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Evaluation and Comparison of High Spatial Resolution Gridded Precipitation by TRMM, ERA5, and PERSIANN-CCS Datasets on the Upstream of the Maroon Basin, Iran

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ABSTRACT: Precipitation is a vital variable in hydrological studies which its applications and disciplines can be seen widely in water resources management. This parameter differs significantly over location and time; the lack of suitable data for precipitation results in difficulties in hydrological predictions. Therefore, the availability of this parameter in high spatial and temporal resolution is of great importance. Satellite precipitation estimation systems can provide information in areas where the data is not available. So, studying the accuracy of this type of data is very crucial. In this study, precipitation data from three satellite data sets, TRMM, ERA5, and PERSIANN-CCS, for the Idenak region, located in the southwestern part of Iran, (with four stations including Dehno, Ghale-Raeesi, Idenak, Margoon) from 2003 to 2014 was used and evaluated on the daily, monthly and annual basis. The results of this study indicate that the estimation of annual and monthly precipitation data obtained with the ERA5 model and TRMM has a better fit with the observation data in terms of precipitation values and spatial distribution, respectively. On the daily basis, the evaluation results show that at all stations, other than Margoon, the ERA5 model has been more appropriate concerning RMSE and CC values and provides better results. Moreover, according to the CSI values, in the detection of rainy and non-rainy days, the best detection is associated with the ERA5 model at all stations except the Ghale-Raeesi station while PERSIANN-CCS model has the higher ability at this station.

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1- Introduction

Rain is considered an important component of the hydrological cycle and a key environmental meteorology parameter [1]; it is known to be the primary input for most hydrological systems [2]. The traditional precipitation estimation method has been the point measurement that relies heavily on field studies and then is generalized to a surface or region. A dense rain-gauge grid is generally unavailable even in developing countries, and it often includes incorrect data or large gaps [3]. This situation has been exacerbated by a further decline in the number of rain-gauge stations due to financial issues or lack of proper maintenance [4]. As a weakness, the fairly disperse distribution of rain-gauges often leads to poor precipitation patterns [5]. However, providing high-resolution spatial precipitation data according to observations from point measurements is difficult work [6]. Satellite precipitations have been recognized as a major approach to precipitation measurement in recent decades [7, 8]. Remote sensing data provide a new way of identifying the spatial and temporal variation of precipitation with high precision [9]. Satellite data are capable of covering the precipitation systems on a semi-global scale, regardless of mountainous and oceanic terrain, compared to ground measurements such as rain-gauges and radars. Ground rain-gauges have various problems such as high data deficits, wind effects, low number of stations, etc. [10]. Also, ground-based radar measurements are influenced by signal weakness, the dispersion of the return surface, and the uncertainty of the reflective-precipitation relationship [11]. Therefore, satellite precipitation is widely used in many environmental applications such as precipitation characteristic analysis, hydrologic modeling [12], and drought monitoring [13]. A large number of precipitation-based satellite estimations and open-source analysis data with the 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 [14, 15]. If a method is found that precipitation value measurements at stations without statistic data can be reached, then this method might assist to complete ground measurements in the future. Also, at locations where ground measurement does not exist, data processing by this method 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 [16], and their values vary from region to region. For example, Duan et al., (2016)and independent ground data are available from a network of 101 rain gauges during 2000–2010. The eight products include the Version 7 TRMM

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(Tropical Rainfall Measuring Mission evaluated eight types of rain networking data in Italy [2]. Their assessment was carried out on temporal (daily, monthly, and yearly) and spatial (network and basin) scales; the results indicate that the CHIRPS, TRMM, and CMORPH_BLD data provide the best data, whereas the Global Meteorological Forcing Dataset (PGF) provides the worst estimation. Worqlul et al., (2017) the network of observation stations for rainfall is sparse and unevenly distributed. Satellite-based products have the potential to overcome this shortcoming. The objective of this study is to compare the advantages and the limitation of commonly used high-resolution satellite rainfall products (Climate Forecast System Reanalysis (CFSR evaluated CFSR, TMPA-3B42, and ground precipitation data as inputs for hydrological models in scarce data areas [17]. Their results reveal that the TMPA-3B42 is not capable of describing rain time changes, and also both rain-gauge and CFSR reanalysis data are properly capable of producing river flow data. Poméon et al., (2017) evaluated the remote sensing data and reanalysis data in the West African region and compared it with the available rain-gauge data [18]. Their study shows that the satellites, which their input data are infrared and microwave, provide better results. Tan and Santo, (2018) compared the GPM IMERG, TMPA 3B42, and PERSIANN-CDR networking data in Malaysia based on statistical indicators, and their results indicate that all data sets other than the PERSIANN-CDR are appropriate [19]. Gao et al., (2018) compared the two high-resolution monthly satellite data sets in Xinjiang, China; the results show that the CHIRPS data are more accurate than the PERSIANN-CDR on a monthly and annual basis [20]. Gorjizade et al. (2019) evaluate the accuracy of ERA-Interim, CHIRPS, and PERSIANN-CDR at the upstream of the Maroon Dam result show ERA-Interim has the best performance from the three gridded datasets in the correct detection of rainy days [21]. In Table 1, the details of some research work carried out in the world are presented on the gridded datasets.

Since weather stations in Iran are dispersed and have incomplete information, comparing and evaluating the performance of satellite precipitation data are very necessary that can be also useful to improve the performance of future versions of satellite precipitation data. Therefore, the purpose of this study is to evaluate the consistency of PERSIANN-CCS, ERA5, and TRMM models in the Idenak region with local measurements. It should be noted that this study is one of the first studies to use the ERA5 model in this region, Iran, and the world.

2- Material and Methods

2.1.Study Area

Maroon dam basin is one of the sub-basins of the Maroon-Jarahi River basin located in southwestern Iran in Kohgiluyeh and Boyer Ahmad Province. The area of this region where is located in the geographical range of 50 ° 15 ‘ to 51° 10 ‘east and 30 ° 44’ to 31 ° 21 ‘ north is about 2750 km^2. The highest and lowest elevations of this area are 3482 and 585 meters respectively. In the present study, according to the data approved by the Ministry of Energy, the daily precipitation data of four stations including Dehno, Ghale-Raeesi, Idenak, and Margoon in the study area between 2003 and 2014 with the characteristics given in Table 2 has been used. Figure 1 shows the geographic location of the study area.

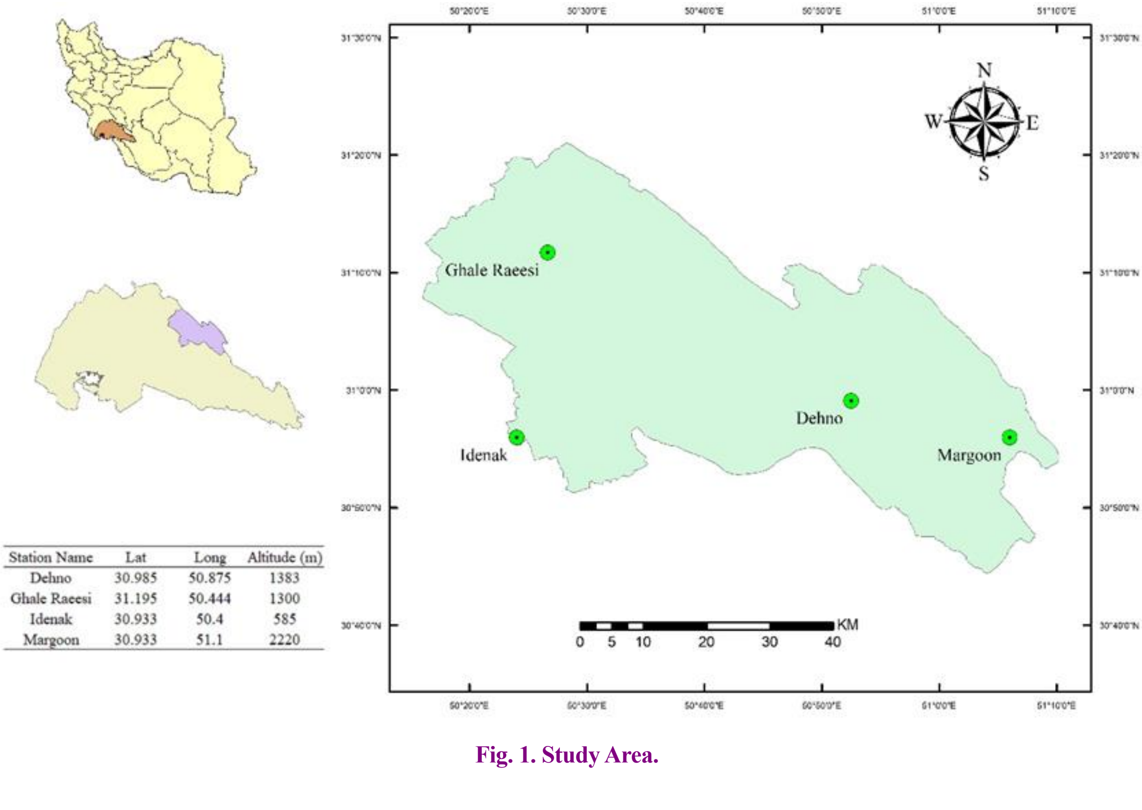

Fig. 1. Study Area.

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

Researchers	Study area	Period	CC	RMSE (mm/day)	POD	Refrence
Gorjizade et al., (2019)	Upstream of maroon basin, Iran	1 jan 2003 to 31 Dec 2014	0.364-0.636	4.864-9.980	0.282-0.419	[25]
Tan and Santo, (2018)	Malaysia	12 March 2014 to 29 February 2016	0.5–0.6	12.94–14.93	0.86–0.89	[19]
Wang et al., (2017)	Mekong River Basin, Thailand	April to January 2016	0.58	-	0.73	[26]
Yuan et al., (2017)	Chindwin River Basin, Myanmar	April to January 2016	0.22–0.32	9.1–24.7	0.12–0.21	[27]
Tan et al., (2017)	Singapore	April 2014 to January 2016	0.53	11.83	0.78	[12]
Xu et al., (2017)	Southern Tibetan Plateau	May to October 2014	0.46	7.16	0.69	[8]
Kim et al., (2017)	Korea, Japan	March to August 2014	0.53–0.68	6.68–23.41	0.6–0.73	[28]
Tang et al., (2016)	China	April to December 2014	0.96	0.5	0.91	[29]
Sharifi et al., (2016)	Iran	March 2014 to February 2015	0.4–0.52	6.38–19.41	0.46–0.7	[30]
Sahlu et al., (2016)	Blue Nile Basin	May to October 2014	0.55	-	0.87	[31]
Ning et al., (2016)	China	April 2014 to November 2015	0.68	6.43	0.79	[32]
Guo et al., (2016)	China	12 March 2014 to 31 March 2015	0.93	0.56	-	[33]
Tang et al., (2015)	Ganjiang River Basin, China	May to September 2014	0.62–0.9	4.44–13.09	-	[34]

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

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

Dataset Name	Coverage	Spatial resolution	Type	Data Use
TRMM-3B42-V7	50°N–50°	0.25° × 0.25°	Satellite-Gauge	1 Jan 2003-31 Dec 2014
ERA5	Global	0.25° × 0.25°	ReAnalysis	1 Jan 2008-31 Dec 2014
PERSIANN-CCS	Global	0.04° × 0.04°	Satellite-Gauge	1 Jan 2003-31 Dec 2014

2.2. Precipitation Dataset

In this study, the data series of TRMM, ERA5, and PERSIANN-CCS were considered to evaluate precipitation data. So, in this section, a general overview of each data series is presented. The general profile of the data series used is given in Table 2.

2.2.1. TRMM dataset

The TRMM satellite was launched on November 28, 1997, in collaboration with the United States and Japan's space agency, in an almost circular orbit at an altitude of 403 kilometers, with an angle of 35 degrees to the equator orbit, with a period of 91.5 minutes. This satellite aimed to improve precipitation estimates in the tropics, which includes a large amount of earth precipitation, to use the satellite's data to measure precipitation at land levels especially those that do not have statistic data and recorded information. The TRMM satellite precipitation sensors include precipitation radar, TRMM microwave image sensor, and infrared and visible scanners. The products of this satellite are classified into three levels. TRMM's climate products have a variety of outputs that, the latest product is called 3B42-V7. In this study, the daily precipitation data of the last product with a spatial resolution of 0.25 ° was used.

2.2.2. ERA5 Dataset

ERA5 is a new reanalysis data set (fifth generation) developed by the European Center for Medium-Range Weather Forecasts (ECMWF). The most significant upgrades of this dataset are a better spatial network (31 km vs. 79 km), higher temporal resolution (one hour versus 3 hours), a 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 compared to ERA-Interim [22] (Urraca et al., 2018)the new global reanalysis from the ECMWF, and COSMO-REA6, the regional reanalysis from the DWD for Europe. Daily global horizontal irradiance data were evaluated with 41 BSRN stations worldwide, 294 stations in Europe, and two satellite-derived products (NSRDB and SARAH. The dataset covers data from 1950 to the near present time, but while the information is being extracted, only the information for the period 2008-2018 is available. In this study, daily precipitation data of ERA5 with a spatial resolution of 0.25 ° was used, and the data were extracted by using ECMWF_Web_API. The instructions for downloading the data are described in the following link.

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

2.2.3. PERSIANN-CCS Dataset

PERSIANN-based satellite data is a precipitation estimation algorithm using remote sensing in which the basic algorithm is based on an artificial neural network. The basic input of this model is the temperature 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 because the distance of this type of satellite is much higher than that of polar satellites. By using these images, PERSIANN estimates the precipitation rate at a given time [23] (Hong et al., 2004). To increase the 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-CCS data is the developed generation of PERSIANN-based satellite data. PERSIANN-CCS-based satellite data generation algorithm can classify clouds based on altitude, geographic range, and texture diversity (gender) of the clouds. In this study, daily precipitation data of PERSIANN-CCS using a spatial resolution of 0.04 degrees was used.

2.3. Evaluation Indicators

Precipitation data obtained with the rain-gauge stations do not match the satellite precipitation dataset due to differences in scale [2] (Duan et al., 2016)and independent ground data are available from a network of 101 rain gauges during 2000–2010. The eight products include the Version 7 TRMM (Tropical Rainfall Measuring Mission. Rain-gauge data are scaled to the same scale as satellite-based precipitation with different interference techniques, such as Inverse Weighting (IDW), Thiessen Polygon, and Kriging methods. However, any interpolation method has its advantages and disadvantages. Also, the function of each interpolation method varies from region to region, and the uncertainties and errors of the interpolation methods are also added to this process. Therefore, the rain-gauge data are important to ensure the accuracy of the satellite data [20] (Gao et al., 2018). In this study, the IDW method and the spatial analysis were used for annual and monthly evaluation. Furthermore, to daily evaluation, the precipitation data of the cells including the rain-gauge were extracted, and the overall assessment (continuous statistical criteria) and precipitation detectability (categorized statistical criteria) was implemented to analyze these data. These criteria are presented in Table 3.

In this table, the Correlation Coefficient (CC) represents the linear correlation between observation data and simulation data which varies from -1 to 1. CC = 0 indicates that there is no linear correlation between observation and estimated data; values -1 and 1 show a completely negative and positive correlation respectively [19] (Tan and Santo, 2018). 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 [24] (Worqlul et al., 2014). Based on RMSE values, the quality of the simulation is assessed. The Relative Bias (BIAS) shows how much the simulated values differ from the observed values. If this value is greater than zero, the model estimates the precipitation more, and if it is smaller than zero, it indicates that precipitation is estimated by the model less, and if the

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

Statistical metric	Equation	Optimal value
Correlation Coefficient (CC)	$CC = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2}\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2}}$	1
Root mean squared error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - G_i)^2}{n}}$	0
Bias	$BIAS = \frac{\sum_{i=1}^{n}(P_i)}{\sum_{i=1}^{n}(G_i)} - 1$	0
Probability of detection (POD)	$POD = \frac{H}{H+M}$	1
False ALARM ratio (FAR)	$FAR = \frac{F}{H+F}$	0
Critical success index (CSI)	$CSI = \frac{H}{H+M+F}$	1

value is equal to zero, it indicates that there is no error.

In addition, three statistical classification indices including False Alert Rate (FAR), Probability of Detection (POD), and Critical Success Index (CSI) were used to assess the accuracy of the model in determining the occurrence of precipitation. FAR which is the ratio of registered participation number to all registered precipitation represents a part of the estimated precipitation spots of the model lacking precipitation in the ground station. The optimal value of FAR is zero. POD is the ratio of the accurate estimated precipitation number to the total precipitation registered in ground stations, and its optimal value is one. CSI which is a combination of false alert of the estimation and missed events is a function of POD and FAR. This index expresses the probability of recognizing rainy and non-rainy days, and its optimum value is one.

Moreover, in Table 3, P_i 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.

3- Results and Discussion

3- 1- Evaluation and comparison of statistical indicators

The present paper compares the satellite precipitation estimated by the TRMM, ERA5, and PERSIANN-CCS to the observed precipitation of four rain-gauge stations located in the study area. Annual, Monthly, and daily evaluation of satellite precipitation productions was performed for all Stations, and the spatial comparison of the data sets with observational data has been presented at the monthly and annual scale.

Annual and Monthly Evaluation

For Dehno, Ghale-Raeesi, Idenak, and Margoon stations, the evaluation results have been provided by the CC, RMSE, and BIAS indicators monthly in Figure 2. BIAS values for monthly precipitation indicate that the BIAS values of the PERSIANN-CCS model at all stations except Dehno station are more than other models while at the Dehno Station, the TRMM model has the highest BIAS values. Moreover, BIAS values represent the overestimation and under-estimation of PERSIANN-CCS, ERA5, and TRMM models. For example, at Dehno Station, the monthly precipitation of the TRMM model is low for all months except July, August, and October, and it is over-estimated in the PERSIANN-CCS in April, May, August, and October, and underestimated for the rest of the months. Furthermore, monthly precipitation is overestimated at the Idenak station obtained by the ERA5 model at all months, except for September, and in September, its values are estimated to be lower than that of observation precipitation by 70 percent. Relatively, the lowest BIAS values in the Dehno and Margoon stations are obtained with the ERA5 model whereas, at the Ghale-Raeesi and Idenak stations, the lowest BIAS values are reached by the TRMM model.

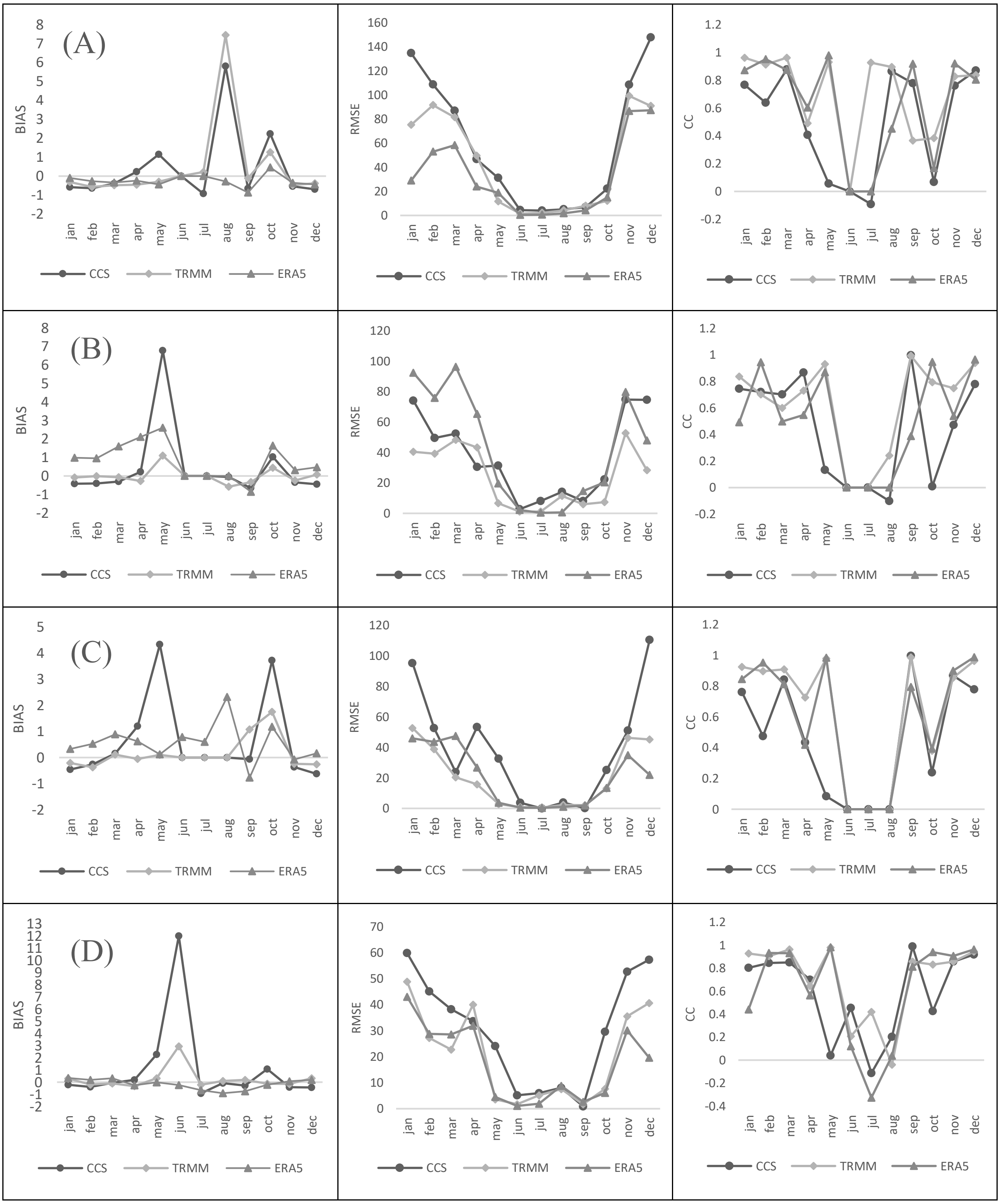

Fig. 2. Comparisons of the three statistical indices from ERA5, TRMM and PERSIANN-CCS against gauge observations.

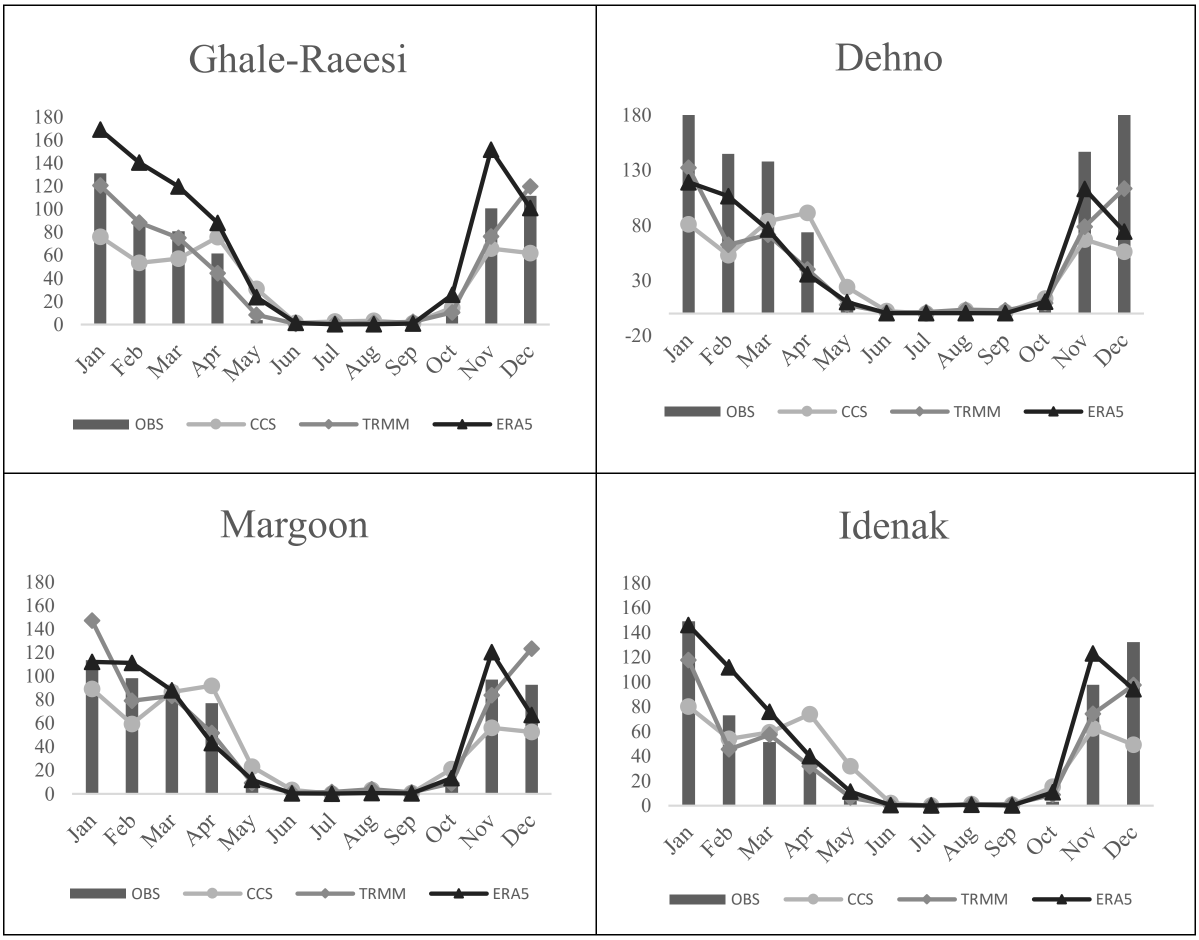

Fig. 3. Variations of monthly-mean precipitation over 2003–2014 from TRMM, ERA5 PERSIANN-CCS and gauge observations

Considering the RMSE values shown in Fig.2, it is concluded that the accuracy of model estimation varies in different stations and months, for instance, at the Ghale-Raeesi station, in April, the RMSE value of the PERSIANN-CCS model is better than that of the other two models which indicates that PERSIANN-CCS model is more suitable in April and at the Ghale-Raeesi station. However, precipitation values do not differ significantly in warm months of the year due to fairly accurate estimation of the satellite data precipitation rate that estimates precipitation in the warm months of year zero and close to zero. As a result, the ERA5 and TRMM data provide better results, for example, ERA5 at the Dehno station and TRMM at Ghale-Raeesi station have higher consistency than data from the two other models.

In addition, according to the CC values shown in Fig. 2, based on the highest CC values in different months in all four stations, satellite data can be used to complete the precipitation data series where there are missing data, or data are unreliable. For example, in January at Dehno Station, the best model for completing data was TRMM, and in February, at the Ghale-Raeesi Station, the ERA5 model, and in December, at Dehno Station, the PERSIANN-CCS model could be employed to complete missing data.

The mean monthly precipitation values for rain-gauge observations and satellite estimates are presented in Fig.3. In this figure, it is shown that the highest precipitation values occur from November to April, and the maximum precipitation occurs in January. According to Fig.3, in all monthly precipitation estimations, TRMM is in good agreement with observational data. As mentioned above, in June, July, August, and September, TRMM, ERA5, and PERSIANN-CCS models and observational data are consistent. Therefore, it can be concluded that in the warm months of the year, all three satellite models have worked well because their values are in good agreement with observational data. In Fig.3, the differences between each model and the observational data are determined on a monthly scale, for example, at the Margoon Station, the TRMM model in January, May, October, and December has overestimation, and the precipitation rate in February, March, April, and November has been underestimated.

Using the IDW method, observational data were interpolated and their spatial distribution was plotted. Then two satellite products were compared with the plotted spatial distributions. It should be noted that PERSIANN-CCS has a higher spatial resolution (0.04 degrees) than that of the

TRMM model (0.25 degrees). Fig.4.1 and 4.2 represent the spatial distribution of the average monthly precipitation values for the Idenak region in the evaluation years. It is clearly seen that the observation precipitation in the eastern region of Idenak is higher than elsewhere due to the higher height of the east of the study area. Moreover, areas with high precipitation are concentrated near the Margoon station at the altitudes of the beginning of the basin. According to Fig.4.1 and 4.2, in all months, the minimum and maximum monthly precipitation rates estimated by ERA5 and then TRMM are closer to those of observational data compared to PERSIANN-CCS. However, the spatial distribution of precipitation in the ERA5 model varies with that of observational values. Also, in the west of the study area, the highest precipitation rate occurred where the Ghale-Raeesi station is located, but in both the TRMM and PERSIANN-CCS models, this distribution is accurately predicted. The values of the annual precipitation series are shown in Fig.5. The annual TRMM and PERSIANN-CCS data from 2003 to 2014 and the annual ERA5 data from 2008 to 2014 are implemented to analyze the long-term precipitation characteristics of this region. As it is known, TRMM and PERSIANN-CCS satellite models have been underestimated for most of the years while the ERA5 model has overestimated all stations except Dehno Station. For instance, at the Ghale-Raeesi station, the annual observational precipitation value was 697 mm in 2009 while this value is about 617, 664, 836 mm obtained with the TRMM, PERSIANN-CCS, and ERA5 models respectively.

To investigate spatial features, spatial variations of the average annual precipitation values during the assessment period are shown in Fig.6. According to Figure 6, the region where the highest precipitation rate occurs annually is the half-eastern part of the study area near Dehno Station which is correctly predicted by the TRMM and PERSIANN-CCS models. However, the highest precipitation level estimated by the ERA5 model shows that the highest precipitation rate occurs in the half-western part of the study area. Although, regardless of the spatial distribution of precipitation by satellite models, the precipitation estimation range of the ERA5 model compared to other models is closer to the observational precipitation range. Furthermore, the lowest annual precipitation estimated by the TRMM and PERSIANN-CCS models is where the Ghale-Raeesi Station is nearly located whereas that of the ERA5 model is near the location of the Margoon Station. However, based on observational data, the minimum annual precipitation value occurs at the basin outlet where the Idenak station is located, and the basin has the lowest basin height.

3.1.1. Daily evaluation

Table 4 compares the statistical results of daily precipitation estimation between the rain gauge and the TRMM, ERA5, and PERSIANN-CCS models. According to Table 4, based on the RMSE statistic index, the ERA5 model has the best performance on the daily scale at all stations. This means that the best estimate is obtained with the ERA5 model at the mentioned stations. Therefore, the best estimate associated with Margoon station and the stations of Ghale-Raeesi and Idenak, and Dehno are at the following ranks. Since the most inappropriate model is known by the highest RMSE of the model, it is concluded that the worst estimation has been performed by the PERSIANN-CCS model at all stations, and the highest RMSE is associated with Dehno Station. This indicates that the estimates by satellite models differ in different locations. Because the RMSE for the estimates in all models and stations is less than 10, this represents a great simulation performed by three models.

According to the BIAS statistics in Table 4, it is concluded that the estimation of TRMM and PERSIANN-CCS models was low at all stations. However, in the ERA5 model, in all stations, except for the Dehno station, there is an overestimation, and the maximum BIAS is associated with the Dehno station in the PERSIANN-CCS data set. This means that in this model, the average daily precipitation rate is estimated to be about 46 percent lower than the actual one, and the lowest BIAS is related to the Margoon station in the TRMM model. It is also clear that the maximum BIAS range is associated with the Dehno station and the lowest is related to the Margoon station.

The correlation coefficient values of the observational and modeled data indicate that the daily correlation coefficient obtained with the ERA5 model is higher than that of the two other models in all stations. Furthermore, the best correlation coefficient is 0.73 which is reached by the ERA5 model and is associated with the Margoon station while the lowest CC is obtained with the PERSIANN-CCS model and is associated with Ghale-Raeesi Station. In addition, to complete lost data at these stations, it is possible to employ models whose CC values are higher.

The POD, FAR and CSI indicators were implemented to determine the limitation of precipitation detection using satellite precipitation algorithms. Table 5 illustrates the classification indicators for Dehno, Ghale-Raeesi, Idenak, and Margoon stations. The highest and lowest POD values are associated with TRMM at the Idenak station (equal to 0.49) and the Ghale-Raeesi station (equal to 0.2) respectively. POD=0.49 means that 49% of the days when the precipitation occurred has been correctly predicted by the model. Also, since the high values of FAR indicate that the number of non-rainy days estimated by the model is not in good agreement with the observational data, the highest FAR is obtained with the TRMM model at the Idenak station. This means that more than 41 percent of the predictions indicate rainy days while the rain has not actually happened. The smallest FAR value is obtained with the ERA5 model at Ghale-Raeesi Station at 7.3%.

Also, the highest and lowest CSI values are 46.5% and 18% which are reached by the ERA5 model at Idenak station and the TRMM model at the Ghale-Raeesi station respectively. CSI=0.465 means that the accuracy of the model in the determination of rainy days and non-rainy days is 46.5%. According to the CSI values given in Table 5, it is concluded that at all stations except the Ghale-Raeesi station, ERA5 model, and the Ghale-Raeesi station, the PERSIANN-

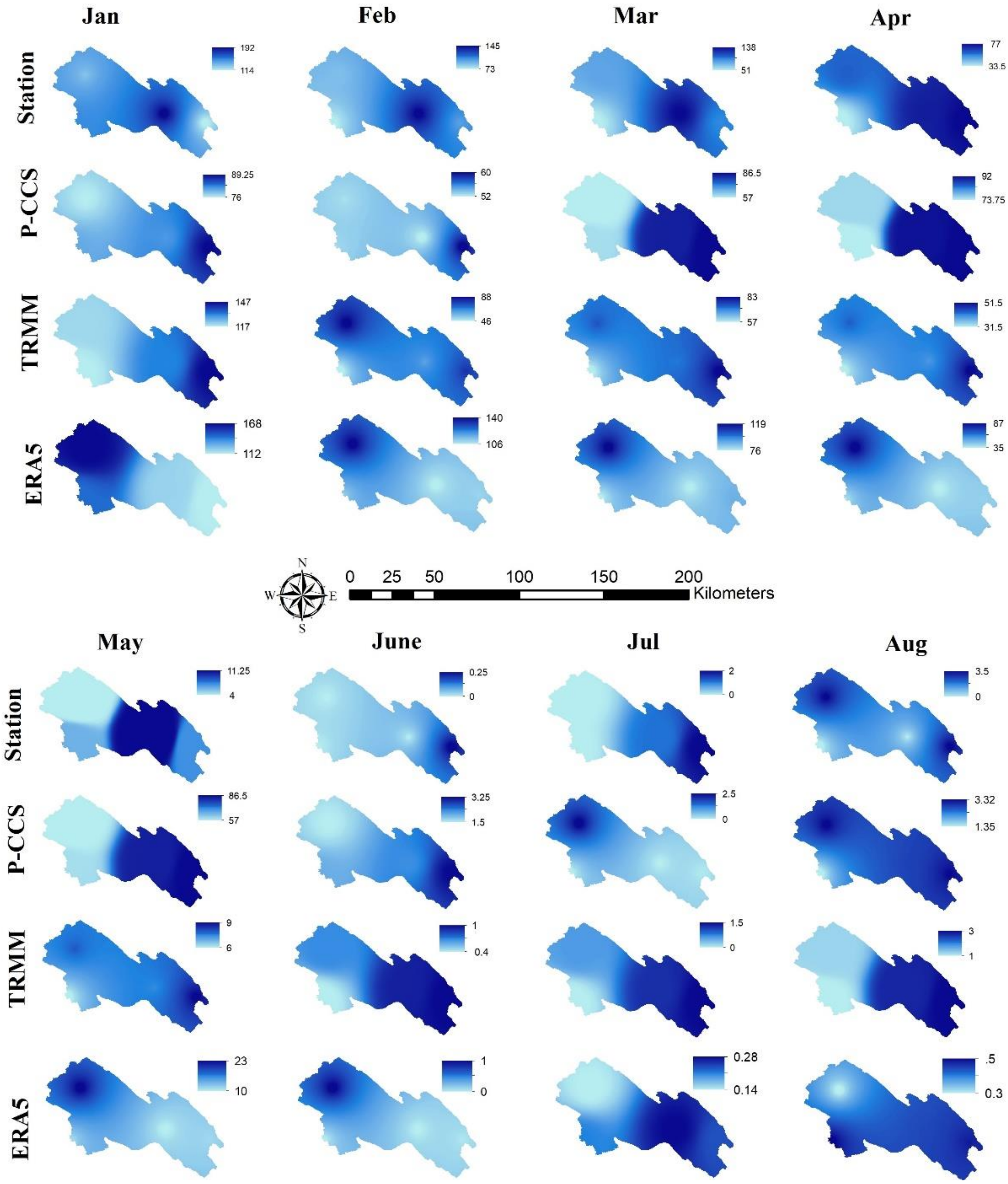

Fig. 4.1. Spatial distribution of monthly mean precipitation for the period from 2003 to 2014.

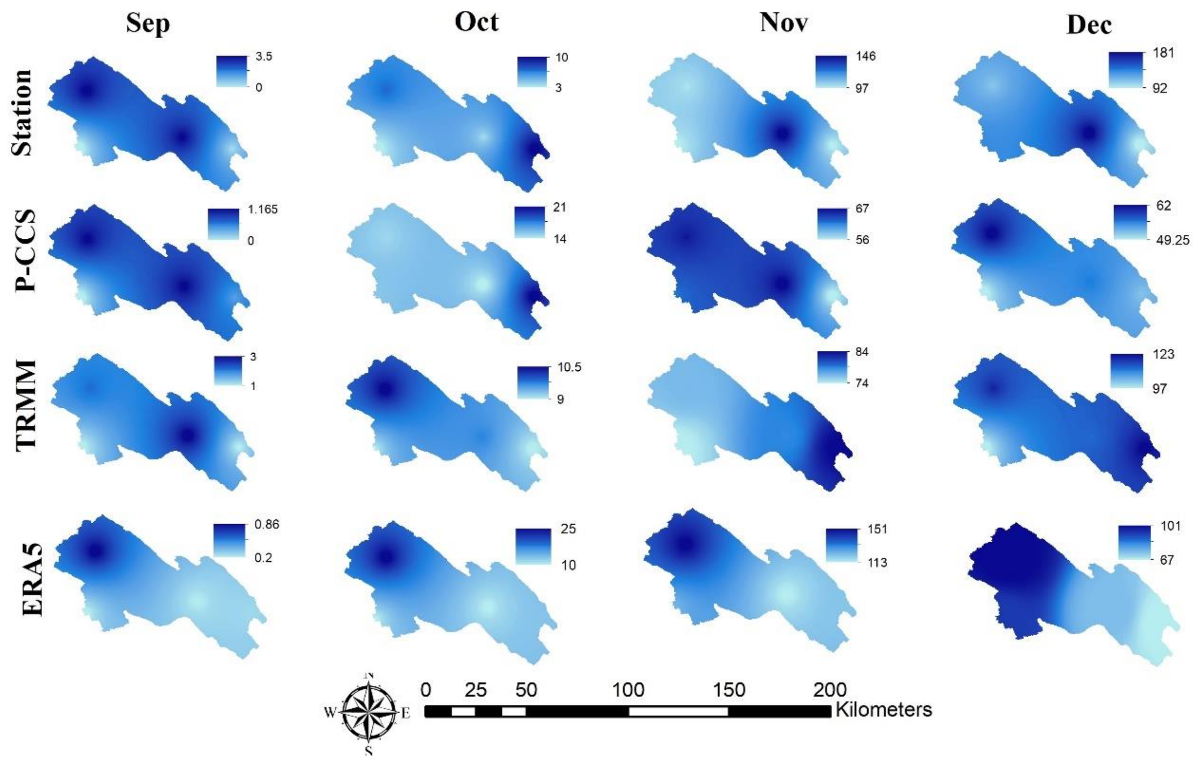

Fig. 4.2. Spatial distribution of monthly mean precipitation for the period from 2003 to 2014.

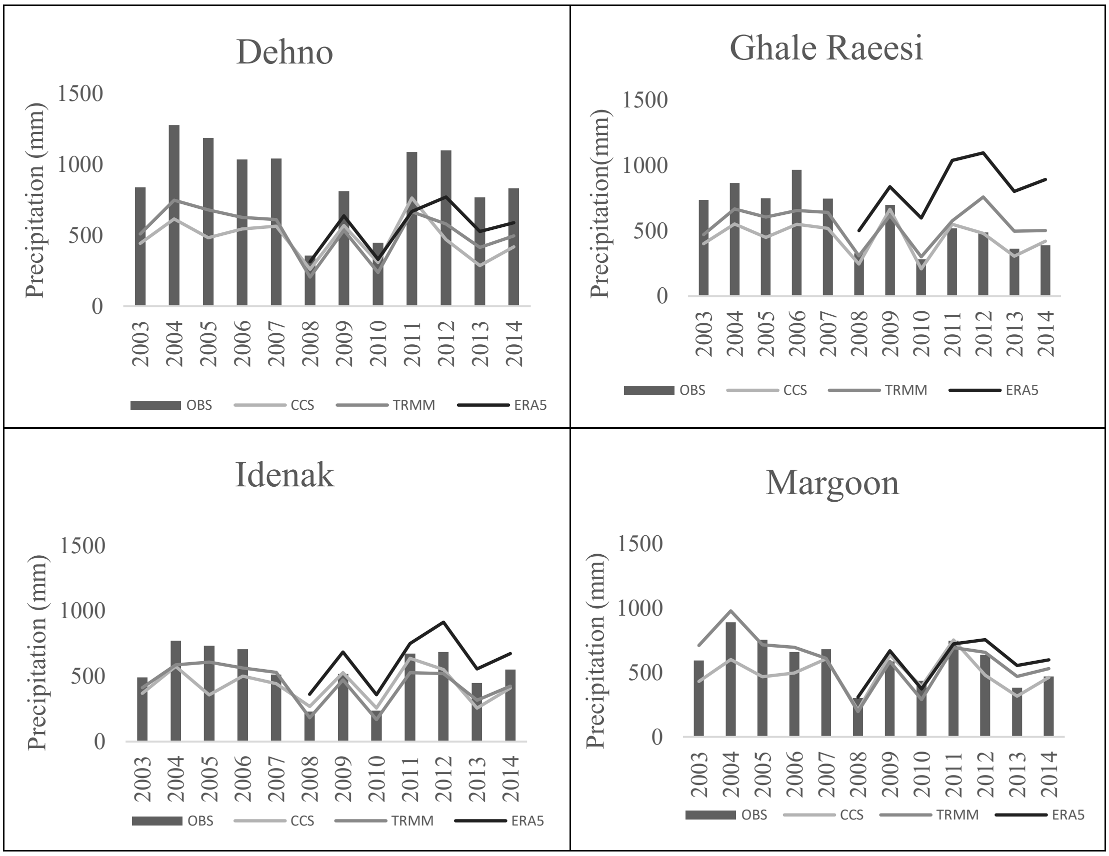

Fig. 5. Variations of annual-mean precipitation from gauge observations and TRMM, ERA5 and PERSIANN-CCS.

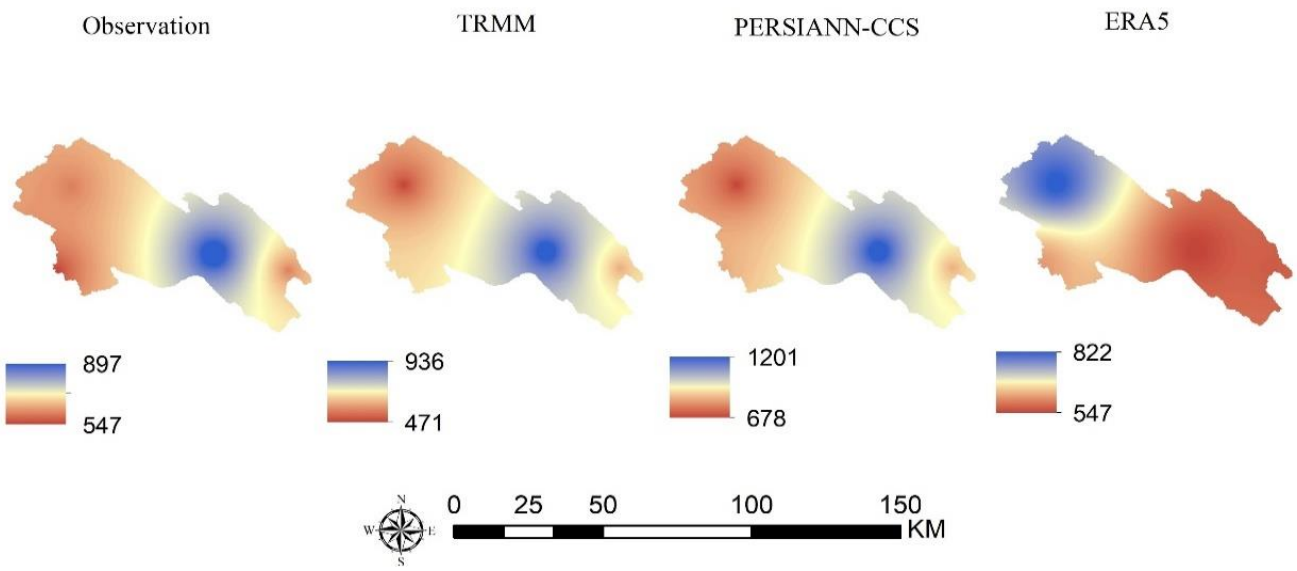

Fig. 6. Spatial distribution of annual mean precipitation in evaluation years.

Table 4. Comparison of daily precipitation between the precipitation gauges and the TRMM, ERA5, and PERSIANN-CCS from 01 Jan 2003 to 31 Dec 2014.

Station	Datasets Name	RMSE	BIAS	CC
Dehno	PERSIANN-CCS	9.83	-0.46	0.43
	TRMM	9.24	-0.41	0.53
	ERA5	7.24	-0.29	0.65
Ghale-Raeesi	PERSIANN-CCS	7.009	-0.25	0.36
	TRMM	6.59	-0.07	0.52
	ERA5	6.08	0.88	0.64
Idenak	PERSIANN-CCS	7.36	-0.21	0.38
	TRMM	6.58	-0.19	0.57
	ERA5	5.15	0.28	0.72
Margoon	PERSIANN-CCS	6.06	-0.18	0.45
	TRMM	6.95	-0.001	0.56
	ERA5	4.21	0.117	0.73

CCS model has higher accuracy than that of the other models for correct detection of rainy and non-rainy days.

4- Conclusions

This study evaluates and compares the annual, monthly, and daily precipitation data of observational-satellite data of TRMM and PERSIANN-CCS over the period 2003-2014 and the ERA5 reanalysis model for the period of 2008-2014 with observational data in the region of Idenak at 4 weather stations of Dehno, Ghale-Raeesi, Idenak, and Margoon.

The annual precipitation distribution has been generated by the IDW method to assess annual precipitation, and the estimated and observed datasets were compared. To monthly assessment, spatial precipitation distribution maps have been generated, and CC, RMSE, and BIAS evaluation indicators were also calculated. In addition to evaluation indicators, the classification indicators of FAR, POD, and CSI were also implemented.

In estimating annual precipitation, the results indicate that the ERA5 and TRMM data are in good agreement with observational data than the PERSIANN-CCS data. However, in terms of the spatial distribution of precipitation, the TRMM model is more consistent with observational data since the highest observational and estimated precipitation obtained with the TRMM model are for the eastern part of the study area while that of the ERA5 model is observed in the western part.

Table 5. Comparison of daily precipitation Statistical classification indices between the precipitation gauges and the TRMM, ERA5, and PERSIANN-CCS from 01 Jan 2003 to 31 Dec 2014.

Station	Datasets name	POD	FAR	CSI
Dehno	PERSIANN-CCS	0.398	0.375	0.321
	TRMM	0.225	0.267	0.208
	ERA5	0.403	0.201	0.36
Ghale-Raeesi	PERSIANN-CCS	0.334	0.346	0.28
	TRMM	0.206	0.315	0.188
	ERA5	0.247	0.073	0.242
Idenak	PERSIANN-CCS	0.418	0.396	0.328
	TRMM	0.493	0.412	0.366
	ERA5	0.487	0.09	0.465
Margoon	PERSIANN-CCS	0.41	0.340	0.338
	TRMM	0.315	0.32	0.273
	ERA5	0.438	0.144	0.407

Monthly precipitation results are consistent with annual precipitation results, but daily, at all stations, based on the RMSE and CC values, the best model for estimating daily precipitation was ERA5. It was found that the TRMM and PERSIANN-CCS models underestimate the precipitation rate while the ERA5 model overestimates it at all stations except the Dehno Station. Moreover, based on the CSI index (Combined POD and FAR indices) at all stations except the Ghale-Raeesi station, the ERA5 model is more capable of detecting the correct rainy and non-rainy days which indicates that in this area, appropriate reanalysis data performs better than satellite-gauge data.

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