University of Birjand
Water Harvesting Research Vol. 7, No. 2, Autumn & Winter 2024, Original paper p. 175-193
10.22077/JWHR.2024.7930.1146

Comparative Analysis of the Performance of Gridded Precipitation Products Over Iran

Ali Gorjizade[a&*], Ali Moridi[b]

[a]Assistant Professor, Department of Hydrology and Water Resources, Faculty of Water and Environmental Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran
[b]Associate Professor, Department of Water and Environmental Engineering, Faculty of Civil, Shahid Beheshti University, Tehran,Iran.

*Corresponding Author, E-mail address: a.gorjizadeh@scu.ac.ir
Received: 22 July 2024/ **Revised**: 12 August 2024/ **Accepted**: 26 August 2024

Abstract

Precipitation provides the most crucial input for hydrological modeling. Rainfall Estimation from rain gauges is the most common and traditional method have been used widely to measure rainfall at catchment scales. In many developing countries, a dense rain-gauge grid is generally unavailable, suffering from a sparse station distribution at high altitudes or in rural areas. Recent advances in remote sensing technologies have provided precipitation data with high spatial and temporal resolution. Accurate information on the benefits and deficits of these datasets is often lacking, especially over Iran. This study aims to provides a comprehensive evaluation of a good variety of state-of-the art precipitation datasets against 41 synoptic gauge observations, as a reference in the period of 2013 to 2020 over Iran. In particular, the performance of ERA5 as reanalysis, PERSIANN as satellite based, CHIRPS and PERSIANN-CDR as satellite-gauge precipitation products at daily, monthly and annual scale has been assessed. Statistical metrics, precipitation detection capability and false alarm ratio have been used to measure the accuracy of each product over spatial and time scales. The result show that over annual and daily scale PERSIANN-CDR product outperforms, and over daily scale PERSIANN-CDR and CHIRPS products perform well compared to ERA5 and PERSIANN products. The CHIRPS and PERSIANN-CDR products deliver reliable and useful ability of precipitation detection comparing to other products.
Keywords: Evaluation indicators, Gridded datasets, Iran, Precipitation estimation.

1. Introduction

Precipitation is a major component of the hydrological cycle and a key environmental meteorology parameter of the environment (Li and Shao, 2010), it is known to be the primary input for most hydrological system (Duan et al., 2019). Rain gauges are considered the traditional method for measuring rainfall. They have been used historically to provide rainfall quantities and rates at a single point in space, and then generalized to a surface area. A dense rain-gauge grid is generally unavailable even in developing countries, particularly in mountainous areas where majority of rainfall takes place, and it often includes incorrect data or large gaps. Besides, rain gauge measurements are costly for data monitoring and data maintenance (Bitew and Gebremichael, 2011). Although rain gauge observations still show the most accurate measurement, the sparse and heterogeneous spatial distribution of rain gauges often results in inaccurate precipitation pattern. Hence, it is difficult to provide spatial data of precipitation with high resolution from traditional rainfall observations obtained from rain gauge stations (Wilheit, 1986).

There are some problems associated with the rain-gauge and radars measurement; Ground rain-gauge have various problems such as high data deficits, wind effects, low number of stations and etc. (Maggioni et al., 2016). Also, ground-based radar measurements are influenced by the signal weakness, the dispersion of the return surface and the uncertainty of the reflective precipitation relationship (Einfalt et al., 2004). In the recent decades satellite precipitations have been recognized as a major approach to precipitation measurement. Remote sensing data provide a new way of identifying the spatial and temporal variation of precipitation with high precision (Xie and Xiong, 2011). Compare to the ground measurements such as rain-gauge and radars, satellite data are capable of covering the precipitation systems in a semi-global scale, regardless of mountainous and oceanic terrain.

A large number of precipitation-based satellite estimations and open-source analysis data with high spatial and temporal resolution is available in free and can be used to complete the rain-gauge data or even can be replaced with these types of measurements. (Fujihara et al., 2014).

Generally, precipitation data can be categorized as the 4 following groups (Gorjizade et al., 2019):

A- Rain-gauge data, based on the only observations from rain-gauge station, generated by using various interpolation methods. For instance, the monthly rainfall data of GPCC and CPC, are often available on a spatial scale larger than 0.5 degrees.

B- Reanalysis data, based on reanalysis of historical data, by using atmospheric or numerical models of predicting weather. Inputs to these models are combination of satellite data and atmospheric observation at a specific location, for instance, NCEP-NCAR and ECMWF

C- Satellite based data, by using infrared waves, microwaves or combination of those. For instance, TMPA 3B42 RT V7

D- Satellite-Rain gauge data, based on combination of satellite and rain-gauge data. In this case biases of precipitation data reduced significantly. For instance, PERSIANN, CMORPH. The data for this group is available on a spatial scale of 0.25 degrees or less

At locations where ground measurement does not exist, data processing by using one of the above-mentioned methods can be used to measure the precipitation values at a faster rate and more appropriate time. Over the past decades, as a result of many efforts done to produce satellite data, precipitation data are widely available at temporal and spatial scales Tapiador et al. (2012), and their values vary from region to region.

Poméon et al. (2017) evaluated remote sensing and reanalysis data in the West African region, by comparing with the available rain-gauge data; The results indicate that satellites data which use a multitude of input data, namely infrared and microwave satellite data, as well as observations from rain gauges, outperforms compared to others.

Alijanian et al. (2017) evaluated precipitation pattern over Iran, by comparing products of CMORPH ،PERSIANN-CDR ، PERSIANN ،TRMM ،MSWEP. Results indicate higher ability of PERSIANN-CDR to estimate precipitation. Tan and Santo (2018) compared GPM, IMERG, TMPA-3B42 and PERSIANN-CDR networked data in Malaysia. The results, using statistical indices, indicate all data except from PERSIANN-CDR are sufficiently appropriate. Gao et al. (2018) compared two monthly satellite data sets with high resolution in Xinjiang -China. The results show that, on a monthly and annual basis, CHIRPS presents more accurate data than the PERSIANN-CDR. Gorjizade et al. (2020) evaluate the accuracy of ERA-Interim, P-CCS and TRMM at Lidnek- Iran. Results show ERA-Interim has the best performance in the region. Wang et al. (2021) evaluated precipitation products in Yang-Tse river catchment. Results indicate that GLDAS products do not have appropriate performance. Rao et al. (2024) evaluates 11 sets of gridded precipitation products over the Qinghai-Tibet Plateau, the results of their research showed that the CMFD precipitation product performed better than other products at meteorological sites from the National Meteorological Information Center (NMIC), with average daily and monthly correlation coefficients (CCs) of 0.55 and 0.94 and root mean square errors (RMSEs) of 3.78 and 0.44 mm/d, respectively

In the table 1, the details of some research work carried out in world and the achieved results are presented.

Since weather stations in Iran are dispersed and have incomplete information, evaluating the performance of satellite precipitation data in regions such as Iran of which considerable parts of area recognized as arid or semi-arid regions, are very necessary. The comparison focuses on the identification of which product is the most accurate and that provides reliable rainfall pattern.

It can be also useful to improve the performance of future versions of satellite precipitation data. This study aims to evaluate consistency of ERA5, CHRIPS, PERSIANN and PERSIANN-CDR precipitation products, which includes reanalysis, satellite based and satellite- rain gauge data, with local measurement of precipitation in synoptic station across the Iran.

Table 1. Comparison of evaluation studies at daily scale estimation.

Reference	Study area	Period	CC	RMSE (mm/day)	POD
Rao et al. (2024)	over the Qinghai-Tibet Plateau	2010-2017	0.55	3.78	-
Gomis-Cebolla et al. (2023)	over Spain	1951–2020	0.5-0.9	2-8	-
Gorjizade et al. (2022)	Maroon Dam basin	2003-2014	0.5	5.5	0.42
Gorjizade et al. (2020)	Idenak, Iran	2003-2014	0.36-0.73	4.21-9.83	0.493
Tan and Santo (2018b)	Malaysia	12 March 2014 to 29 February 2016	0.5–0.6	12.94–14.93	0.86–0.89
Wang et al. (2017)	Mekong River Basin, Thailand	April to January 2016	0.58	-	0.73
Yuan et al. (2017)	Chindwin River Basin, Myanmar	April to January 2016	0.22–0.32	9.1–24.7	0.12–0.21
Tan and Duan (2017)	Singapore	April 2014 to January 2016	0.53	11.83	0.78
Kim et al. (2017)	Korea, Japan	March to August 2014	0.53–0.68	6.68–23.41	0.6–0.73
Tang et al. (2016b)	Ganjiang River Basin, China	May to September 2014	0.62–0.9	4.44–13.09	-
Tang et al. (2016a)	China	April to December 2014	0.96	0.5	0.91
Sharifi et al. (2016)	Iran	March 2014 to February 2015	0.4–0.52	6.38–19.41	0.46–0.7
Sahlu et al. (2016)	Blue Nile Basin	May to October 2014	0.55	-	0.87
Ning et al. (2016)	China	April 2014 to November 2015	0.68	6.43	0.79
Guo et al. (2016)	China	12 March 2014 to 31 March 2015	0.93	0.56	-

Updated and modified from the Table 9 adopted in Tan and Santo (2018b).

It is notable that gauge observation is still the main and most reliable source of rainfall data. Hence, comparing the results of satellite precipitation products with ground observation is thoroughly fair and expected to leads us to the reliable results. The main purposes of this study can be named as follows:

1- Spatio-temporal investigation of quantitative accuracy of satellite precipitation products (SPP) on daily, monthly and annual scales.
2- Quantitative investigation of SPP accuracy in prediction of precipitation occurrence for various intensities, in 9 regions across Iran.
3- Spatial analysis of existing errors in prediction of precipitation occurrence, in 9 regions across Iran.

This study will help scientists working over Iran to use reliable and accurate gridded rainfall estimate products to monitor and assess meteorological hazards.

2. Materials and Methods

2.1. Study area

Iran (25°-40° N, 45°-60° E) is located in the world’s dry belt, with annual precipitation of 250mm or a third of the global average, ranging from 50mm in the deserts to 1600mm on the Caspian coast. Iran is one of the most mountainous countries bordering the Gulf of Oman, the Persian Gulf, and the Caspian Sea. Sixty percent of Iran is covered by mountains. The central parts of the country comprise two dry deserts: the Dasht-e-Kavir and the Dasht-e-Lut. The country’s topography is dominated by two mountain ranges; The Alborz, a major mountain range along the Caspian Sea, located in northern Iran on the Iranian Plateau, with a maximum altitude of approximately 5000 m, and the Zagros Mountains cross the country from northwest to southeast, reaches a maximum altitude of approximately 3500m. These two ranges play an influential role in determining the amount and distribution of rainfall over the country. Maximum precipitation falls on the Alborz and Zagros slopes, facing north and west, respectively, where the mean annual rainfall is more than 1200 mm. while considering the changes in topography, precipitation varies drastically to less than 50 mm or 100 mm in other regions. Fifty-two percent of precipitation falls on 25% of the country's land area; resulting in a lack of water resources and potential water crises in the near future.

This study used data sets from different sources including in situ observation data, remotely sensed data, and reanalysis data. Herein, the station data were used to evaluate the accuracy of the satellite-based, satellite-gauge rainfall products and reanalysis data.

2.2. Synoptic rain gauge-network data of Iran Meteorological Organization

The synoptic gauge data have passed Iran Meteorological Organization quality control procedures such as checking location (latitude, longitude and elevation), consistency with other meteorological parameters, tests for data homogeneity, filling data gaps. In this study, precipitation data of 41 synoptic weather stations in the period from 2012 to 2019 were used. It should be noted that the synoptic stations are more reliable because of occurring less human error in the process of observation Fallah et al. (2020). This study focuses on the time period 2012–2019 since, according to recorded stations 'time series, the overall availability of the station measurements at daily, monthly and annual scales is highest in these years. Figure 1 shows the spatial distribution of the above-mentioned synoptic gauge stations over Iran.

While the validation approach utilizing 41 synoptic stations provides a robust framework for assessing the precipitation products, there are inherent limitations related to the spatial distribution of these stations that must be recognized. These factors may influence the overall results and interpretations of the study:

Uneven Geographic Coverage:

The synoptic stations are not uniformly distributed across Iran, with certain areas, particularly remote and mountainous regions, having fewer stations. This uneven coverage can lead to biases in the validation process, as local precipitation events in these underrepresented areas may not be adequately captured.

Influence of Topography:

The complex topography of Iran can significantly affect precipitation patterns. Areas with high elevation and rugged terrain may experience localized weather phenomena that are difficult to measure accurately with ground stations. As a result, the representativeness of the synoptic stations in these regions may be limited.

Operational Challenges:

Some synoptic stations may face operational issues, particularly in remote locations, leading to incomplete or intermittent data availability. This can introduce gaps in the dataset, affecting the reliability of the validation results.

Seasonal and Temporal Variability:

Validation results may be impacted by temporal variations in station operation, especially during peak precipitation seasons. If certain stations are not consistently operational during critical periods, it could skew the validation and reduce confidence in the findings.

2.3. Precipitation Dataset

In this study, the data series of ERA5, CHIRPS, PERSIANN and PERSIANN-CDR were considered to evaluate precipitation data. The selection of ERA5, CHIRPS, PERSIANN, and PERSIANN-CDR was based on several criteria relevant to our study in the context of Iran:

1. Data Availability and Coverage: These datasets are widely accessible and provide comprehensive spatial and temporal coverage for the study area in Iran, making them suitable for our analysis.

2. Validation and Credibility: Each of these products has been subject to validation studies in similar climates. For instance, ERA5, as a reanalysis product, combines various observational data sources, while CHIRPS has proven effective for monitoring precipitation in arid and semi-arid regions like Iran.

3. Diversity of Methodologies: By including both satellite-derived (CHIRPS, PERSIANN) and reanalysis (ERA5) products, we aimed to capture a range of methodologies and their reliability in measuring precipitation in the region. This diversity allows for a more robust comparison and enhances the overall analysis.

4. Relevance to Local Studies: Literature in the field has shown that these datasets perform satisfactorily in Persian Gulf countries and are relevant for water resource management and agricultural planning, which are critical issues in Iran. The information of these products is given in Table 2. In this section, a general overview and profile of the data series are presented.

ID	NAME	long	lat	ELEVATION
1	11-044	57.36	37.29	1810
2	11-902	55.29	37.93	80
3	17-222	48.03	35.29	1789
4	21-163	47.2	33.39	880
5	22-010	49.88	31.63	840
6	22-058	49.72	30.23	14
7	24-020	53.33	28.37	700
8	26-036	54.31	27.64	831
9	29-016	61.24	26.63	885
10	29-107	59.64	26.58	721
11	36-002	46.53	36.42	1823
12	38-001	45.6	38.23	1630
13	41-062	49	34.86	1625
14	41-101	51.15	36.03	1790
15	41-211	51.65	35.87	1950
16	42-007	50.75	32.73	2173
17	42-112	54.13	31.49	2451
18	42-203	55.75	29.87	2408
19	42-528	51.62	32.81	1582
20	43-134	52.47	30.29	2046
21	44-008	57.14	28.72	1734
22	45-004	59.05	28.65	610
23	45-201	59.99	29.86	1123
24	46-010	52.8	32.97	1910
25	47-063	56.83	37.25	1157
26	47-108	54.41	34.05	981
27	47-110	55.03	35.43	826
28	47-126	57.41	35.18	866
29	47-908	56.58	36.68	1250
30	52-002	62.35	27.62	1335
31	64-022	60.53	36.16	917
32	40704	47.07	38.43	1391
33	40726	45.72	36.75	1351.8
34	40743	57.65	36.21	962
35	40765	45.87	34.45	545
36	40782	48.28	33.44	1147.8
37	40791	56.95	33.6	711
38	40809	59.28	32.89	1491
39	40811	48.74	31.34	22.5
40	40827	60.03	31.54	1188
41	40829	61.54	31.09	489.2

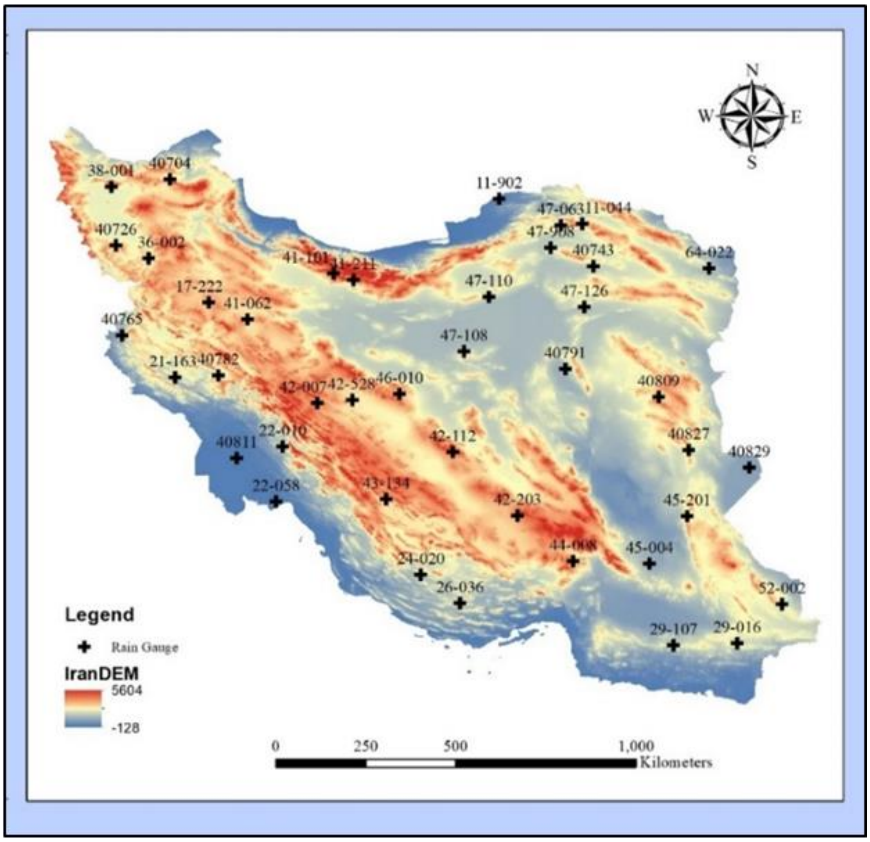

Fig. 1. Spatial distribution of selected synoptic weather stations over Iran

Table 2. Summary of gridded precipitation products to be evaluated in this study

Datasets Name	Coverage	Spatial resolution	Temporal resolution	Category	Time period
ERA5	Global	0.25° × 0.25°	daily	Reanalysis	2012-2019
CHIRPS	60°N-60°S	0.05° × 0.05°	daily	Satelite-Gague	
PERSIANN	60°N-60°S	0.25° × 0.25°	daily	Satelite	
PERSIANN-CDR	60°N-60°S	0.25° × 0.25°	daily	Satelite-Gague	

2.3.1. ERA5

ERA5 is a new reanalysis data set (fifth generation) developed by the European Center for (ECMWF). The most significant upgrades of this dataset, in comparison with ERA-Interim are a better spatial network (31 km vs. 79 km), higher temporal resolution (one hour versus 3 hours), 12 higher number of vertical surfaces (137 vs. 60), a new NWP model (IFS_Cycle_41r2) and an increase in the amount of data for data assimilation (Urraca et al., 2018). The dataset covers data from 1950 to the near present time. In this study, daily precipitation data of ERA5 with a spatial resolution of 0.25 ° was used, and the data was extracted by using ECMWF_Web_API. The instructions for downloading the data is described in the following link.

https://software.ecmwf.int/wiki/display/CKB/How+to+download+ERA5data+via+the+ECMWF+Web+API.

2.3.2. CHIRPS

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset builds on previous approaches to 'smart' interpolation techniques and high resolution, long period of recorded precipitation estimates based on infrared Cold Cloud Duration (CCD) observations. CHIRPS data are available in 6 hours to 3 months.

CHIRPS is a quasi-global rainfall data set with relatively high spatial resolution (°0.05 × °0.05) and long-term temporal coverage from 1981 to near real time (Funk et al., 2015), whose processing chain blends satellite and gauge rainfall estimates. The latest version of the data (second version) can be downloaded through the following link. CHIRPS used to monitor drought and climate changes in a quasi-global scale, also used for analysis of long-term trend (Gao, Zhang, Ren, et al., 2018). In this study, daily gridded precipitation data of CHIRPS with a spatial resolution of 0.05 ° was used.

http://chg.geog.ucsb.edu/data/chirps/

2.3.3. PERSIANN

PERSIANN-based satellite data is a precipitation estimation algorithm using remote sensing in which the basic algorithm is based on artificial neural network. The basic input of this model is the temperature of above the cloud obtained with the images of the cloud-infrared spectra from geosynchronous satellites including GoEs8 and GoEs9. The characteristic feature of geosynchronous satellite imagery is the high time resolution although the spatial resolution of these images is low due to the fact that the distance of this type of satellites is much higher than that of polar satellites. By using these images, PERSIANN estimates the precipitation rate at a given time (Hong et al., 2004). In order to increase spatial resolution, the algorithm implements the images of the TRMM NOAA13 and NOAA14 satellites which are polar orbit types and also the artificial neural network to obtain the spatial resolution of 0.25 * 0.25 degrees at the half-hour time step. PERSIANN data are available for public use through the CHRS Data Portal at http://chrsdata.eng.uci.edu

2.3.4. PERSIANN-CDR

The PERSIANN-CDR data set is jointly developed by the University of California and the NOA, provides data from 1983 (Ashouri et al., 2015). PERSIANN-CDR uses from IR and MW satellite data, in rainfall estimation. Unlike the PERSIANN product, which is available in real time and regularly on the basis of satellite measurements, PERSIANN-CDR delivers GPCP data to estimate the rainfall (Tan and Santo, 2018b) In this study, PERSIANN-CDR daily precipitation data is used with spatial resolution of 0.25°.

2.4. Methodology

The first stage before using rain gauge precipitation data, is data preparation, which firstly checks the data for continuity and consistency. The continuity of a record may be broken with missing data due to many reasons such as damage or fault in a rain gauge during a period. To ensure continuity, missing values in each precipitation data set, are estimated using data of neighboring stations. To ensure consistency, double mass-curve technique is used. This technique is based on the principal that when each recorded data comes from the same parent population, they are consistent.

Precipitation data obtained from rain-gauge stations do not match the satellite precipitation dataset due to differences in scale (Duan et al., 2016). To resolve this issue and do a fair comparison between SPPs and the precipitation gauges, pixel-to-pixel approach was conducted, where the precipitation values of gauges that located within the same pixel were averaged and compared. We only considered pixels that contain at least one precipitation gauge in this assessment to ensure a more accurate comparison. In case that there is no any rain gauge station within the same pixel, by using different interference techniques, such as Inverse Weighting (IDW), Thiessen Polygon, and Kriging methods, average value for this pixel is assigned.

Several widely used statistical indices were selected to quantitatively evaluate the accuracy and error of satellite precipitation products against the ground observations data in 41 rain-gauge stations across Iran. Figure 2 illustrates the procedure used and the steps taken to meet the goal of the study.

2.5. Evaluation Statistics

In this study, IDW method, spatial analysis and Teylor diagram were used for annual and monthly evaluation, respectively. Furthermore, in order to do daily evaluation, five continuous statistics including 3 evaluation statistics (continuous statistical criteria), RB, RMSE, CC and 2 precipitation detectability (categorized statistical criteria), POD, FAR were implemented to analyze these data. These criteria are presented in the Table 3.

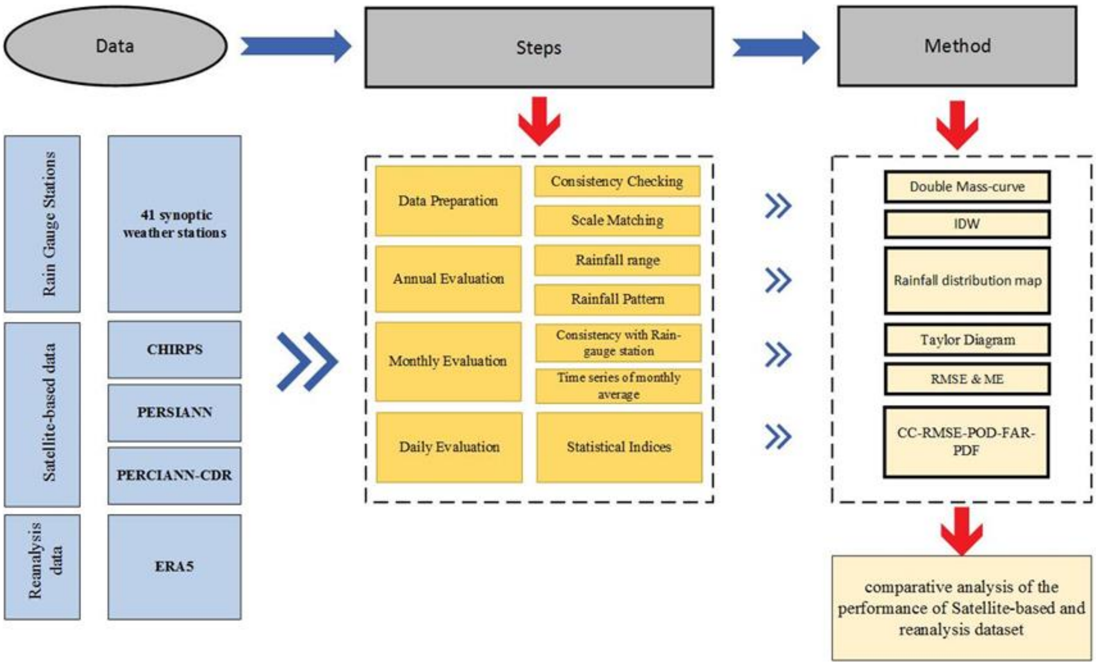

Fig. 2. Flowchart of the methodology of study and the corresponding steps

The relative bias (RBias) is defined as the difference between rain gauge observations and satellite rainfall estimates, shows how much the simulated values differ from the observed values and can be either positive or negative. A negative bias indicates underestimation of rainfall while a positive bias indicates overestimation. Underestimation will lead to values less than 1, and overestimating to values greater than 1. Root Mean Square Error (RMSE) which calculates a weighted average in accordance with the square error shows the difference between the distribution of observational data and the distribution of satellite estimates (Worqlul et al., 2014). The correlation coefficient (CC) is used to assess the agreement between gridded precipitation and rain gauge observations. The value of CC is such that $-1 < CC < +1$. A CC value of exactly +1 indicates a perfect positive fit, while value of exactly –1 indicates a perfect negative fit. If there is no linear correlation or a weak linear correlation, CC is close to 0 (Tan and Santo, 2018b).

The Taylor diagram provides a graphical framework that allows a suite of variables from a variety of one or more models or reanalysis to be compared to reference data. Taylor diagrams provide a concise statistical summary of how well patterns match each other in terms of their correlation, their root-mean-square difference and the ratio of their variances. This diagram is the result of three statistical criteria (STDEV, CC, RMSE). Each data set contains a real data, represented by a separate point in the Taylor chart; clearly the points are closer to the real point, have better performance according to the 3 above-mentioned statistics.

In addition, two categorical statistical indices (Wilks, 2011), including the probability of detection (POD) and false alarm ratio (FAR) are used to assess the rain-detection capabilities of satellite rainfall estimations. POD represents the ratio of the correct identification of rainfall by satellite product to the number of rainfall occurrences observed by reference data; FAR denotes the proportion of cases in which the satellite records rainfall when the rain gauges do not; POD and FAR range from 0 to 1, with 1 being a perfect POD and 0 being a perfect FAR.

Pi is the predicted value, G_i is the observed value, H is the number of times that the observed rain is correctly detected, M is the number of observations that the observed rain has not been detected, and F is the number of times that precipitation has not occurred, but the model has shown the occurrence of the precipitation.

Table 3. List of the statistical metrics used in the evaluation of precipitation products.

Optimum Value	Equations	the statistical metrics
1	$CC = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2}\sqrt{\sum_{i=1}^{n}(P_i - P)^2}}$	Correlation Coefficient
۰	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - G_i)^2}{n}}$	Root-mean-square error
۰	$RB = \frac{\sum_{i=1}^{n}(P_i - G_i)}{\sum_{i=1}^{n}(G_i)}$	Relative Bias
1	$POD = \frac{H}{H + M}$	POD
۰	$FAR = \frac{F}{H + F}$	FAR

3. Results and Discussion

3.1. Climatology

The average precipitation of Iran is 250 mm and the coefficient of variation (CV) varies from 18% in north to 75% in southeast of the country (Dinpashoh et al., 2004). The maximum is about 1,800 mm on the Caspian seashore and about 400 mm in the sloping region of Alborz and Zagros mountains. The ranges of rainfall decrease to less than 100 mm annually depending on the location in the central and eastern parts of Iran.

3.2. Comparison of the Spatial Distribution of Annual Rainfall Between In-Situ Observation and gridded Rainfall Products

The overall analysis of the spatial distribution of annual mean rainfall averaged over years of 2012- 2019, illustrates the performance of each data set used in this study in comparison with the ground observation data, as shown in Figure 4. According to the results from measurements in rain gauge stations, a pattern of higher precipitation is commonly found in the northern and north-western regions of Iran, while lower precipitation is distributed over the middle part of study domain. The rainfall values in the western parts of Iran are higher than eastern regions. The results of gridded precipitation data verified this matter.

It can be seen that the range of rainfall estimation from PERSIAAN and PERSIAAN-CDR products are between 0-250 mm and 0-550 mm, respectively. While the PERSIANN product (figure 4) highly underestimate annual average over the whole study domain, PERSIANN-CDR performs well over the study area, and in accordance with the range of precipitation data obtained from rain gauge stations. The products of ERA5 and CHIRPS exhibit a wide range of rainfall between 0-1750 mm. The CHIRPS shows good correlation with rain gauge data specifically over the northern parts of Iran, where highest values of rainfall are recorded. However, CHIRPS slightly overestimate annual precipitation in that region.

3.3. Spatial Evaluation Using Standard Deviation, correlation coefficient, and RMSE Over Monthly Scale

To evaluate the satellite rainfall estimates products with accuracy, the performance of each product over monthly scale in various regions of Iran, have been measured in all directions, using Taylor diagram. It is used to quantify the degree of correspondence between the SPPs and observed data in terms of three statistics of CC, RMSE error, STDEV. In Figure 5 it can be seen that CHIRPS product exhibits a perfect correlation with ground observation in north-west of Iran. While P-CDR product shows relative agreement with ground observation in the west and east parts of Iran, products of ERA5 illustrate strong relationship with rain gauge data in the south-east of Iran. The approximate correlation coefficient values for the above-mentioned relationships lies between 0.8-0.9.

Also, Figure 5 shows that the lowest bias is registered in the central parts of Iran, regions in which high-pressure air masses reduce rainfall values. Contrary to the central part, in the north and west parts of Iran, highest rainfall values lead to the highest biases. The product of CHIRPS in the northern part Iran shows highest biases, which indicating a significant overestimation in that area.

3.4. Comparison of Average Monthly Rainfall Time Series of Grounds Observed Data with Gridded Rainfall Products

To analyze the trend of monthly rainfall, time series of monthly average precipitation during 2012 to 2019 depicted to show which product has a good rainfall distribution over the study domain. Figure 6 presents the spatial distribution of in situ rain gauge data, CHIRPS, P-CDR, ERA5, PERSIANN, averaged over short and long rains. During rainy seasons highest values of rainfall is recorded around 55mm, while precipitation values decrease by half during short rains. Figure 6 shows the general pattern of monthly rainfall time series, including recognition of wet and dry seasons, several peaks and troughs captured by all precipitation products. It can be seen that PERSIANN products, specifically during long rain, poorly capture rain values over the study domain, and slightly underestimates seasonal rainfall in comparison with ground observations. Hence, before using of PERSIANN precipitation products in any hydrological simulations, they should be reviewed.

Overall, the performance of ERA5 and P-CDR in capturing long rains are relatively good compared to other products used in this study, though they slightly overestimate seasonal rainfall along the studied period. It is notable that ERA5, P-CDR and CHIRPS products perform well in estimation lowest values of rainfall.

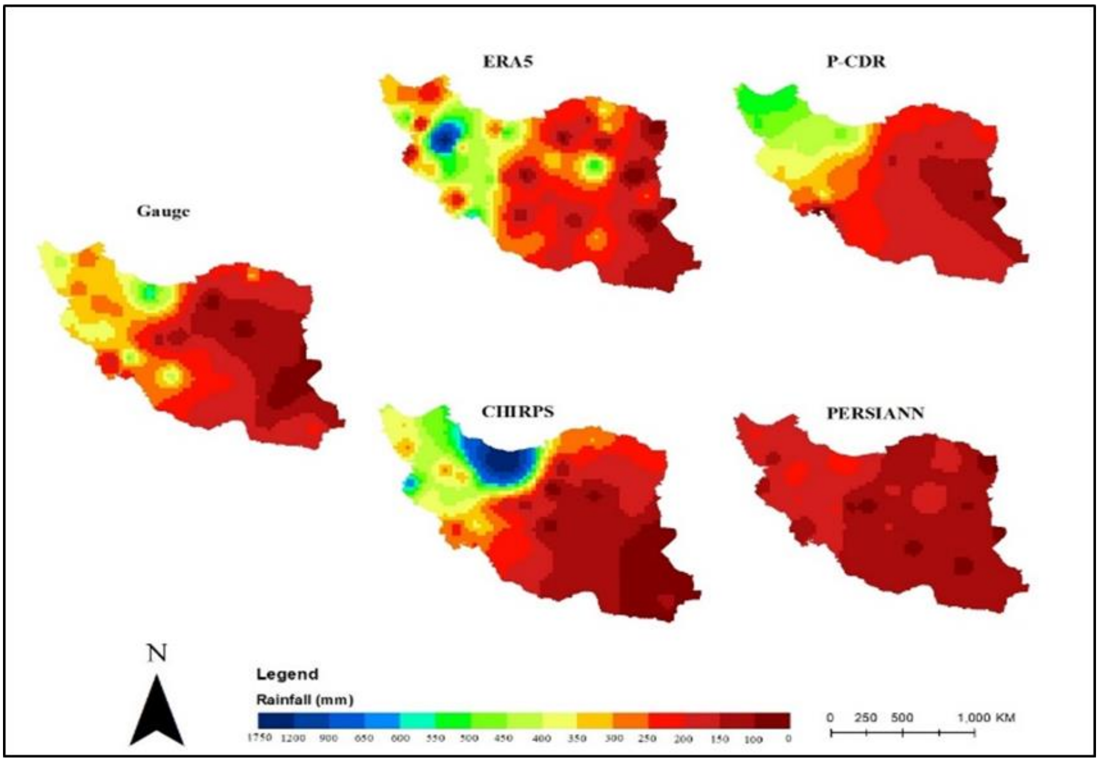

Fig. 4. Spatial patterns of average annual precipitation (2012–2019)

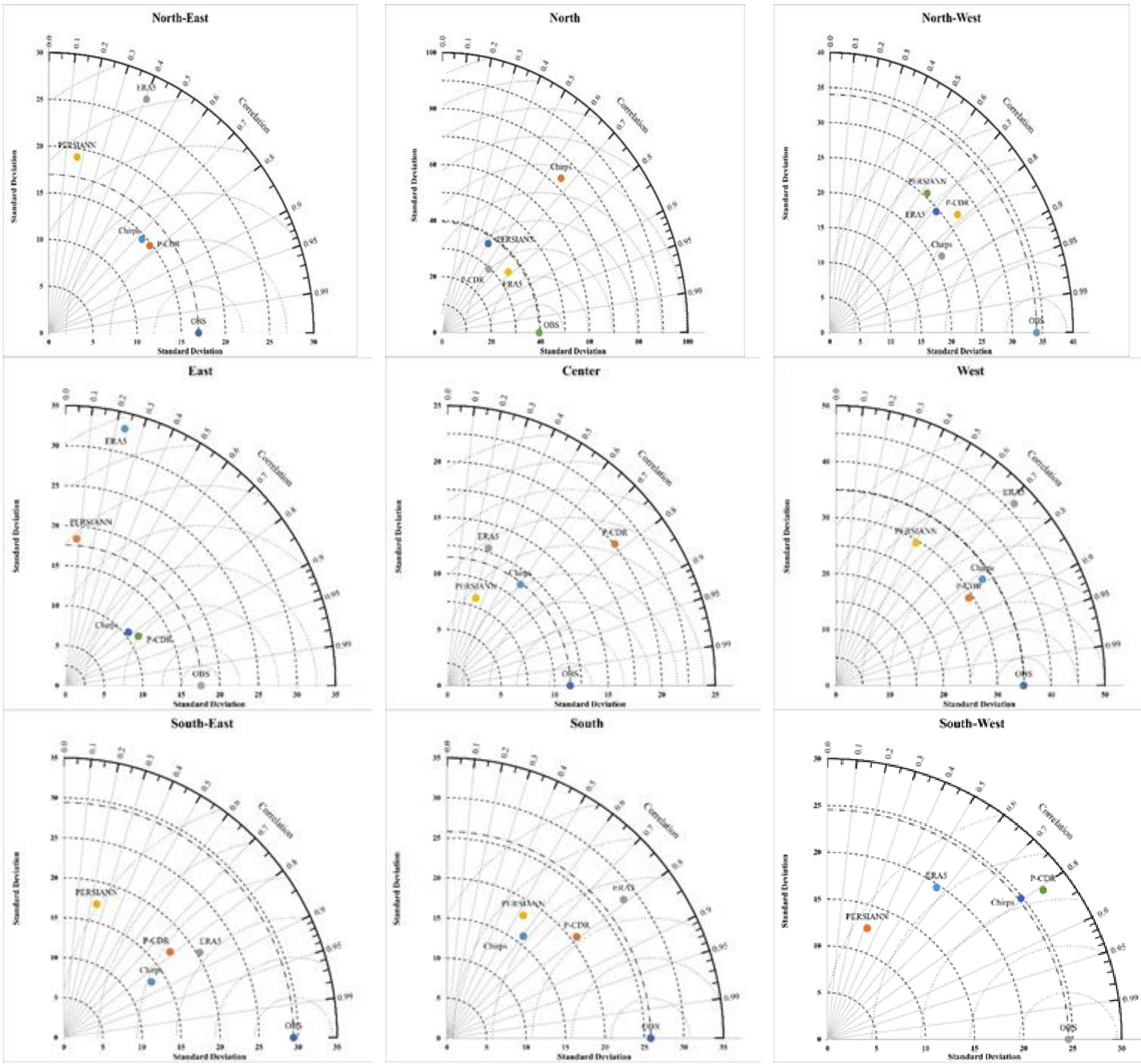

Fig. 5. Taylor Diagram showing the evaluation of the satellite-based rainfall products against ground observation (gauge) data over various regions

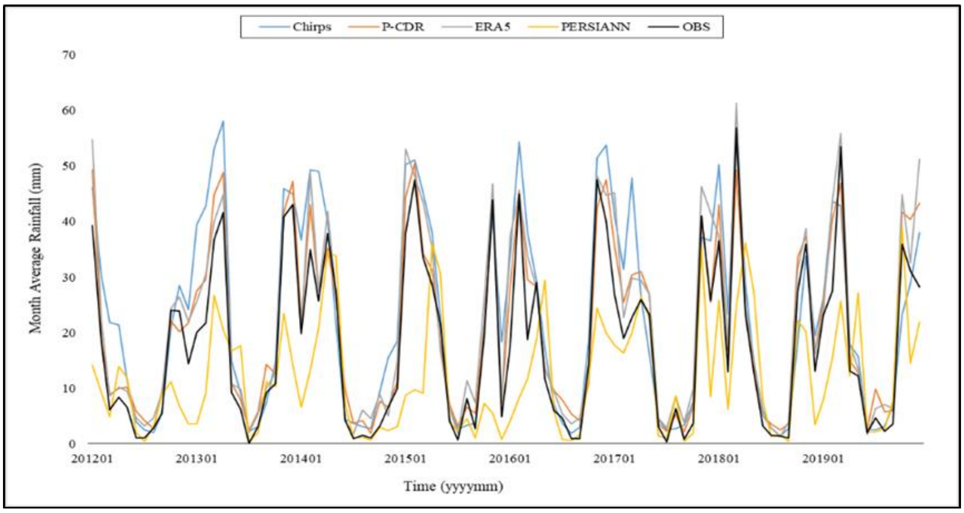

Fig. 6. Time series of monthly average precipitation during 2012 to 2019

3.5. Evaluation of temporal variability trend of monthly average precipitation of Gridded Rainfall Products with the RMSE and the ME

Through the general analysis of monthly mean error, according to the figure 7, it was found that the PERSIANN product registered highest RMSE compared to the other products, ranging form-38 to 18. Also, it can be seen that in the years of 2015 and 2016 a sharp drop in RMSE values occurred, which indicates abnormally performance of PERSIANN product in rainfall estimation.

Figure 7 shows that, based on RMSE indicator, P-CDR outperforms against other products in capturing short and long rains. Figure 8 illustrates the seasonal distribution of RMSE(8-a) and ME(8-b) are varying from one product to another and from a season to another. Figure 8 exhibits RMSE values during the short rains season, start to decrees from March and reach to the lowest values (approximately 2 mm) in June, July, August and September. This is while during the large rain's seasons (Sep-Feb), RMSE values increase drastically. The P-CDE product has a very low RMSE compared to PERSIANN and other products (Figure 8-a), which means that it outperforms against other products in capturing short rains. Overall, except from PERSIANN product, the trend of RMSE variations is the same for the all-above-mentioned products from Jan to Dec. Figure 8-a shows that P-CDR and ERA5 product captured significantly low errors contrary to the products of PERSIANN and CHIRPS. The products of P-CDR and ERA5 present the highest RMSE in January, while CHIRPS and PERSIANN reveal the maximum error in March and in February, respectively.

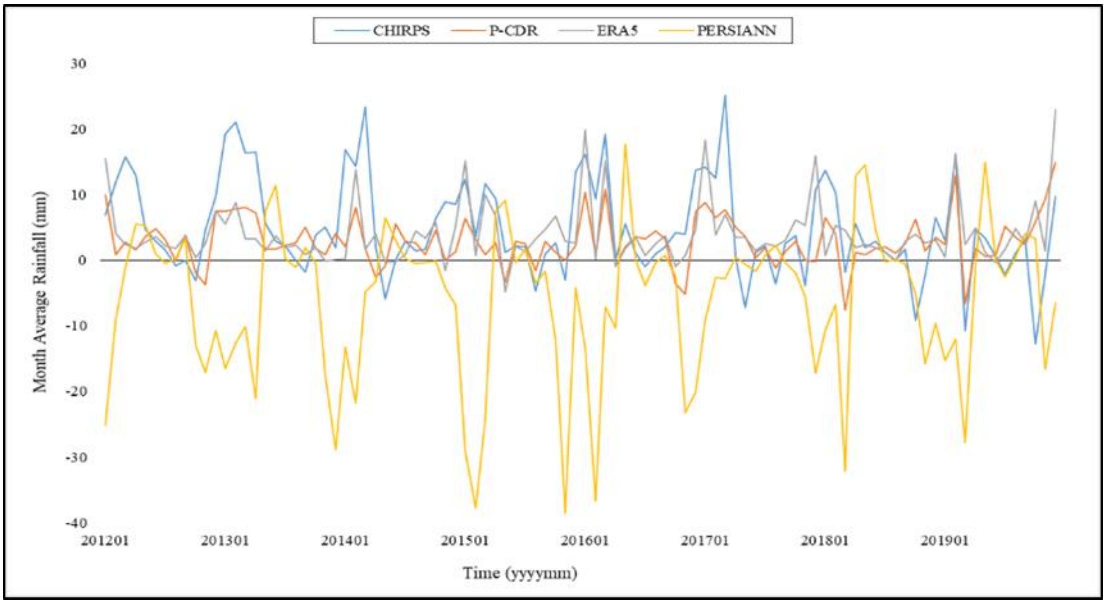

Fig. 7. Time series of monthly average error during 2012 to 2019

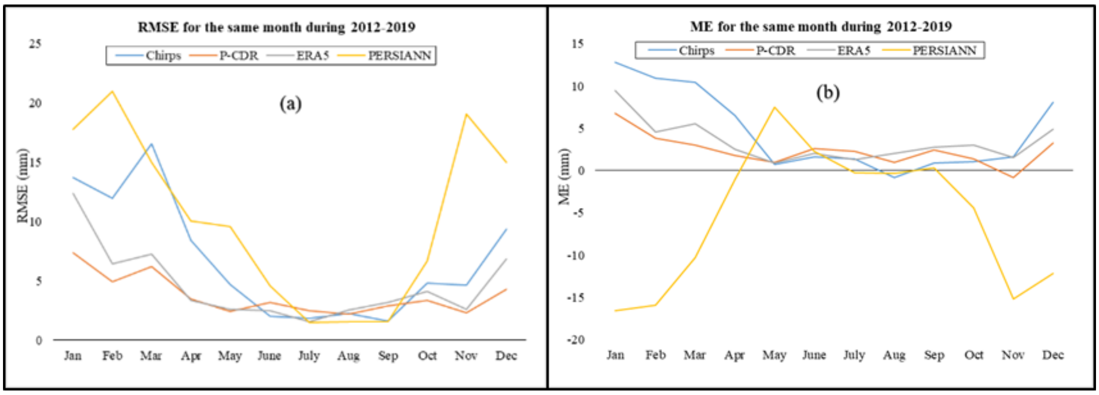

Fig. 8. Average (a) RMSE and (b) ME of four precipitation products over 2012 to 2019

Figure 8-b carries out that the ME variation for the all products ranging from -15 to + 15. Likewise, PERSIANN RMSE ranging from -15 to +10 over Jan to May, and from 0 to -15 over Sep to Nov. This can be a sign that PERSIANN performance in capturing long rains is poor.

3.6. Daily Assessment of Grounds Observed Data and Satellite-Based Rainfall Products

The annual and monthly scales analysis is not enough to evaluate the performance of the satellite-based rainfall estimates products. Therefore, an evaluation on daily scale for the period of 2012-2019 is of more concern. Figure 9 presents the correlation coefficient values between Grounds Observed Data and Satellite-Based Rainfall Products.

As presented by figure 9, pixels with purple color indicate regions which have higher correlation coefficient and in contrast pixels with green color on the map exhibits areas which have poor or even invers correlation coefficient. The averaged correlation coefficient over Iran presented by CHIRPS and P-CDR products at 0.37 and 0.35, respectively. This enable to see that in more than half of the study area, CC values for both CHIRPS and P-CDR products are between 0.35 to 0.6. Contrary, analysis shows that the two products of ERA5 and PERSIANN have a very low CC value of 0.09 and 0.03, respectively. Likewise, the maximum recorded values of CC by ERA5 and PERSIANN products are 0.3 and 0.2, respectively, showing the poor performance of these datasets in capturing rainfall values.

The evaluation results show that in some parts of Iran, an inverse correlation exists between PERSIAAN products and ground observation. As presented by figure 9, the P-CDR denotes high CC values in southern, western and south-western regions of Iran.

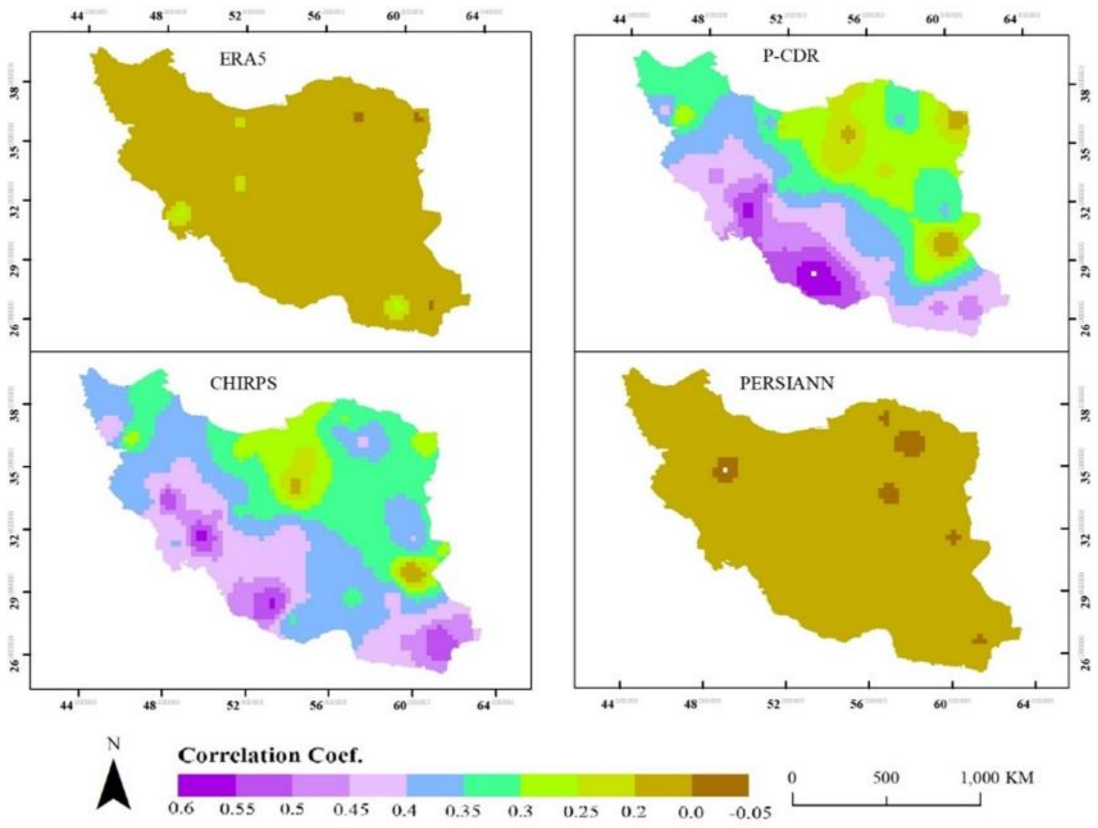

Fig. 9. CC between Ground observation and gridded precipitation product at daily time scale

While in other parts of the study area, the best results captured by CHIRPS. The analysis expresses the suitability of the mentioned products to fill the excising gaps in daily precipitation dataset. Overall, CC values are presenting the compatibility of P-CDR and CHIRPS with ground observation data, while ERA5 and PERSIANN do not show any meaningful correlation.

3.7. Spatial Evaluation of Gridded Rainfall Products with the RMSE and RB

Figure 10 shows the relative biases between ground observation and gridded rainfall products at daily scale. As it can be seen, all products exhibit negative bias in majority of the study area, meaning that they overestimate the amount of daily rainfall detected. whereas PERSIANN-CDR presents a vast rate ranging from -2 to +2, ERA5 demonstrates ranges from 0 to +8 meaning that it underestimates the amount of daily rainfall detected specifically in the central parts of Iran.

The overall analysis shows that PERSIANN denotes a relatively lowest biases, ranging from 0 to +1, in detecting precipitation values. Figure 11 shows Root-mean-square error of daily precipitation between ground observation and gridded rainfall products at daily scale.

As presented by figure 11, except from PERSIANN, all products show uniform spatial distribution, increasing from west to the east regions. It can be figured out that P-CDR and CHIRPS are the highest quality precipitation products over the study area. In the light of RMSE values, P-CDR has the best performance ranging from 0 to 5 mm. This enables to see that in the case of non-recording gauge stations, products of P-CDR can provide a better representation of the rain gauge data. In contrary, PERSIANN has undergone the worst performance among others, with RMSE values ranging from 5 to 8 mm. The overall analysis shows that the two products of ERA5 and CHIRPS have a very high RMSE, presenting a considerable overestimation of rainfall values. It is in agreement with the results of CHIRPS RMSE values in the northern parts of Iran ranging between 5 to 14 mm.

3.8. The daily assessment of precipitation detection capability and False Alarm Rate of Gridded rainfall products

The figure 12 shows the performance and precipitation detection capability of gridded products on daily time scale. As it can be seen, the performance of all products is found to be improved moving from eastern regions of Iran towards western parts. The daily assessment of the performance and the precipitation detection capability allowed to depict that CHIRPS and ERA5 products present the highest and lowest detection ability compared to other products, respectively.

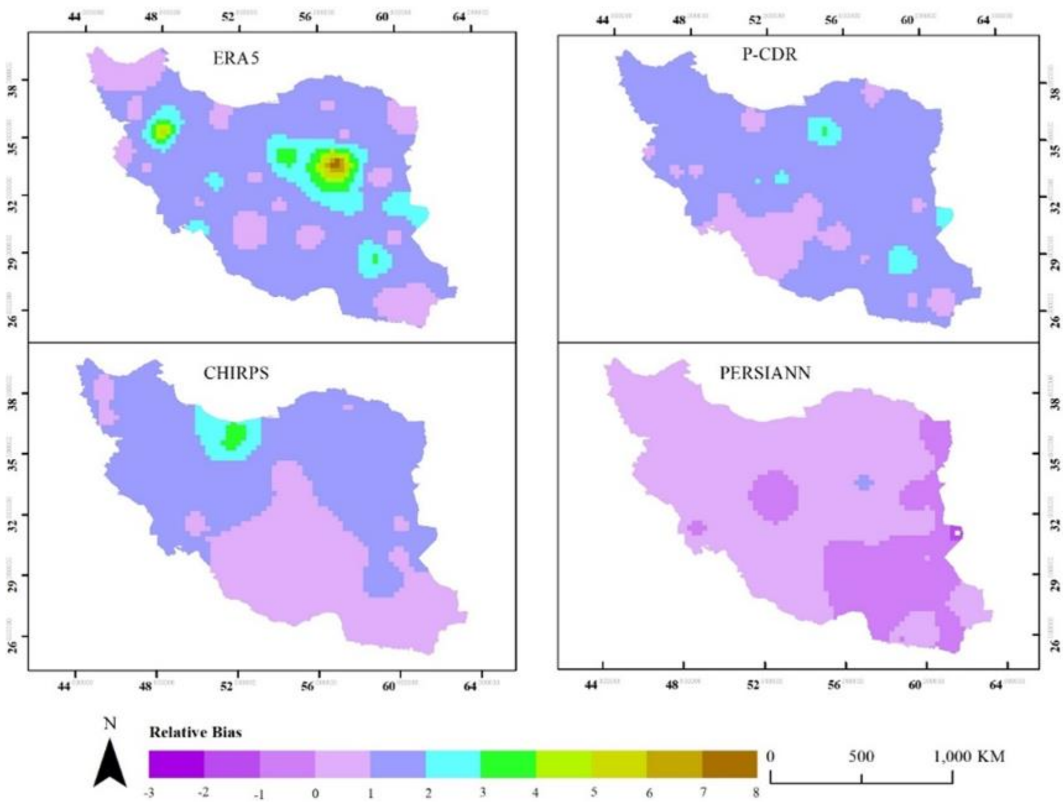

Fig. 10. Relative bias between Ground observation and gridded precipitation product at daily time scale.

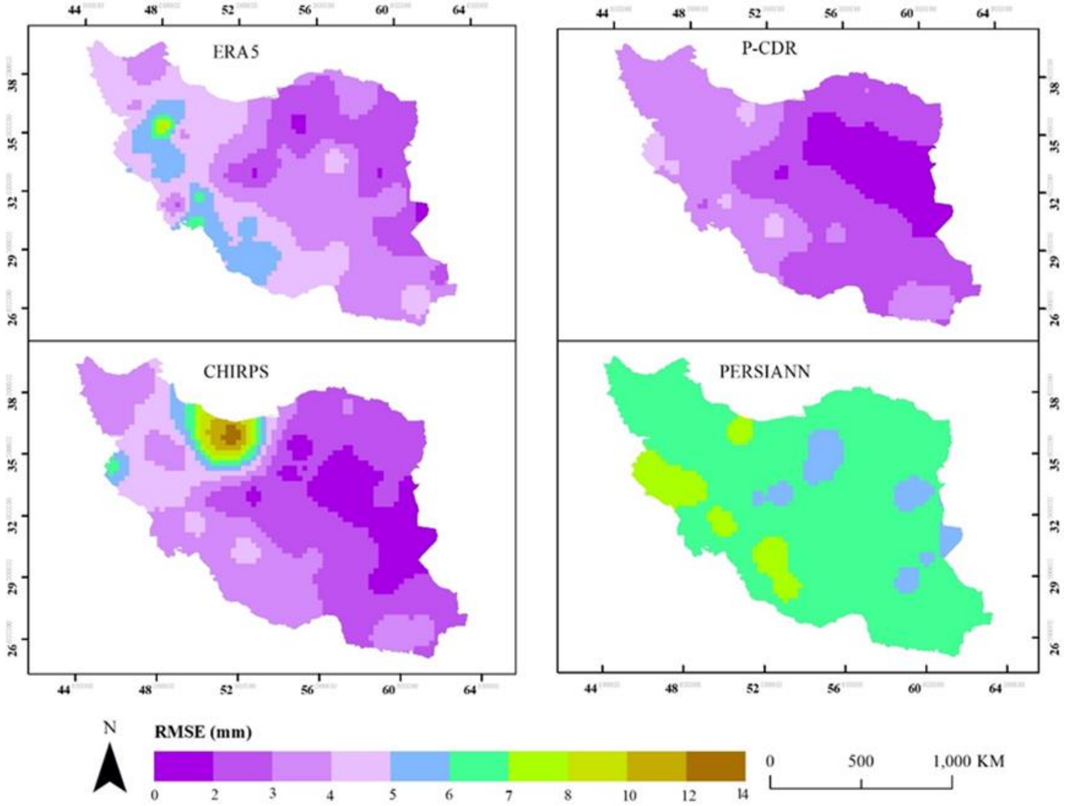

Fig. 11. RMSE between Ground observation and satellite -based precipitation product at daily time scale.

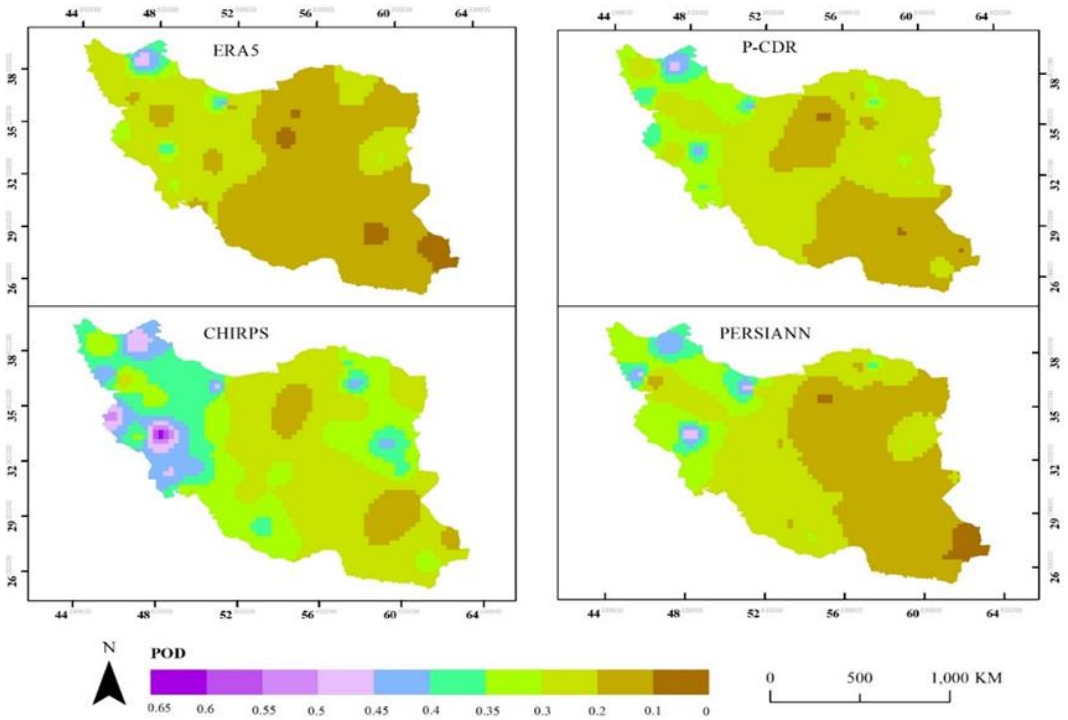

Fig. 12. Probability of Detection of daily precipitation of gridded products

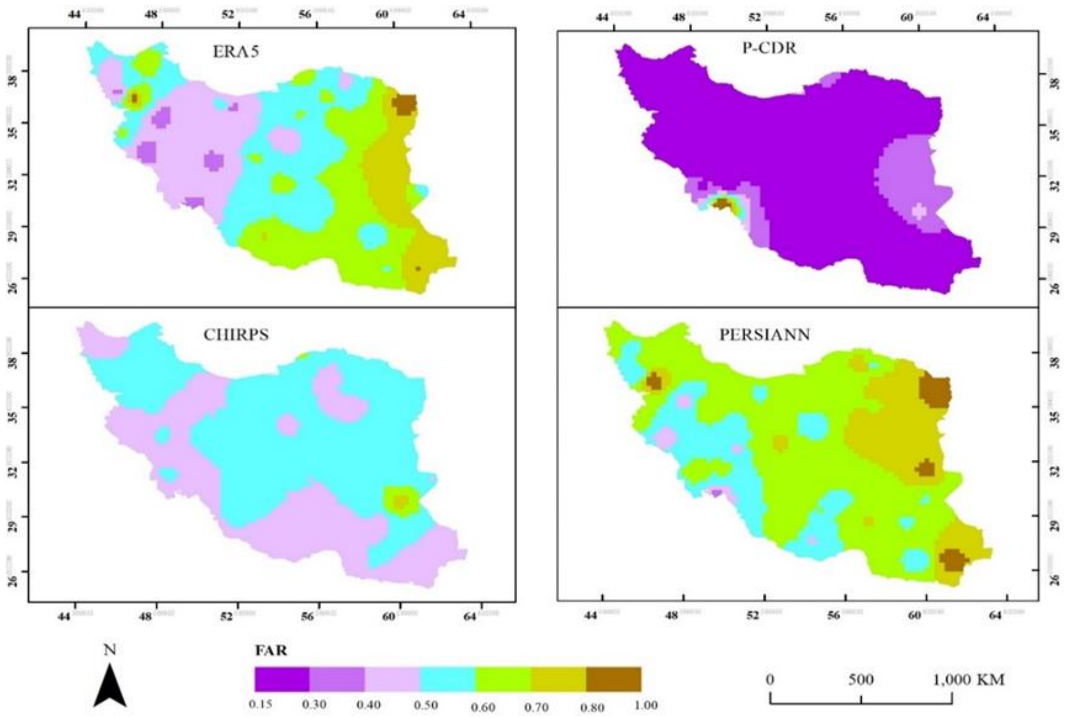

Fig. 13. False Alarm Rate of daily precipitation by gridded products

As presented through figure 13, over whole study area except from some south-western parts of Iran, the P-CDR denotes a relatively low FAR compared to other products expressing that there are approximately the same rainfall events observed compared to the detected events, whereas in the rest parts of Iran, CHIRPS exhibits the best performance compared to the other products.

3.9. Spatial Evaluation of daily precipitation intensities using probability density function (PDF)

Figure 14 shows PDF (Tan and Santo, 2018b) computed from the SPPs and the precipitation gauges over Iran, for seven classes of daily precipitation intensities. All the precipitation gauges and SPPs show that the highest percentage is at a precipitation class between 0 and 1 mm/day, specifically in southern, eastern and central parts of Iran, whereas the lowest percentage occurs at a precipitation class of > 50 mm/day, specifically in northern, north-western, north-eastern and western parts of Iran.

The performance of the PERSIANN-CDR product is the worst in capturing all classes of precipitation event, while the performance of the other SPPs relatively good for precipitation classes between 1 and 50 mm/day. In all regions of the study area, P-CDR shows the highest percentage at precipitation classes between 0.1-1 and 1- 2 mm/day, and the lowest percentage of no rainy days. It is evident that P-CDR predicts a larger number of rainy days compered to the other products.

All the SPPs tend to overestimate the percentage of precipitation in southern, west-southern and east-southern of Iran. In the northern regions, CHIRPS overestimate the percentage of precipitation classes more than 50 mm/day.

Generally, at majority of precipitation classes, all the SPPs tend to overestimate precipitation intensities, which is in agreement with the results of a study undertaken by Tan and Duan (2017). All the SPPs tend to underestimate the number of light (0 to 1 mm/day) and violent (> 50 mm/day) precipitation events, but overestimate the moderate and heavy precipitation (1 to 50 mm/day) classes. In all regions of Iran, except from southern, west-southern and east-southern parts, all SPPs products present highest percentage at precipitation class between 2-5 mm/day, while precipitation gauges exhibit the highest percentage at precipitation class between 0.1-1 mm/day.

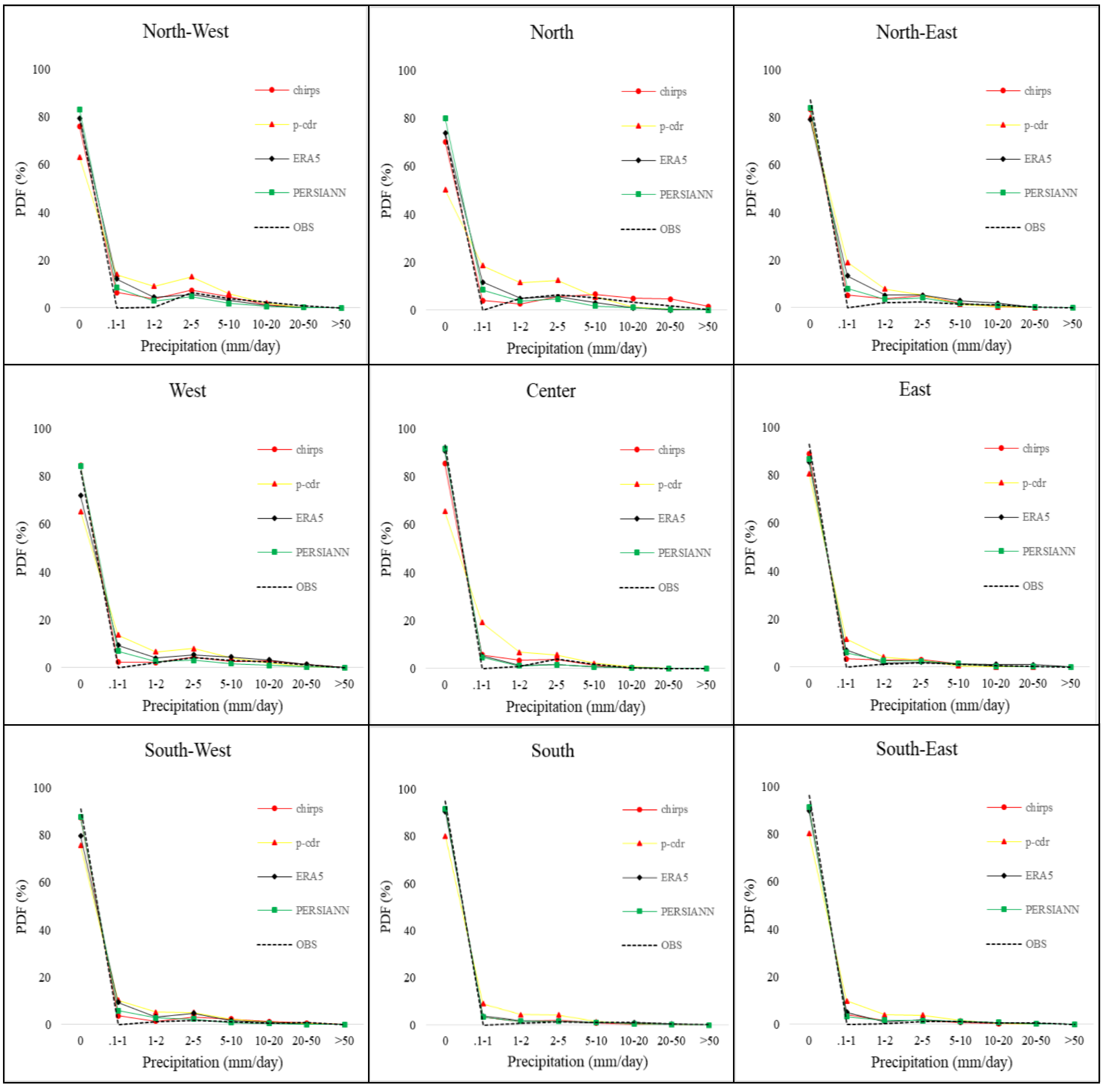

Fig.14. Probability density function (%) of the evaluated SPPs and rain-gauge station for the whole period over Iran

4. Conclusion

This study assessed the comparative analysis of the performance of rainfall estimates data set to evaluate the accuracy of each product and then depict which product highly performs and provides a reliable caption of rainfall amount over the study domain for a common period from 2012 to 2019. Ground observed data from 41 stations have been taken as a reference to evaluate point-to-pixel the performance of ERA5 as reanalysis data, PERSIANN as gridded data, P-CDR and CHIRPS as Satellite-Rain gauge data on monthly, annual, and daily time scale. Annual evaluation performed using IDW method, providing continues precipitation data set over study area. Monthly assessment of precipitation data and monthly evaluation of precipitation time series conducted using Taylor diagram in 9 defined regions throughout Iran. The capabilities of daily precipitation were validated with three main statistical metrics (CC, RMSE and RB). Also, the SPPs' performance examined in term of the precipitation detection ability, False Alarm Rate of daily precipitation and probability density function (PDF), in 9 different regions over study area. The main findings of the study are summarized, as follows:

On annual scale, the P-CDR product outperforms compared to other satellite-based rainfall products with averaged precipitation range between 0-250 mm over the whole study domain. The CHIRPS product overestimates the precipitation values although it shows a good spatial precipitation pattern, in agreement with ground observation data set. In contrary PERSIANN performed poorly in capturing spatial precipitation pattern. Also, PERSIANN underestimate the rainfall values over the study area. On monthly scale, the performance of the satellite-based rainfall data set is varying from one product to another, one season to another and from one region to another. The CHIRPS and P-CDR product outperforms compared to other satellite-based rainfall products with CC at 0.85 in northern-west and western regions of study domain. Monthly assessment of precipitation time series of SPPs exhibits that performance of ERA5 and P-CDR is found to be the best in capering monthly peaks of precipitation. On daily scale, products of CHIRPS and P-CDR present more consistency with ground observation data set, whereas ERA5 and PERSIANN do not show a significant correlation. Overall P-CDR with the lowest RMSE value, outperforms against other products in capturing precipitation estimation. The results denote that in cases which lack of reliable observed data leads to imposing considerable errors to the estimation, P-CDR products as a supplementary data, or even suitable alternative of in situ rain gauge data, can be reliable source of data useful for hydrological application. The findings of this research are consistent with Alijanian et al. (2017).

The daily assessment of the performance and the precipitation detection capability allowed to depict that relatively CHIRPS products present a good detection ability compared to the rest of precipitation products. Also, in term of FAR, P-CDR outperformed with the lowest amount of FAR. In term of Probability density function, in most regions of Iran the highest percentage is at precipitation class between 2-5 mm/day, while precipitation gauges exhibit the highest percentage at precipitation class between 0.1-1 mm/day.

In light of our findings, we recommend the following areas for future research:

Testing Datasets in Diverse Climatic Regions:

Future studies could focus on applying the validated precipitation datasets in various climatic regions of Iran. Investigating how these products perform in different environmental contexts could provide insights into their overall adaptability and reliability.

Exploring Advanced Precipitation Products:

Research could also explore the performance of other advanced precipitation products or models, such as numerical weather prediction systems or machine learning-based methods. A comparative analysis would be beneficial to assess improvements over traditional datasets.

Integration of Remote Sensing Data:

Incorporating satellite-derived precipitation data could address some limitations identified in this study, particularly in remote areas. Future research could evaluate the synergies between ground-based and satellite observations to enhance precipitation estimation.

5. Acknowledgments

The authors acknowledge the journal editors and reviewers for their insightful comments and suggestions on this paper. They also acknowledge the research council of Shahid Chamran University of Ahwaz and Shahid Beheshti University of Tehran for Comprehensive support for this scientific work.

6. Disclosure Statement

No potential conflict of interest was reported by the authors

7. References

Alijanian, M., Rakhshandehroo, G. R., Mishra, A. K., & Dehghani, M. (2017). Evaluation of satellite rainfall climatology using CMORPH, PERSIANN-CDR, PERSIANN, TRMM, MSWEP over Iran. *International Journal of Climatology*. https://doi.org/10.1002/joc.5131

Ashouri, H., Hsu, K. L., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., Nelson, B. R., & Prat, O. P. (2015). PERSIANN-CDR: Daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society*, *96*(1), 69–83. https://doi.org/10.1175/BAMS-D-13-00068.1

Bitew, M. M., & Gebremichael, M. (2011). Assessment of satellite rainfall products for streamflow simulation in medium watersheds of the Ethiopian highlands. *Hydrology and Earth System Sciences*, *15*(4), 1147–1155. https://doi.org/10.5194/hess-15-1147-2011

Dinpashoh, Y., Fakheri-Fard, A., Moghaddam, M., Jahanbakhsh, S., & Mirnia, M. (2004). Selection of variables for the purpose of regionalization of Iran's precipitation climate using multivariate methods. *Journal of Hydrology*, *297*(1–4), 109–123.

Duan, Z., Liu, J., Tuo, Y., Chiogna, G., & Disse, M. (2016). Evaluation of eight high spatial resolution gridded precipitation products in Adige Basin (Italy) at multiple temporal and spatial scales. *Science of The Total Environment*, *573*, 1536–1553. https://doi.org/10.1016/j.scitotenv.2016.08.213

Duan, Z., Tuo, Y., Liu, J., Gao, H., Song, X., Zhang, Z., Yang, L., & Mekonnen, D. F. (2019). Hydrological evaluation of open-access precipitation and air temperature datasets using SWAT in a poorly gauged basin in Ethiopia. *Journal of Hydrology*. https://doi.org/10.1016/j.jhydrol.2018.12.026

Einfalt, T., Arnbjerg-Nielsen, K., Golz, C., Jensen, N.-E., Quirmbach, M., Vaes, G., & Vieux, B. (2004). Towards a roadmap for use of radar rainfall data in urban drainage. *Journal of Hydrology*, *299*(3–4), 186–202. https://doi.org/10.1016/j.jhydrol.2004.08.004

Fallah, A., Rakhshandehroo, G. R., Berg, P., Sungmin, O., & Orth, R. (2020). Evaluation of precipitation datasets against local observations in southwestern Iran. *International Journal of Climatology*. https://doi.org/10.1002/joc.6445

Fujihara, Y., Yamamoto, Y., Tsujimoto, Y., & Sakagami, J.-I. (2014). Discharge Simulation in a Data-Scarce Basin Using Reanalysis and Global Precipitation Data : A Case Study of the White Volta Basin. *Journal of Water Resource and Protection*, *06*(6), 1316–1325. https://doi.org/10.4236/jwarp.2014.614121

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, *2*, 150066. https://doi.org/10.1038/sdata.2015.66

Gao, F., Zhang, Y., Chen, Q., Wang, P., Yang, H., Yao, Y., & Cai, W. (2018). Comparison of two long-term and high-resolution satellite precipitation datasets in Xinjiang, China. *Atmospheric Research*, *212*, 150–157. https://doi.org/10.1016/j.atmosres.2018.05.016

Gao, F., Zhang, Y., Ren, X., Yao, Y., Hao, Z., & Cai, W. (2018). Evaluation of CHIRPS and its application for drought monitoring over the Haihe River Basin, China. *Natural Hazards*. https://doi.org/10.1007/s11069-018-3196-0

Gomis-Cebolla, J., Rattayova, V., Salazar-Galán, S., & Francés, F. (2023). Evaluation of ERA5 and ERA5-Land reanalysis precipitation datasets over Spain (1951–2020). *Atmospheric Research*, *284*, 106606. https://doi.org/https://doi.org/10.1016/j.atmosres.2023.106606

Gorjizade, A., Akhond-Ali, A., Shahbazi, A., & Moridi, A. (2019). Comparison and Evaluation of precipitation estimated by ERA-Interim, PERSIANN-CDR and CHIRPS models at the upstream of Maroon dam. *Iran-Water Resources Research*, *15*(1), 267–279. https://doi.org/20.1001.1.17352347.1398.15.1.20.7

Gorjizade, A., Akhoond-Ali, A. M., Shahbazi, A., & Moridi, A. (2020). Evaluation and comparison of high spatial resolution gridded precipitation by TRMM, ERA5 and PERSIANN-CCS datasets on the upstream of the maroon basin, Iran. In *AUT Journal of Civil Engineering* (Vol. 0). Amirkabir University of Technology. https://doi.org/10.22060/AJCE.2020.17043.5610

Gorjizade, A., Akhoond-Ali, A., Shahbazi, A., & Salmannia, F. (2022). Derivation of rainfall events using the gridded rainfall data using optimal combination of global rainfall datasets. *Knowledge of Water and Soil*, *32*(2), 43–58.

Guo, H., Chen, S., Bao, A., Behrangi, A., Hong, Y., Ndayisaba, F., Hu, J., & Stepanian, P. M. (2016). Early assessment of Integrated Multi-satellite Retrievals for Global Precipitation Measurement over China. *Atmospheric Research*, *176–177*, 121–133.

Hong, Y., Hsu, K.-L., Sorooshian, S., & Gao, X. (2004). Precipitation Estimation from Remotely Sensed Imagery Using an Artificial Neural Network Cloud Classification System. *Journal of Applied Meteorology*, *43*(12), 1834–1853. https://doi.org/10.1175/JAM2173.1

Kim, K., Park, J., Baik, J., & Choi, M. (2017). Evaluation of topographical and seasonal feature using GPM IMERG and TRMM 3B42 over Far-East Asia. *Atmospheric Research*, *187*, 95–105. https://doi.org/10.1016/j.atmosres.2016.12.007

Li, M., & Shao, Q. (2010). An improved statistical approach to merge satellite rainfall estimates and raingauge data. *Journal of Hydrology*, *385*(1–4), 51–64. https://doi.org/10.1016/j.jhydrol.2010.01.023

Maggioni, V., Meyers, P. C., & Robinson, M. D. (2016). A Review of Merged High-Resolution Satellite Precipitation Product Accuracy during the Tropical Rainfall Measuring Mission (TRMM) Era. *Journal of Hydrometeorology*, *17*(4), 1101–1117. https://doi.org/10.1175/JHM-D-15-0190.1

Ning, S., Wang, J., Jin, J., & Ishidaira, H. (2016). Assessment of the Latest GPM-Era High-Resolution Satellite Precipitation Products by Comparison with Observation Gauge Data over the Chinese Mainland. *Water (Switzerland)*, *8*(11), 481. https://doi.org/10.3390/w8110481

Poméon, T., Jackisch, D., & Diekkrüger, B. (2017). Evaluating the performance of remotely sensed and reanalysed precipitation data over West

Africa using HBV light. *Journal of Hydrology*, *547*, 222–235. 10.1016/j.jhydrol.2017.01.055

Rao, P., Wang, F., Yuan, X., Liu, Y., & Jiao, Y. (2024). Evaluation and comparison of 11 sets of gridded precipitation products over the Qinghai-Tibet Plateau. *Atmospheric Research*, *302*, 107315. https://doi.org/https://doi.org/10.1016/j.atmosres.2024.107315

Sahlu, D., Nikolopoulos, E. I., Moges, S. A., Anagnostou, E. N., & Hailu, D. (2016). First Evaluation of the Day-1 IMERG over the Upper Blue Nile Basin. *Journal of Hydrometeorology*, *17*(11), 2875–2882. https://doi.org/10.1175/JHM-D-15-0230.1

Sharifi, E., Steinacker, R., & Saghafian, B. (2016). Assessment of GPM-IMERG and other precipitation products against gauge data under different topographic and climatic conditions in Iran: Preliminary results. *Remote Sensing*, *8*(2), 135. https://doi.org/10.3390/rs8020135

Tan, M. L., & Duan, Z. (2017). Assessment of GPM and TRMM precipitation products over Singapore. *Remote Sensing*, *9*(7), 720. https://doi.org/10.3390/rs9070720

Tan, M. L., & Santo, H. (2018a). Comparison of GPM IMERG, TMPA 3B42 and PERSIANN-CDR satellite precipitation products over Malaysia. *Atmospheric Research*, *202*, 63–76. https://doi.org/10.1016/j.atmosres.2017.11.006

Tan, M. L., & Santo, H. (2018b). Comparison of GPM IMERG, TMPA 3B42 and PERSIANN-CDR satellite precipitation products over Malaysia. *Atmospheric Research*, *202*, 63–76. https://doi.org/10.1016/j.atmosres.2017.11.006

Tang, G., Ma, Y., Long, D., Zhong, L., & Hong, Y. (2016). Evaluation of GPM Day-1 IMERG and TMPA Version-7 legacy products over Mainland China at multiple spatiotemporal scales. *Journal of Hydrology*, *533*, 152–167.

Tang, G., Zeng, Z., Long, D., Guo, X., Yong, B., Zhang, W., & Hong, Y. (2016). Statistical and Hydrological Comparisons between TRMM and GPM Level-3 Products over a Midlatitude Basin: Is Day-1 IMERG a Good Successor for TMPA 3B42V7? *Journal of Hydrometeorology*, *17*(1), 121–137. https://doi.org/10.1175/JHM-D-15-0059.1

Tapiador, F. J., Turk, F. J., Petersen, W., Hou, A. Y., García-Ortega, E., Machado, L. A. T., Angelis, C. F., Salio, P., Kidd, C., Huffman, G. J., & de Castro, M. (2012). Global precipitation measurement: Methods, datasets and applications. In *Atmospheric Research*, *104*, 70–97.

Urraca, R., Huld, T., Gracia-Amillo, A., Martinez-de-Pison, F. J., Kaspar, F., & Sanz-Garcia, A. (2018). Evaluation of global horizontal irradiance estimates from ERA5 and COSMO-REA6 reanalyses using ground and satellite-based data. *Solar Energy*, *164*, 339–354. https://doi.org/10.1016/j.solener.2018.02.059

Wang, W., Lin, H., Chen, N., & Chen, Z. (2021). Evaluation of multi-source precipitation products over the Yangtze River Basin. *Atmospheric Research*, *249*, 105287. https://doi.org/10.1016/j.atmosres.2020.105287

Wang, W., Lu, H., Zhao, T., Jiang, L., & Shi, J. (2017). Evaluation and comparison of daily rainfall from latest GPM and TRMM products over the Mekong River Basin. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *10*(6), 2540–2549. https://doi.org/10.1109/JSTARS.2017.2672786

Wilheit, T. T. (1986). Some comments on passive microwave measurement of rain. *Bulletin - American Meteorological Society*. https://doi.org/10.1175/1520-0477

Wilks, D. (2011). *Statistical methods in the atmospheric sciences*.

Worqlul, A. W., Maathuis, B., Adem, A. A., Demissie, S. S., Langan, S., & Steenhuis, T. S. (2014). Comparison of rainfall estimations by TRMM 3B42, MPEG and CFSR with ground-observed data for the Lake Tana basin in Ethiopia. *Hydrology and Earth System Sciences*, *18*(12), 4871–4881. https://doi.org/10.5194/hess-18-4871-2014

Xie, P., & Xiong, A.-Y. Y. (2011). *A conceptual model for constructing high-resolution gauge-satellite merged precipitation analyses*. *116*. https://doi.org/10.1029/2011JD016118

Yuan, F., Zhang, L., Wah Win, K. W., Ren, L., Zhao, C., Zhu, Y., Jiang, S., & Liu, Y. (2017). Assessment of GPM and TRMM multi-satellite precipitation products in streamflow simulations in a data sparse mountainous watershed in Myanmar. *Remote Sensing*, *9*(3), 302.