

A comparison between high-resolution satellite precipitation estimates and gauge measured data: case study of Gorganrood basin, Iran

Donya Dezfooli, Banafsheh Abdollahi, Seyed-Mohammad Hosseini-Moghari and Kumars Ebrahimi

ABSTRACT

The aim of this paper is to evaluate the accuracy of the precipitation data gathered from satellites including PERSIANN, TRMM-3B42V7, TRMM-3B42RTV7, and CMORPH, over Gorganrood basin, Iran. The data collected from these satellites (2003–2007) were then compared with precipitation gauge observations at six stations, namely, Tamar, Ramiyan, Bahlakeh-Dashli, Sadegorgan, Fazel-Abad, and Ghaffar-Haji. To compare these two groups, mean absolute error (MAE), bias, root mean square error (RMSE), and Pearson correlation coefficient criteria were calculated on daily, monthly, and seasonal basis. Furthermore, probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) were calculated for these datasets. Results indicate that, on a monthly scale, the highest correlation between observed and satellite-gathered data calculated is 0.404 for TRMM-3B42 at Bahlakeh-Dashli station. At a seasonal scale, the highest correlation is calculated for winter data and using PERSIANN data, while for the other seasons, TRMM-3B42 data showed the best correlation with observed data. The high values of RMSE and MAE for winter data showed that the satellites provided poor estimations at this season. The best and the worst values of RMSE for studied satellites belonged to Sadegorgan and Ramiyan stations, respectively. Furthermore, the PERSIANN gains a better CSI and POD while TRMM-3B42V7 showed a better FAR.

Key words | CMORPH, daily precipitation, PERSIANN, remote sensing, statistical evaluation, TRMM

Donya Dezfooli
Banafsheh Abdollahi
Seyed-Mohammad Hosseini-Moghari
Kumars Ebrahimi (corresponding author)
Department of Irrigation & Reclamation
Engineering,
University of Tehran,
Karaj,
Iran
E-mail: ebrahimik@ut.ac.ir

INTRODUCTION

Global precipitation observations are of paramount importance in climate studies and examination of hydrological models. Therefore, accurate precipitation measurement at global and local scales plays a crucial role in a better understanding of the climate, hydrological cycle, simulation of hydrological processes and weather forecasts (Qin *et al.* 2014; Cai *et al.* 2015; Milewski *et al.* 2015). Given the fact that rain gauge stations are scattered and are accessed with substantial delays, it seems necessary to resort to other ways of precipitation estimations (Ghajarnia *et al.* 2015). Over the past three decades, a number of studies have been performed to develop different methods of

precipitation measurements through making use of satellite images in order to improve the accuracy and make precipitation estimates in regions that lack comprehensive and reliable data (Liu *et al.* 2015).

The only direct source of precipitation measurement is rain gauges, which might sometimes lack accuracy due to various reasons, including errors made by users, device failure, and sensitivity and the impossibility of installing recorders in impassable regions. Furthermore, due to limitations in the number of rain gauge stations, no proper spatial distribution could be envisaged for precipitation. Providing an overhead spatial coverage, satellites are nowadays

capable of making precipitation estimates for the entire world. Thanks to such developments, access has been provided to precipitation data, especially in developing countries such as Iran in which there are no reliable precipitation data in many areas (Moazami *et al.* 2016).

Evaluations of precipitation data provided by satellites have been used in many areas, including drought studies (Zargar *et al.* 2011; Zeng *et al.* 2012; Aghakouchak *et al.* 2015; Sahoo *et al.* 2015; Toté *et al.* 2015), humidity forecast (Gupta *et al.* 2014), and flood (Curtis *et al.* 2007; Nguyen *et al.* 2015; Shah & Mishra 2016) and in rainfall-runoff modeling (Hong *et al.* 2006; Meskele & Moradkhani 2009; Behrangi *et al.* 2014; Falck *et al.* 2015; Sun *et al.* 2015; Toté *et al.* 2015; Zubieta *et al.* 2015).

Making use of satellite images, various methods have been developed that rely on precipitation estimate algorithms including Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Sorooshian *et al.* 2000; Hsu *et al.* 2012), Climate Prediction Center (CPC), Morphing technique product (CMORPH; Joyce *et al.* 2004), Tropical Rainfall Measuring Mission (TRMM), and Multi-sensor Precipitation Analysis (TMPA) (Huffman *et al.* 2007). The evaluation of satellite rainfall estimates accuracy in comparison to precipitation observation gauge has been carried out in different spatial and temporal resolutions over several regions and basins of the world (Cohen Liechti *et al.* 2012; Kizza *et al.* 2012; Chen *et al.* 2013; Gao & Liu 2013; Xue *et al.* 2013; Conti *et al.* 2014).

Prior to any operational use, it is required to compare the satellite precipitation data with rain gauge observations, ensure their accuracy, and correct them to the extent possible. Several studies have been done in this regard across the world.

Hong *et al.* (2007) analyzed PERSIANN dataset in the northwest of Mexico and showed that it provides reasonable temporal-spatial precipitation estimation in the region under study. Ebert *et al.* (2007) concluded that the data provided by CMORPH show the best daily precipitation probability of detection (POD) in England and Australia. Jiang *et al.* (2012) compared precipitation data provided by CMORPH, TMPA-3B42V6, and TMPA-3B42RT with rain gauges in the southern part of China. They reported that TMPA-3B42V6 showed the best conformity with the rain

gauges' observation. Qin *et al.* (2014) analyzed precipitation data provided by TRMM-3B42, TRMM-3B42RT, CMORPH, and GSMaP1 in China. TRMM-3B42 provided the best estimation regarding precipitation data at observation stations. Yuan *et al.* (2017) compared streamflow simulation with TRMM-3B42 and Global Precipitation Measurement (GPM) in Myanmar and reported the superiority of TRMM-3B42. According to Katiraie-Boroujerdy *et al.* (2017), for evaluation of PERSIANN-CDR data and TRMM-3B42V7 with an *in-situ* rain gauge, TRMM-3B42 and PERSIANN-CDR, respectively, tend to overestimate and underestimate the results. Both satellite products show better correction and RMSEs for the annual mean of consecutive dry periods in comparison to the wet periods. Hobouchian *et al.* (2017) evaluated the accuracy of TRMM-3B42V7, TRMM-3B42RT, CMORPH, and Hydro-Estimator (HYDRO) over the slopes of the subtropical Andes. Their study revealed that errors decrease in winter. Moreover, all satellite data underestimated the precipitation during their analyzed period. Tan & Duan (2017) compared the performance of GPM with TRMM over Singapore at daily, monthly, seasonal, and annual scales. They showed that the monthly results outperform other time scales and, overall, GPM revealed slightly better performance in comparison with other measurements.

Given the importance of precipitation data as primary data in many studies on water resources and lack of an accumulated rain gauge network in many regions of developing countries, impassable ones in particular, it seems necessary to make further use of satellite data to estimate precipitation in various regions. Therefore, scientists have made an effort to assess the accuracy of the data at various spatial and temporal scales. Three large-scale studies have been conducted to assess the accuracy of satellite-driven precipitation in Iran. Moazami *et al.* (2013) studied the accuracy of the data provided by PERSIANN and TRMM-3B42V7 on 47 precipitation events that occurred in winter and spring in Iran over the years 2003 to 2006. Moazami *et al.* (2016) conducted another regional study on four datasets, namely, PERSIANN, CMORPH, TRMM-3B42RT V7, and TRMM-3B42V7 at a daily scale. Since these studies were conducted at different times, the obtained results for the same region were different, suggesting the significance of different time scales in precipitation estimations. In addition, Darand

et al. (2017) studied TMPA at daily and monthly scales in Iran over the years 1998 to 2013. However, there are three points missing in previous studies: (1) datasets' performance at smaller scales, such as basins, is of paramount importance, (2) the analysis of performance variability of datasets at smaller spatial scale and inter-basin, and (3) the assessment of datasets at monthly and seasonal scales, which could be of great assistance in drought studies. The present study aims to assess the reliability and accuracy of the daily, monthly, and seasonal precipitation data provided by PERSIANN, TRMM-3B42V7, TRMM-3B42RT V7, and CMORPH over the Gorganrood basin located in the northeast of Iran. To the best of our knowledge, there is not any record of study regarding this issue in the literature. Steps involved in the present study are as follows.

MATERIALS AND METHODS

Case study

Occupying an area of 11,380 km², Gorganrood basin is located in the northeast of Iran and southeast of the Caspian Sea. It stretches from north to the basin of Lower Atrak, from south to the basins of the Salt Desert, from west to the Caspian Sea, and from southwest to Neka River basin. Alborz heights encompass the southern and eastern parts of the basin. Regarding the geographical location, it is located between the latitudes of 36° 33' and 37° 45'N and longitudes of 54° 03' and 56° 13'E. Its highest and lowest altitudes are approximately 600 and 26 meters above sea level, respectively. The annual mean precipitation at Gorganrood basin varies from 300 mm in the northern and

southern parts to 1,000 mm in its central part. The maximum precipitation is in the lower regions in the fall as well as the high altitude regions and the regions far from the bank in the winter. The annual mean temperature ranges from 18 °C at low altitude regions to 7.5 °C in southern heights. The annual mean evaporation changes from 1,000 mm at the bank to over 2,000 mm in high altitude regions and the regions far from the bank (non-coastal areas). The Gorganrood watershed consists of many small and large rivers, which together form two main rivers named Gorganrood and Gharehsoo. Running east to west, they flow into the Caspian Sea. The basin's rivers have a rainfall–snow regime and a considerable amount of their annual discharge occurs in non-agricultural seasons, spring flood, and summer flood in some years. The present study made use of daily precipitation data collected from the six stations of Tamar, Ramiyan, Bahlakeh-Dashli, Sadegorgan, Fazel-Abad, and Ghaffar-Haji over the years 2003–2007. Table 1 shows the properties of these stations while Figure 1 depicts their geographical locations.

PERSIANN

PERSIANN is a precipitation estimation algorithm that employs remote sensing information through an artificial neural network. It has been developed to estimate rainfall at a resolution of 0.25° × 0.25° (Sorooshian *et al.* 2000). Its approach is to calibrate infrared (IR) data through estimation of passive microwave (PMW). It performs by updating parameters at any time that PMW estimations are available. Estimations are made by IR waves and then calibrated by PMW. The algorithms of PERSIANN retrieve precipitation data from satellites, obtain data from visible to

Table 1 | Details regarding the utilized rain gauge stations of the basin

Station	Type	Longitude	Latitude	Elevation (m)	Average annual precipitation (mm)	Average annual temperature (°C)
Tamar	Evaporation station	55° 56'	37° 56'	132	537	17.9
Ramiyan	Rain gauge	55° 08'	37° 01'	200	858	16.6
Bahlakeh-Dashli	Evaporation station	54° 47'	37° 04'	24	392	17.2
Sadegorgan	Evaporation station	54° 46'	37° 12'	12	332	18.1
Fazel-Abad	Rain gauge	54° 45'	37° 12'	–22	435	17.5
Ghaffar-Haji	Evaporation station	54° 08'	37° 00'	210	674	17.2

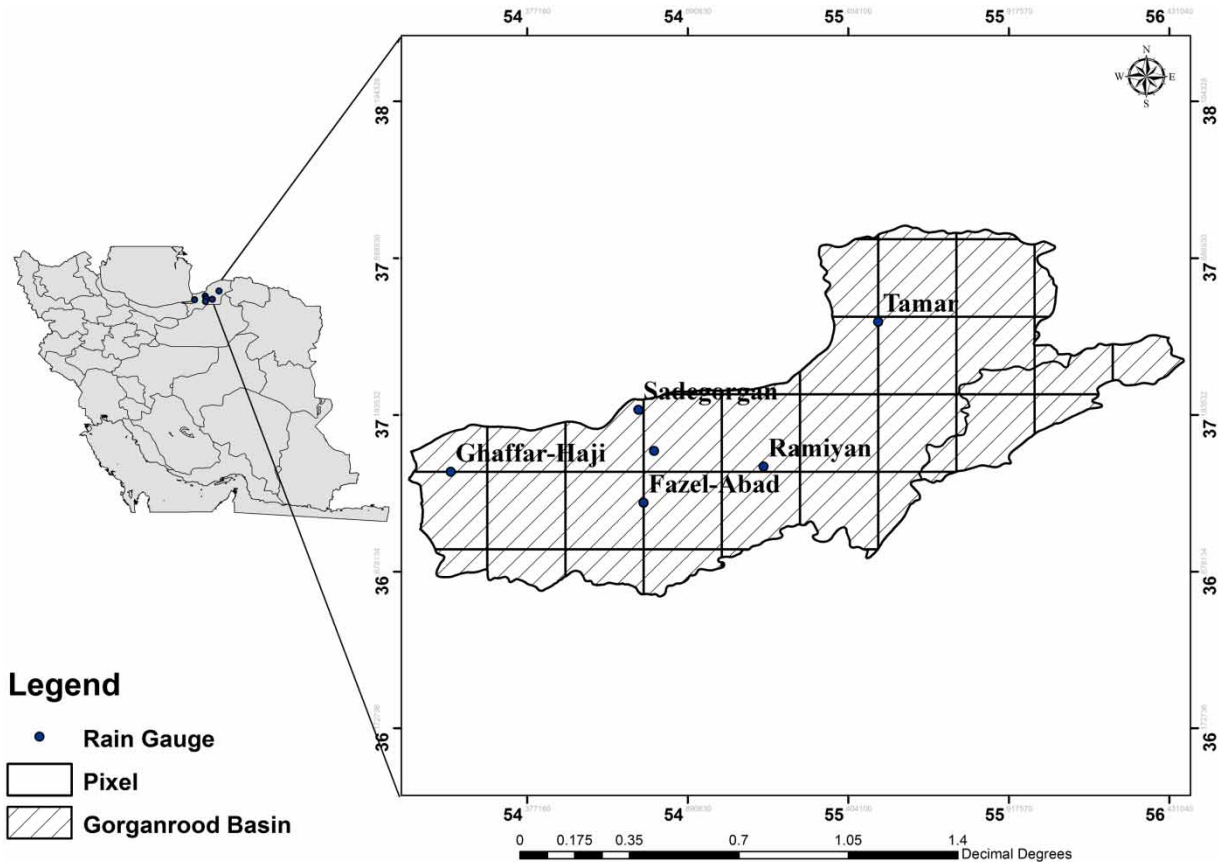


Figure 1 | Grid reference of satellite data along with the location of the utilized rain gauge stations.

IR images from Geostationary Earth Orbital (GEO) satellites, and extract PMW images from Low Earth Orbital (LEO) satellites (Hsu *et al.* 2012). Its parameters are regularly updated by low-orbital satellite images including F15, F14, DMSP F13, NOAA-16, NOAA-15, and TRMM. Making use of this method, it is possible to recursively perform calibration conformity in different regions (Hsu & Sorooshian 2009; Ghajarnia *et al.* 2015). Relying primarily on IR wave information, and used since 1979, PERSIANN has properly estimated historical precipitation over the past three decades (Ashouri *et al.* 2015). The data are available at <http://chrsdata.eng.uci.edu/>.

TRMM-3B42/3B42RT V7

TRMM satellite was designed on 27 November 1997 for a joint space mission between National Aeronautics and Space Administration (NASA) and Japanese Aerospace

Exploration Agency (JAXA). Its mission was to estimate precipitation in tropical areas, which constitutes a significant part of precipitation on Earth (Simpson *et al.* 1988). It enjoys a $0.25^\circ \times 0.25^\circ$ spatial resolution and a 3-hourly temporal resolution (Huffman & Bolvin 2015; Kenabatho *et al.* 2017). A couple of versions of data have been produced so far since launching this satellite. The present paper makes use of TRMM-3B42V7 and TRMM-3B42RT V7 products. These products are generated in four phases: (1) the precipitation estimations made by microwave are combined and calibrated; (2) the calibrated microwave precipitation is used to create IR precipitation estimations; (3) IR and microwave estimations are put together; and (4) the data are rescaled to a monthly basis (Huffman *et al.* 2007; Huffman & Bolvin 2015). RT is a near-real version of TRMM-3B42. The difference between these two versions is that the data provided by TRMM-3B42 are corrected by rain gauge observations while no correction is made in data provided by

TRMM-3B42RT (Qin *et al.* 2014). The data are available on the NASA website at <https://pmm.nasa.gov/data-access/downloads/trmm>.

CMORPH

CMORPH was introduced by Joyce *et al.* (2004) in the NOAA climate prediction center. The output of CMORPH is the precipitation volume based on satellite images. It has been available on the NOAA website (<ftp://ftp.cpc.ncep.noaa.gov/precip/>) since December 2002. LEO-based PMW data from different sources, such as TRMM, F-13, F-14, F-15, and F-16, are used by CMORPH to estimate the relevant rain rate with the help of a morphing method. Moreover, infrared data retrieved from geostationary satellites are used to estimate the cloud systems motion with propagation vectors (Ashouri *et al.* 2015; Land Information System 7.1 Reference Manual 2015). The data provided are accessible at a spatial resolution of 0.07° ($8 \times 8 \text{ m}^2$), $0.25^\circ \times 25^\circ$, and temporal resolution of 30 minutes, 3 hourly, and daily. Its latitude coverage is 60S–60N (Habib *et al.* 2012). Table 2 summarizes the specifications of these four datasets.

The present study makes use of two sets of precipitation data, namely, (1) daily observation data collected from studied stations over Gorganrood basin and (2) daily precipitation data gathered from PERSIANN, TRMM-3B42V7, TRMM-3B42RT V7, and CMORPH over the period from September 2003 to September 2007. As mentioned earlier, Figure 1 depicts the locations and the corresponding networks of rain gauge stations.

Evaluation statistics

Four evaluation statistics, namely, bias, mean absolute error (MAE), root mean square error (RMSE), and Pearson

correlation coefficient (PCC) were used to assess the reliability of precipitation data provided by the above-mentioned datasets (for more details, see Kottegodda & Rosso (2008)). These criteria are defined as follows:

1. Bias: the mean difference between precipitation estimated by datasets and that of observation station. Bias is either positive or negative, which respectively represents overestimation and underestimation of the observed precipitation volume.

$$\text{Bias} = \frac{\sum_{i=1}^N (P_{S_i} - P_{O_i})}{N} \quad (1)$$

2. MAE: the mean magnitude of the errors.

$$\text{MAE} = \frac{\sum_{i=1}^N |P_{S_i} - P_{O_i}|}{N} \quad (2)$$

3. RMSE: measures the mean magnitude of the errors; the higher the RMSE the greater the error.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (P_{S_i} - P_{O_i})^2}{N}} \quad (3)$$

4. PCC: the mean deviation of two variables from their means divided by their standard deviations. The values range between -1 and 1 .

$$\text{PCC} = \frac{\sum_{i=1}^N (P_{S_i} - \bar{P}_S)(P_{O_i} - \bar{P}_O)}{\sqrt{\sum_{i=1}^N (P_{S_i} - \bar{P}_S)^2} \sqrt{\sum_{i=1}^N (P_{O_i} - \bar{P}_O)^2}} \quad (4)$$

where P_{S_i} is the precipitation estimated by datasets on the i th day, P_{O_i} is the observed precipitation volume on the i th

Table 2 | Summarized estimates of four precipitation satellites including PERSIANN, CMORPH, TRMM-3B42V7, and TRMM-3B42RT V7

Name	Temporal resolution	Space resolution	Domain	Corrected by gauges	Period	Reference
PERSIANN	0.5 hr	0.25°	60N ~ 60S	No	2000–present	Ashouri <i>et al.</i> (2015)
TRMM-3B42	3 hr	0.25°	50N ~ 50S	Yes	1998–present	Huffman & Bolvin (2015)
TRMM-3B42RT	3 hr	0.25°	50N ~ 50S	No	1998–present	Huffman & Bolvin (2015)
CMORPH	0.5 hr	$\sim 0.07^\circ$	60N ~ 60S	No	2002–present	Joyce <i>et al.</i> (2004)

day, N is the daily occurrence of precipitation, $\overline{P_S}$ is the mean precipitation estimated by datasets for N occurrence of daily precipitation in any pixel, and $\overline{P_O}$ is the mean precipitation volume at observation stations for N occurrence of daily precipitation.

Statistics classification indexes including POD, FAR, and CSI are used in the present study to evaluate the precipitation estimations made by datasets under study.

POD shows the ratio of the correct detection of datasets' precipitation to the overall occurrence of precipitation at observation stations.

$$POD = \frac{a}{a + c} \quad (5)$$

FAR shows the cases in which precipitation has been predicted by datasets while no precipitation occurred at the observation stations.

$$FAR = \frac{b}{a + b} \quad (6)$$

CSI shows the ratio of the correct precipitation by datasets.

$$CSI = \frac{a}{a + b + c} \quad (7)$$

where a represents the number of correct predictions of precipitation made by datasets, b represents the number of occurrences in which the precipitation is predicted by datasets while no precipitation occurs at observation stations, and c represents the number of incorrect prediction of precipitation made by datasets. At the best case possible, the values of POD, FAR, and CSI are 1, 0, and 1, respectively.

RESULTS

The present study compared the precipitation estimated by PERSIANN, TRMM-3B42V7, TRMM-3B42RT V7, and CMORPH datasets to those observed at the following rain gauge stations, namely Tamar, Ramiyan, Bahlakeh-Dashli, Sadegorgan, Fazel-Abad, and Gaffar-Haji over the

Gorganrood basin located in Iran. The evaluation was made over the period from September 2003 to September 2007 and the impact of seasonal changes was taken into account.

Figure 2 shows the comparison made at a monthly scale between the precipitation estimation data provided by these four datasets and the observed precipitation at Tamar, Ramiyan, Bahlakeh-Dashli, Sadegorgan, Fazel-Abad, and Ghaffar-Haji stations over the studied period. As Figure 2 illustrates, all four datasets in contrast with the observed data, indicate the same locations for maximum and minimum precipitations. It can be said that the behavior of all four time series at monthly scale resembles the observation data; and in many cases, the increase and decrease in the observed precipitations are consistent with the precipitation estimated by satellites. Moreover, TRMM-3B42V7 shows the best conformity with the observation data over Gorganrood basin, followed by CMORPH, TRMM-3B42RT V7, and PERSIANN in the order of their appearance. At this scale, the highest correlation is related to TRMM-3B42V7 at Bahlakeh-Dashli station, which is equal to 0.404, while the lowest correlation is related to TRMM-3B42RT V7 at Tamar station and is equal to 0.145.

Table 3 presents the mean precipitation taken from the daily-observed data and the daily precipitation estimated by four datasets in each month. For all stations, the highest mean precipitation estimated by these four datasets occurred in January, April, July, August, September, October, November, and December and it was less than the mean observed data. In February, the mean precipitations estimated by PERSIANN and TRMM-3B42RT V7 were higher than mean observed data while the mean precipitations measured by CMORPH and TRMM-3B42V7 in this month were less than the mean observed data. Contrary to the estimations made by the other three datasets, the estimation made by PERSIANN in March was also higher than the mean observed precipitation. It is worth noting that the precipitation estimations made by all four datasets in spring, in June and May in particular, were higher than the mean observed data.

Table 4 shows the standard deviation of daily-observed precipitation data and the daily precipitation estimations made by the datasets in each month. The highest and the

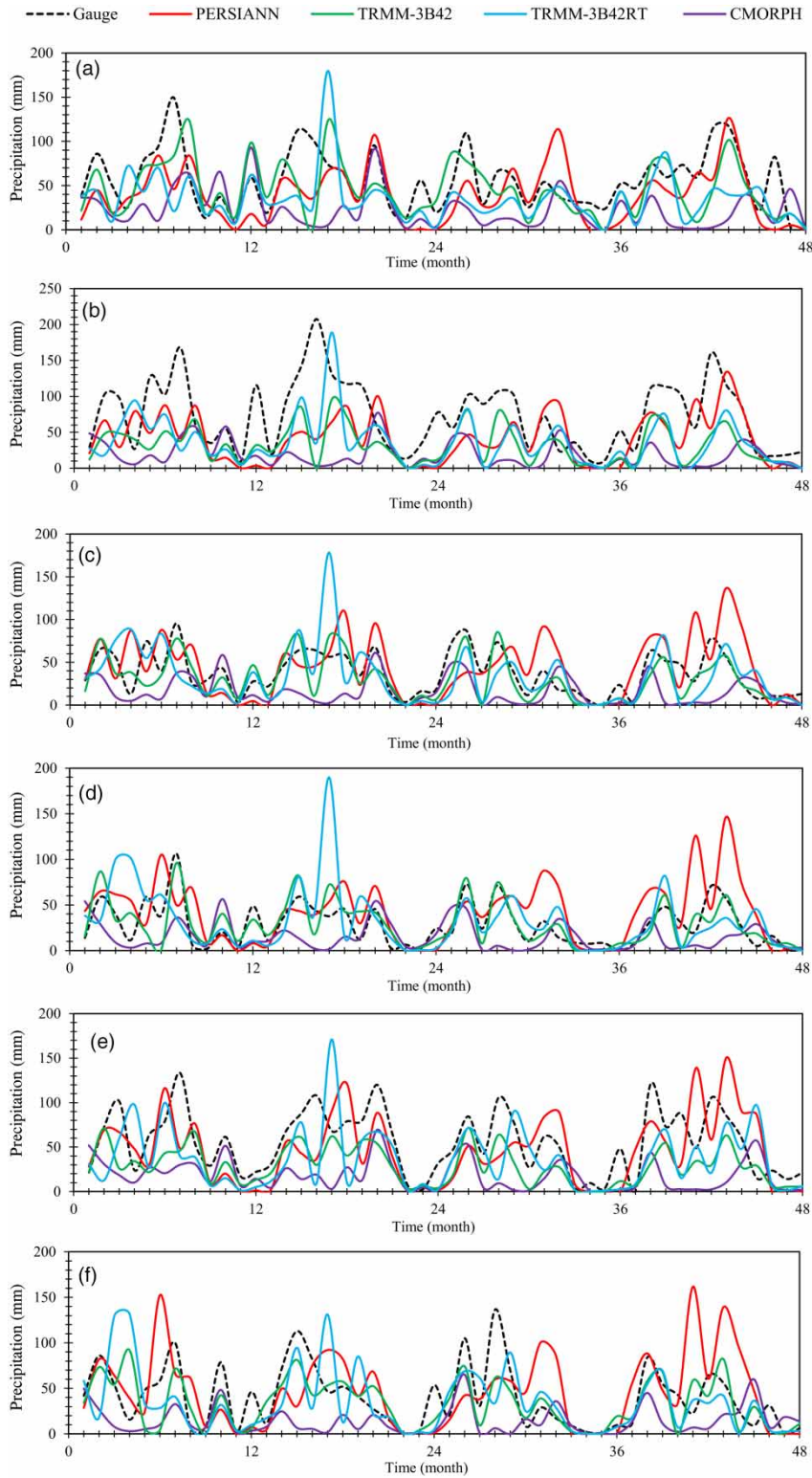


Figure 2 | Comparison of observed and estimated precipitation of PERSIANN, TRMM-3B42, TRMM-3B42RT, and CMORPH versus each other at monthly scale in Gorganrood basin: (a) Tamar, (b) Ramiyan, (c) Bahlakeh-Dashli, (d) Sadegorgan, (e) Ghaffar-Haji, and (f) Fazel-Abad.

Table 3 | The mean precipitation for daily-observed data and daily precipitation estimated by four datasets in each month

	Average											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tamar												
Observed data	2.225	2.258	2.586	2.367	2.133	0.754	1.294	0.766	1.060	1.283	2.750	2.096
PERSIANN	1.154	2.054	2.052	1.535	3.002	0.986	0.158	0.049	0.218	0.544	1.772	1.160
TRMM-3B42	0.822	2.078	1.710	2.044	2.172	0.844	0.718	0.458	1.420	1.328	2.507	1.749
TRMM-3B42RT	1.080	2.330	1.359	1.441	1.563	1.044	0.482	0.379	0.866	0.956	1.362	1.277
CMORPH	0.230	0.396	0.381	0.895	2.013	0.960	0.671	0.536	1.045	0.717	1.028	0.323
Ramiyan												
Observed data	1.658	1.675	1.621	1.589	1.113	0.565	0.504	0.238	0.661	1.063	2.171	1.750
PERSIANN	1.500	2.280	2.176	1.530	2.934	0.637	0.117	0.088	0.036	0.784	1.900	1.424
TRMM-3B42	1.045	1.528	1.493	1.467	1.355	0.412	0.385	0.205	0.472	0.622	2.064	1.705
TRMM-3B42RT	1.308	2.588	1.365	1.624	1.695	0.699	0.334	0.154	0.430	0.696	1.461	1.943
CMORPH	0.169	0.298	0.215	0.588	1.826	0.778	0.573	0.256	0.313	0.855	1.143	0.297
Bahlakeh-Dashli												
Observed data	1.658	1.675	1.621	1.589	1.113	0.565	0.504	0.238	0.661	1.063	2.171	1.750
PERSIANN	1.696	2.306	2.471	1.708	2.613	0.754	0.114	0.113	0.041	0.816	2.116	1.589
TRMM-3B42	1.180	1.377	1.322	1.524	1.158	0.449	0.316	0.222	0.495	0.560	2.043	1.455
TRMM-3B42RT	1.369	2.413	1.373	1.520	1.239	0.599	0.215	0.139	0.389	0.485	1.461	2.074
CMORPH	0.171	0.166	0.211	0.532	1.380	0.712	0.591	0.168	0.237	0.795	1.183	0.232
Sadegorgan												
Observed data	1.330	1.290	1.417	1.376	0.758	0.157	0.403	0.106	0.599	0.423	1.661	1.425
PERSIANN	1.460	2.232	2.359	1.559	2.294	0.639	0.135	0.015	0.065	0.953	1.901	1.703
TRMM-3B42	1.138	1.418	0.751	1.468	0.952	0.407	0.381	0.178	0.427	0.547	1.900	1.534
TRMM-3B42RT	1.530	2.697	1.133	1.331	0.961	0.586	0.270	0.075	0.132	0.655	1.135	2.363
CMORPH	0.114	0.128	0.235	0.546	1.016	0.699	0.615	0.120	0.264	0.984	1.104	0.239
Fazel-Abad												
Observed data	2.717	2.158	2.504	2.271	2.282	0.903	0.819	0.302	0.988	0.833	2.888	2.542
PERSIANN	1.289	2.630	2.996	1.798	2.769	1.151	0.162	0.063	0.022	0.780	2.125	1.635
TRMM-3B42	1.225	1.258	1.001	1.239	1.413	0.539	0.342	0.161	0.279	0.573	1.876	1.354
TRMM-3B42RT	1.140	2.817	1.567	1.307	1.568	1.264	0.190	0.101	0.126	0.743	1.343	2.119
CMORPH	0.342	0.283	0.445	0.608	1.357	0.966	0.501	0.104	0.171	0.824	1.278	0.358
Ghaffar-Haji												
Observed data	2.305	1.556	1.578	1.893	0.611	0.330	0.902	0.045	0.929	0.705	2.888	2.103
PERSIANN	1.730	2.802	2.940	1.852	2.511	0.605	0.215	0.012	0.070	0.868	2.183	1.505
TRMM-3B42	1.639	1.384	1.045	1.568	0.844	0.496	0.390	0.074	0.413	1.056	2.166	1.773
TRMM-3B42RT	1.674	2.427	0.866	1.347	0.471	0.479	0.306	0.072	0.208	1.169	1.443	2.956
CMORPH	0.141	0.117	0.456	0.509	0.732	0.678	0.468	0.186	0.163	0.798	1.347	0.224

lowest standard deviations of observed data were seen in November and August, respectively. In general terms, the standard deviation of the observed data was higher than

that of the estimated data in all stations, suggesting that the calculated precipitation data have a limited dispersion. The standard deviation of precipitation data estimated by

Table 4 | The standard deviation of daily-observed precipitation data and the daily precipitation estimations made by the datasets in each month

	STDEV											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tamar												
Observed data	5.357	5.611	5.631	6.146	6.993	2.085	4.036	2.945	5.046	5.486	8.043	4.915
PERSIANN	2.492	4.410	3.880	3.502	4.909	3.956	0.848	0.231	1.082	1.681	4.288	2.533
TRMM-3B42	3.459	7.396	4.852	7.006	5.716	2.622	2.005	1.533	6.656	5.448	7.358	6.399
TRMM-3B42RT	3.592	9.814	3.615	6.369	3.138	3.587	1.600	1.661	4.054	4.369	4.680	5.339
CMORPH	0.965	1.717	1.200	3.909	5.298	3.482	3.366	2.753	5.336	3.045	3.296	1.002
Ramiyan												
Observed data	4.741	5.460	4.276	4.412	3.256	1.948	2.573	1.073	2.552	4.510	5.896	4.956
PERSIANN	3.125	5.350	4.300	3.528	4.737	2.079	0.787	0.583	0.229	2.552	4.165	3.057
TRMM-3B42	4.502	6.061	5.182	4.900	4.684	1.384	1.557	0.732	1.786	2.380	6.362	5.018
TRMM-3B42RT	4.088	9.452	3.941	5.956	4.146	2.517	1.303	0.459	1.969	3.158	5.279	5.715
CMORPH	0.727	1.052	0.683	2.415	4.630	3.197	3.062	1.327	1.319	4.019	3.872	1.061
Bahlakeh-Dashli												
Observed data	4.741	5.460	4.276	4.412	3.256	1.948	2.573	1.073	2.552	4.510	5.896	4.956
PERSIANN	3.724	5.980	4.946	3.908	4.226	2.408	0.757	1.109	0.324	3.065	4.290	3.806
TRMM-3B42	4.345	5.473	4.987	5.065	3.305	1.662	1.392	1.154	2.533	2.585	6.335	4.914
TRMM-3B42RT	4.540	9.838	4.067	6.248	3.422	2.740	0.864	0.706	2.420	2.858	5.141	6.357
CMORPH	0.731	0.534	0.615	2.241	3.935	3.373	3.052	0.786	1.212	3.380	4.289	1.006
Sadegorgan												
Observed data	4.305	4.344	4.059	4.330	2.620	0.797	1.510	0.711	2.680	1.831	4.916	3.692
PERSIANN	3.476	6.727	4.948	3.652	3.525	2.088	1.270	0.168	0.511	3.949	4.275	3.485
TRMM-3B42	4.177	4.981	3.196	5.030	2.587	1.796	1.644	0.904	2.430	2.277	5.909	4.851
TRMM-3B42RT	5.038	9.907	3.549	5.934	2.720	2.952	1.247	0.395	0.753	3.543	3.955	7.037
CMORPH	0.401	0.438	0.651	2.117	3.115	2.807	2.852	0.478	1.244	4.798	3.739	0.961
Fazel-Abad												
Observed data	9.185	5.739	5.887	5.929	6.734	3.681	3.648	1.151	3.771	3.112	8.509	7.558
PERSIANN	2.731	7.082	5.607	4.198	4.279	4.064	1.025	0.481	0.154	2.838	4.432	3.387
TRMM-3B42	3.903	4.540	3.615	4.152	3.516	1.868	1.482	0.681	1.080	2.879	5.084	4.435
TRMM-3B42RT	4.463	10.271	4.953	5.782	3.907	5.668	0.891	0.389	0.478	3.982	4.182	5.939
CMORPH	1.155	0.689	1.004	2.224	3.947	3.482	2.767	0.479	0.739	3.979	4.313	1.002
Ghaffar-Haji												
Observed data	10.215	5.525	4.344	5.867	1.697	1.386	3.887	0.298	3.577	3.679	7.561	6.352
PERSIANN	3.976	9.180	6.340	4.359	4.477	2.418	1.573	0.115	0.601	2.815	4.531	3.375
TRMM-3B42	6.323	4.375	4.275	5.041	2.846	2.822	1.946	0.473	2.138	3.794	6.399	6.765
TRMM-3B42RT	6.299	6.873	2.769	4.726	1.862	2.302	1.524	0.412	0.995	4.550	5.337	8.301
CMORPH	0.556	0.439	1.279	2.025	1.951	2.321	2.555	0.733	0.608	4.416	4.878	0.942

CMORPH in December, January, February, March, and April for all stations was considerably lower than those of the observed data. Furthermore, the calculated values in

PERSIANN for standard deviation indicated that compared to other months, the estimated precipitation data in September had less dispersion. In fall, the highest and lowest

standard deviations for all datasets were seen in November and October, respectively.

Table 5 shows the mean values of evaluation criteria at daily and monthly scales. On a monthly scale, all datasets have underestimated at Tamar, Ramiyan, and Fazel-Abad stations. At Bahlakeh-Dashli and Ghaffar-Haji stations, PERSIANN has overestimated while other datasets have underestimated the precipitation data. At Sadegorgan, all datasets except for CMORPH have overestimated the precipitation data.

The correlation coefficient on a daily scale is trivial in the way that the highest and the lowest correlation values of the data provided by PERSIANN with the daily precipitation were 0.244 and 0.106 observed at Sadegorgan and

Ramiyan stations, respectively. As for TRMM-3B42V7, the highest and the lowest correlation coefficients were also observed at these two stations at 0.397 and 0.183, respectively. The lowest correlation values on a daily scale were observed in CMORPH and TRMM-3B42RT V7 datasets at Fazel-Abad station at 0.142 and 0.239, respectively. The highest correlation values of these two datasets were seen at Ghaffar-Haji station (0.231) and Bahlakeh-Dashli station (0.366).

As Table 6 illustrates, PERSIANN, TRMM-3B42V7, and TRMM-3B42RT V7 underestimated precipitation data in fall for all stations except Sadegorgan. PERSIANN overestimated in winter at Bahlakeh-Dashli, Sadegorgan, and Ghaffar-Haji stations while it underestimated at Tamar,

Table 5 | The comparison of the performance criteria for TRMM-3B42RT V7, CMORPH, PERSIANN, and TRMM-3B42V7 based on daily and monthly scales

Station	Criteria Scale	PCC		RMSE		BIAS		MAE	
		Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
Tamar	PERSIANN	0.218	0.293	5.843	5.259	-0.553	-0.556	2.343	2.441
	TRMM-3B42	0.287	0.307	6.487	5.712	-0.340	-0.344	<u>4.186</u>	2.458
	TRMM-3B42RT	0.177	0.294	6.516	5.613	-0.695	-0.698	1.377	2.450
	CMORPH	0.297	0.316	5.606	5.006	-1.074	-1.088	1.985	1.989
Ramiyan	PERSIANN	<u>0.106</u>	<u>0.221</u>	8.732	<u>7.611</u>	-1.062	-1.069	3.183	<u>3.201</u>
	TRMM-3B42	0.183	0.330	8.666	7.327	-1.360	<u>-1.368</u>	2.804	2.822
	TRMM-3B42RT	0.145	0.286	<u>8.928</u>	7.530	-1.229	-1.239	2.956	3.210
	CMORPH	0.243	0.334	8.263	7.027	<u>-1.789</u>	-1.809	2.450	2.463
Bahlakeh-Dashli	PERSIANN	0.199	0.272	4.983	4.351	0.184	0.186	2.029	2.042
	TRMM-3B42	0.337	0.404	4.632	3.919	-0.232	-0.234	1.553	1.563
	TRMM-3B42RT	0.228	0.384	5.431	4.372	-0.128	-0.128	1.732	2.042
	CMORPH	0.366	0.381	3.943	3.422	-0.694	-0.705	1.252	1.258
Sadegorgan	PERSIANN	0.244	0.344	4.472	3.701	0.417	0.420	1.722	1.733
	TRMM-3B42	0.397	0.386	3.961	3.313	0.015	0.012	1.324	1.331
	TRMM-3B42RT	0.210	0.381	5.116	3.955	0.126	0.128	1.523	1.730
	CMORPH	0.315	0.387	3.490	2.968	-0.419	-0.427	1.080	1.084
Fazel-Abad	PERSIANN	0.199	0.313	6.492	5.653	-0.308	-0.307	2.481	2.495
	TRMM-3B42	0.309	0.357	5.938	5.099	-0.852	-0.858	2.054	2.062
	TRMM-3B42RT	0.142	0.287	7.203	6.133	-0.603	-0.605	2.422	2.528
	CMORPH	0.239	0.319	5.968	5.118	-1.211	-1.222	1.922	1.929
Ghaffar-Haji	PERSIANN	0.191	0.292	6.221	5.033	0.204	0.206	2.247	2.262
	TRMM-3B42	0.328	0.362	5.656	4.657	-0.214	-0.217	1.810	1.821
	TRMM-3B42RT	0.231	0.348	6.189	4.920	-0.164	-0.165	1.925	2.222
	CMORPH	0.278	0.351	5.107	3.910	-0.816	-0.826	1.410	1.418

Table 6 | Evaluated criteria for PERSIANN, TRMM-3B42V7, TRMM-3B42RT V7, and CMORPH at seasonal scale

Season	Station	Dataset	PCC	RMSE	BIAS	MAE	Dataset	PCC	RMSE	BIAS	MAE
Autumn	Tamar	PERSIANN	0.353	5.813	-0.884	0.147	TRMM-3B42	0.358	6.803	-0.793	0.164
	Ramiyan		<u>0.159</u>	<u>9.539</u>	<u>-1.367</u>	<u>0.218</u>		<u>0.311</u>	<u>9.096</u>	-1.390	<u>0.189</u>
	Bahlakeh-Dashli		0.232	5.657	-0.154	0.151		0.392	5.283	-0.178	0.111
	Sadegoran		0.285	4.421	0.349	0.122		0.503	3.794	0.255	0.088
	Fazel-Abad		0.347	6.593	-0.574	0.165		0.381	6.424	-0.698	0.139
	Ghaffar-Haji		0.186	6.492	-0.449	0.169		0.371	6.531	-0.463	0.155
	Tamar	TRMM-3B42RT	0.283	6.862	-0.822	0.153	CMORPH	0.432	5.771	-1.329	0.123
	Ramiyan		<u>0.251</u>	<u>9.260</u>	<u>-1.335</u>	<u>0.189</u>		<u>0.317</u>	<u>8.923</u>	<u>-1.935</u>	0.160
	Bahlakeh-Dashli		0.310	5.905	-0.321	0.129		0.399	4.675	-0.905	0.092
	Sadegoran		0.396	4.777	0.198	0.103		0.398	3.724	-0.388	0.078
	Fazel-Abad		0.328	6.930	-0.660	0.149		0.385	6.250	-1.242	<u>0.124</u>
	Ghaffar-Haji		0.304	7.153	-0.049	0.168		0.355	5.552	-1.082	0.116
Winter	Tamar	PERSIANN	0.157	6.118	-0.604	0.223	TRMM-3B42	0.109	7.201	-0.793	0.194
	Ramiyan		<u>0.124</u>	<u>11.350</u>	<u>-1.587</u>	<u>0.281</u>		<u>0.007</u>	<u>12.130</u>	<u>-1.864</u>	<u>0.269</u>
	Bahlakeh-Dashli		0.177	6.307	0.503	0.181		0.173	6.141	0.170	0.142
	Sadegoran		0.237	5.907	0.668	0.155		0.150	5.315	0.313	0.122
	Fazel-Abad		0.193	8.189	-0.162	0.223		0.272	7.132	-0.432	0.168
	Ghaffar-Haji		0.256	8.582	0.491	0.199		0.273	7.032	-0.194	0.152
	Tamar	TRMM-3B42RT	0.101	7.702	-0.758	0.200	CMORPH	0.157	5.539	-1.973	0.139
	Ramiyan		-0.004	<u>12.594</u>	<u>-1.801</u>	<u>0.290</u>		0.074	<u>11.117</u>	<u>-3.273</u>	<u>0.214</u>
	Bahlakeh-Dashli		0.089	7.430	0.039	0.167		0.099	4.820	-1.437	0.098
	Sadegoran		0.064	7.247	0.415	0.160		0.067	4.186	-1.159	0.080
	Fazel-Abad		-0.002	9.975	-0.632	0.232		0.154	7.062	-2.070	0.151
	Ghaffar-Haji		0.076	8.347	-0.173	0.182		<u>0.058</u>	6.460	-1.548	0.112
Spring	Tamar	PERSIANN	0.171	6.793	0.161	0.204	TRMM-3B42	0.312	6.233	0.332	0.168
	Ramiyan		<u>0.041</u>	<u>7.601</u>	0.219	<u>0.221</u>		<u>0.188</u>	<u>6.941</u>	0.291	<u>0.169</u>
	Bahlakeh-Dashli		0.261	4.491	0.770	0.145		0.331	3.769	0.764	0.097
	Sadegoran		0.208	4.450	<u>0.957</u>	0.134		0.258	3.941	<u>0.965</u>	0.089
	Fazel-Abad		0.258	6.306	0.122	0.185		0.266	5.667	0.091	0.153
	Ghaffar-Haji		0.199	5.067	0.498	0.155		0.416	2.889	0.332	0.095
	Tamar	TRMM-3B42RT	0.290	5.811	-0.694	0.151	CMORPH	0.260	6.148	-0.671	0.150
	Ramiyan		<u>0.183</u>	<u>6.949</u>	<u>-0.855</u>	<u>0.181</u>		0.181	<u>6.989</u>	<u>-1.087</u>	0.166
	Bahlakeh-Dashli		0.359	3.998	-0.022	0.101		0.406	3.583	-0.277	0.089
	Sadegoran		0.239	4.176	0.079	0.090		0.274	3.608	-0.080	0.079
	Fazel-Abad		0.237	6.521	-0.526	0.173		<u>0.137</u>	6.094	-1.045	<u>0.580</u>
	Ghaffar-Haji		0.405	4.115	-0.017	0.086		0.283	3.368	-0.253	0.078
Summer	Tamar	PERSIANN	<u>0.289</u>	3.991	0.899	0.069	TRMM-3B42	<u>0.376</u>	4.309	-0.581	<u>0.086</u>
	Ramiyan		0.349	<u>4.873</u>	<u>-1.107</u>	<u>0.076</u>		0.543	<u>4.367</u>	<u>-0.961</u>	0.074
	Bahlakeh-Dashli		0.458	2.048	-0.379	0.030		0.511	2.059	-0.195	0.039
	Sadegoran		0.573	1.411	-0.298	0.020		0.525	1.662	-0.136	0.032

(continued)

Table 6 | continued

Season	Station	Dataset	PCC	RMSE	BIAS	MAE	Dataset	PCC	RMSE	BIAS	MAE
	Fazel-Abad		0.415	2.997	−0.621	0.047		0.382	3.062	−0.533	0.054
	Ghaffar-Haji		0.464	2.571	−0.548	0.039		0.416	2.889	−0.096	0.050
	Tamar	TRMM-3B42RT	<u>0.333</u>	3.903	−0.462	<u>0.079</u>	CMORPH	<u>0.310</u>	4.346	−0.301	<u>0.083</u>
	Ramiyan		0.418	<u>4.636</u>	− <u>0.857</u>	0.078		0.506	<u>4.356</u>	− <u>0.789</u>	0.071
	Bahlakeh-Dashli		0.479	2.066	−0.217	0.034		0.561	1.823	− 0.136	0.033
	Sadegoran		0.505	1.579	− 0.204	0.027		0.504	1.762	−0.037	0.032
	Fazel-Abad		0.360	3.076	−0.549	0.050		0.485	2.883	−0.439	0.048
	Ghaffar-Haji		0.442	2.571	−0.415	0.045		0.466	2.594	−0.339	0.045

Ramiyan, and Fazel-Abad stations. TRMM-3B42RT V7 slightly overestimated at Sadegorgan in the winter. CMORPH and TRMM-3B42V7 underestimated in winter in all stations. While PERSIANN overestimated in all stations except for Ramiyan in spring, TRMM-3B42RT V7 overestimated at Ghaffar-Haji, Bahlakeh-Dashli, and Sadegorgan stations and underestimated at Tamar, Ramiyan, and Fazel-Abad stations. TRMM-3B42V7 overestimated at Sadegorgan and Ghaffar-Haji stations while it underestimated at other stations. CMORPH also underestimated in all stations except Sadegorgan. TRMM-3B42RT V7, TRMM-3B42V7, and CMORPH underestimated in all stations in the summer and PERSIANN also underestimated in all stations except Bahlakeh-Dashli. Generally, it can be said that the highest correlation between the precipitation data collected from the datasets and the observation data was seen in the summer data while the lowest one for all datasets was detected in the winter data. Furthermore, it can be said that PERSIANN shows the best correlation in winter, while in other seasons TRMM-3B42V7 enjoys the best correlation with the observation data.

A comparison of the biases shows that TRMM-3B42V7 and TRMM-3B42RT V7 provided reasonable estimations at Sadegorgan, Bahlakeh-Dashli, and Ghaffar-Haji stations. By comparing the biases obtained from six stations by PERSIANN, it could be inferred that this algorithm often overestimates the precipitation volume in spring, in May in particular, while it underestimates the precipitation in the summer.

RMSE and MAE criteria were used to ensure the accuracy of the estimations. High values of RMSE and MAE in the winter indicate that no reasonable estimation was

made by datasets in this season while the lowest values of RMSE and MAE were observed in the summer at the studied stations. Regarding all four datasets, the lowest and highest values of RMSE were detected at Sadegorgan and Ramiyan stations, respectively. In all seasons, the lowest value of MAE was observed at Sadegorgan station. Thus, it could be said that all datasets had a good performance at Sadegorgan station, which is located at a low altitude (12 m), while they could not make proper estimations at Ramiyan station, which is located at a high altitude (200 m). In fact, rainfall estimations are exposed to many factors that may affect precipitation. According to Gottschalck *et al.* (2005), Hong *et al.* (2007), and Romilly & Gebremichael (2011), factors including precipitation volume, seasonal precipitation patterns, precipitation regime, and the region's properties affect the precipitation estimations made by TRMM-3B42, TRMM3B42RT, and PERSIANN datasets. Elevation has an undeniable effect on the precipitation estimation. Hong *et al.* (2007) claimed that the bias of PERSIANN is height-dependent in a way that it underestimates light precipitation at high elevations while it overestimates heavy precipitation at low elevations. For example, PERSIANN in Ghaffar-Haji and Ramiyan stations, which have an elevation of 200 and 210 meters above sea level, respectively, has underestimated light precipitations. In comparison, TRMM at high elevation regions tends to underestimate. On a daily scale, bias values in Tamar are −0.340 and −0.695, in Ramiyan are −1.360 and −1.229, and in Ghaffar-Haji are −0.214 and −0.164 for TRMM-3B42V7 and TRMM-3B42RT V7, respectively. On the contrary, bias values at stations with low elevation such as Bahlakeh-Dashli are −0.232 and −0.128 and in Sadegorgan

are 0.015 and 0.126 for TRMM-3B42 and TRMM3B42RT, respectively. CMORPH in all stations is underestimated but in high elevation stations like Tamar, Ramiyan, and Ghaffar-Haji, as bias on a daily scale is -1.074 , -1.789 , and -0.816 , respectively, the precipitation has been estimated more reliably. Table 6 summarizes evaluation statistics in all six stations for all the seasons studied. The highest values are in bold and the lowest values are underlined in this table.

Three indices of CSI, FAR, and POD were examined to determine the limitations in precipitation detection faced by satellite-based precipitation estimation algorithms. The highest values of CSI and POD at 0.593 and 0.275, respectively, belonged to PERSIANN at Fazel-Abad station while the lowest value of FAR belonged to TRMM-3B42V7 at Sadegorgan station. High values of POD indicate that the datasets have detected rainy days properly while high values of FAR suggest that the number of non-rainy days detected by datasets does not show a reasonable conformity with the number observed at the stations. CSI of approximately 0.3 also reveals that both datasets at the stations under study have been inefficient in differentiating rainy days from non-rainy ones. Figure 3 shows the values of these three indices at studied stations. CMOPRH possesses a POD ranging from 0.42 to 0.57, a FAR from 0.64 to 0.75, and a CSI from 0.21 to 0.25 while TRMM-3B42RT V7 has a POD ranging from 0.27 to 0.33, a FAR ranging from 0.61 to 0.72, and a CSI ranging from 0.17 to 0.21. It can be inferred from Figure 3 that the four studied datasets have a low performance in accurately estimating the number of wet and dry days.

In their analysis of meteorological drought, Sahoo et al. (2015) applied information provided by TRMM-3B42V6, TRMM-3B42V7, and TRMM-3B42RT V7 and found that comparing them with other TRMM products TRMM-3B42V7 shows the best performance. These results are consistent with those obtained in the present study. Romilly & Gebremichael (2011) studied the precipitation data over Utopia river basin provided by CMORPH and concluded that precipitations were underestimated in winter while overestimated in summer. However, it was revealed in the present study that both datasets have underestimated precipitations over Gorganrood basin. Cohen Liechti et al. (2012) analyzed precipitation data collected from

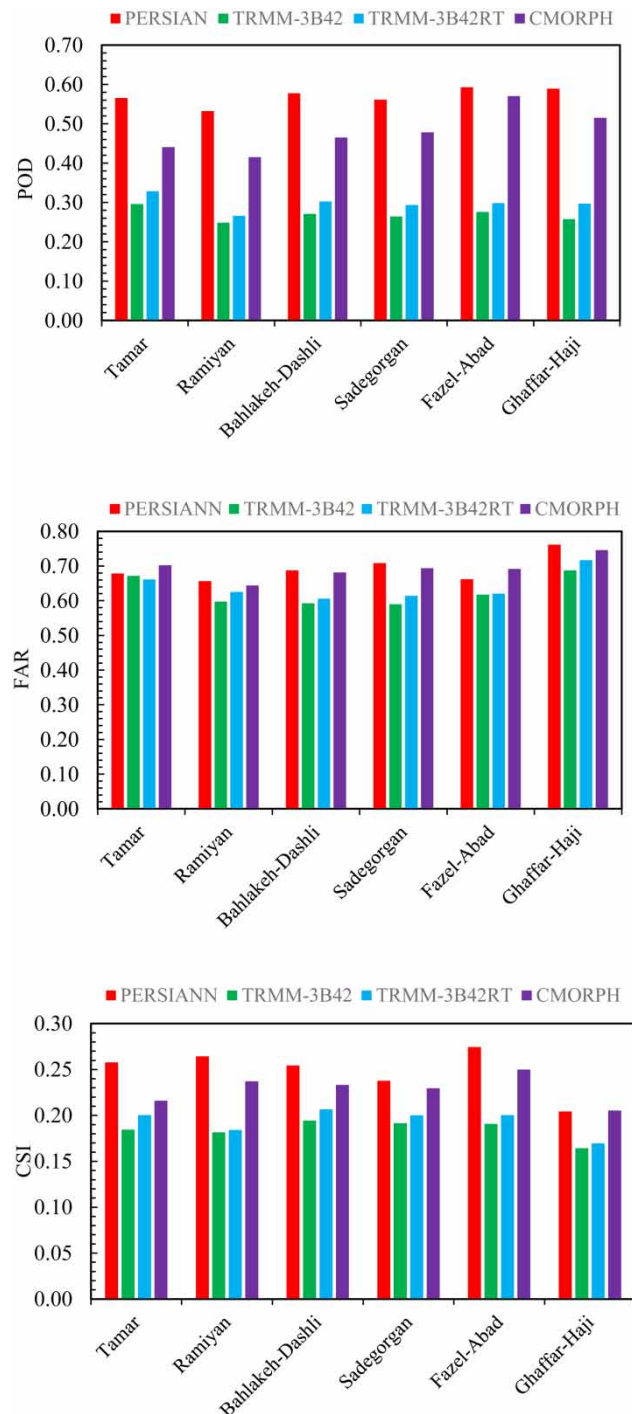


Figure 3 | Average of POD, FAR, and CSI criteria.

CMORPH and TRMM-3B42 in Africa and concluded that both datasets have overestimated precipitation, compared to observed precipitation. It is contrary to the results

obtained in the present study over the Gorganrood basin. Furthermore, the results revealed that precipitation estimations made through microwaves are generally better than those provided through infrared waves. TRMM-3B42 shows a better conformity with the observation data because of the corrections made at observation stations. It is in line with the results obtained by Gao & Liu (2013), Milewski *et al.* (2015), and Moazami *et al.* (2016).

As mentioned previously, Moazami *et al.* (2013) used 47 precipitation events and concluded that PERSIANN made acceptable precipitation estimations in surrounding areas of the Alborz Mountains. However, Moazami *et al.* (2016) conducted a study on a daily scale on the data provided by four datasets and reported that PERSIANN and TRMM-3B42RT overestimate the precipitation in northern parts of Iran and in the Alborz Mountains. Darand *et al.* (2017) concluded that both TMPA products delivered an appropriate correlation with observation stations in terms of precipitation estimation; however, they tend to underestimate the precipitation in northern parts of Iran. The results obtained from the present study indicated that the variability of datasets' performance occurs on the smaller spatial scale and they deliver various performances in different regions of a basin. Therefore, they should be used more cautiously and assessed specifically for the given area.

It is worth mentioning that performing this research in developing countries always encounters limitations such as the length of time series of data and the number of rain gauges. Moreover, the overall assessment requires further analysis of the datasets' performance based on high-density rain gauge networks relying on long-term statistics that cannot be achieved in the developing countries. However, all available data series used and analyzed for Gorganrood basin in this study were without any gaps. Therefore, this approach is suggested to be evaluated in areas having more *in-situ* data.

CONCLUSION

Knowledge about the exact precipitation volume plays a crucial role in water resources management. In this regard, due to lack of a spatial distribution of rain gauge stations and delays in access, it is necessary to find proper ways of

making precipitation estimations. Making use of satellite-driven data could be considered as one of the most applicable methods in this regard. The present study aimed to assess the accuracy of precipitation data provided by PERSIANN, TRMM-3B42V7, TRMM-3B42RT V7, and CMORPH datasets on daily, monthly, and seasonal scales. Thus, the precipitation data at six stations in the Gorganrood basin were used over a period of 2003–2007. Having analyzed the accuracy of these datasets, it was concluded that TRMM-3B42V7 made the best estimations over Gorganrood basin. Furthermore, estimations made during hot seasons (summer in particular) enjoyed a higher accuracy while estimations made during cold seasons (winter in particular) were not accurate enough. The reason is that the ice existing in the air during cold seasons in low-lying areas is recognized as precipitation by satellites' microwave sensors and thus leads to overestimation of precipitation. The highest correlations belonged to Sadegorgan, Fazel-Abad, and Bahlakeh-Dashli stations, that are located at a lower altitude compared to other stations. The results obtained from daily, monthly, and seasonal analyses showed that the data provided by satellite data on monthly and seasonal scales are more reliable. Hence, it could be concluded that the data provided by satellites could be an alternative to observation precipitations on monthly scales or beyond. Overall, in this study, TRMM-3B42V7 performed better than the other datasets.

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