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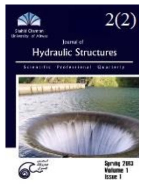

Hydrological Assessment of Daily Satellite Precipitation Products over a Basin in Iran

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Abstract

In order to measure precipitation as the main variable for estimating the runoff and designing hydraulic structures, the satellite algorithm products that have the proper spatial and temporal coverage, can be used. In this study, at first, the daily streamflow simulation of Sarough-Cahy River from the Zarinehroud basin was conducted through the artificial neural network (ANN) and ground data of daily precipitation, temperature and discharge for the years of 1988 to 2008. The developed network was trained, validated and tested. Then, in order to evaluate the products of satellite precipitation algorithms in streamflow simulation which is the aim of this study, daily satellite rainfall data of PERSIANN, TMPA-3B42V7, TMPA-3B42RT and CMORPH between 2003 and 2008 were used as an input data to the trained ANN model. Considering indices of R2, RMSE and MAE implemented for evaluations, the results indicated that satellite rainfall algorithms are able to simulate runoff efficiently over the study area.

Keywords: Satellite Precipitation Products (SPPs), Simulation, Daily streamflow, Artificial Neural Networks (ANNs), Basin

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1. Introduction

Since the most catchments of Iran country lack of hydrometric stations with long-term data, using methods that help them in estimating runoff from precipitation is of considerable

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importance. Hydrologic models as useful methods to simulate flow, is one of the early stages of planning and management of water resources [1]. Several rainfall-runoff models have been proposed for flow estimation, among which the artificial neural network (ANN) due to non-linear structure has a high potential in modeling complex and non-linear processes such as precipitation-runoff [2]. On the one hand, precipitation is the key input variable in hydrological modeling and temporal and spatial distribution of it has a significant impact on surface flows [3]. Knowing the temporal and spatial distribution of rainfall and understanding its effect on river flow is one of the cases that lead to proper management of water resources in the catchment area [4]. In fact, relatively accurate and reliable estimations of precipitation, as the main variable of hydrological models play an important role in modeling and forecasting output hydrographs [5].

In order to develop methods for estimating precipitation using satellite images, remote sensing algorithms using satellite technology, on a global scale with temporal and spatial resolutions, respectively less than 3 hours and 0.25 degree were provided. Therefore, one of the sources of world-class precipitation estimation is the product derived from satellite precipitation estimates algorithms (SRE) [6]. Now, the highest precipitation data is collected from ground rainfall stations. However, the network of precipitation measurement stations in most areas and particularly in developing countries such as Iran, do not have a proper spatial coverage. Furthermore, due to their pointed measurements of precipitation, it is not possible to show the precipitation value in areal form, which can be a significant limitation for hydrological applications. Thus, satellite estimates of precipitation with high spatial and continuous coverage over areas with different physiographic conditions, can be a good alternative for the ground stations [7]. However, in order to use this set of data, it is necessary to evaluate their error quality and characteristics in different places. Then, precipitation estimation using satellites are important sources to achieve more complete monitoring of precipitation and water resources in Iran where the distribution of ground stations is too scattered [5]. This is while the efficiency assessment of satellite precipitation products (SPPs) in runoff simulation as input data into hydrological models, has less been attended over Iran.

In this study, we first deal with the evaluation of ANN in simulating daily streamflow of Sarough-Chay river from the Zarinehroud basin. Then, in order to investigate the performance of satellite precipitation algorithms in simulating the streamflow, which is the purpose of this study, a series of daily satellite rainfall products named Precipitation Estimation from Remotely Sensed Information using ANN (hereafter PERSIANN), Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (hereafter TMPA-3B42V7 and TMPA-3B42RT), and Climate Prediction Center (CPC) Morphing Technique (hereafter CMORPH) will be used as input to the trained model.

2. Research background

In the past two decades, using satellite rainfall estimates (SREs) has had a significant growth to measure rainfall and great efforts have been done in the field associated with their careful performance and error analysis [5]. Also, the models based on ANN have been used in many studies for simulating the watershed runoff.

Kalyskan et al. [8] examined TRMM satellite rainfall data in Tapajv river basin, the main tributaries of the Amazon River, located in Brazil. They used TRMM satellite daily rainfall data and ground rain gauge data as input for MGB-IPH hydrological model and compared the results of the calculations with observed hydrographs. The results showed that satellite data of TRMM-3B42 can be used as input to the distributed rainfall-runoff models over the tropical basins of South America. Stisen and Sandholt [9] evaluated three satellite products, including

PERSIANN, CMORPH and TRMM-3B42 as input in MIKE SHE hydrological model over the Senegal river basin and found that the performance of TRMM -3B42 is better than other satellite products .

Behrangi et al. [10] evaluated the efficacy of satellite precipitation products (SPPs) to simulate runoff at the basin scale. For this purpose, five products of satellite algorithms named TMPA-RT, TMPA-V6, CMORPH, PERSIANN and PERSIANN-adj were implemented as inputs to SAC-SMA hydrological model in order to simulate the runoff in monthly and 6 hours scales. The results for all five kinds of products in different rainfall intensities as well as different seasons were compared with each other and the ability of each product to capture the runoff with respect to its errors and uncertainties was expressed.

Lee et al. [11] compared TRMM satellite rainfall data with rain gauge data at different time scales and evaluated the performance of TRMM data to simulate hydrological processes in Yangtze river basin of Znjyng in China. Simulation of monthly hydrological processes showed that TRMM satellite rainfall data can be useful for simulating the flow over the basin. Moazami et al. [5] compared three satellite rainfall estimation algorithms (PERSIANN, TMPA-3B42V7 and TMAP-3B42RT) with rain-gauge data over the whole country of Iran and , concluded that TMPA-3B42V7 product with values of Mbias =-1/47 mmd^{-1}, *RBias*= -13.6%, MAE = 4.5, RMSE = 6.5 mmd^{-1} , and correlation coefficient of 0.61 represents better estimates of daily precipitation than two other products.

Dawson and Willlbay [12], Tokar and Johnson [13], Tokar and Marcus [2], and Zhang [14], have also acknowledged the ability of ANNs to model the non-linear phenomena. Tokar and Marcus [2] compared the ANN and conceptual models to estimate the runoff of Fraser river watershed in Colorado. They reported the accuracy of achievement to an appropriate answer for predicting the runoff in the neural network compared to conceptual models. Soltani [15] by comparing the performance of conceptual models and ANN in simulating the rainfall-runoff process concluded that neural network requires less information and also is calibrated and verified faster compared to other models.

3. Materials and Methods

3.1. Study area

Zarinehroud basin (45°45 to 15°47 east longitude and 30°35 to 45°36 north latitude) with an approximate area of 11841 km^2 is widespread in the southeast of Urmia Lake in northwestern part of Iran. In this research, Sarough-Chay river sub-basin of Zarinehroud was chosen with area of 2403.8 km^2, due to completeness of its rain gauge data named TAKAB and its hydrometric station named Safakhaneh (See Figure 1).

3.2. Data

Ground data of daily rainfall, average temperature and discharge from 1988 to 2008 have been used to simulate the streamflow in this study. The first 10 years from 23/09/1988 to 22/09/1998 is intended for training the proposed ANN model, the 5 years from 23/09/1998 to 22/09/2003 for the validation, and the rest 5 years from 23/09/2003 to 21/9/ 2008 for testing the model. The daily precipitation data of PERSIANN, TMPA-3B42V7, TMPA-3B42RT and CMORPH products were derived through the aggregation of 3-hour time resolution. However, the spatial scale of satellite data is in square pixel size with 0.25 degree, thus, a rainfall value for each satellite product is obtained at each pixel [5]. Figure 2 shows the pixels network over the whole country of Iran which composed of 0.25 degree pixels.

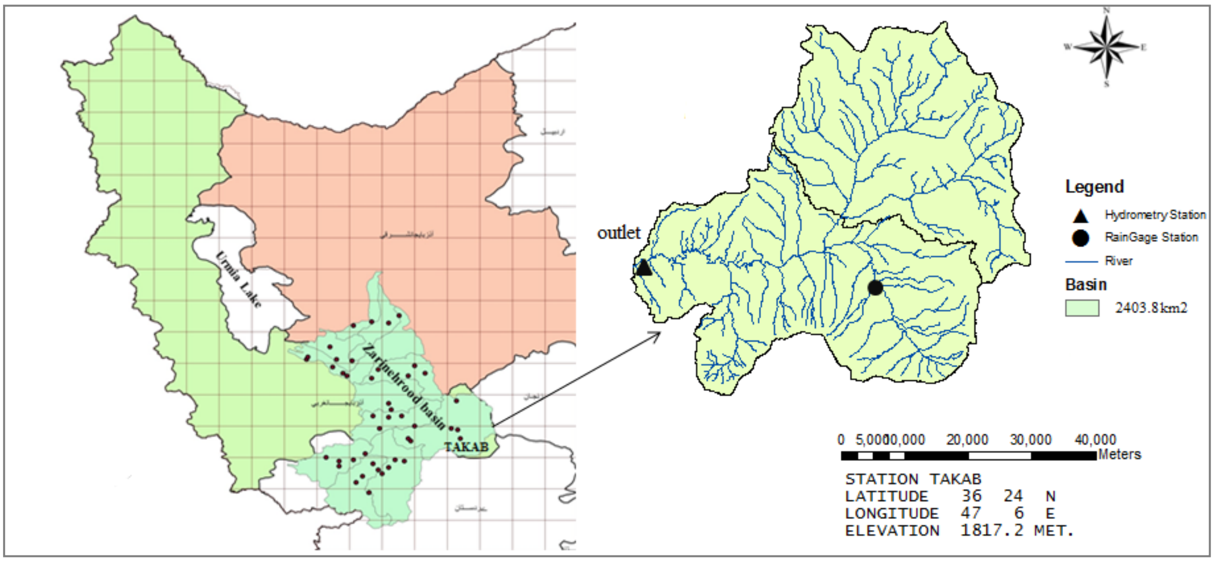


Figure 1. The study area of Sarough-Chay river sub-basin

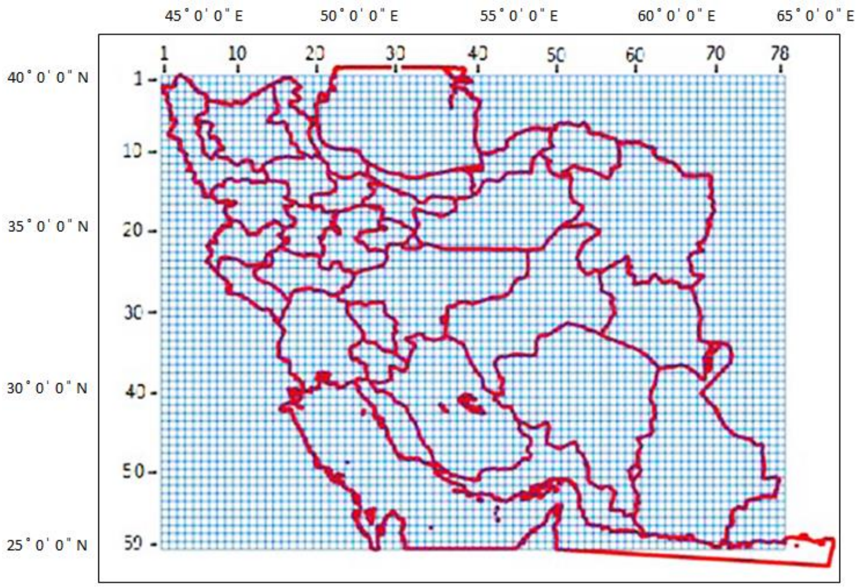


Figure 2. Satellite pixels network over the whole country of Iran

In this study, the daily precipitation data between 2003 and 2008 of those satellite pixels in which rain gauges are located were used. In Figure 3 Iran map covered by satellite pixels, the distributed rain gauge stations throughout the country and the location of studied satellite pixel with its rain gauge are displayed.

3.3. ANN modeling

The ANN consists of a very simple and highly interconnected processor called a neuron. A neuron is an information-processing unit that is fundamental to the operation of a neural network, and consists of a weight and an activation function (Figure 4).

The weights are the most important parameters acting as the memory of ANN, and the activation function provides nonlinear mapping potential with the network. The manner in which the neurons of ANNs are structured determines the architecture of ANNs [16]. In general, there are three fundamentally different classes of network architecture. The first is a single-layer feedforward network, without hidden layers. The second is a multilayer feedforward network, with more than one hidden layer. The third is a recurrent neural network, with at least one feedback loop. In this study, the multilayer feedforward neural network (MFNN) with one hidden layer was used, because it is able to approximate most of the nonlinear functions demanded by practice [17]. The weight parameters on the links between neurons are determined by the training algorithm.

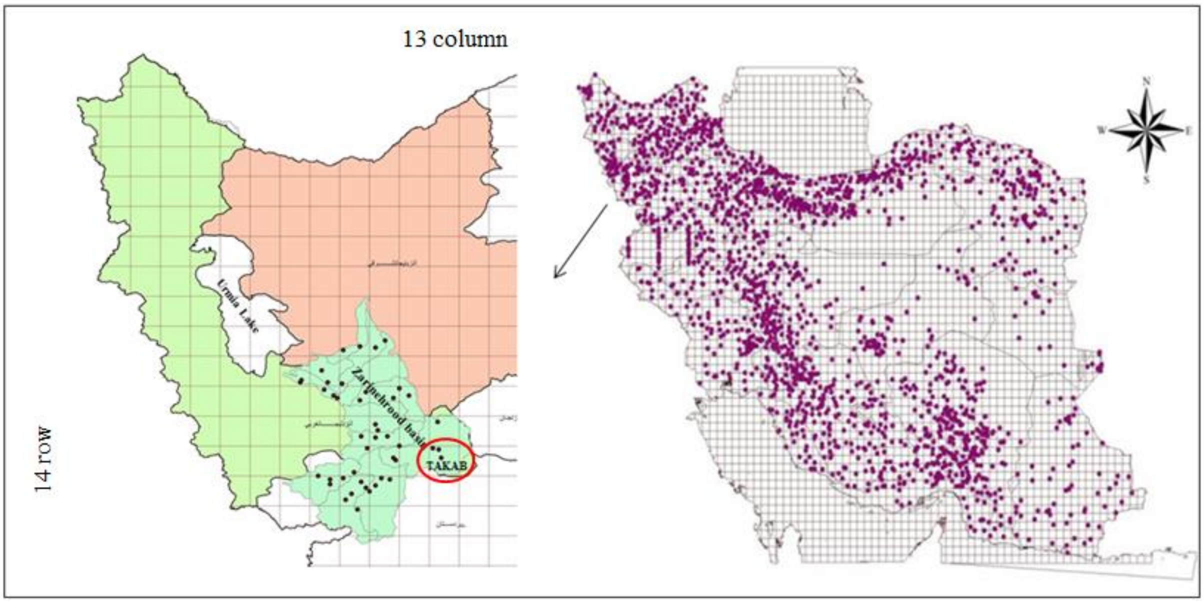


Figure 3. Location of rain gauge stations in the satellite pixels over throughout Iran country and the study area

The most common and standard algorithm is the backpropagation training algorithm, the central idea of which is that the errors for the neurons of the hidden layer are determined by back-propagation of the error of the neurons of the output layer, as shown in Fig.4. There are a number of variations in backpropagation training algorithms on the basic algorithm that are based on other standard optimization techniques, such as the steepest descent algorithm, conjugate gradient algorithm, and Newton's method.

Among various backpropagation methods, the Levenberg-Marquardt (LM) algorithm has been very successfully applied to the training of ANN to predict streamflow and water quality, providing significant speedup and faster convergence than the steepest descent-based algorithm, and conjugate gradient-based algorithms [18].

In this study, the Levenberg-Marquardt (LM) algorithm was applied to train the network.

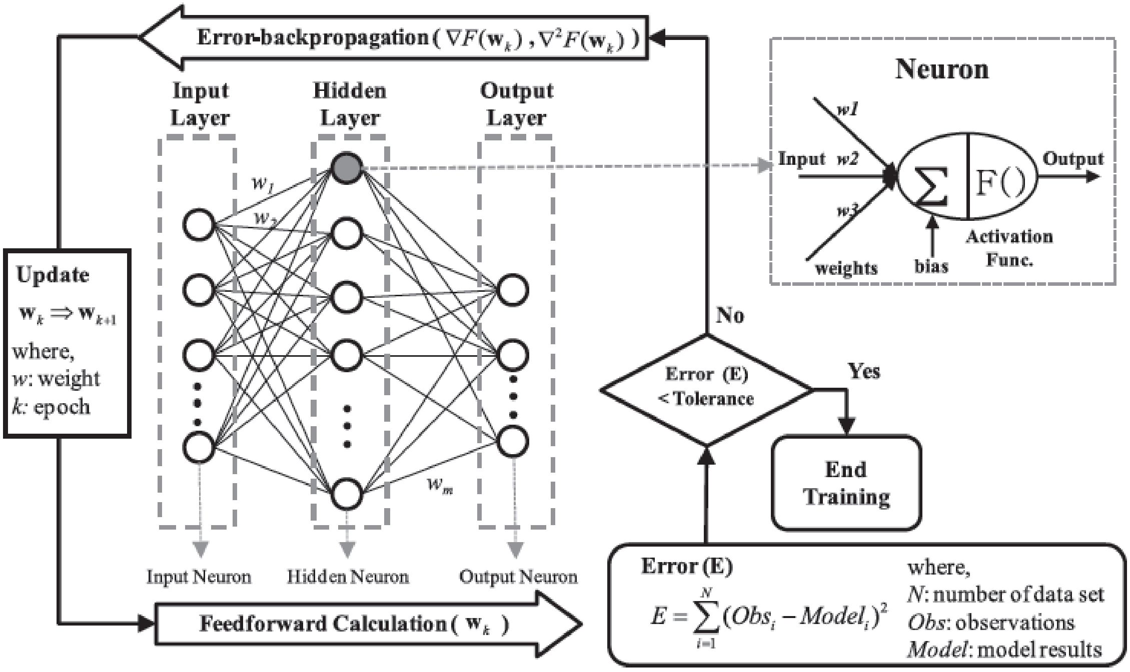


Figure 4. Schematic diagram of backpropagation training algorithm and typical neuron model [19]

3.4. Evaluation criteria

To evaluate simulation results, the coefficient of determination (R^2) and indicator of Root Mean Square Error (*RMSE*) which gives more weight to larger errors than the index of Mean Absolute Error (*MAE*) are used as equations (1) to (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}[(Q_{obs})_i - (Q_{sim})_i]^2}{\sum_{i=1}^{n}[(Q_{obs})i - \overline{Q}_{obs}]^2} \quad (1)$$

$$RMSE = Se = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[(Q_{obs})_i - (Q_{sim})_i]^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(Q_{obs})_i - (Q_{sim})_i\right| \quad (3)$$

Where Q_{obs} and Q_{sim} are respectively observed and simulated flow, $\overline{Q}_{obs}$ is the mean observed flow and n is the number of data.

4. Results and Discussion

In this study, to simulate daily streamflow rate by ANN, according to the autocorrelation between daily time series of rainfall and runoff, as well as the use of hydrological observations at different time delays, the patterns presented in table 1 have been implemented as inputs into model [2], [13]. Then the best pattern in the test phase of network is selected.

Table 1. The patterns used as inputs to the ANN model

Model 1	$Q(t) = f\,(P(t-1), P(t), T(t))$
Model 2	$Q(t) = f\,(P(t-1), P(t), Q(t-1))$
Model 3	$Q(t) = f\,(P(t-1), P(t), T(t), Q(t-1))$
Model 4	$Q(t) = f\,(P(t-2), P(t-1), P(t), T(t))$
Model 5	$Q(t) = f\,(P(t-2), P(t-1), P(t), Q(t-1))$
Model 6	$Q(t) = f\,(P(t-2), P(t-1), P(t), T(t), Q(t-1))$
Model 7	$Q(t) = f\,(P(t-3), P(t-2), P(t-1), P(t), Q(t-1))$

Where, Q indicates the daily discharge, P height of daily rainfall, T mean daily temperature of basin, and t time step of calculations by model.

In this method, a three-layer Perceptron and training function propagation model were used. Using trial and error, the number of neurons in the middle layer and the number of repetitions was obtained in order to achieve optimal function with the aim of minimizing the error factor. The activation function of the middle layer is Logsig (hidden layer with 10 neurons) and the output layer activation function is Purelin neuron linear function with the number of outlets. And also due to the use of stimulant function Logsig, the data were normalized between (1 and 0). The results of network assessment in the test phase with the input patterns are shown in Table 2.

Table 2. Evaluation ANN with various input patterns during network testing

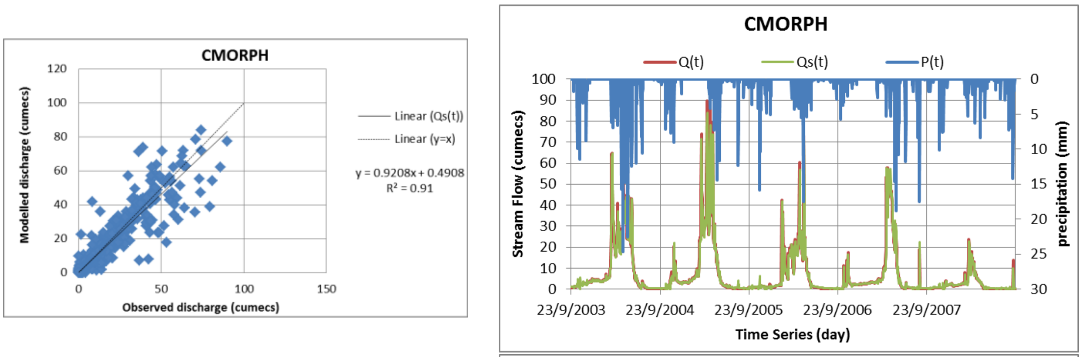
Models \ Evaluation	*Sy*	*Se*	*Se/Sy*	R^2
Model 1	10.33	6.20	0.59	0.15
Model 2	11.70	4.79	0.41	0.77
Model 3	10.33	3.71	0.36	0.78
Model 4	10.33	5.55	0.54	0.21
Model 5	11.88	3.49	0.29	0.91
Model 6	10.33	3.45	0.33	0.88
Model 7	11.98	3.59	0.31	0.90

Where *Sy* is Standard Division of flow observations, *Se* is root mean square error and R^2 represents the coefficient of determination between observed and simulated discharges. If *Se* is significantly smaller than *Sy*, the model will provide an accurate prediction. Conversely, if *Se* is equal to or greater than *Sy*, the model prediction will not be accurate [2]. Therefore, the less ratio of *Se/Sy* leads to the higher accuracy of streamflow prediction by model [13]. According to the values expressed in table 2, the input pattern of No. 5 in the network test phase as well over the study area was superior to other patterns and hence is selected as the final pattern. Furthermore, in order to evaluate the efficiency of satellite-based precipitation estimate algorithms using evaluation criteria, daily precipitation derived from PERSIANN, TMPA-3B42V7, TMPA-3B42RT and CMORPH were used as input to trained network instead of rain gauge data to simulate daily streamflow. The obtained results are represented in table 3 and figures 5(a) to 5(d) that show the scatter plots of simulated against observed discharges (respectively named as Q_s and Q), as well as time series of precipitation (P), Q, and Q_s for each satellite product separately.

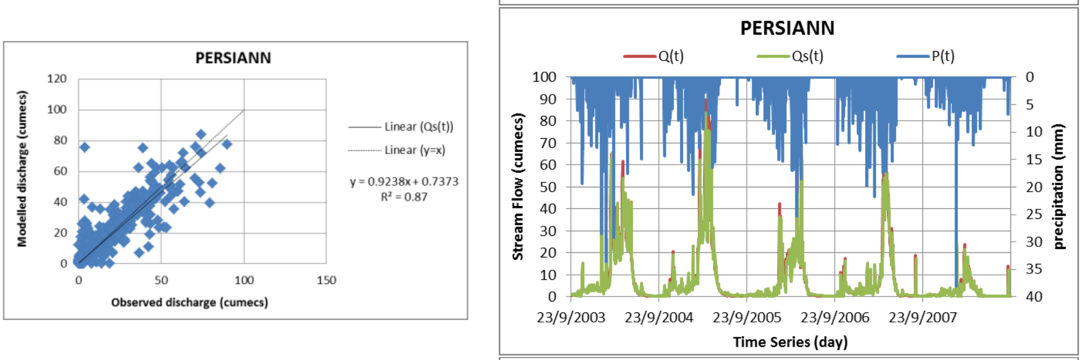
Table 3. The results of runoff simulation with satellite rainfall estimates and ANN

Satellite Precipitation Products	R^2	*RMSE*	*MAE*
PERSIANN	0.87	4.44	1.69
CMORPH	0.91	3.77	1.30
TMPA-3B42V7	0.89	3.88	1.51
TMPA-3B42RT	0.88	4.24	1.64

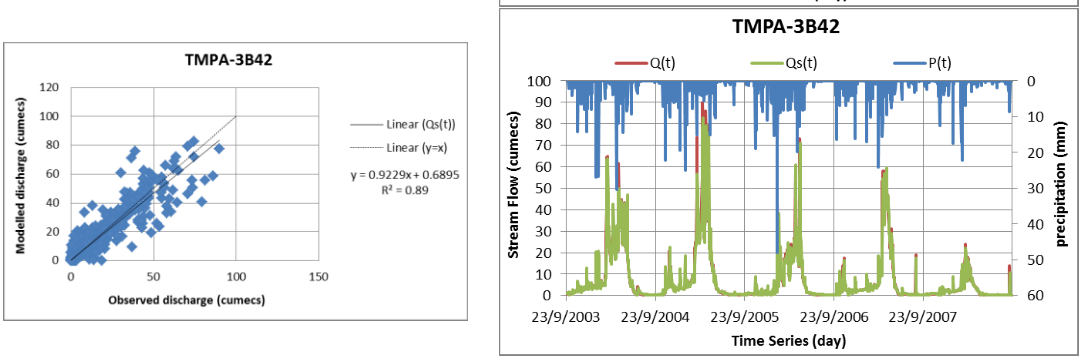
a)



b)



c)



d)

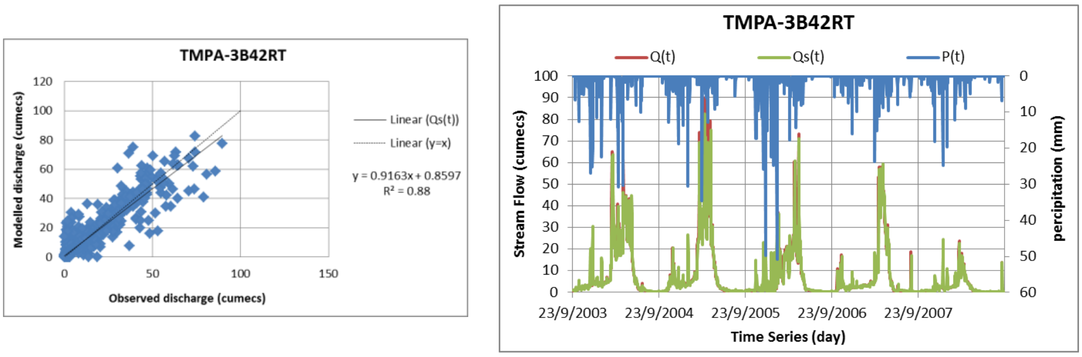


Figure 5. The scatter plots of modeled against observed discharges for a) CMORPH, b) PERSIANN, c) TMPA-3B42, and d) TMPA-3B42RT products

According to the values of indices for simulated daily streamflow in table 3, the rainfall data of CMORPH has higher performance in discharge simulation. Also, the value of *MAE* shows fewer errors in estimating the streamflow rate and can be a good supplementary to rain gauges for runoff simulation by ANN over areas with sparse ground stations. Ebert et al. [20] and Joyce et al. [21] also showed that satellite products of CMORPH have the best chance for detection the daily rainfall. In addition, it can be concluded that estimations of satellite rainfall algorithms have very close performance to the rain gauges data.

5. Conclusion

At first, the daily streamflow simulation of Sarough-Chay river from the Zarinehroud basin was conducted through the ANN and ground data of daily precipitation, temperature and discharge. Then the developed training network was validated and tested. Next, in order to evaluate the satellite precipitation products in streamflow simulation which is the aim of this study, daily rainfall data of PERSIANN, TMPA-3B42V7, TMPA-3B42RT and CMORPH were used as the input to the trained network. According to the shared assessment period in simulating the daily streamflow with ground and satellite data, the satellite precipitation data was in agreement with the rain gauge measurements and thus can be a good complementary to them particularly over areas with sparse ground stations for runoff simulation by ANN. However, the performance of CMORPH satellite product in simulating the runoff of is better than the three other algorithms. The values of error indices of CMORPH are also lower than other algorithms, which represents the lower error of the model to estimate the streamflow rate and are inconsistent with the findings of Ebert et al. [20], Joyce et al. [21] and Romily and Jebermichael [22]. Therefore, it can be used as the main variable in estimating the basin runoff due to the proper temporal and spatial coverage.

Finally, considering the key role of the precipitation variable in hydrological modeling and availability of satellite data for the whole country, further investigations regarding the possibility of using data generated by different algorithms of satellite precipitation estimates instead of rain gauges as input variables to hydrological models are suggested to simulate more accurate runoff in catchments of the country.

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