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Evaluation and Comparison of Precipitation Datasets by Reanalysis and Satellite Models in Different Parts of Iran

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Abstract

Rainfall is a crucial component of the hydrological cycle and plays a key role in water resource planning. Recent research has investigated the use of gridded data as a supplement to and replacement for traditional rain gauge measurements, particularly in areas with limited gauge coverage. Gridded precipitation data offering a structured method to represent precipitation patterns across large regions by dividing the data into grids. This enables more precise spatial analysis of precipitation distribution and variability. The study assessed the accuracy of six high-resolution gridded rainfall product estimates (ERA5, ERA-Interim, CMORPH, PERSIANN, PERSIANN-CDR, and PERSIANN-CCS) at 12 rain gauge stations in Iran at various time scales. Comparisons with rain gauge network data using statistical and graphical methods revealed that ERA5, ERA-Interim, and PERSIANN-CDR data outperformed other models on annual and monthly scales, so that the highest correlation coefficient in monthly scale was obtained by ERA5 model at Doroodzan station with correlation coefficient of 0.93. Also, the results on a daily scale indicate the appropriateness of the output data of the reanalysis models (ERA5, ERA-Interim) compared to other models in such a way that the lowest RMSE value in all stations except Sefidroud Dam is related to the reanalysis data and the lowest RMSE value is equal to with 0.78 mm at the Chahnimeh station and the highest value of the correlation coefficient equal to 0.63 corresponds to the Karaj dam rain gauge station; Also, in correctly detecting rainy and non-rainy days, ERA5 model has the most accuracy in all stations.

Keywords: Evaluation Indicators, Iran Dams, Rainfall Estimation, Reanalysis Data, Satellite Data.

1. Introduction

Precipitation is considered as an important component of the hydrological cycle and the key parameter from the environmental and meteorological point of view (Li and Shao, 2010) and a very important input in applied sciences such as hydrology, meteorology, weather forecasting, and agriculture. (Duan et al., 2016). In addition, precipitation can be employed in various fields such as creating accurate understanding of hydrological balance, water resources management, and flood forecasting. The spatial and temporal qualities of rainfall affect hydrological processes such as runoff production and soil moisture content. Therefore, accurate measurements of rainfall and the development of spatial and temporal distribution maps are quite challenging. Due to the vast spatial and temporal variation of precipitation, it is desirable to obtain precipitation data with high spatial and temporal accuracy. Measurement of precipitation by rain-gauge data and through the field studies is considered as one of the common methods in rainfall estimation. However, the inappropriate spatial distribution of these rain gauges reduces the accuracy of the rainfall pattern (Javanmard et al., 2010). On the other hand, the presence of statistical deficiencies and the heterogeneity in the time series of the collected data make it difficult to use these data in hydrological models (Brunetti et al., 2006). It is also worth noting that the generalization of the measured data to points lacking statistics imposes a significant error to the calculations. Therefore, in most of the developing countries, a dense rain estimating network is not available at all or often involves statistical deficiencies (Bitew and Gebremichael, 2011). This situation has been worsened by decreasing the number of rain gauge stations due to financial problems or lack of proper maintenance (Adjei et al., 2012). Therefore, the use of measured point data to provide precise spatial information of precipitation is a difficult task (Jia et al., 2011). In other words, although the observations from the rain-gauge stations can fully show the most accurate measurements at the desired locations, as noted, inappropriate spatial distribution of these stations reduces the accuracy of the rainfall model(Javanmard et al., 2010). The measurement of rainfall data from a limited number of rain-gauge stations, especially in areas where these stations have been distributed inappropriately, does not provide accurate information regarding the rainfall variations in surface. Also, the data obtained from the rain-gauge stations only reflects the rainfall conditions in the neighborhood and its values are not valid for farther places (Collischonn et al., 2008). Meanwhile, global and continental remote-sensing precipitation products are becoming increasingly available with reasonable spatial and temporal resolutions for application in hydrological and climatic studies. Therefore, these may provide an alternative for traditionally measured rainfall at weather stations. A major advantage of using such data is the improved spatial distribution compared to weather stations. With the advancement of remote sensing techniques and satellite-based reanalysis algorithms in past decades, these data are a good source for measuring rainfall data (Hobouchian et al., 2017). Therefore, precipitation measurement based on satellite data has been recognized as the main approach to rainfall measurement in recent decades (Tan et al., 2015; Xu et al., 2017). Satellite remote sensing data as a novel approach provide highly accurate spatial and temporal variations of rainfall (Xie and Xiong, 2011). In addition, in comparison with ground measurements such as rain-gauges and radars, satellite data can globally cover precipitation systems regardless of mountainous and oceanic terrain. In general, rain-gauge data include problems such as lack of data, lack of installed station. Moreover, these data are affected by wind and heavy rains, they lose their measurement accuracy (Maggioni et al., 2016). The efficiency of rainfall measurement stations under the influence of heavy winds is reduced to more than 50% (Sieck et al., 2007) and is affected by heavy rainfalls by 30% (Humphrey et al., 1997). Likewise, Geostationary radar-based rainfall estimates are affected by signal weakness, dispersion of the return level and the uncertainty of rainfall-reflector relation (Einfalt et al., 2004). Therefore, satellite precipitation products are widely used in many environmental applications such as analysis of rainfall qualities, hydrologic modeling (Tan and Duan, 2017) and drought monitoring (Tao et al., 2016). A large number of satellite-based rainfall estimates and reanalysis data with high spatial and temporal separation are available and can be used to complete precipitation data or even replace these measurements (Fujihara et al., 2014; Thiemig et al., 2013) Evaluation studies showed that the satellite precipitation estimates can still contain substantial biases and errors, and a further merging or blending satellite precipitation estimates with rain gauge data can result in improved precipitation products (Ebert et al., 2007; Xie and Xiong, 2011). Over the past decades, great efforts have been made to generate gridded precipitation products, thereby leading to the increasing availability of precipitation datasets at different spatial and temporal resolutions over the global scale (Tapiador et al., 2012). These data can be broadly classified into four categories (Duan et al., 2016).

A- Gauge-only products that build only on observations from rain gauge stations using different interpolation methods, these widely used products for example include the Global Precipitation Climatology Centre (GPCC)[1] monthly precipitation product (Schneider et al. 2014, 2015), the Climatic Research Unit (CRU)[2] monthly precipitation (Harris et al., 2014) and the Climate Prediction Center (CPC)[3] unified gauge-based analysis of global daily

1- Global Precipitation Climatology Centre
2- Climatic Research Unit
3- Climate Prediction Center

precipitation (Chen et al., 2008). These products are often available at a spatial resolution greater than 0.5°.

B- Data obtained from reanalysis of historical data by numerical weather predictions or atmospheric models that use a combination of satellite and in-situ observations of various atmospheric properties as inputs. These data are called reanalysis data (Balsamo et al., 2015). National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR)[1] and European Centre for Medium-Range Weather Forecasts (ECMWF)[2] are in this group (Balsamo et al., 2015).

C- Satellite-only products. These data are extracted by using IR, MV or IR-MV combined information. Multi-satellite precipitation analysis (TMPA)[3] 3B42 RT V7 and Tropical Rainfall Measuring Mission (TRMM)[4]are in this group of products.

D- Satellite-gauge products that combine two individual (gauge-only and satellite-only) products together through different bias correction or blending procedures. The CMORPH (Joyce et al., 2004) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al., 1997) are in this group. Such products are often available at the spatial resolution of 0.25°or finer.

The rain measurement instrument at the surface of the planet, in addition to direct use of rain gauges, does not come out of this series. If precipitation measurements would be possible through some of these methods at stations which have defective data, then these data can be used to complete ground measurements in the future. Also, in places where ground measurement is not possible, by processing these types of data, precipitation measurement can be done faster and at a more suitable time. Over the past decades, many efforts have been made to produce satellite data, so precipitation is widely available at temporal and spatial scales (Tapiador et al., 2012). These values vary from one region to another. (Duan et al., 2016) evaluated eight high spatial resolution gridded precipitation products in Adige Basin located in Italy in daily, monthly and annually basis. Evaluation results showed that in terms of overall statistical metrics the CHIRPS, TRMM and CMORPH_BLD comparably rank as the top three best performing products, while the PGF performs worst. (Worqlul et al., 2017) evaluated the advantages and the limitation of commonly used high-resolution satellite rainfall products CFSR (Climate Forecast System Reanalysis) and Multi-Satellite Precipitation Analysis (TMPA) 3B42 as input to hydrological models and as compared to sparsely and densely populated network of rain gauges. The results of comparisons between CFSR and 3B42 data with the gauged rainfall indicated that CFSR data captured the pattern and volume of gauged rainfall well while 3B42 did not. In other words, TMPA 3B42 data is not capable of describing temporal rain changes. However, the two data of rain-gauging and reanalysis data of CFSR are well able to create the river current data. (Poméon et al., 2017) conducted an investigation to evaluate ten freely available satellite and reanalysis datasets for six differently sized and located basins in West Africa. These data were compared with rain-gauge dataset. Results showed that best results were achieved by datasets which use a multitude of input data, namely infrared and microwave satellite data, as well as observations from rain gauges (usually GPCC) for bias correction. Tan and Santo, (2018) performed a comparison between GPM IMERG, TMPA 3B42 and long-term PERSIANN-CDR products in Malaysia. The results showed that all the SPPs (satellite precipitation products) perform well in annual and monthly precipitation measurements and precipitation detection ability, except the PERSIANN-CDR. Gao et al., (2018) evaluated and compared two long-term monthly satellite precipitation datasets of CHIRPS (Climate

1- National Centers for Environmental Prediction–National Center for Atmospheric Research

2- European Centre for Medium-Range Weather Forecast

3- Trmm Multi-satellite Precipitation Analysis

4- TRMM (Tropical Rainfall Measuring Mission) Multi-satellite Precipitation Analysis

Hazards Group Infrared Precipitation with Stations data) and PERSIANN-CDR, with in-situ measurements from 105 meteorological stations in Xinjiang, China. Results showed that PERSIANN-CDR and CHIRPS had similar correlations with observed data. However, CHIRPS outperformed PERSIANN-CDR with the smaller errors and bias, and PERSIANN-CDR tended to overestimate the precipitation in the rain season (from May to September). Kim et al., (2019) evaluated precipitation extremes over the Asian domain using observation and modeling studies. They highlighted the importance of accurate precipitation datasets for understanding extreme precipitation events, which are particularly relevant to regions with complex terrain such as Iran. In Iran, Gorjizade et al., (2019) evaluate the accuracy of some of these data types, including high-resolution spatial data consist of ERA-Interim, CHIRPS and PERSIANN-CDR at the upstream of the Maroon Dam on daily, monthly and annual timescales. In the daily rainfall estimation, like the monthly rainfall, the best estimate is the ReAnalysis product (ERA-Interim product), which has the best estimate of precipitation in all stations. Tang et al., (2020) conducted a comprehensive comparison of the Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG) with nine satellite and reanalysis datasets. They found that GPM IMERG exhibited improvements over the last two decades, indicating advancements in satellite precipitation products. Bandhauer et al., (2022) conducted an evaluation of daily precipitation analyses in the E-OBS (v19.0e) and ERA5 datasets by comparing them to regional high-resolution datasets in European regions. Their research focused on assessing the performance of these datasets in capturing daily precipitation, particularly in European regions. The findings of this study contribute to the understanding of the strengths and limitations of different precipitation datasets in a specific geographical context. 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, some of the studies done in the world is presented on the remote sensing data set.

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

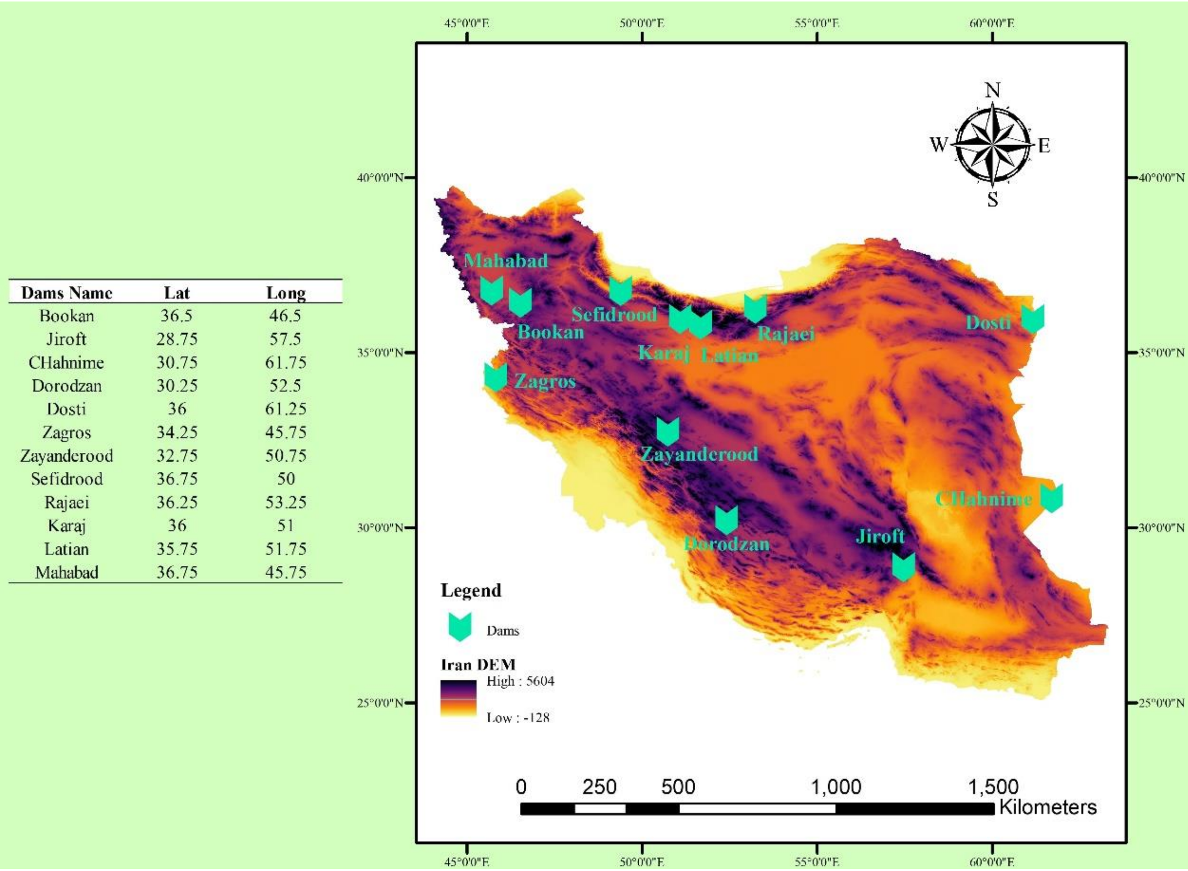
Reference	Study area	Period	CC	RMSE (mm/day)	POD
Rao et al. (2024)	over the Qinghai-Tibet Plateau	2010-2017	0.55	3.78	-
Gomis-Cebolla et al. (2023)	over Spain	1951–2020	0.5-0.9	2-8	-
Gorjizade et al. (2022)	Maroon Dam basin	2003-2014	0.5	5.5	0.42
Tan and Santo (2018)	Malaysia	12 March 2014 to 29 February 2016	0.5–0.6	12.94–14.93	0.86–0.89
Sharifi et al. (2016)	Iran	March 2014 to February 2015	0.4–0.52	6.38–19.41	0.46–0.7

Unfortunately, meteorological stations in Iran are scattered and have incomplete information; therefore, it is very necessary to evaluate the performance of satellite precipitation products in Iran, where most of the regions are arid and semi-arid. This study can also be useful in improving the performance of future versions of gridded rainfall data. Therefore, the purpose of this study is evaluating the appropriateness of CMORPH, ERA5, ERA-Interim, PERSIANN, PERSIANN-CCS and PERSIANN-CDR models in Iran, with local measurements in daily, monthly and annual basis. So far, such a study has not been conducted in Iran based on the information of rain gauge stations in the dams as the main sources of water storage.

2. Materials and Methods

2.1. Study area

In this study, recorded data by rain-gauge stations in-situ of 12 dams in different parts of Iran were collected. Figure 1 shows the location of dams and their geographic coordinates. In this study, we tried to select dams which cover almost the major part of the country. Considering that the operation period of these dams is different and also the data of satellite models are available in different periods, we have tried to evaluate and compare satellite and measured data in their joint period. Table 2 shows the operation years of these dams.



Dams Name	Lat	Long
Bookan	36.5	46.5
Jiroft	28.75	57.5
CHahnime	30.75	61.75
Dorodzan	30.25	52.5
Dosti	36	61.25
Zagros	34.25	45.75
Zayanderood	32.75	50.75
Sefidrood	36.75	50
Rajaei	36.25	53.25
Karaj	36	51
Latian	35.75	51.75
Mahabad	36.75	45.75

Fig. 1. Study area

2.2. Precipitation datasets

In this study, six satellite precipitation products were used to evaluate the performance of satellite data. Table 3 examines the details of the spatial coverage of each data set, the pixel length and width, and the type of data generation algorithm.

2.2.1. CMORPH

The CMORPH model was presented in 2004 by Joyce et al. at the NOAA Climate Prediction Center and has been available from December 2002 at ftp://ftp.cpc.ncep.noaa.gov. The CMORPH model is a method used to combine the cloud system advection vectors, derived from images of the infrared satellite data, and passive microwave signals to estimates precipitation in different places (Joyce et al., 2004). In time when these images are available, a relationship will be established between the precipitation obtained from these images and high cloud temperature obtained from infrared images. By utilizing this relationship, when the microwave images are not available, the amount of precipitation would be estimated.

More information on this technique is presented in Joyce et al. reference. Precipitation prediction in this model is available in two versions of CMORPH.x (Koutsouris et al., 2016) and CMORPH1.0. Initially, no bias correction and no rain gauge data were used in the CMORPH technique for previous Version 0.x product. The latest (Version1.0) CMORPH products include three different products: the raw satellite-only precipitation product (CMORPH_RAW)[1], bias corrected product (CMORPH_CRT)[2] and

1- Raw satellite-only precipitation product
2- Bias corrected product
3- satellite-gauge blended product

satellite-gauge blended product (CMORPH_BLD)[3]. The RAW product belongs to the "satellite-only" category while the CRT and BLD products belong to the "satellite-gauge" category and rain-gauge stations. In this study the product of (CMORPH_RAW) has been used.

Table 2. Studied time period in this study

Dams	ERA5	ERA-Interim	CMORPH	PERSIANN	PERSIANN-CDR	PERSIANN-CCS
Bookan	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Chahnime	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Doroodzan	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Ilam	2008-2017	2001-2017	2005-2018	2001-2018	2001-2018	2003-2018
Jiroft	2009-2017	2009-2017	2009-2018	2009-2018	2009-2018	2009-2018
Karaj	2008-2012	2000-2012	2005-2012	2000-2012	2000-2012	2003-2012
Latian	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Mahabad	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Rajaei	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Sefidrood	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Zayanderood	2008-2017	2000-2017	2005-2018	2000-2018	2000-2018	2003-2018
Zagros	2011-2017	2011-2017	2011-2018	2011-2018	2011-2018	2011-2018

Table 3. Summary of gridded precipitation products to be evaluated in this study.

Datasets Name	Coverage	Temporal resolution	Spatial resolution	Period	Category	Refrence
ERA5	Global	1 h	0.25° × 0.25°	1950-Present	ReAnalysis	ECMWF
ERA-Interim	Global	3 h	0.75° × 0.75°	1979-Present	ReAnalysis	(Dee et al., 2011)
CMORPH	60°N-60°S	0.5 h	0.25° × 0.25°	2002-Present	Satelite-Gague	(Joyce et al, 2004)
PERSIANN	60°N-60°S	1 h	0.25° × 0.25°	2000-Present	Satelite-based	(Ashouri et al, 2015)
PERSIANN-CDR	60°N-60°S	Daily	0.25° × 0.25°	1983-(delayed)Present	Satelite-Gague	(Ashouri et al, 2015)
PERSIANN-CCS	Global	0.5 h	0.04° × 0.04°	2003-present	Satelite-based	(Sorooshian et al., 2015)

2.2.2. ERA-Interim

ERA-Interim is the fourth generation of reanalysis data. This data has been generated by the ECMWF with a precision of 0.75 * 0.75. Also, these data are updated every month. Generally speaking, a re-analysis of a system for generating a cluster of data is called reanalysis. Reanalysis data are obtained from the combination of the results of short-term forecasts which are acquired by Numerical Weather Precipitation models (NWP) with observational data. The model predictions, which are called initial guesses, are derived from the input data into the model and the data assimilation and the mathematical relation defined for the model (Balsamo et al., 2015; Dee et al., 2011). Since model predictions are always associated with uncertainties, this initial prediction is optimized by controlling with existing observational data, in order to reduce the prediction error. The ECMWF Center has been able to provide ERA-interim data after providing two data sets ERA-15 and ERA-40, according to the feedback provided by the above data. ERA-interim data is a more advanced generation of the two earlier versions (Dee et al., 2011). In this study, ERA-Interim daily precipitation data was used with a spatial resolution of 0.25 ° and the method of data extraction using the ECMWF Web API. These data can be ordered after registration by following link:

http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/

2.2.3. ERA5

ERA5 is a new (fifth generation) re-analysis data set developed by the ECMWF European Weather Forecasting Center. The most important difference in comparison with ERA-Interim are as follow:

Using a 2016 rather than a 2006 version of the ECMWF data assimilation system, using higher horizontal resolution ~30km rather than ~79km, and using more number of levels 137 rather than 60, higher time resolution 1 hour rather than 3 hours, new analyses of sea-surface temperature and sea-ice concentration, changes in use of satellite data on ozone (youreka et al., 2018). Data cover the period from 1950 to 1978 but at the time of extraction only information for the period 2008-2018 is available. In this study, daily rainfall data of ERA5 was used with a spatial resolution of 0.25 °. Data extraction was done using ECMWF Web API. The instructions for downloading the data are listed below.

https://software.ecmwf.int/wiki/display/CKB/How+to+download+ERA5+data+via+the+ECMWF+Web+API.

2.2.4. PERSIANN

Satellite-based data of PERSIANN model is a rainfall estimation algorithm using remote sensing and an artificial neural network. The base algorithm is based on an artificial neural network. Shu et al. developed the model at the University of Arizona in 1999. The approach of this algorithm is to calibrate infrared (IR, infrared) data with non-active microwave measurements (PMW, Microwave Passive). This is done by updating the parameters at any time available for PMW estimation. In fact, estimates are made by IR waves and then calibrated with PMW. The base inputs of this model are the high temperature clouds produced by images of the infrared spectrum, which are obtained by Earth-circuit satellites, GoEs8 and GoEs9. The significant features of Earth-circuit satellite imagery are high temporal resolution. However, the spatial resolution of this image is low due to the greater distance of this satellite from the Earth than polar satellites.

Using these images, PERSIANN estimates the rainfall intensity at a given time (Homg et al., 2004). In order to increase spatial resolution, this algorithm uses satellite images of the TRMM, NOAA14 and NOAA13 satellites, which are of polar circuit types, as well as artificial neural network, to make spatial resolution of 0.25 * 0.25 degrees with a half-hour time interval. Among high-resolution, satellite-based, precipitation estimation algorithms, PERSIANN, because of its primary reliance on infrared information that dates back to 1979, is very suitable for estimating historical precipitation over the past three decades.

2.2.5. PERSIANN-CDR[1]

The PERSIANN-CDR dataset is jointly developed by the University of California and the NOAA and is available since 1983 (Ashouri et al., 2015). The existing PERSIANN algorithm provides global precipitation estimates using combined IR and PMW information from multiple GEO (Geostationary Orbit Earth) and LEO (Low Orbit Earth) satellites. The algorithm uses an artificial neural network (ANN) model to extract cold-cloud pixels and neighboring features from GEO longwave infrared images and associates variations in each pixel's brightness temperature to estimate the pixel's surface rainfall rate (Hsu et al., 1997; Sorooshian et al., 2000). The PERSIANN algorithm uses infrared data from GridSat-B1, which is derived from GOE satellites. The output from the PERSIANN model without the use of microwave data (PMW) - (where this data is not available) – and without any data modification is called Persiann-B1. To reduce the biases in the PERSIANN-estimated precipitation while preserving the spatial and temporal patterns in high resolution, 2.5° monthly GPCP precipitation data were utilized. The bias-corrected PERSIANN precipitation estimates maintain a monthly total consistent with the monthly GPCP (Global Precipitation climatology project) product. The final product, called the PERSIANN-CDR (for Climate Data Record). In this study, daily precipitation data of PERSIANN-CDR using a spatial resolution of 0.25 ° was used.

2.2.6. PERSIANN-CCS[2]

PERSIANN-CCS is upgraded generation of satellite-based PERSIANN data. As mentioned before, The PERSIANN algorithm fits the pixel brightness temperature and its neighbor temperature textures, in terms of means and standard deviations, to the calculated pixel rain rates based on an Artificial Neural Network (ANN) model. With

1- Climate Data Record

2- Cloud classification System

development of the PERSIANN Cloud Classification System (CCS) is introduced. Instead of direct pixel-to-pixel fitting of infrared cloud images to the rain rate, the PERSIANN CCS takes into account image segmentation and objective classification methods to process cloud images into a set of disjointed cloud-patch regions; informative features are extracted from cloud patches and classified into a number of patch groups based on the similarity of selected features, such as the patch size and texture. In this study, PERSIANN-CCS daily rainfall data with spatial separation of 0.04 were used. The following figure displays the structure of PERSIANN -CCS model.

2.3. Evaluation Indices

In the present study, different statistical and categorical indices were adopted to qualitatively and quantitatively evaluate the precision of the six SPPs. IDW[1] methodology and spatial analysis were used for annual evaluation. Also, Taylor Diagram was used for monthly evaluation and finally, three RB, RMSE and CC evaluation indices and three classification indicators of POD, FAR and CSI were used for daily evaluation.

As mentioned, Taylor's diagram is used for monthly evaluation. The Taylor diagram (Taylor, 2001) has been developed using standard deviation values, correlation coefficient and CRMSE[2], for observational data and all satellite models of precipitation estimating. This graph shows the three indicators (STDEV, CC and CRMSE) at each point. Each diagram contains a real data represented by a separate point in the Taylor chart; obviously, the point closer to the real point, has better proficiency as a point of defined indictors.

Also, three evaluation indicators and three classification indexes were used for daily evaluation. The following table shows the computational relationships of these indices.

In the table 5, Pi is the predicted value and Gi is the observed value. H is the number of times the observed rain is correctly detected and F is the number of observed rain that is not detected. Also, M is the number of times that rainfall has not occurred, but the model has shown the occurrence of precipitation.

Table 5- List of the statistical metrics used in the evaluation of precipitation products.

Optimized Value	Equation	Statistical Index
1	$CC = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2}\sqrt{\sum_{i=1}^{n}(P_i - P)^2}}$	The correlation coefficient
0	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - G_i)^2}{n}}$	Root Mean Square Error
0	$RB = \frac{\sum_{i=1}^{n}(P_i - G_i)}{\sum_{i=1}^{n}(G_i)}$	Relative Bias
1	$POD = \frac{H}{H+M}$	Probability of Detection (POD)
0	$FAR = \frac{F}{H+F}$	False Alarm Ratio (FAR)
1	$CSI = \frac{H}{H+M+F}$	Critical Success Index (CSI)

- The Person correlation coefficient (CC) assesses the correlation between satellite precipitation products and rain gauge observations. The value of this parameter varies from -1 to 1. CC = 0 indicates that there is no linear correlation between observed and estimated data. The values of -1 and 1 of this parameter indicate a completely negative and positive correlation, respectively (Tan and Santo, 2018).

- Root Mean Square Error (RMSE) measures the difference between the distributions of the ground observed rainfall and the distribution of satellite rainfall estimation and calculates a weighted average error, weighted according to the square of the error (Worqlul et al., 2014).

- Relative Bias is a measure of how does the average satellite rainfall magnitude compared to the ground rainfall observation.

1- Inverse Distance weighting

2- Centered root mean square between estimation and observation

If this value is greater than zero, it indicates that the rainfall model is estimated to be greater than the observed value, and if it is smaller than zero, then it is shown that rainfall is estimated by the model less. If this amount is Equal to zero, then there is not any error.

- Three FAR, POD and CSI classification indexes were used to determine the accuracy of the model in detecting the occurrence of precipitation.
- Probability of Detection (POD), shows how often rain occurrences are correctly detected by satellite, and the optimal value is equal to one.
- The FAR, the ratio of the false reported precipitation by model, while actually rain did not occur, to the total recorded rainfall. The optimal value for this parameter is zero.
- The Critical Success Index (CSI) provides no unique verification information since it is a function of both FAR and POD, understanding its behavior can help identify which component would be more beneficial to target in a warning strategy. This indicator expresses the probability of true detection of rainy and non-rainy days. The optimum value is one.

As previously mentioned, the present study evaluates the results of estimated rainfall by ERA5, ERA-Interim, CMORPH, PERSIANN, PERSIANN-CCS, PERSIANN-CDR satellites and observational precipitation of 12 rain-gauge stations in-situ of some dams in Iran. This assessment is based on the observational data available at the rain-gauge stations and rainfall estimation models in different years, on daily, monthly and annual scales.

3. Results and Discussion

3.1. Annual and monthly estimates

Fig. 2 shows the mean annual precipitation values measured by the rain-gauge stations and estimated precipitation values by satellite models. As it is shown in this figure, rainfall by CMORPH model at all stations except for the Chahnime, Sefidrud and Zayanderud has been estimated less than observation rates. The estimated value of these stations was less than 250 mm.Estimated precipitation values by PERSIANN-CCS model in all stations except Doroodzan and Ilam were more than observational values. Meanwhile, the highest estimate of rainfall was estimated at the Rajaee station by the ERA5 model at around 900 mm and the lowest estimate of precipitation was at Chahnime station by the ERA5 model at about 45 mm. This is while, the highest and lowest average observed rainfall was at Shahid Rajaee and Chahnime rain-gauge Station, respectively (560 mm and 40 mm).

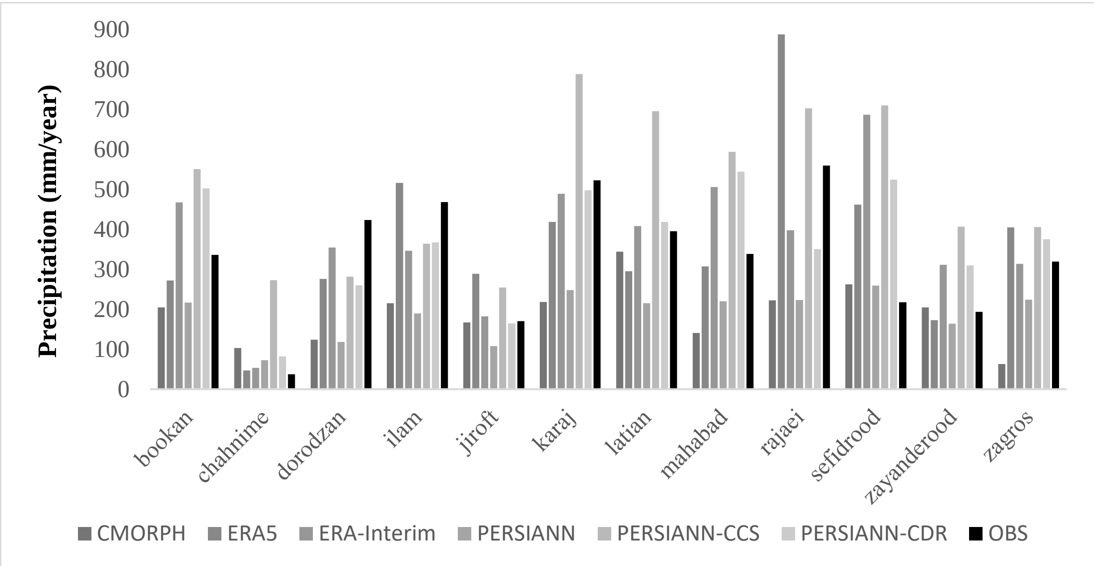


Fig. 2. Total annual precipitation measured from gauges and precipitation datasets

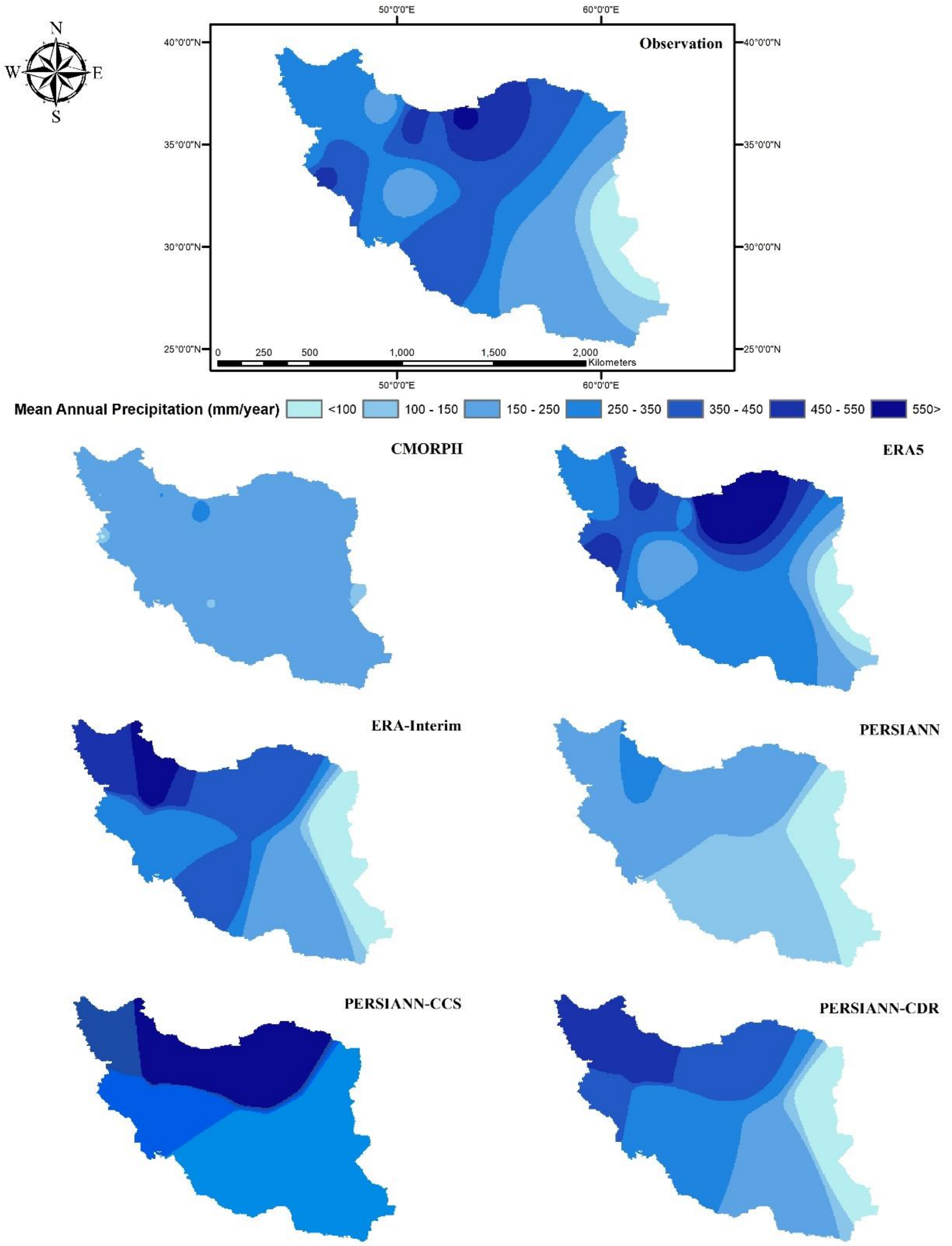


Fig. 3. Spatial pattern of observational data and estimated annual rainfall

The main advantage of the IDW (Inverse Distance Weighted) method for rain interpolation is that it is a simple and intuitive way to estimate values at unsampled locations based on the surrounding sample points. IDW assumes that values at any given moment are more closely related to nearby points than those further away, making it a suitable method for spatially distributed data like rainfall. In this study, using the IDW method, precipitation data of the existing stations was subsequently interpolated and the fully covered patterns were generated in Fig. 3. This shape represents the variation in the annual rainfall in Iran. As you can see, ERA5, ERA-Interim, and PERSIANN-CDR data are more consistent with the average annual observed rainfall. On the other hand, the results of the two CMORPH and PERSIANN-CCS models indicate that the two models are less consistent with observational data in most parts of Iran. Precipitation estimate by the CMORPH model in most parts of Iran range from 150 to 250 mm / year and was under estimate. This is while, rainfall estimate by the PERSIANN-CCS model was higher than the observational data and was over estimated. All precipitation products from the above-mentioned satellites have estimated rainfall in eastern Iran (Chahnime location), less than elsewhere. Rainfall estimates are also rising by satellite models from the east to the north.

For evaluation and comparison of monthly rainfall data of models with observational precipitation data, the Taylor diagram for all stations is presented in Figures 4.1 and 4.2. As can be seen, on the monthly scale, the ERA5, ERA-Interim and PERSIANN-CDR models show the best correlation coefficient among different stations.

At the stations of Drozden, Ilam, Karaj, Latyan, Mahabad, Rajaee and Zagros, the ERA5 models, at Bukan, Chahnime, Jiroft and Zayanderud stations, ERA-Interim models and finally at the Sefidrud station, the PERSIANN-CDR model showed the highest correlation coefficients. On the other hand, the lowest correlation coefficient in all stations except the Chahnime, Ilam and Rajaee have been provided by the CMORPH model.

The highest correlation coefficient in the monthly scale was provided by ERA5 model at Doroodzan Station with a correlation coefficient of 0.93 and the lowest correlation coefficient calculated by PERSIANN model at Rajaee Station at 0.04. According to Figures 4.1 and 4.2, the most and least standard deviations of observational data were recorded at Doroodzan and Chahnime stations with values of 55.75 and 7.015. Also, the highest and lowest standard deviations of estimated data are shown in the results of PERSIANN-CCS and CMORPH satellite models with values of 59.91 and 7.23.

3.2. Daily evaluation

Table 6 shows the results of the evaluation and comparison of the accuracy of satellite data in the estimation of precipitation values using the parameters mentioned. In this table, each of the RMSE, BIAS, and CC evaluation indicators and the POD, FAR, and CSI classification indices are depicted for each satellite precipitation product and at different stations. The results show that, at the Buccan Station, the ERA5 model has the highest correlation coefficient (0.3417), and then the ERA-Interim model with the 0.3151 was ranked as a second. As Table 6 shows, the obtained RB values indicate that the computational rainfall which is estimated by three models of CMORPH, ERA5 and PERSIANN, were under estimate and estimated rainfall by three other models were over estimate.

As already mentioned, RMSE is one of the other criteria for evaluating the accuracy of data estimation. The results of Table 6 indicated that the lowest RMSE is related to the ERA5 model at 3.3348 mm / day and the highest value is related to the PERSIANN-CCS model with 5.4448 mm / day. Due to the presence of RMSE in the range of 0 to 10, simulations of rainfall data by the ERA5 model were excellent at Bukan Station. In other words, the ERA5 model is very suitable for simulating daily rainfall data in the Bukan Dam area. Considering the higher RMSE provided by the ERA5 model in comparison with other models, it can be concluded that the model can be used to complete the data series and replace the lost data.

Similarly, in each station, the parameters of Table 6 can be used to analyze the accuracy of the resulting data. These results indicate that based on RMSE values at all stations except Ilam, Jiroft, Rajaee, Sefidrud and Zagros on the daily scale, the best model of rainfall estimation was ERA5. Meanwhile at mentioned stations ERA- Interim was the best estimator of daily precipitation. Also, at the Sefidrud station the best model was PERSIANN-CDR.

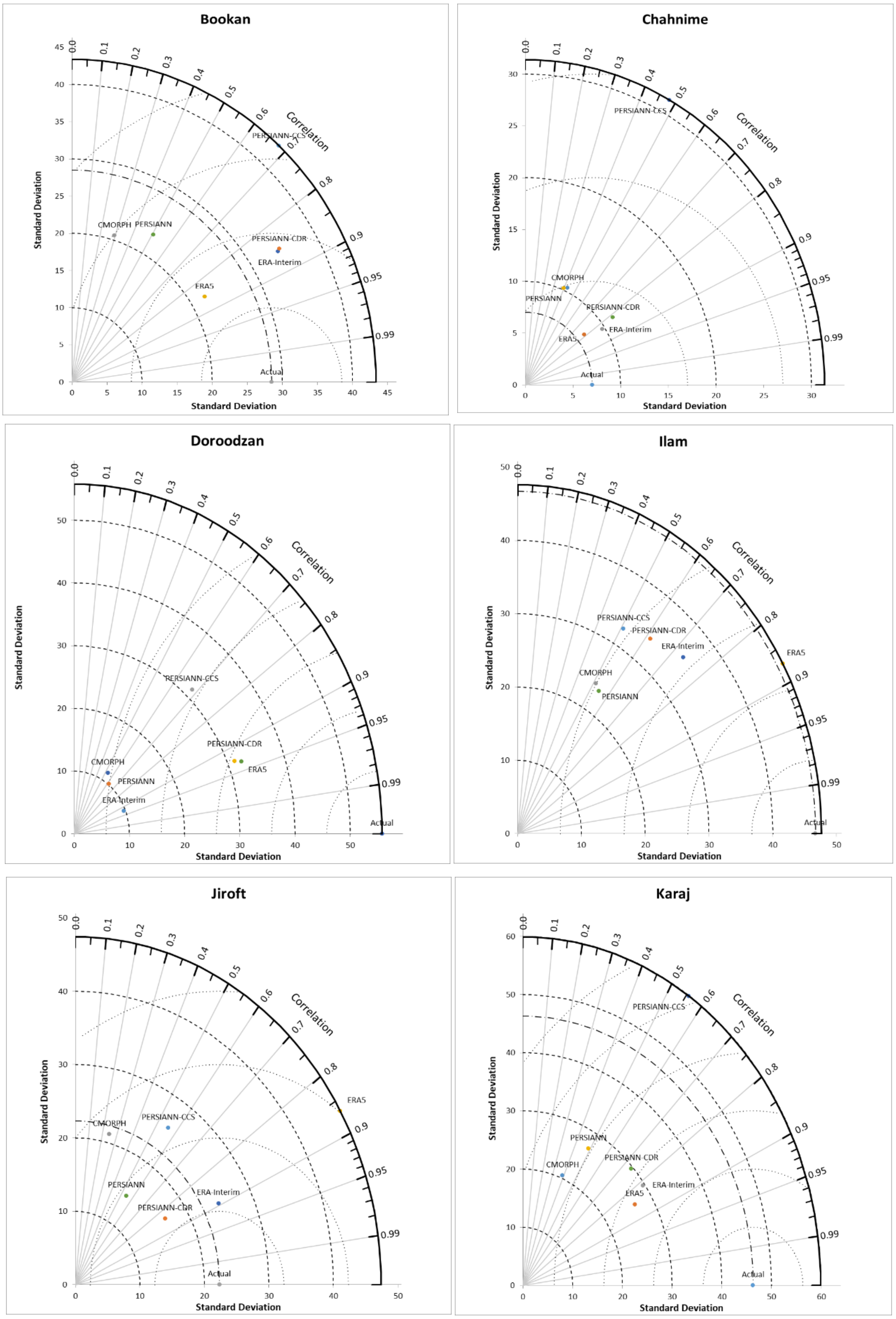


Fig. 4-1. Taylor diagram graphical presentation for evaluation satellite monthly precipitation

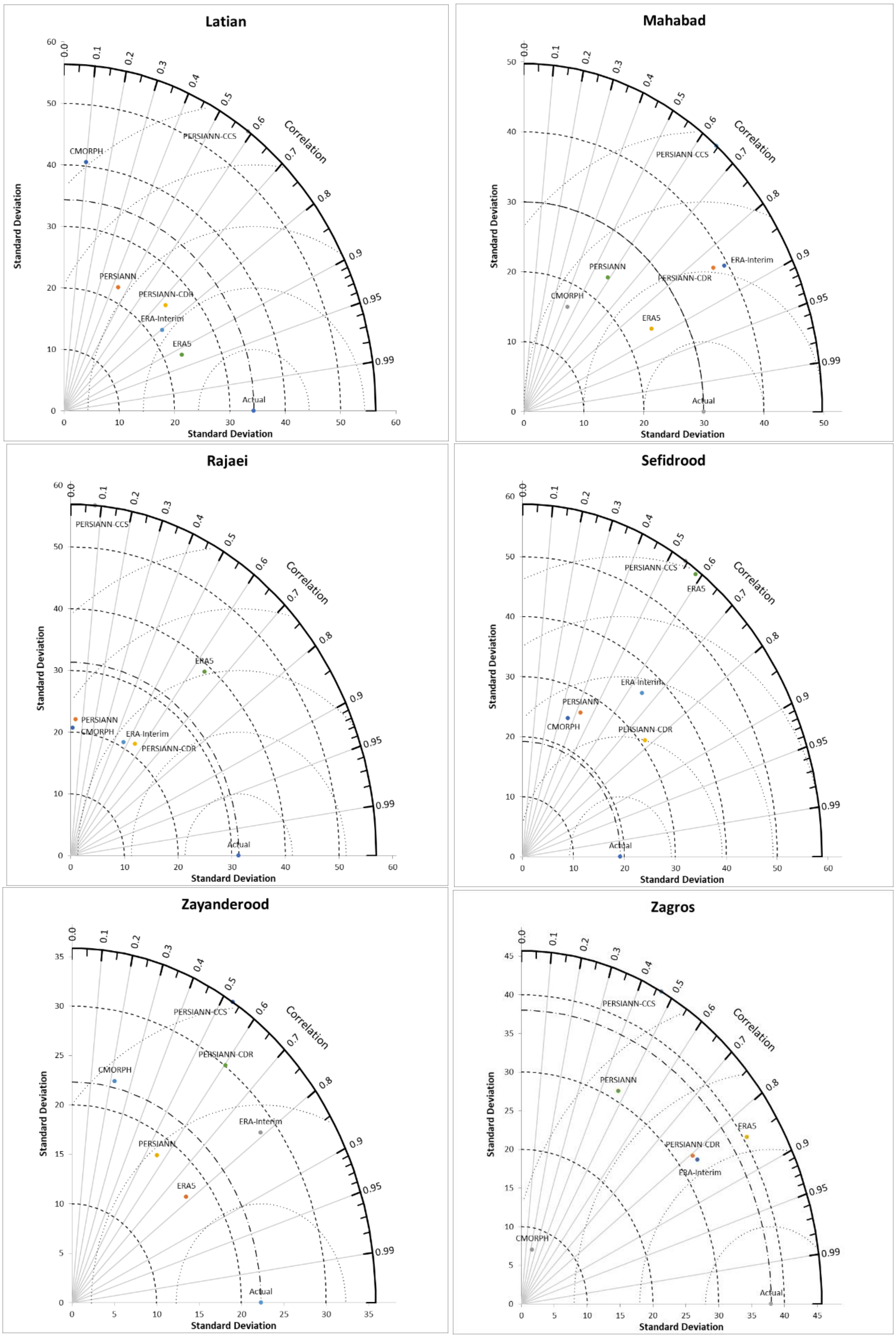


Fig. 4-2. Taylor diagram graphical presentation for evaluation satellite monthly precipitation

As mentioned earlier, one of the other criteria for assessing the accuracy of rainfall data is the correlation coefficient. This parameter is also suitable for completing unrecorded data. Based on this parameter, the best model for estimating precipitation in Jiroft and Sefidrud was ERA-Interim and in all other stations was ERA5 model. In accordance with Table 6, the range of variations of these parameters is visible. The results indicate that the CC parameter variation range at all stations was from 0.0062 at Zagros station (by CMORPH) to 0.6278 at Karaj Station (by ERA5 model), and the absolute variation range of RB in the range of 0.002 at Karaj station (by PERSIANN-CDR) up to 6.08 (by PERSIANN-CCS) and the range of variations of the RMSE parameter was in the range of 0.78 mm / d at the Chahnime station (by ERA5) to 7.80 at Rajaee Station (by PERSIANN-CCS).

Three POD, FAR and CSI indexes were evaluated to assess the estimated rainfall detection limits by satellite algorithms and its values are shown in Table 6 at all stations. The highest POD value was obtained by ERA5 model at all stations except Karaj dam station. This value was obtained at the Karaj Station by the PERSIANN-CCS model and is equal to 0.4699. The amount of POD obtained at this station, recorded its highest value. POD=0.4699 means that 46.99 percent of the rainy days are correctly predicted by the model. Among other parameters, the CSI parameter can be mentioned. The highest value of observed CSI, with a value of 0.43, is related to ERA5 and ERA-Interim models at Karaj Station. This means that the accuracy of the model in the determination of rainy days and non-rainy days is 43%. As previously mentioned, FAR is another parameter for evaluating the accuracy of estimated rainfall data. High FAR values indicate that the number of non-rainy days estimated by the model and the recorded station data are not good matches. The highest amount of FAR (equal to 0.8421) has recorded at the Zagros station and was related to the CMORPH model, which means that, while 84.21% of the predictions indicate rainy days, this fact has not really occurred. Also, the lowest amount of FAR was related to the ERA-Interim model at the Zayanderud Station (equal to 0.05).

In order to evaluate the daily rainfall intensity, the probability density function method (PDF[1]) was used (Tan and Santo, 2018). This method helps capture statistical properties of precipitation data and provides valuable insights into spatial patterns of precipitation. Ultimately, it improves the accuracy of rainfall interpolation from satellite products in regions where direct measurements are lacking. In general, rainfall intensity is divided into eight different groups according to the World Meteorological Organization (WMO2) standards (0-0.1 mm / d, 0.1-1 mm / d, 1-2 mm / d, 2-5 mm / d, 5- 10 mm per day, 10-20 mm per day, 20-50 mm per day and more than 50 mm per day) (Tan and Duan, 2017).

Figures 5.1 and 5.2 represent the amount of PDF calculated by rainfall estimation models and observation station's rain-gauge data. In all observational and computational precipitation, the highest and lowest number of precipitation in all stations are related to the intensity of 0 to 0.1 mm / day and more than 50 mm / day, respectively. The best performance of all models ranges from 0 to 0.1 mm per day and more than 50 mm per day and their worst performance is in the range of 0.1 to 1 mm per day. In all stations, except for Rajaee station, the percentage of rainfall occurrence with intensity of 0 to 0.1 mm / day were over estimated. In the following figures, the estimated rainfall intensity by observational data and satellite models are shown. For example, at Bukan Station, about 85% of observations have low rainfall rates (less than 1 mm / h), 12% indicate the intensity of 0.1 to 20 mm per day, and only about 3% of observations indicate heavy rainfall (over 20 mm per day)

1- Probability Density Function
2-World Meteorological Organization

Table 6. Evaluation Indexes for daily precipitation

Station	Datasets Name	RMSE (mm)	RB	CC	POD	FAR	CSI
Bookan	CMORPH	3.901	-0.406	0.105	0.201	0.487	0.17
	ERA5	3.334	-0.22	0.341	0.356	0.331	0.30
	ERA-Interim	3.785	0.407	0.315	0.3	0.153	0.29
	PERSIANN	3.872	-0.349	0.106	0.28	0.617	0.19
	PERSIANN-CCS	5.444	0.625	0.104	0.281	0.536	0.21
	PERSIANN-CDR	4.114	0.498	0.178	0.257	0.323	0.23
Chahnime	CMORPH	1.398	1.844	0.078	0.059	0.388	0.06
	ERA5	0.783	0.428	0.619	0.247	0.303	0.22
	ERA-Interim	0.958	0.464	0.582	0.219	0.247	0.20
	PERSIANN	1.443	0.982	0.157	0.149	0.486	0.13
	PERSIANN-CCS	3.142	6.085	0.168	0.117	0.369	0.11
	PERSIANN-CDR	1.133	1.285	0.296	0.122	0.221	0.12
Doroodzan	CMORPH	5.1717	-0.657	0.186	0.115	0.42	0.11
	ERA5	4.912	-0.232	0.386	0.37	0.273	0.33
	ERA-Interim	5.578	-0.164	0.419	0.34	0.187	0.32
	PERSIANN	5.667	-0.709	0.216	0.321	0.609	0.21
	PERSIANN-CCS	5.887	-0.309	0.207	0.274	0.577	0.20
	PERSIANN-CDR	5.456	-0.387	0.348	0.228	0.377	0.20
Ilam	CMORPH	5.976	-0.514	0.141	0.275	0.516	0.21
	ERA5	5.389	0.115	0.463	0.353	0.197	0.33
	ERA-Interim	4.855	-0.037	0.407	0.303	0.254	0.28
	PERSIANN	5.205	-0.495	0.248	0.285	0.527	0.22
	PERSIANN-CCS	5.905	-0.07	0.178	0.234	0.561	0.18
	PERSIANN-CDR	5.1350	-0.016	0.266	0.207	0.347	0.19
Jiroft	CMORPH	3.855	0.102	0.081	0.174	0.504	0.15
	ERA5	3.744	0.747	0.506	0.280	0.318	0.25
	ERA-Interim	2.711	0.103	0.529	0.28	0.327	0.25
	PERSIANN	2.956	-0.376	0.197	0.253	0.655	0.17
	PERSIANN-CCS	3.702	0.53	0.168	0.21	0.571	0.16
	PERSIANN-CDR	2.7545	-0.059	0.355	0.174	0.332	0.16
Karaj	CMORPH	5.066	-0.534	0.063	0.276	0.449	0.23
	ERA5	3.068	0.062	0.627	0.389	0.145	0.37
	ERA-Interim	3.957	-0.007	0.574	0.329	0.07	0.32
	PERSIANN	4.798	-0.524	0.26	0.461	0.487	0.32
	PERSIANN-CCS	6.357	0.436	0.313	0.47	0.363	0.37
	PERSIANN-CDR	4.571	-0.002	0.368	0.362	0.171	0.34
Latian	CMORPH	4.494	-0.132	0.024	0.226	0.41	0.20
	ERA5	2.9073	-0.222	0.622	0.452	0.184	0.41
	ERA-Interim	3.209	0.037	0.538	0.279	0.056	0.27
	PERSIANN	3.959	-0.449	0.227	0.434	0.488	0.30
	PERSIANN-CCS	6.058	0.709	0.266	0.424	0.359	0.34

Station	Datasets Name	RMSE (mm)	RB	CC	POD	FAR	CSI
	PERSIANN-CDR	3.808	0.082	0.327	0.316	0.171	0.30
Mahabad	CMORPH	3.723	-0.568	0.112	0.257	0.574	0.19
	ERA5	2.6404	-0.057	0.622	0.422	0.157	0.39
	ERA-Interim	3.187	0.541	0.597	0.372	0.066	0.36
	PERSIANN	3.68	-0.332	0.257	0.387	0.506	0.28
	PERSIANN-CCS	5.812	0.743	0.174	0.370	0.422	0.29
	PERSIANN-CDR	3.902	0.627	0.355	0.322	0.208	0.30
Rajaei	CMORPH	5.2700	-0.599	0.02	0.285	0.538	0.21
	ERA5	4.64	0.539	0.594	0.464	0.143	0.43
	ERA-Interim	4.262	-0.301	0.465	0.454	0.114	0.43
	PERSIANN	5.37	-0.602	0.038	0.368	0.71	0.19
	PERSIANN-CCS	7.806	0.295	0.01	0.341	0.651	0.21
	PERSIANN-CDR	5.0529	-0.385	0.14	0.367	0.483	0.27
Sefidrood	CMORPH	3.475	0.242	0.069	0.187	0.467	0.16
	ERA5	5.767	1.7	0.301	0.342	0.449	0.27
	ERA-Interim	3.808	2.143	0.433	0.21	0.073	0.21
	PERSIANN	3.241	0.2004	0.1679	0.298	0.483	0.23
	PERSIANN-CCS	6.342	2.282	0.124	0.286	0.402	0.24
	PERSIANN-CDR	3.585	1.407	0.258	0.252	0.203	0.24
Zayanderood	CMORPH	3.294	0.03	0.061	0.135	0.472	0.12
	ERA5	2.191	-0.089	0.576	0.33	0.253	0.30
	ERA-Interim	2.613	0.6118	0.564	0.265	0.057	0.26
	PERSIANN	2.7745	-0.125	0.332	0.317	0.4628	0.25
	PERSIANN-CCS	4.1605	1.092	0.2346	0.283	0.4187	0.24
	PERSIANN-CDR	2.89	0.586	0.4316	0.237	0.2439	0.22
Zagros	CMORPH	4.417	-0.792	-0.006	0.086	0.842	0.06
	ERA5	4.5305	0.369	0.452	0.215	0.201	0.20
	ERA-Interim	4.095	0.0569	0.437	0.215	0.208	0.21
	PERSIANN	4.563	-0.179	0.312	0.186	0.4868	0.16
	PERSIANN-CCS	5.975	0.489	0.161	0.158	0.4868	0.14
	PERSIANN-CDR	4.2278	0.1218	0.3729	0.148	0.2416	0.14

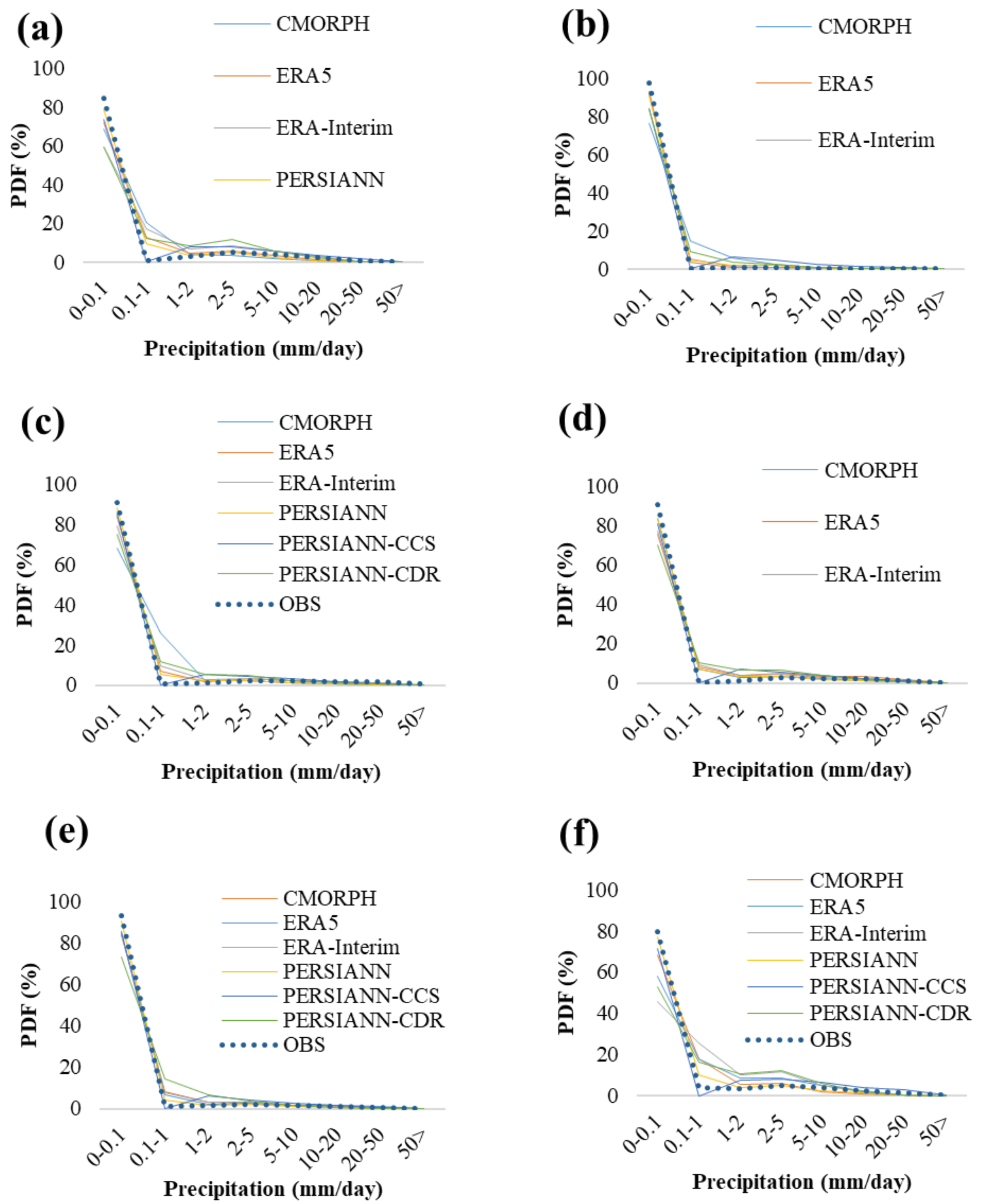


Fig. 5-1. Probability Density Function (PDF) of intensity daily precipitation in (a) Bookan (b) Chahnime (c) Ilam (d) Doroodzan (e) Jiroft (f) Karaj

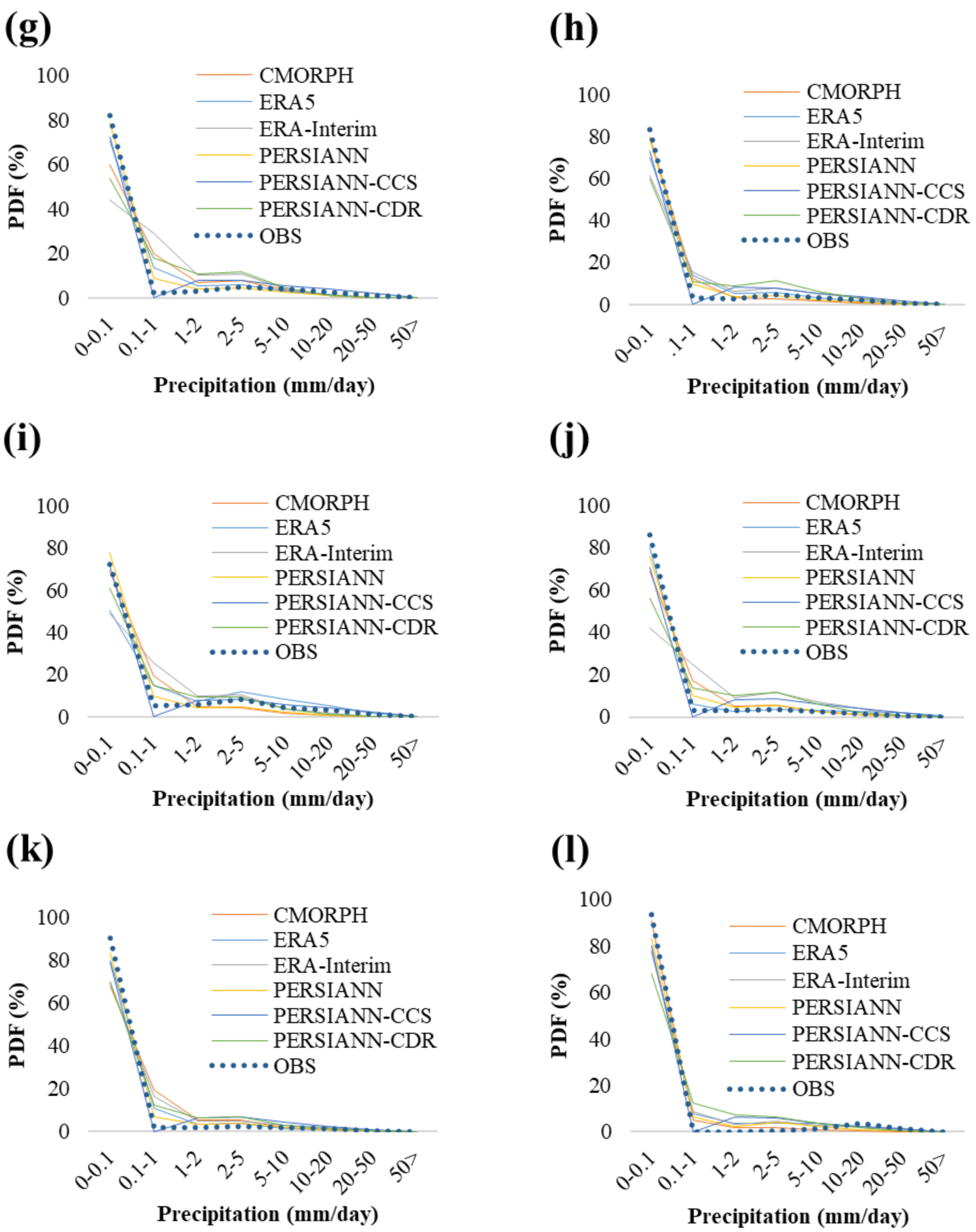


Fig. 5-2. Probability Density Function (PDF) of intensity daily precipitation in (g) Latian (h) Mahabad (i) Rajaei (j) Sefidrood (k) Zayanderood (l) Zagros

4. Conclusion

In this study, various satellite precipitation products from models such as ERA-Interim and ERA5 reanalysis, as well as satellite-gauge data from CMORPH, PERSIANN, PERSIANN-CDR, and TPERSIANN-CCS, were compared with observational data. The study aimed to evaluate the accuracy and consistency of these different precipitation products with ground-based measurements.

Annual rainfall estimates were generated using the IDW method to compare with observed data, while monthly evaluations were conducted using Taylor diagrams to assess data at 12 stations. Daily precipitation evaluations were performed using evaluation indices like CC, RMSE, and RB, as well as classification indices like FAR, POD, and CSI. Probability density function curves were mapped to assess model performance and precision in detecting different rainfall intensities.

The results indicated that reanalysis data from ERA-Interim and ERA5, as well as the PERSIANN-CDR product, showed consistency with observational data. Bias correction techniques were applied to improve the accuracy of estimated precipitation data from satellite models. The study also highlighted the impact of incorporating ground observation data into satellite precipitation products, with better results observed when combining satellite and ground-based data.

Overall, the ERA5, ERA-Interim, and PERSIANN-CDR satellite products showed higher accuracy in estimating precipitation compared to other models. These models were also found to be more suitable for filling data gaps and completing missing information. Further analysis revealed that ERA5 and ERA-Interim models performed better in detecting rainy and non-rainy days, with ERA5 showing the best overall performance among the models evaluated.

The study concluded that satellite precipitation products, particularly from ERA-Interim, ERA5, and PERSIANN-CDR, offer higher accuracy in estimating precipitation and can be valuable for filling data gaps in areas without ground measurements. The results also emphasized the importance of considering different factors, such as spatial resolution and model performance, when evaluating satellite precipitation products for hydrological studies.

5. Disclosure Statement

No potential conflict of interest was reported by the authors

6. References

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