integrated Multi-satellite Retrievals for Global Precipitation Measurements (IMERG), Climate Hazards Group Infrared Precipitation with Station data (CHIRPS), Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis (TMPA) products, Global Satellite Mapping of Precipitation (GSMap), Climate Prediction Center (CPC), and Multisource Weighted-Ensemble Precipitation (MSWEP), are now easily accessible in most parts of the world thanks to advancements in these techniques (Xue et al., 2021). Moreover, satellite-based precipitation products (SPPs) have contributed to the detection of rainfall distributions and have been used in conjunction with traditional rain gauges and meteorological radar observations (Moazami and Najafi, 2021).

On the other side of the coin, Rainfall estimation is sensitive to not only low-intensity, rainfall but also systematic biases, and performs poorly over mountainous regions covered by snow (Moges et al., 2022). Reanalysis products can better characterize large-scale weather systems, but their poor spatio-temporal resolution makes it difficult to detect spatial variability. However, these products may be used to observe precipitation in data-scarce areas, filling data gaps, and assisting in the evaluation of water-related challenges. Generally, because of orographic impacts, complex topography regions have more spatial variability in precipitation over short horizontal distances than plain areas, which must be resolved for better water resource planning and management (Baez-Villanueva et al., 2020).

SPPs and GRGs databases have been widely used not only in hydrologic modeling (Guo et al., 2022) but also in a variety of other fields such as flood modeling (Yoshimoto and Amarnath, 2017), drought monitoring (Hatmoko et al., 2016), soil erosion forecasts. As far as hydrological modeling is concerned, water resource management and hydrological research have both benefited from distributed hydrological models (Setegn and Donoso, 2015). The Hydrologic Simulation Program-Fortran (HSPF) (Bicknell et al., 1996), MIKE SHE (Refsgaard, 1995),

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the Hydrologic Modeling System (HEC-HMS) (Chiang et al., 2022), and the Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012) are only a few examples. These models employ SPPs data to decrease reliance on particular precipitation inputs (Sivapalan et al., 2003). The SWAT model has been widely used since various studies have demonstrated that it can accurately estimate stream-flow in areas with limited data (Arnold and Allen, 1999; Saedi et al., 2021). From a selection of 73 hydrological models, the SWAT model was chosen as the most favored (Ougahi and Mahmood, 2022). The SWAT model was selected due to its extensive application capabilities, user-friendliness, and the fact that it is widely pushed and supported in hydrological processes. The SWAT model can simulate stream-flow in areas with insufficient data (Horton et al., 2022). Among many other hydrological models, the SWAT model has been widely used in river basins across the world for hydrological simulations (Abbaspour et al., 2007; Farokhnia et al., 2019; Jalali et al., 2021). The SWAT repository has a number of articles on the use of SWAT for diverse objectives namely, simulating hydrological processes, water management methods, climate change impact studies, land-use change, soil erosion, and pollutant transport (Yeo et al., 2021).

The Zayandeh-Roud Basin, located in a semi-arid region of Iran, is one of the most vital basins. Water availability and supply have been seriously affected across the river basin due to erratic precipitation patterns, unequal distribution of water resources, frequent lengthy droughts, and human causes. Providing rainfall-runoff models for this watershed seems to be challenging due to the fact that historical GRGs data are insufficient and their spatial locations are inappropriate. In this circumstance, hydrologists tend to investigate whether using SPPs data the basin's runoff can be simulated properly compared to produced models based on GRGs or not. Despite the fact that numerous studies have been carried out in many regions of the world to examine the hydrologic utility of SPPs and GRGs (Al-Areeq et al., 2021; Talchabhadel et al., 2021; Zhou et al., 2022), no studies have yet assessed the hydrologic utility of these in the Zayandeh-Roud Basin. The main objectives of this study are summarized: (i) compare SPPs (PERSIANN-CDR) and GRGs time series, (ii) compare observed and simulated stream-flow in the SWAT model driven by SPPs and GRGs data, and (iii) Analyze how well each precipitation product performs in terms of providing information to the hydrological model. The findings of this research will help the researchers to choose a more accurate precipitation product for stream-flow simulation in the Zayandeh-Roud Basin.

2. CASE STUDY AND DATASET

2.1. Study area

The case study is Chelgerd sub-basin (50°–50.75°E and 32.25°–33°N), which is the main branch of the Zayandeh-Roud Basin in central Iran located in the Zayandeh-Roud River Basin in central Iran. It has a total drainage area of about 1500 km2 (Figure 1). Because of its high elevation, the case study has a distinct climate and hydrology than the rest of the Basin. It receives around 1,400 mm of yearly precipitation. The Chelgerd sub-basin provides most of the basin from which water supply to Isfahan, Chaharmahale Bakhtiari provinces in central Iran for agricultural, industrial, domestic purposes, and other home functions is provided. The presence of high-flow rivers in nearby basins, like Chaharmahale Bakhtiari, has prompted construction of water transfer tunnels to help mitigate the Zayandeh-Roud River Basin's water crisis.

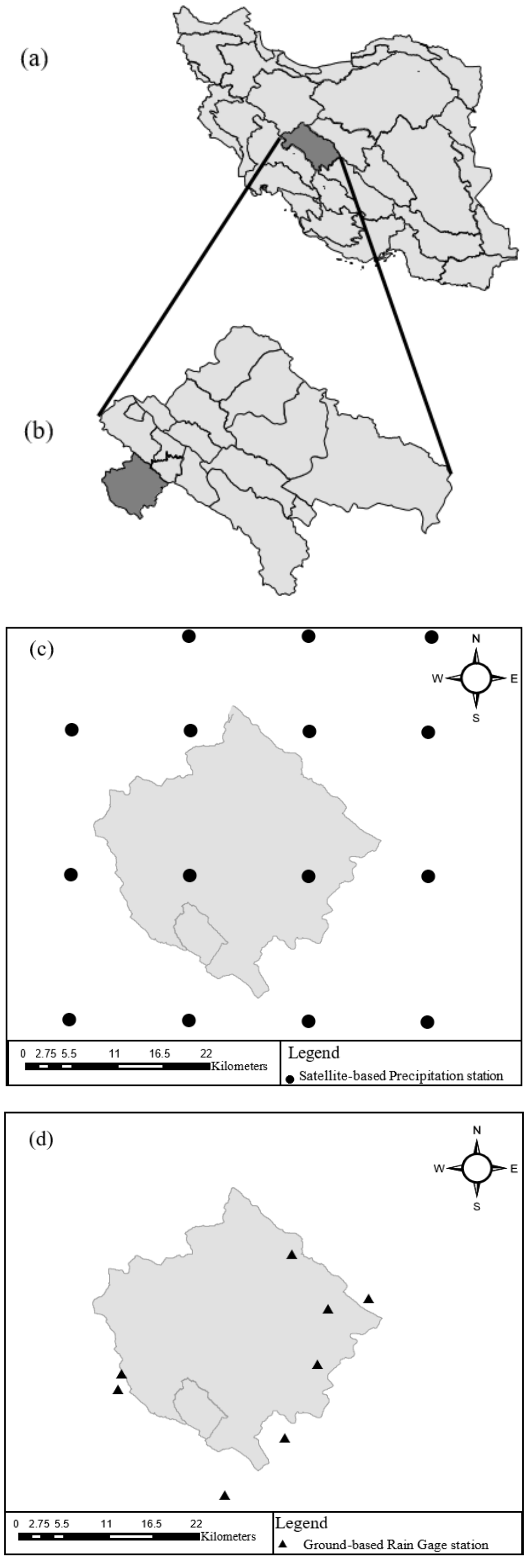

Figure 1. (a) Iran, (b) Zayandeh-Roud Basin, (c) Satellite-based Precipitation station (SPPs) locations in Chelgerd sub-basin, and (d) Ground-based Rain Gauge station (GRGs) locations Chelgerd sub-basin.

2.2. Datasets

The SWAT model is a continuous-time, process-based, semi-distributed software with an efficient computational simulator (Veettil et al., 2021). Based on a digital elevation model, the river basin is split into smaller sub-basins (DEM). These sub-basins are further subdivided into hydrologic response units (HRUs), which are homogenous land use, soil type, and slope units. Data in this study includes several parts; firstly, SPPs data in resolution of 0.25˚ × 0.25˚was obtained from PERSIANN-CDR database. Secondly, in order to collect ground-based climatic data, the information of three rain gauging stations, two climatological stations, two synoptic stations, and one evapotranspiration station were obtained from the Iranian Meteorological Organization (IMO), and Isfahan Regional Water Authority (IRWA). Thirdly, the US National Aeronautics and Space Agency (NASA) provided a DEM map with a cell size of 30 meters. We used a digital vegetation map created by IRWA for the year 2011, which has 10 land-use classes and a spatial resolution of 30×30 m. The produced soil map of the Zayandehrud basin with a spatial resolution of 30×30 m by the IRWA in 2009, which was based on soil investigations and profiles, was used in this study. Finally, the Chelgerd sub-basin contains a tunnel that transports water from nearby basins to the research area. The tunnel's monthly discharge was added to the runoff in the SWAT model. Table 1 summarizes the data used to develop the SWAT model and their sources. According to the mentioned collected data, two SWAT model were developed in order to simulate runoff based on SPPs and GRGs data between 1994 and 2015 for this project.

Data type	Period	Resolution/ Detail	Source
satellite-based precipitation	1994-2015	0.25˚ × 0.25˚	PERSIANN-CDR
Land-use map	2011	30×30 m	IRWA
Soil map	2009	30×30 m	IRWA
DEM	2018	30×30 m	NASA
Precipitation & Temperature	1994-2015	Evapotranspiration	IMO
Precipitation & Temperature	1994-2015	Climatology	IRWA
Precipitation	1994-2015	Rain gauge	IRWA
Runoff	1994-2015	Ghale-Shahrokh	IRWA
Tunnel Discharge	1994-2015	Koohrang	IRWA

* PERSIANN-CDR: Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks–Climate Data Record; DEM: Digital Elevation Model; NASA: National Aeronautics and Space Agency; IMO: Iranian Meteorological Organization; IRWA: Isfahan Regional Water Authority.

Table 1. Data description and sources.

3. METHODS

The methodology in this study includes two main parts: first, PERSIANN algorithm and the process of preparing satellite-based precipitation time series for modeling is discussed. The PERSIANN-CDR precipitation product was developed to fill the gap of existing a long-term, high-resolution, and consistent, precipitation at a scale relevant to climate studies. The PERSIANN-CDR data collection is a multi-satellite high-resolution precipitation product that is publicly available online (ftp:/data.ncdc.noaa.gov/cdr/persiann/files/). It is created using Gridded Satellite (GridSat-B1) Infrared (IR) Data and the PERSIANN algorithm (Sadeghi et al., 2021). Next, the equations by which runoff is simulated using the SWAT model is explained in detail. The flowchart of the proposed method was illustrated in Figure (2).

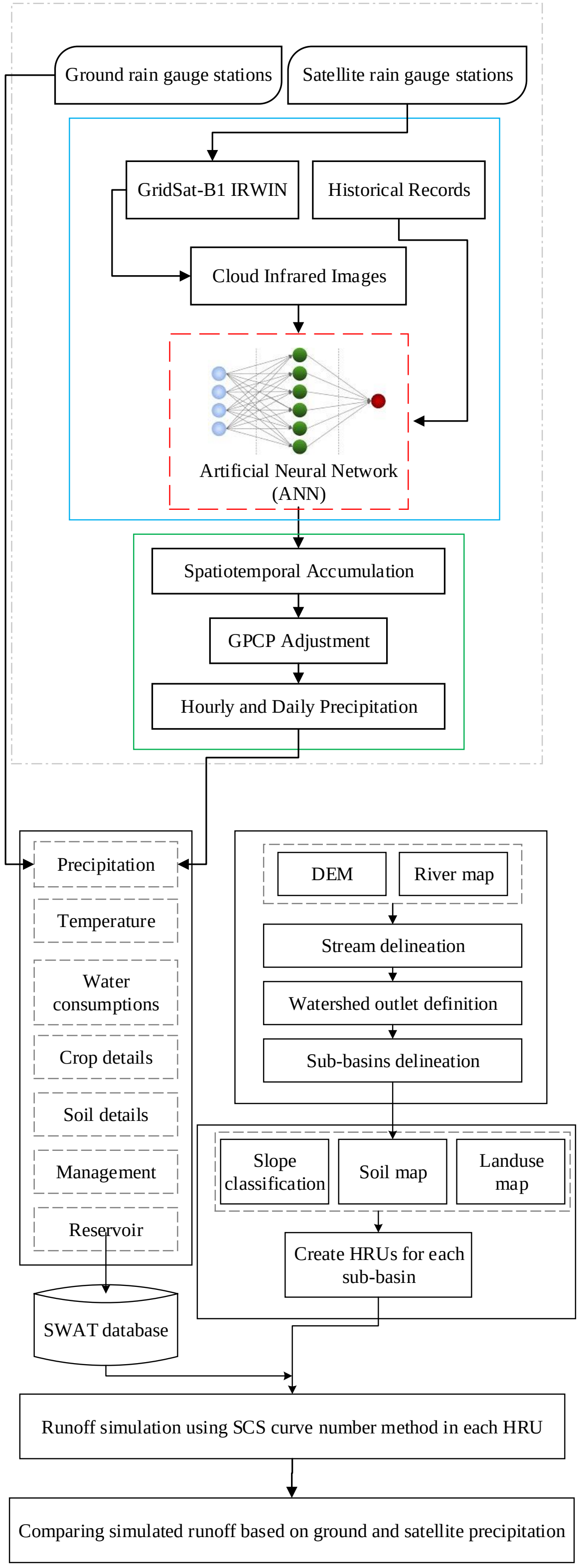

Figure 2. Flowchart of the proposed method for comparing simulated runoff based on SPPs and GRGs data.

3.1. PERSIANN-CDR precipitation estimation algorithm

Using integrated IR and PMW data from different GEO and LEO satellites, the current PERSIANN algorithm predicts worldwide precipitation. The approach uses an artificial neural network (ANN) model to extract cold-cloud pixels and nearby features from GEO long-wave infrared pictures (10.2–11.2 μm), and it links changes in each pixel's brightness temperature with the rate of surface precipitation for that pixel. (Ashouri Talouki, 2014; Sorooshian et al., 2000). For the purpose of estimating rainfall in resolution of 0.25˚ × 0.25˚, the PERSIANN model combines the PMW data from LEO satellites with the CPC globally integrated, full-resolution (4 km, 1/2 hourly) IR data from GEO satellites (Joyce et al., 2010).

In order to circumvent the necessity for PMW observations, the nonlinear regression parameters of the ANN model are trained and maintained unchanged when PERSIANN is applied to estimate rainfall rates retroactively using the 3-hourly GridSat-B1 IRWIN data in CDR product. The reconstruction methodology also includes a bias-adjustment stage based on monthly precipitation data from the GPCP 2.5°. Utilizing GPCP monthly rainfall data, the data creation framework modifies 3-hourly PERSIANN-B1 rainfall predictions to ensure consistency and quality of the data.

3.2. Using monthly GPCP data to adjust daily PERSIANN data

Provided monthly GPCP rainfall at 2.5° resolution is utilized to update the high-resolution PERSIANNB1 estimates to remove any biases in the 3-hourly PERSIANN-B1 estimates while keeping geographical and temporal trends in the high resolution precipitation estimates. For each month of the year, a different adjustment is applied to each 2.5° grid box of PERSIANN-B1 data by which precipitation time series in daily scale are provided.

3.3. Hydrological simulation using the SWAT model

The Agriculture Research Services Division of the United States Department of Agriculture generated the Soil and Water Assessment Tool (SWAT) model. The SWAT model's appealing qualities include robust algorithms for simulating hydrologic processes, a Geographical Information System interface, user-friendly, and public access. To simulate runoff, the SWAT model employs the Soil Conservation Service (SCS) curve number approach created by the SCS. The equation for calculating the SCS curve number is given by:

$$Q_{surf} = \frac{\left(R_{day} - I_a\right)^2}{\left(R_{day} - I_a + S\right)}\ , \tag{1}$$

where Q_{Surf} = the accumulated runoff (mmH_2O)
R_{day} = is the rainfall depth for the day (mmH_2O)
I_a= the initial abstraction (mmH2O)
S = the retention parameter (mmH_2O)

Changes in soils, land use, management, and slope affect the retention parameter regionally, whereas changes in soil water content affect it temporally. The following is the definition of the retention parameter:

$$S = 25.4\left(\frac{1000}{CN} - 10\right), \tag{2}$$

where CN = the day's curve number

$$Q_{surf} = \frac{\left(R_{day} - 0.2S\right)^2}{\left(R_{day} - 0.8S\right)}\ , \tag{3}$$

3.3.1. SWAT model’s agricultural management

Agricultural management was applied to the model using the automatic watering option in the SWAT model after separating the land into several crops. Data on cropping patterns in the Zayandeh-Roud River Basin upstream were obtained from the Isfahan Agricultural Jahad Office and used to assign the irrigated crops. The area under each crop was first used to identify the primary crop(s) in each region due to the broad variety of cropping patterns in the Basin. The Geographic Information System assigned common crops to each SWAT subbasin in the model by using the land-use maps, township boundary maps, and border maps of the sub-basins built in the ArcSWAT model. The most significant crops were ultimately decided to be barley, wheat, potatoes, corn, rice, alfalfa, and.

3.3.2. Model calibration, sensitivity, and uncertainty analysis

The SUFI-2 algorithm in the SWAT-CUP application was performed to the process of model calibration and validationn using the observed runoff. This tool also calculates model uncertainty and parameter sensitivity. All modelling errors are addressed by model prediction uncertainty (Abbaspour et al., 2007). Variables in the model's output are affected by uncertainties in the parameters. Both the p-factor and the r-factor are measures for assessing the model's accuracy and uncertainty. The percentage of observed data bracketed by the 95PPU band is the p-factor. The r-factor is computed by subtracting the observation data's standard deviation from the average thickness of the 95PPU band. A perfect match between the observed and simulated data can be shown by the optimal p-factor and r-factor values, which are 100% and 0%, respectively.. According to (Abbaspour et al., 2015), values of >0.7 for p-factor and <1.5 for r-factor constitute a good calibration result.

3.3.3. The developed models' hydrologic performance

The resulting models' hydrologic performance, accuracy, and efficiency were evaluated using streamflow rates. Both SPPs and GRGs were used to model these discharges. The Coefficient of Determination (R^2) and the Nash–Sutcliffe Efficiency (NS) were used to determine the accuracy of the simulated discharges. Equations (4) and (5) offer the mathematical definitions for R^2 and NS, respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(O_i - O_{mean}\right)\times\left(S_i - S_{mean}\right)}{\sqrt{\sum_{i=1}^{n}\left(O_i - O_{mean}\right)^2 \times \sum_{i=1}^{n}\left(S_i - S_{mean}\right)^2}}\right], \tag{4}$$

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(S_i - O_i\right)^2}{\sum_{i=1}^{n}\left(O_i - O_{mean}\right)^2}\ , \tag{5}$$

where O_i = observed discharges
O_{mean} = average of observed flow
S_{mean} = average of simulated flow
S_i= observed discharges

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4. RESULT AND DISSCUSSION

4.1. Comparing SPPs and GRGs datasets

In order to compare SPPs and GRGs datasets, their annual and monthly time series are illustrated in Figure (3a) and Figure (3b), respectively. As it can be clearly seen in the pictures, the annual and monthly trends of SPPs and GRGs datasets were almost the same, which means that PERSIANN-CDR database presents precipitation time series accurate enough and can be used in hydrological studies in Zayandeh-Roud basin.

Figure (3c) demonstrates the correlation of monthly SPPs and GRGs datasets. Looking at Figure (3c) in more detail, it is evident that the number of points that are under and up of the slope line are roughly the same. This means that the datasets are correlated enough.

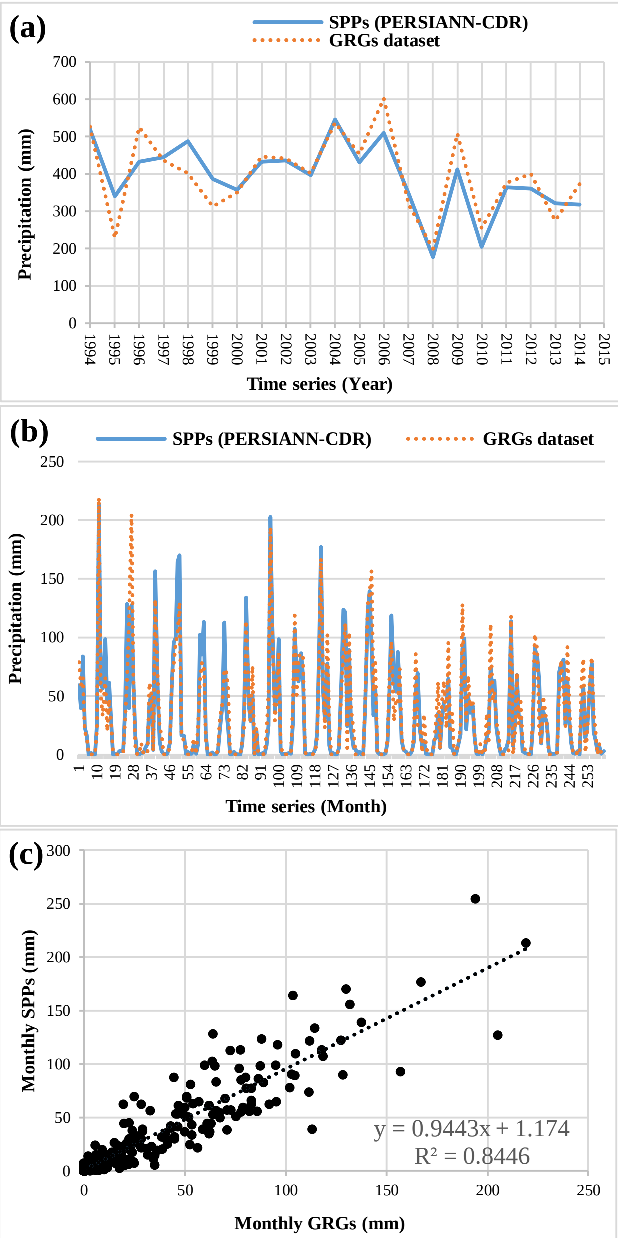

Figure 3. Comparing SPPs and GRGs datasets, (a) Annual time series, (b) Monthly time series, and (c) Time series' correlation.

4.2. SWAT sensitivity analysis

For the sensitivity analysis, a significant number of parameters were initially chosen using SWAT-CUP software. At the 95 percent confidence level, seven hydrologic metrics were sensitive to discharge. CN2, PLAPS, TLAPS, SMFMN, and SMFMX were the most sensitive parameters (Table 2). To prevent identifiability issues with the other hydrologic parameters, the four snow parameters were first calibrated and then deleted from further calibration. SMFMN was the most critical snow parameter.

Parameter	Parameter definition	fixed value
CN2.mgt	SCS runoff curve number	0.03
PLAPS.sub	Precipitation laps rate (mm H_2O/km)	163.43
TLAPS.sub	Temperature laps rate (˚C /km)	4.71
SMFMN.bsn	Minimum melt rate for snow during year (mm H_2O/ ˚C /day)	0.58
SMFMX.bsn	Maximum melt rate for snow during year (mm H_2O/ ˚C /day)	1.03
SFTMP.bsn	Snowfall temperature (˚C)	0.75
GW_REVAP.gw	Groundwater revap. coefficient	0.02
ALPHA_BF.gw	Base flow alpha factor (days)	0.32
RCHRG_DP.gw	Deep aquifer percolation fraction	0.42
CH_N2.rte	Manning's "n" value for the main channel	0.03
SMTMP.bsn	Snow melt base temperature (˚C)	0.30
REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm H_2O)	9.25
SOL_K1.sol	Saturated hydraulic conductivity of first soil layer (mm/hr)	0.46
SOL_BD1.sol	Moist bulk density of first soil layer (Mg/m^3)	-0.04

Table 2. Ultimate actual magnitides of sensitive parameters to discharge.

4.3. SWAT calibration and validation

At the Ghaleshahrokh station, a p-factor of 0.54 was achieved for the simulated runoff using GRGs dataset over the calibration period (Table 3), indicating that the 95PPU bracketed 54 percent of the observed data.

Period	Indicator	Simulated runoff by GRGs	Simulated runoff by SPPs
Calibration (1994-2008)	p-factor	0.54	0.52
	r-factor	0.42	0.41
	NS	0.81	0.78
	R^2	0.82	0.79
Validation (2009-2015)	p-factor	0.49	0.48
	r-factor	0.51	0.57
	NS	0.72	0.70
	R^2	0.74	0.71

Table 3. Calibration and validation results of the developed SWAT model based on GRGs and SPPs datasets.

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The r-factor was 0.42, suggesting an acceptable amount of discharge uncertainty. These numbers for the simulated runoff using SPPs stood at 52%, and 0.41%, respectively, which means that SWAT model calibration accuracy indicators for both datasets are almost the same. Additionally, NS coefficient for the best-simulated runoffs using GRGs and SPPs datasets stood at 0.81, and 0.78, respectively, which means that both simulated runoffs are accurate enough in order to be used in hydrological studies.

For the validation period (2009-2015), which had similar climatic and hydrologic circumstances to the calibration period, satisfactory findings were yielded, as well. The p-factor was 0.49, and the r-factor was 0.51 for simulated runoff using GRGs dataset (Table 3). These values were 0.48 and 0.57 for the SPPs dataset (Table 3), respectively.

Figures (4) shows the best time series of simulated runoff per SWAT model using GRGs and SPPs datasets, and observational runoff during the calibration and validation periods.

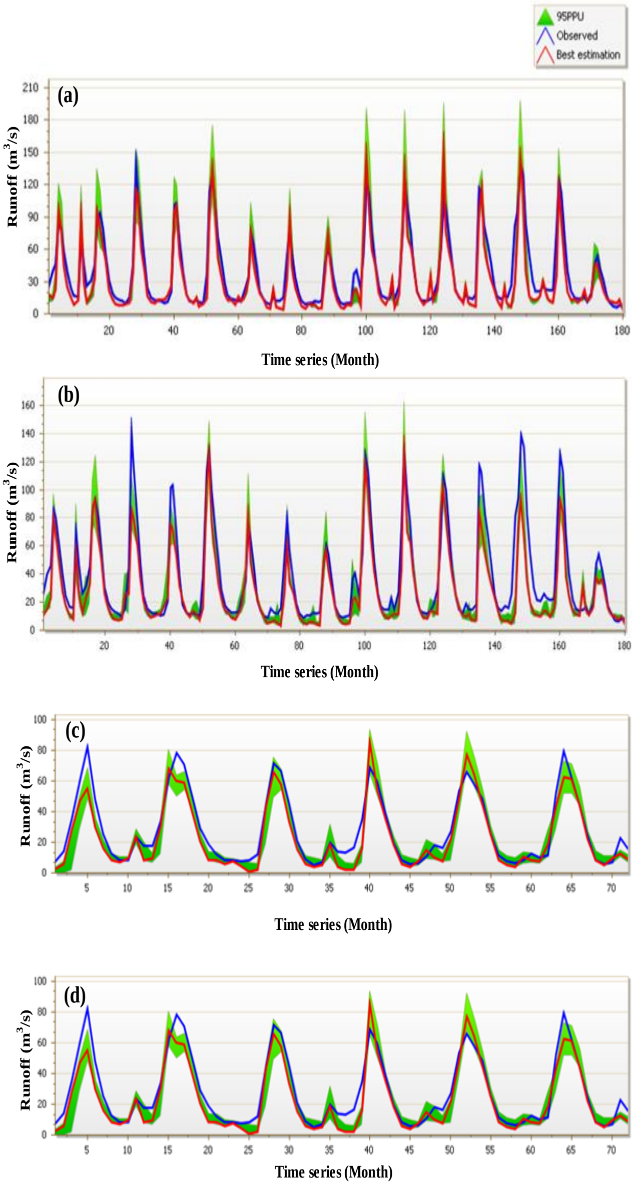

Figure 4. Discharge calibration results for the period of 1994–2008 using (a) GRGs dataset and (b) SPPs dataset. Discharge validation results for the period of 2009–2015 using (c) GRGs dataset and (d) SPPs dataset.

Simulated runoff per SWAT model using SPPs datasets, observational runoff, and monthly average precipitation during the study time period are demonstrated in Figure 5. According to the chart, it can be clearly concluded that SPPs dataset performed properly regarding runoff simulation. This means that in the area of Zayandeh-Roud basin where there is inadequate GRGs datasets, SPPs dataset will be a suitable replacement in order to be applied to hydrological models and lack of accurate precipitation records in this fundamental basin in central Iran will be solvable.

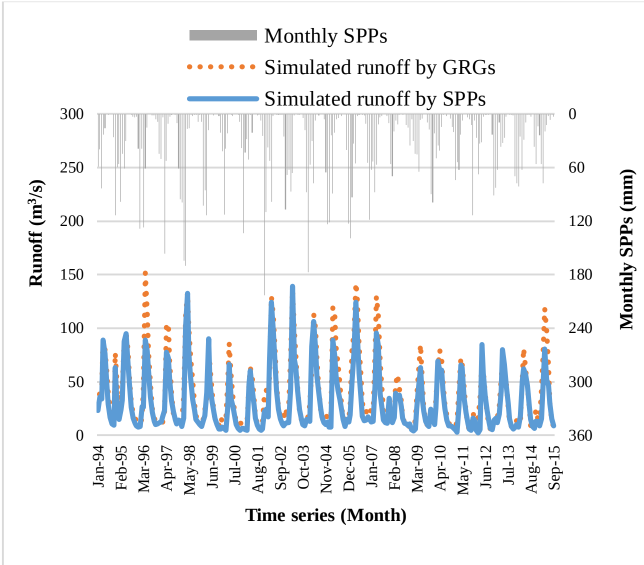

Figure 5. Time series of the best runoff simulated by the SWAT model using GRGs and SPPs datasets, and PERSIANN-CDR total monthly precipitation over the period of 1994-2015.

5. CONCLUSION

Access to reliable meteorological data has always been critical to the advancement of hydrological research. Consequently, many satellite-based precipitation products (SPPs) have been developed in recent years. This study compared the use of satellite-based and gauge-based gridded precipitation products for hydrologic modelling in the Chelgerd sub-basin, which is the main branch of the Zayandeh-Roud Basin in central Iran. In this regard, two different SWAT models were developed in order that the hydrological performance of GRGs and SPPs datasets simulating runoff were evaluated. The results illustrated that the SWAT model calibration accuracy indicators for developed models was almost the same. P-factor, r-factor, NS, and R^2 coefficients stood at 0.54, 0.52, 0.81, and 0.82 simulated runoff using GRGs dataset and 0.52, 0.41, 0.78, and 0.79 for simulated runoff using SPPs dataset over the calibration period.

Even though a basin in the center of Iran was chosen as a case study in this research, this method can be employed in various basins, especially dry and semi-arid basins to evaluate the performance of satellite-based precipitation compared to ground-based rainfall records. Precisely, watersheds with high water demand where the number of rain gauge stations are insufficient to be used in hydrological models. Despite its inherent difficulties, this technique could be applied to catchments and bigger case studies.

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